The increasing focus on sustainability is pushing companies to update their production systems. However, current quality management approaches, focused on mass production and minimal variations, might hinder this shift. Zero Defect Manufacturing (ZDM), an emerging quality approach, leverages Artificial Intelligence (AI) to monitor products and processes in real-time, allowing for early defect detection and prevention. However, successfully adopting AI-driven ZDM requires expertise in AI and production, along with overcoming technological and organizational challenges.

This licentiate thesis aims to investigate the adoption of AI-driven ZDM in production systems, examining its impacts, challenges, and facilitators during the development process. The research involved collaboration with a heavy-duty transmission component company and explored real-world AI for ZDM in production, providing practical adoption insights. The findings provide recommendations that pave the way for a future of sustainable manufacturing.

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FACILITATING THE ADOPTION OF AI-DRIVEN ZERO DEFECT MANUFACTURING IN PRODUCTION SYSTEMS

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Abstract

The increasing focus on sustainability is pushing companies to update their production systems. These systems need to facilitate the production of products with the latest sustainable technologies and innovations, while also producing these new products with lower environmental impact. To maintain high customer satisfaction, these systems must consistently deliver high-quality products. However, current quality management approaches, focused on minimal variations, might hinder this shift.

Zero Defect Manufacturing (ZDM), an emerging quality approach, leverages Artificial Intelligence (AI) to monitor products and processes in real-time, allowing for early defect detection and prevention. Many production systems generate vast amounts of data which is often not used to its full potential. Research shows that AI has the potential to unlock the hidden insights within this data, leading to transformative improvements in quality and overall efficiency. However, successfully adopting AI-driven ZDM requires expertise in AI and production while also overcoming technological and organizational challenges.

The purpose of this licentiate thesis is to investigate the adoption of AI-driven ZDM in production systems, examining its impacts, challenges, and facilitators during the development process. The research involved collaboration with a company producing transmission components for the heavy-duty automotive industry. A two-year case study was conducted, enabling the in-depth exploration of data throughout the development of four real-world AI-driven ZDM applications in a production system. This approach provided valuable insights into the practicalities of adopting AI to ensure ZDM.

The findings show that successful implementation requires specific prerequisites: lean manufacturing practices lay the groundwork for AI integration, a high-impact quality issue motivates investment and data collection, collaboration among diverse experts is crucial, and robust IT capabilities ensure smooth data storage and analysis. Furthermore, anomaly-detection AI models and the generation of "plausible defects" are key enablers for overcoming data limitations in complex defect detection. The study emphasizes the importance of early engagement to identify data needs, define extraction methods, and address potential implementation limitations. In addition, it recommends an iterative approach to continuously improving the solution and incorporating feedback throughout the process. This comprehensive approach can pave the way for a future of sustainable manufacturing, leading to significant cost savings and increased customer satisfaction.
Sammanfattning

Den ökande fokuseringen på hållbarhet driver företag att uppdatera sina produktionssystem. Dessa system behöver underlätta produktionen av produkter med den senaste hållbara tekniken och innovationerna, samtidigt som de producerar dessa nya produkter med lägre miljöpåverkan. För att behålla hög kundnöjdhet måste dessa system konsekvent leverera produkter av hög kvalitet. Emellertid kan nuvarande kvalitetsledningsmetoder, som fokuserar på minimala variationer, möjlichen hindra denna förändring.

Zero Defect Manufacturing (ZDM), en framväxande kvalitetsmetodik, utnyttjar Artifificiell Intelligens (AI) för att övervaka produkter och processer i realtid, vilket möjliggör tidig upptäckt och förebyggande av defekter. Många produktionssystem genererar enorma mängder data som ofta inte används till sin fulla potential. Forskning visar att AI har potential att låsa upp dolda insikter inom denna data, vilket leder till transformerande förbättringar av kvalitet och övergripande effektivitet. Emellertid krävs det expertis inom AI och produktion, tillsammans med att övervinna teknologiska och organisatoriska utmaningar, för att framgångsrikt anta AI-driven ZDM.

Syftet med denna licentiatavhandling är att undersöka antagandet av AI-driven ZDM i produktionssystem, och att granska dess påverkan, utmaningar och möjliggörare under utvecklingsprocessen. Forskningen involverade samarbete med ett företag som producerar transmissionskomponenter för den tunga fordonstrad. En tvåårig fallstudie genomfördes, vilket möjligjorde djupgående utforskning av data under utvecklingen av fyra AI-drivna ZDM applikationer i ett produktionssystem. Denna metod gav värdefulla insikter i praktisk användning av AI för att säkerställa ZDM.

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Nicolas Leberruyer
Eskilstuna, March 2024
List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.


Work distribution: Nicolas initiated the paper and is the main author of the paper. He conducted the literature review and the case study. Jessica supported with ideas, structure and readability of the paper. Mats supported with the description of the methodology. Sara supported with the description of the developed AI solution. Jessica, Mats, and Sara gave comments to improve the structure and readability of the text.


Work distribution: Nicolas initiated the paper and is the main author of the paper. He conducted the literature review and the case study. Jessica, Mats, and Sara gave comments to improve the structure and readability of the text.


Work distribution: Nicolas initiated the paper and is the main author of the paper. He conducted the literature review and the case study. Mats provided support in refining the methodology and in highlighting the contributions. Jessica supported with ideas on the framework to use for the analysis. Mats and Jessica gave comments to improve the structure and readability of the text.
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1. Introduction

This section presents the research background, the problem statement, the research purpose and research questions and the scope of this thesis.

1.1 Research background

Customer satisfaction is vital for company success in today’s competitive world, and offering high-quality products is crucial for market share and profit (Thangiah et al., 2018). The growing focus on sustainability has raised two new things to consider for manufacturers. On one hand, they face the pressure to adapt their production processes and materials to minimize environmental impact. On the other hand, this focus on sustainability creates a demand for faster product adaptation (Jaeger et al., 2020; Bag et al., 2022). As consumers become more aware of the latest sustainable technologies and innovations, they expect manufacturers to develop and release new, even more environmentally friendly products at a quicker pace (Joyce et al., 2016). This creates a challenge for manufacturers: they need to not only produce in a sustainable manner, but also develop a culture of continuous improvement and rapid innovation to keep pace with evolving consumer preferences and technological advancements in the realm of sustainability. Current quality management approaches have been developed during an industrial period of mass production with the goal of achieving minimal variations through product commonality and process repeatability. Six Sigma and total quality management are two examples of well-known quality management approaches in today’s industrial production systems (Bhuiyan et al., 2005). These approaches provide tools to increase production system efficiency, minimize waste, and solve problems, and manufacturing companies have used continuous improvements in lean manufacturing for decades.

The need to consider customers’ desires into account has been a key driving force behind switching the production system to mass customization and even a mass personalization paradigm (Coronado et al., 2004). In this change of focus, resilience, reconfigurability, and flexibility are crucial components of competitiveness (Piccarozzi et al., 2018). As the quantity of similar products decreases due to product customization, it becomes more difficult to monitor their quality and processes using conventional statistical methods. This shows that the capacity to monitor quality may limit personalization; consequently, new ways for monitoring quality must be created (Da Silveira et al., 2001).
Zero Defect Manufacturing (ZDM) has emerged as a strategic approach addressing the need for defect-free production in the digital age. This shift reflects the growing demand for a data-driven approach to achieve higher quality in increasingly complex production systems (Powell et al., 2022). ZDM consists of a product-oriented approach which involves checking products, often at different stages, to find and fix problems (Azamfirei et al., 2023) and a process-oriented approach which focuses on monitoring and maintaining production equipment for optimal performance, preventing defects altogether (Psarommatis et al., 2020a). Furthermore, combining ZDM principles with AI offers a powerful pathway for defect prevention and waste reduction.

AI has emerged as a powerful and transformational technology with a wide range of applications. AI has the ability to drive sustainable development in the economic, societal, and environmental spheres (Goralski et al., 2020). Despite the vast amounts of data collected by companies, the integration of AI into quality management systems remains limited. Many companies cite a lack of emphasis on AI as a contributing factor to this gap, hindering the extraction of useful insights and the reduction of defects (Fragapane et al., 2023). AI acts as a key enabler for ZDM by analysing vast amounts of production data, identifying potential defects early on, and uncovering hidden patterns even before product completion (Caiazzo et al., 2022; Powell et al., 2022). This advancement goes beyond traditional quality approaches by combining data from various sources, including materials, processes, equipment, and machines (Caiazzo et al., 2022; Powell et al., 2022). This integration enables real-time monitoring, improved process optimization, and continuous learning, ultimately securing product quality (Haenlein et al., 2019; Kusiak, 2017).

Nevertheless, Betti et al. (2019) from the World Economic Forum (WEF) observed that companies’ adoption of Industry 4.0 technologies, which includes AI, has been slow. In 2018, the WEF started the lighthouse program to showcase best practices of Industry 4.0 technology adoption at scale. The WEF started scanning more than 1,000 leading manufacturers in all industries and geographical areas and, by January 2019, the WEF had selected 16 factories as “lighthouse factories” to demonstrate and promote what Industry 4.0 technologies can achieve (Betti et al., 2019). In January 2023, 132 lighthouse factories confirmed the possibility of influencing throughput, costs, or lead time using Industry 4.0 technologies. These lighthouse factories consider the adoption of Industry 4.0 technologies as a key lever to achieve strategic imperatives such as productivity, sustainability, and resilience. In those lighthouse factories, almost all use-cases report the use of AI, advanced analytics, machine learning, or predictive analytics (Betti et al., 2023). The WEF has estimated that about 10 million factories exist around the world to support in their transition. Despite AI’s potential to boost productivity, sustainability, and workforce capabilities, many companies struggle to implement and scale AI (Armutak et al., 2022). Therefore, the WEF recently published a guide-
line to help companies capture the full value of AI by fostering stakeholder collaboration and knowledge sharing (Basso et al., 2023).

1.2 Problem statement

Applying AI to ZDM is not a straightforward process and requires overcoming several challenges, including the lack of a standardized approach to collecting data from production systems. Often, a custom solution is required, but this is a highly time-consuming undertaking (Ngo et al., 2016). The development of an AI application requires many competencies; it is not sufficient to focus on only the development of AI models, as domain expertise from production specialists is also necessary (Caiazzo et al., 2022). Furthermore, to use the full potential of AI for ZDM, the quality of the data and the ability to learn from historical examples for predicting future outcomes are critical. Recent studies, on the other hand, say that the data quality is not good enough and that there are not enough or balanced data points about how defects are distributed compared to approved products (T. Lee et al., 2016; Kim et al., 2018; Bertolini et al., 2021). Although previous research has highlighted AI as a key technology contributing to ZDM (Caiazzo et al., 2022; Powell et al., 2022), interactions with industry are lacking as more research is done in laboratories than in industrial plants (Psarommatis et al., 2020a). According to Psarommatis et al. (2020a), defect detection on 2D products is mature whereas 3D products’ defect detection is not; moreover, the automotive business is under-researched despite the benefits of employing ZDM strategies there. Another study found that more attention should be given to the beginning of the manufacturing lifecycle to reduce and eliminate the propagation and, hence, the cost of defective products (Psarommatis et al., 2020b). Despite AI’s potential in industry, industrial applications are still few and limited to a small group of international companies (Bertolini et al., 2021). The majority of manufacturing companies lack a thorough plan and framework for integrating AI into their existing business models and processes (J. Lee et al., 2019).

Organizational challenges around technology, processes, and people can slow or impede AI adoption. One of the main barriers to the widespread industrial adoption of AI is the lack of a clear understanding of the AI technology and the lack of awareness of what can be achieved (LaValle et al., 2010). The economic and productive impact of real-world manufacturing is seldom discussed in the literature, making it harder for companies to understand the importance of this technology (Caiazzo et al., 2022).

In addition, limitations due to the technology itself and its flaws are also encountered. Generally, problems are related to the dataset needed to train the AI models. Indeed, if data is collected directly on the field, issues related to missing, bad quality, or even insufficient data are frequently encountered (Bertolini et al., 2021; J. Lee, 2020). A typical case is for defect detection
when the objective is to distinguish very common events from rare ones (i.e., defects). Indeed, when one sample class has many more samples than the other, it creates a bias in the AI models, known as an imbalanced dataset (Bertolini et al., 2021). Lastly, an extensive understanding of machinery and potential problems is frequently required to process the data effectively. However, this knowledge is often difficult to find and creates the need to interact and involve more people, thereby posing an additional obstacle to effective implementation (Caiazzo et al., 2022).

1.3 Research purpose and research questions

The **purpose** of this licentiate thesis is to investigate the adoption of AI-driven ZDM in production systems. Three research questions have been formulated to help accomplish this purpose.

**Research Question 1 (RQ1):** What are the **impacts** of adopting AI-driven ZDM in production systems?

**Research Question 2 (RQ2):** What **challenges** hinder the adoption of AI-driven ZDM in production systems?

**Research Question 3 (RQ3):** How can we **facilitate** the adoption of AI-driven ZDM in production systems?

1.4 Scope

The research project originated from an industrial need to develop a strategy and acquire expertise for building a roadmap dedicated to a specific innovative technology—namely Artificial Intelligence. The scope was to look into how AI can be used, what benefits it might have for the company’s production system and where it is suitable to apply. Following some preliminary investigations, the purpose was set to investigate the adoption of AI-driven ZDM in production systems. Therefore, research questions are of the exploratory type, with "what" and "how" questions, and the research is classified as applied research, which entails gaining insights that might lead to the establishment of theoretical frameworks to explain how to best implement a new technology in an organization.

This research examines the adoption of AI in an industrial production context with a focus on people, process, and technology. The objective of this study is not the technological advancement of AI per se, but rather the application of existing knowledge and the consequent adaptation of existing processes. However, the findings could contribute to the advancement of AI technologies.
This licentiate thesis (half-time of the PhD: 2.5 years into the doctoral studies) focuses on defect detection strategies for complex industrial products. The detection of defects is the starting point for implementing ZDM and also constitutes the foundation for the development of the other ZDM strategies (Psarommatis et al., 2020a). In order to generate solutions to the research questions, the researcher performs a longitudinal case study in the automotive sector, specifically from a company that manufactures transmission components for heavy-duty vehicles. Each application of AI-driven ZDM is intended to provide insights that can be applied to different sorts of similar industries. However, limitations to this generalization will be stated. Within the scope of this research, we define AI adoption in production systems as the strategic integration of artificial intelligence applications into existing manufacturing processes and infrastructure. This integration aims to achieve positive advancements in efficiency, performance, or other key metrics. To enable ZDM, one must maximize the benefits of the ZDM framework for the considered production system to ensure that the solution is used in a sustainable manner, meaning that its use will remain over time.

1.5 Outline of the thesis

The remainder of this thesis contains the frame of reference, the research methodology, a summary of the appended papers, and the results. Finally, there is a discussion chapter. The three papers that support this thesis are added at the end.
2. Frame of reference

This chapter presents the frame of reference for this research. It starts by defining key topics, such as production systems and Zero Defect Manufacturing. Then a description of industrial artificial intelligence and its implementation is given. Finally, strategies to study technology adoption in production systems are discussed.

2.1 Zero Defect Manufacturing

In this research, the focus is on the production system, which is defined as a coordinated arrangement, ranging in complexity, of people, materials, tools, machines, software, facilities, and processes working collaboratively to transform raw materials into finished products (Bellgran et al., 2010). It encompasses organized technology, personnel, energy, and information, extending beyond the factory floor to include aspects such as planning, scheduling, quality control, inventory management, and logistics (Groover, 2015).

2.1.1 Quality management

Quality management is a multifaceted discipline that encompasses various methodologies, philosophies, and techniques aimed at ensuring that products meet or exceed customer expectations. To obtain quality, organizations must first establish their goals, policies, and vision. In the literature, three managerial processes that help organizations achieve their goals are often discussed (Juran et al., 2010):

- Quality planning (also known as quality by design) is the systematic process of creating products and services to achieve new objectives while also meeting the needs of customers. "Quality does not happen by accident; it must be planned."

- Quality control is a universal managerial process for ensuring operational stability, preventing negative change, and "maintaining the status quo". Quality control is also defined as "a process for meeting established goals by evaluating and comparing actual performance to planned performance and taking action on the difference."

- Quality improvement is the process of achieving breakthrough levels of performance by removing waste and faults in order to lower the cost of low-quality products. "All improvement takes place project by project... and in no other way".
The term "quality" is inherently subjective and has several meanings depending on the context. In the context of production, quality means conformance to specifications and an emphasis on "doing right the first time" (Crosby, 1979). Poor quality is associated with high levels of scrapping and reworking efforts. In this context, quality improvements are expected to result in cost reductions which Crosby (1979) refers to "conformance to requirements". Higher quality, as defined from the user’s perspective, refers to enhanced functionality, more features, and other enhancements that come at a higher cost. Hence, Deming (1986) said "quality should be aimed at the needs of the customer, present and future". This thesis supports Juran’s "fitness for use" definition of quality which emphasizes that quality consists of two components: the product must be "free from deficiencies" and must possess "features of products" that meet customer expectations, thereby offering a comprehensive view of quality (Juran et al., 2010).

The approach emphasized in quality improvement initiatives involves addressing both technical aspects, such as processes and technology, and human factors like training, motivation, and teamwork. It highlights the importance of not relying exclusively on advanced technology or process optimization, but also considering factors such as individuals’ skills, involvement, and commitment to quality improvement initiatives (Juran et al., 2010). This holistic perspective remains influential in modern operation management practices, as proven by publications such as "The Toyota Product Development System: Integrating People, Process, and Technology" (Morgan et al., 2006).

2.1.2 Challenges in product quality evaluation
Determining product quality can be a complex and challenging process. Complex products with intricate sub-components pose inspection challenges, often due to internal workings not being accessible or due to too hot conditions (J.-C. Ren et al., 2022). In such cases, dynamic performance testing becomes the only way to evaluate specific quality aspects. However, designing a comprehensive test that captures all potential failure modes while keeping to production cycle time constraints proves to be a hard task.

Further complicating matters, dynamic testing generates a multitude of time-dependent parameters. Combining these parameters for a holistic quality evaluation and establishing clear pass/fail criteria present difficulties (Jia et al., 2023). Uncontrolled variables present in the test environment might also have a negative impact on data accuracy, dependability, and consistency. Mitigating their influence in industrial contexts is a continuing issue (Alrufaihi et al., 2022).

Different customer usage patterns might also create different quality requirements, which historically were from distinct geographical zones, but this
is no longer necessarily true, making it difficult to divide customers into separate categories to rationalize the customization (Chen et al., 2019).

The subjective nature of many quality measurements is another obstacle to the quality evaluation being totally trustworthy. Aspects like aesthetics, smell, taste, sound, and touch are inherently tied to individual perceptions. To illustrate, Ladegaard et al. (2002) demonstrate that training operators to analyse the quality of pump engines is not only difficult, but also time-consuming despite the need for extensive training. The lock industry also employs the tactile sense of humans to evaluate the quality of locks (Andersson et al., 2022). Acceptable noise levels within an automobile, for instance, are entirely subjective and dependent on the driver’s tolerance level, auditory capacity, and personal preferences. Numerous recent publications have proposed methods for standardizing and regulating these human-centric measurements, demonstrating the significant investment that the automotive industry has made in this field (Jin et al., 2021; Wang et al., 2021; Liu et al., 2021; Qian et al., 2021).

Statistical quality control is commonly used for monitoring production processes; however, it has limitations (Bisgaard et al., 2005; Zan et al., 2020). This vulnerability originates from its assumptions:

- **Steady state**: This statistical quality control presumes a stable monitored variable with a constant mean and standard deviation, adhering to a normal distribution.
- **Known limits**: It operates under the assumption that historical data provides established upper and lower limits.
- **Uncorrelated variables**: This statistical quality control assumes that the monitored variables exist in isolation, free from any correlation with one another.
- **Trend interpretation**: Recognizing and interpreting emerging trends can be a complex endeavor.

These limitations become particularly pronounced when dealing with complex quality evaluations. In such scenarios, the time-dependent nature of means and standard deviations, coupled with intricate parameter correlations, renders the notion of absolute limits hard to define and apply. Understanding these problems can help develop better product quality evaluation methodologies. The persistent pursuit of this objective is crucial for achieving customer satisfaction and driving organizations ahead in today’s highly competitive environment.

### 2.1.3 ZDM framework

In the 1960s, the "zero defects" concept was first introduced in the United States. The principles inspired Japanese businesses like Toyota to adopt zero defects (Kolesar, 1994; *History of Toyota* 2023). This led to the widespread adoption of quality control practices in Japan. In subsequent decades, new
quality management approaches emerged, such as Six Sigma, Lean Production, and Total Quality Management. These approaches all share the goal of achieving zero defects. By employing statistical methods and data-driven decision-making, organizations can systematically identify areas for improvement, reduce defects, enhance efficiency, and ultimately deliver higher-quality products or services. Examples of the tools include scatter diagram, control chart, regression analysis, statistical process control, pareto analysis, and design of experiment.

ZDM is a new paradigm that goes beyond standard quality management methodologies like Total Quality Management and Six Sigma (Powell et al., 2022). The acceleration of digital transformation in the industrial sector has been critical in enabling the realization of the ZDM paradigm, due primarily to the advancement of sensor technology and the industrial internet of things.

ZDM is structured around four strategies: detection, repair, prediction, and prevention (Psarommatis et al., 2020a), as illustrated in Figure 2.1. ZDM can be applied using two different approaches: product-oriented (focusing on defective parts) and/or process-oriented (focusing on defective equipment).

![Figure 2.1. ZDM strategies](image)

First, the reactive strategies encompass detection, which involves utilizing manufacturing data to identify defects at the earliest possible stage, and repair, a strategy aimed at addressing the root cause of defects. Detection is by far the largest strategy addressed in the technical literature (Caiazzo et al., 2022; Powell et al., 2021), which has shown that it is often an enabler for the two proactive strategies (Psarommmatis, 2021).
The prediction strategy leverages incoming material and production system data to forecast output outcomes. This strategy proves effective in industrial systems where product quality relies on dimensions and geometry, such as multi-stage machining and assembly processes (Powell et al., 2022). For scenarios where direct action can be taken on the production system, a preventative strategy demands comprehensive knowledge of the production process and finds applicability in continuous or multistage machining processes where effective countermeasures can be introduced for the compensation of product defects and/or the correction of process defects (Powell et al., 2022).

The detection strategy is the most commonly used strategy, receiving strong interest among academics and practitioners (Fragapane et al., 2023; Powell et al., 2022). According to Fragapane et al. (2023), digital inspection and monitoring, as well as Failure Mode and Effect Analysis (FMEA), are the most widely used methods for defect detection and prevention. These methods are also mature quality evaluation methods.

Nevertheless, the literature claims that Digital Twins (DT) and AI are the two main enabling technologies for ZDM, with several articles covering the architectural and monitoring systems perspectives of ZDM (Powell et al., 2022).

DT offer a holistic approach by integrating production scheduling and optimizing the production system, ensuring the utilization of the most effective ZDM strategies. Typically, DT are integrated with simulation and modeling techniques, enabling efficient planning and decision support for process optimization. Their implementation aims to enhance information sharing and foster collaboration within manufacturing, ultimately reducing defects (Caiazzo et al., 2022; Powell et al., 2022; Psarommatis et al., 2020a). However, Fragapane et al. (2023) also note that DT are used very sparsely, mainly due to the lack of an implementation strategy and usage understanding in companies.

Caiazzo et al. (2022) demonstrate that there is still a low priority on applying AI to detect defects. Users lack knowledge of complex root-cause dynamics; therefore, deviations and errors are primarily resolved by human experience (Caiazzo et al., 2022). Fragapane et al. (2023) explain how AI and Big Data analytics are underutilized. Their findings indicate that generic or simple analyses are still preferred for anomaly detection. It is not surprising that the prediction approach is rarely used. According to the same study, respondents felt that the main limitation of current quality management systems and methods is a lack of emphasis on applying AI to detect defects (Fragapane et al., 2023).
2.2 Artificial Intelligence

2.2.1 Industrial AI: Empowering production with data-driven decisions

AI encompasses the entire infrastructure necessary for intelligent behavior, which includes sensors, intelligence techniques like Machine Learning (ML), and actuators for executing decisions (Russell et al., 2022). According to leading AI textbooks, the field is defined as the study of "intelligent agents," which are systems capable of perceiving their environment and taking actions to maximize goal achievement (Russell et al., 2022). There are various techniques for making systems intelligent, with ML standing out as particularly promising (J. Lee, 2020). ML enables agents to learn from examples, utilizing data-driven methods to discern patterns and predict future outcomes. This research focuses on a specific application of AI within industry: leveraging data for automated analysis and decision-making in production systems. AI, in a broader sense, encompasses various techniques that attempt to replicate human intelligence across many fields. Industrial AI, however, tailors these techniques to solve industry-specific problems, such as optimizing production lines or predicting equipment failures.

Figure 2.2. Nonexhaustive industrial AI framework, adapted from Peres et al. (2020), J. Lee et al. (2018), and Zhang et al. (2019)
Figure 2.2 presents a conceptual framework that emphasizes the main capabilities and technologies that companies must possess based on design principles in order to enable industrial AI and, hence, contribute to supporting the smart production paradigm. It is not intended to list exhaustively all of the elements that industrial AI can include, but rather the major ones that are frequently mentioned in the literature to provide a comprehensive understanding. To be able to integrate AI into a production system, there are many key elements that need to be in place first (Peres et al., 2020). Industrial AI encompasses various enabling technologies such as data acquisition, storage, analytics, platform technology, operations technology, and human–machine interaction (Peres et al., 2020). Platform technologies enable different technologies to work together smoothly while ensuring cybersecurity and system integrity. Operations technology transforms analytics into actionable insights, enabling a shift to data-driven production for optimized operational management. Human–machine interaction is essential to empower stakeholders for seamless interaction and maximize the benefits of industrial AI (Peres et al., 2020).

Design principles for successful industrial AI include real-time capability, which is deemed essential for converting AI predictions and insights into actions at both the process level and the entire factory level (Peres et al., 2020). Interoperability is the means by which machines, people, and data may be connected meaningfully in order to communicate information successfully. Industrial AI solutions in the real world need human operators and engineers. Workers are still taking full responsibility for their actions, and AI is being used as a decision-support system. A completely symbiotic relationship between humans and AI has yet to be developed; therefore, humans in the loop are listed as a key design principle. Robustness implies that the AI model’s insights must be consistent over time and adjust for perturbations. Since the COVID pandemic, there has been a significant rise in the academia for resilience, especially in supply chain management (Zhang et al., 2019). Service-oriented means that industrial AI can be structured as self-contained microservices to foster adaptation and integration.

Among the capabilities, self-awareness, self-predictability, and self-optimization follow the different data analytics steps described by the Gartner Analytic Ascendancy Model (Maoz, 2013). Self-aware corresponds to the diagnostic analytic and answers the question “Why did it happen?” Self-predictability answers the question “What will happen?” and self-optimization uses prescriptive analytics techniques to answer the question “How can we make it happen?” Self-learning and self-decision imply a high degree of system integration. Self-learning means that the system is capable of independent learning for reasoning, which can enable logical rules and support the self-decision capability. Autonomous AI systems are meant to work in complex environments and adapt to changing conditions in order to achieve their objectives (Zhang et al., 2019; Peres et al., 2020).
2.2.2 From exploration to impact: The AI model journey

Implementing AI entails two primary processes: the model development cycle (Dev) and the model deployment and IT operations lifecycle (Ops) (Kordon, 2020). The development phase encompasses the development cycle, emphasizing the exploration and evaluation of various solutions to select the optimal one for the use case. Subsequently, during the operational phase, the focus shifts to monitoring, tracking of the model’s performance, and updating it as necessary (Kordon, 2020).

Development phase

Several methodologies for developing AI models have been developed. Figure 2.3 shows the CRISP-DM process which has become an industry-proven data-mining process (Mariscal et al., 2010) and consists of six phases that describe the complete lifecycle of a data science project, from business understanding to deployment (Chapman, 2000; Wirth et al., 2000).

![CRISP-DM process diagram](image)

*Figure 2.3. CRISP-DM process diagram. Source: Chapman (2000) and Wirth et al. (2000)*

Since the foundation of CRISP-DM, various methodologies have emerged, like eXtreme Programming (XP), tailored for specific needs such as exploration or agility (Auer et al., 2002). CRISP-DM serves as a foundational reference for understanding the steps required to develop an AI model and achieve deployment. Furthermore, it has been the methodology of choice in
sectors such as healthcare, signal processing, engineering, education, logistics, production, sensors and wearable applications, tourism, warfare, sports, and law (Martínez-Plumed et al., 2021). This demonstrates the versatility of this methodology and how, with only slight adjustments, it covers many different application areas.

Operational phase

In the journey from development to operational deployment of AI solutions, several crucial steps ensure the model’s effectiveness and reliability in real-world applications (Kordon, 2020). The process involves setting up deployment infrastructure, packaging the model for deployment, integrating it into the target application, and implementing robust monitoring and logging mechanisms to track performance (Paleyes et al., 2022). Security considerations, scalability testing, and version control practices are also essential (Paleyes et al., 2022). Documentation and knowledge transfer ensure that stakeholders are equipped to maintain and support the deployed model effectively. Continuous improvement through feedback gathering and model iteration completes the process, enabling organizations to harness the predictive capabilities of AI models to drive business value (Kordon, 2020; Paleyes et al., 2022).

2.2.3 AI-driven ZDM

AI is a key enabling technology for ZDM, as it can be used to analyse large amounts of data from production systems (Powell et al., 2022; Caiazzo et al., 2022). This data can be used to identify potential defects early on, particularly prior to the product’s completion. One major advancement with ZDM is its capacity to combine data from a variety of sources, including not only quality evaluation tests but also data on materials, manufacturing processes, equipment, and machines (Psarommatis et al., 2020a).

Various AI technologies contribute to enhancing quality, including computer vision and predictive analytics. Computer vision, a branch of AI, encompasses systems trained to recognize visual inputs such as images and videos, frequently applied in quality-focused tasks like printed circuit board inspection (Zhou et al., 2023). Deep learning methods are commonly employed in computer vision for tasks like object identification, image classification, localization, and segmentation (Z. Ren et al., 2022).

Predictive analytics leverages historical data to identify patterns and forecast future events, finding widespread applications across manufacturing domains, from predicting customer orders to optimizing supply chains and facilitating predictive maintenance (Seyedan et al., 2020; Zonta et al., 2020).

Anomaly detection algorithms use data to create a representation of a normal sample, flagging deviations from this norm as anomalies. Such algorithms can be used for applications in diverse fields, including finance (Hilal et al.,
2022), medicine (Tschuchnig et al., 2022), cybersecurity (Fernandes et al., 2019), and predictive maintenance (Kamat et al., 2020). In manufacturing, anomaly detection is commonly employed to identify visual defects, but there exists literature acquired during quality evaluation tests. For instance, in aircraft blade manufacturing, an anomaly detection model called principle component analysis is used to analyze strain data from piezoelectric sensors to detect damage (Gharibnezhad et al., 2015). Similarly, anomaly detection models have been used in automotive rim production to identify defects in a multi-step hot forging process by analyzing data from hydraulic presses (Lindemann et al., 2020). These AI models assign anomaly scores to samples, but a significant challenge lies in determining an appropriate classification threshold to distinguish anomalies as defects, a task often refined through domain expertise and iterative processes.

Computer and electronics manufacturing accounts for around 25% of research on using AI models to improve production line output quality, followed by chemical production (18%) and metal industry (13%) (Kang et al., 2020).

2.2.4 Challenges for industrial AI adoption

AI is very common on online platforms such as Google, Amazon, and Facebook, where plentiful data makes it possible to train AI models. In this paradigm, AI is used to identify opportunities in available data and is extensively employed in digital spaces such as e-commerce (Pallathadka et al., 2023). In the industry, AI usage is relatively uneven: larger companies and industries that adopted digital technology early on are more inclined to use AI (Bertolini et al., 2021). High tech and telecommunications are among the top sectors in the industry, which have long invested in digital technologies and pioneered the use of digital tools for their key products and operations. However, compared to the overall degree of digitalization, even these industry sectors are far behind in AI adoption (Bughin et al., 2017). Although the impact of AI applications on production processes is well understood, the full potential of their deployment has yet to be realized (Center et al., 2022; Ransbotham et al., 2020). One of the main reasons suggested by J. Lee (2020) is that industrial AI needs to move away from opportunity-oriented divergent applications (like what is seen when the data comes from internet) and toward problem-oriented convergent applications that arrive at conclusions and answers. He also insists that, to really show the value of AI, the focus should be put on solving problems that have not been solved in the past rather than inventing new demands or searching for alternatives to problems that have already been solved (J. Lee, 2020).
Commonly reported challenges for AI integration into companies’ operations are as follows (J. Lee, 2020; Center et al., 2022; Taisch et al., 2020; Wuest et al., 2016; Chryssolouris et al., 2023):

Technical challenges:
- Limitations in sensor usage due to harsh environmental conditions and restricting access to critical data for AI development and deployment.
- AI adoption is complex due to issues such as the nature of the process, sensor characteristics, desired analysis granularity, time constraints, and a lack of established AI models.
- Computational power requirements for implementing AI-based tools, posing additional obstacles to adoption in industrial settings.

Organizational challenges:
- Challenges with stakeholder buy-in.
- The lack of a strategic approach and effective leadership communication.
- A lack of explainability and trust in AI models in manufacturing.
- Unrealistic expectations due to a mismatch between AI capabilities and operational needs.
- Data silos and the absence of a data governance structure.

Financial and resource challenges:
- Substantial customization efforts for many industrial use cases.
- Lack of expertise at the interface of AI and operations.
- Costs associated with legacy systems, equipment, engineering, recurring, and training, hindering the integration of new sensors in industrial environments.

The technical challenges are data-related issues: data availability refers to the challenge of merging data coming from different sources to maximize the impact of the AI model due to heterogeneous formats and standards. The absence of data governance causes the data to suffer from the 3Bs: Broken, Bad quality and lacks Background information, making it hard to deploy AI at scale (J. Lee, 2020). Instead, J. Lee (2020) suggests that value is to be created by focusing on industrial problems and constructing the systems and processes to access the relevant data.

The organizational challenges are related to management: management needs to grasp the potential of AI technology and develop their organization’s capabilities to identify AI business applications. Many organizations lack AI expertise, which may limit adoption (Wuest et al., 2016; J. Lee et al., 2018). The challenges for implementing industrial AI, referred to as explainability and trust, refer to the fact that AI models are based on probability and not on reasoning. In other words the outputs are hypotheses rather than the truth. That means that careful consideration needs to be given when developing models (Peters et al., 2017). To avoid the pitfall of causation versus correlation, domain expertise is needed to understand the underlying mechanism of a process or product.
The resource challenges relate to the availability of expert knowledge, which is a human resource issue. AI specialists who can handle business challenges are uncommon; often, domain experts lack AI understanding, and AI experts lack business understanding. Thus firms need to decide if they should build this competency in-house or outsource it (J. Lee, 2020).

2.3 Adopting AI in production systems

2.3.1 The importance of the implementation stage when adopting new technology

One influential theory explains technology adoption as a consequence of individuals or organizations navigating a decision-making process (Rogers, 2003). This framework, represented in Fig. 2.4, with its five-step sequence of knowledge, persuasion, decision, implementation, and confirmation, helps to understand how new technologies are adopted within production systems. The initial stages, knowledge and persuasion, focus on raising awareness and highlighting the benefits of the new technology. The decision phase involves the critical choice of whether to adopt or not. Implementation then focuses on putting the chosen technology into practice, followed by the confirmation stage where ongoing monitoring evaluates and validates its effectiveness (Rogers, 2003).

![Adoption process diagram]

*Figure 2.4. Relations between the adoption process, the implementation stage, and the development of applications (adapted from Rogers (2003)).*

The implementation phase is a critical stage marked by inherent uncertainties regarding the outcomes. The process of putting a new technology into practice becomes challenging due to unforeseen issues in determining the precise steps needed for its development. The implementation phase involves significant customization and a reliance on trial and error, particularly when the new technology itself, such as AI, is evolving at a high pace (Tang et al., 2020).
Within an organizational context, the decision phase prior to implementation typically engages multiple individuals, and those responsible for implementation often differ from the decision-makers. In addition, the organizational structure, designed to provide stability and continuity, may pose resistance to the implementation of new technologies (Rogers, 2003; Klein et al., 1996). Hence, a polarized AI adoption that favors larger firms was observed, widening gaps with potential social implications as AI strengthens advantages for leaders (Calvino et al., 2023). Klein et al. (1996) argued that how well an innovation is used by a group of people in an organization depends on two things: how supportive the organization’s environment is for that innovation and how well the innovation aligns with the values of the people using it.

Various strategies for technology adoption exist. Bandwagon and ceremonial approaches impose the new technology on organizations but are often ineffective (O’Neill et al., 1998). Customization of the technology, which balances standardization and adaptation to better suit the organization’s context, is crucial for successful adoption (Abrahamson et al., 2008; Hillebrand et al., 2011; Piazza et al., 2020). When considering the adoption of new technologies, several key factors come into play. These factors include: advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). Each factor is believed to play a crucial role in the iterative process to customize the AI-driven ZDM approach to a specific production system.

2.3.2 Need for a holistic approach to AI adoption in production systems

J. Lee (2020) identifies three key elements for successful industrial AI adoption: connecting people and things through systems, shifting from experience-based to data-driven decision-making, and continuously optimizing the system by analysing relationships among people, systems, and things. This contrasts with traditional production methods, where these elements often interact rigidly. As highlighted in Section 2.1.1, successful approaches like Toyota Production System emphasize the integration of people, processes, and technology. The Organisation for Economic Cooperation and Development published an analysis of the use of AI in firms across eleven countries "to help ensure that adoption of AI in the world of work is effective, beneficial to all, people-centered, and accepted by the population at large" (Calvino et al., 2023).

Although existing research on ZDM often prioritizes processes over the human element (Powell et al., 2022), the Technology–Organization–Environment (TOE) framework, an organization-level framework that can support to understand how the firm’s context influences technology adoption (Tornatzky et al., 1990), offers a holistic approach. This framework considers three key aspects: the technological context (features and benefits of the technology), the orga-
nizational context (internal factors like size, culture, and resources including communication and employee structures), and the environmental context (external factors like competition, regulations, and market trends). By employing the TOE framework, we can analyse technology adoption in production systems while considering both people and processes within the broader organizational and environmental context.

In recent years, there has been an acceleration of studies in the adoption of AI in manufacturing. Several studies, including Kinkel et al. (2022), Merhi et al. (2023), and Chatterjee et al. (2021), have used the TOE framework to study the factors influencing adoption. Smit et al. (2023) suggest a combined TOE and DOI paradigm, calling for a more complete picture that includes both internal and external factors that affect how AI is adopted in manufacturing.

2.4 Summary

The frame of reference discussed the integration of AI in production systems, particularly within the framework of ZDM. AI technologies are highlighted for their role in quality improvement and defect prevention. Challenges in AI adoption, including technical, organizational, and financial barriers, are mentioned, emphasizing the need for a strategic and holistic approach. The importance of the implementation stage in technology adoption is underscored, alongside the TOE framework as a tool for analysing adoption factors. Overall, the frame of reference emphasizes the potential of AI to transform production systems while acknowledging the complexities involved in its adoption.
3. Research methodology

This section provides a description of the research methodology. It starts with the research approach, describing the thinking behind how to fulfill the purpose of the thesis and the role of the researcher. Then, the research design explains how the different appended papers answer the research questions. The next section justifies the use of the case study methodology. Then a discussion on data collection and analysis presents techniques, tools, and procedures employed to gather, analyse, and interpret data, ensuring the research quality through the research’s validity, reliability, and generalization. Finally, ethical considerations are discussed.

3.1 Research approach

The research done in this thesis aims to apply knowledge to investigate the adoption of AI-driven ZDM in production systems. It can be defined as an implementation work or use of the knowledge to develop applications. This research is context-driven, problem-focused, and involved multidisciplinary teams that worked together for short periods of time on specific problems in the real world (Gibbons et al., 1994).

This thesis investigated the adoption of AI-driven ZDM in production systems. The research started with a comprehensive examination of the core issue, establishing the project’s significance. Subsequently, the desired state of successful adoption was explored, followed by the formulation of research questions designed to show the way towards achieving this objective. To facilitate this investigation, the Design Research Methodology (DRM) framework has been chosen (Blessing et al., 2009).

This research, conducted with an industrial company, adopted a collaborative research approach with value co-production, aligning with the goal of making science relevant for addressing problems (Adler et al., 2004). Furthermore, research that reflects on industry practice and works closely with its prioritized needs and goals is a recipe for contribution impact and innovation (Argote et al., 2000; Sandberg et al., 2011).

To effectively recommend strategies for the adoption of a new technology, it was essential to understand both the complexities of the technology itself and its adoption into actual production systems. This required extensive networking and discussions to gauge how the technology aligns with the company’s
objectives and to assess the company’s readiness for change. Thus, collaborative efforts started, engaging not only managers but also key stakeholders across various functions to discern their most pressing needs.

After identifying the major company issues that align with this new technology, collaborative research was conducted with employees spanning from middle management to shop floor operators. This research aimed to understand how the new technology could address the identified issues and how it could be tailored to suit the company’s specific requirements.

The approach employed in this study distinguishes itself through a "learning by doing" pragmatic approach inspired by collaborative research. Collaborative research views organizations holistically, advocating that meaningful insights arise from making changes and observing outcomes (Baskerville, 1999). An insider role in collaborative research served as the inspiration for this study, which examined the internal processes of the organization with the intention of proposing enhancements (Coghlan, 2007). The origins of this research approach can be found in fields where researchers and practitioners frequently interchange roles, utilizing their everyday experiences as a basis for action and subsequent reflection. Such research encompasses various functions, including change agent, knowledge broker, reflective scientist, self-reflexive scientist, and process facilitator, as described by Wittmayer et al. (2014).

Numerous roles were taken on throughout this research, including working as a data scientist while developing software algorithms, serving as a project leader during efforts to develop AI-driven ZDM applications, mentoring thesis students, and collecting and analysing data for writing and presenting research articles. The self-reflexive scientist role is central to this approach and emphasizes continuous critical self-reflection to recognize and address personal biases, values, and assumptions (Wittmayer et al., 2014).

The following lists are descriptions of the different collaborative characteristics of the research conducted during this thesis. They simply provide readers with a better picture of the level of collaborative research undertaken. The research project was conducted by a collaborative team comprised of university researchers, university-affiliated case company insider researchers (including the author), middle managers for assembly and production engineering, quality engineers, production development engineers, maintenance engineers, IT developers, shop-floor assembly operators, and external AI specialists (primarily thesis students). The research combined two collaborative approaches. First, the author, acting as an insider researcher, actively participated in data collection and analysis. Second, iterative feedback loops with participants allowed for the co-development of solutions and discussions about the findings.

The research environment facilitated collaboration in several ways. Easy access to the workplace (with the author present 1-3 days per week) allowed direct interaction with case company employees and access to data and equipment. Observations of the different production processes could be conducted...
as necessary. In addition, weekly meetings with key personnel leading Industry 4.0 initiatives offered significant insights into the company’s technological advancement, unique requirements, and existing obstacles.

3.2 Research design

As mentioned in the previous section, a Design Research Methodology (DRM) was used in this research. The aim of DRM is to help design research that is more effective and efficient, and it has had a fair amount of impact as a useful approach when research is focused on product and process development (Blessing et al., 2009). It is particularly well-suited for addressing complex design problems that involve understanding user needs, developing solutions, and evaluating their effectiveness.

DRM was selected to fulfil the purpose of this research, which is to investigate the adoption of AI-driven ZDM in production systems. It achieved this by thoroughly addressing the research questions. By investigating impacts (RQ1), challenges (RQ2), and facilitators (RQ3) related to the adoption of AI-driven ZDM in production systems, this study aimed to offer support for facilitating adoption. DRM offered a particularly well-suited approach for comprehensively understanding and evaluating novel design aspects in a rigorous scientific manner. This framework fostered the generation of valid and valuable results. Considering the research purpose, the research questions and the available time, a DRM of type 2 was judged to fit the needs of this thesis (see Figure 3.1), meaning that this thesis aimed to provide a comprehensive overview of the factors impacting the adoption of AI-driven ZDM in production systems.

DRM has recently been utilized in numerous research studies with comparable objectives and contexts. For example, DRM was used to provide new frameworks to help a transformation, the acceptance of novel methods in a manufacturing setting, and new project management approaches. Acerbi et al. (2022) used DRM to propose a model to standardize and structure circular manufacturing data to support manufacturers’ decision-making. Sas-sanelli et al. (2022) used DRM to create a methodology for supporting small and medium-sized enterprises’ digital transformation. Zhai et al. (2021) used DRM to design a framework for predictive maintenance with production scheduling integration. Brandl et al. (2021) employed DRM to demonstrate how agile methods may be applied in the context of complex technical planning projects.

3.3 Case study design and rationale

The case study method was chosen to carry out empirical studies. A case study method was chosen because it can provide a detailed understanding of the
Figure 3.1. Thesis research design: DRM of type 2

A real-time longitudinal case study was carried out to allow for an in-depth examination and analysis of the adoption of AI-driven ZDM in a production system. In this research, a longitudinal case study was conducted at a manufacturing company producing heavy-duty vehicles. The case company has a global industrial footprint, and the production site where the case study was conducted is characterized by advanced manufacturing technology with an almost equal mix of machining with high automation and manual assembly processes for the production of transmission components. The plant provided an excellent context for the case study because it had a historically challenging problem with annoying noise in the cabin of a specific type of vehicle. Despite many efforts by the case company, the problem could only be minimized, not eliminated. As a result, the case company became interested in this project as it was actively working to address and overcome this persistent issue.

In the context of the transmission components plant’s ambition to become world-class in its industry, the case study focuses on the strategic adoption of AI for ZDM. The overarching goal of the company is to position the plant as a
global leader, emphasizing excellence in the production of transmission components. Hence, this research aligned with the plant’s commitment to competitiveness, setting the stage for an in-depth examination of how AI-driven ZDM adoption contributes to the plant’s journey toward achieving the status of the best transmission component plant in the world. The unit of analysis is the adoption of AI-driven ZDM in the production system of the case company, which refers to the plant where the case study was conducted.

3.4 Data collection

In this longitudinal case study, four AI-driven ZDM applications were implemented in different production processes. The application "Axle" and "Gearbox" refer to quality evaluations of final components, while the applications "Picture" and "Certificate" refer to investigations that could lead to quality improvements by enabling more proactive quality strategies. The longitudinal case study was followed in realtime at the transmission component assembly site from September 2021 until January 2024. Figure 3.2 shows the timeline of the different applications of AI made during the case study and the submissions of the appended papers.

<table>
<thead>
<tr>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
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<tbody>
<tr>
<td>Q3</td>
<td>Q4</td>
<td>Q1</td>
<td>Q2</td>
</tr>
<tr>
<td>Application &quot;Axle&quot;</td>
<td>Application &quot;Gearbox&quot;</td>
<td>Application &quot;Picture&quot;</td>
<td>Application &quot;Certificate&quot;</td>
</tr>
<tr>
<td>Data collection</td>
<td>Case study</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paper submitted</td>
<td>Paper I</td>
<td>Paper II</td>
<td>Paper III</td>
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**Figure 3.2.** Relations between the data collection made during the development of applications and papers submitted according to time during this licentiate thesis.

The "Axle" application entailed developing an AI solution to assess the potential of transmission axles to generate irritating noise once mounted on the entire vehicle, based on vibration measurements taken in an axle cleaning cell, which is used to flush residuals from machining operations from the inside of the axles (Leberruyer et al., 2023b; Leberruyer et al., 2023a; Bergvall, 2023). The challenge with this application was that the measured vibrations on the component did not have any correlations with the quality requirements set for the complete product. This work was followed from September 2021 to May 2022 and was restarted from September 2022 to April 2023, providing the
primary source of data for this research and contributing solely to the results reported in Papers I and II and partially to the results presented in Paper III.

The "Gearbox" application involved the development of an AI solution based on audio files to detect anomalous sounds created by transmission gearboxes during quality control testing. Mahinic (2023) presented the technical details in his master's degree thesis. The challenge with this application was that a condition-based solution is already implemented but does not catch all possible defects, making it an interesting application to investigate. This work was first carried out from January 2023 to May 2023. The investigation was again restarted in November 2023 and continued until January 2024, but this time the manual acoustic quality evaluation was the focus of the research. This application contributed partially to the results presented in Paper III.

For both the "Axle" and "Gearbox" applications, the ZDM "detect" strategy was the main focus of research. Inspecting 100% of production is becoming key for smart factories to enable the early detection of defects and avoid their propagation to downstream processes. This is made possible through the proliferation of in-process inspection, also known as in-line inspection or quality control (Chiariotti et al., 2018). The research looked at ways to create feedback control loops to detect defects at the single-component level (i.e., before the entire product is built). It was highlighted in the frame of reference that implementing the ZDM "detect" method necessitated more research, especially when the product is complicated and the production system incorporates more than one stage or machine (Powell et al., 2022).

The "Picture" application involved the creation of an AI solution to analyse the contact patterns created by a drive gear after its installation in the transmission axles. Ström et al. (2023) presents the technical details in their bachelor's degree thesis. The goal here was to identify anomalies in the assembly process that could potentially lead to a defective component. This work was followed from March 2023 until June 2023.

The "Certificate" application employed character identification algorithms to digitize steel certificates from suppliers. This project has no direct impact on product quality, but it enables ZDM's more proactive techniques by supplying data from suppliers that might potentially be used to predict component quality and was therefore included in this case study. This work was followed from January 2023 until March 2023.

These four applications constituted the main source of empirical data for this licentiate thesis.

Data collection was performed using different techniques. Literature reviews were performed to get an overview of the current state of knowledge. For example, to assess what the state of the art is for the use of AI in manufacturing companies to support quality. Documents were used for the part related to business and process understanding. The goal here was to understand the pain points experienced by the manufacturing company and make a diagnosis. Discussions were performed on a weekly basis. This approach
was chosen based on the exploratory nature of the study and to gain an understanding of the manufacturing process and the different steps involved (Säfsten et al., 2020). Discussions were conducted throughout the case study to gain input from those engaged in the investigations. Workshops with both industrial practitioners and academic researchers were used to learn more about the process as well as share ideas and generate ideas. As many as needed direct shop-floor observations of manufacturing processes were made to get a better understanding of the current situation. Measurements from different production processes were retrieved when a measurement system was in place, and sometimes ad hoc measurements were made. Experiments were conducted in order to gain knowledge of the problem at hand and to test different implementations of AI models. These experiments helped the researcher and practitioners to investigate and develop different AI solutions to best address the considered industrial problem. This research benefited greatly from easy access to the company where the AI-driven ZDM applications were implemented, as described in Section 3.1. This close proximity facilitated open discussions with employees across various departments, including operations, aftermarket, product development, and IT. Throughout the two-year case study, data collection occurred both informally (through ongoing conversations) and formally (through specific meetings focused on application development). A research journal was maintained to document all observations and activities undertaken throughout the case study. This journal was updated regularly to ensure a complete and accurate record of the research process. An overview of the qualitative data collected is presented in Table 3.1, and the quantitative data can be found in Table 3.2.

### 3.5 Data analysis

Data analysis involved a combination of qualitative and quantitative analyses. A prerequisite was to organize the collected data while ensuring that field notes, e-mails, conversations and performance metrics are properly labeled and stored in a structured manner.

For qualitative data, thematic analyses was conducted by identifying recurring themes, patterns, and key insights related to the experiences, challenges, and perceptions of stakeholders involved in the AI adoption process. Categorizing information was made to identify similarities or differences across the data (Clarke et al., 2017; Kiger et al., 2020).

Quantitative data analysis was mostly used to evaluate test data and compare AI models in Papers I and II. Relevant metrics such as accuracy, vibration levels, and any other performance indicators such as confusion matrix for binary classifiers were analysed (Sankhye et al., 2020).

Cross-validation was employed to validate the results by comparing the data collected from various sources. Within the qualitative data analyses, it helped
### Table 3.1. Qualitative data collection

<table>
<thead>
<tr>
<th><strong>Technique</strong></th>
<th><strong>Description</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Meetings</td>
<td>1 hour every 2 weeks during application development, involving quality engineers, production process owners, AI initiative coordinator, and AI developers. Goal was to discuss status reports and plan future actions.</td>
</tr>
<tr>
<td>Workshops</td>
<td>2 hours, 2 times per application project, involving quality engineers, production process owners, AI initiative coordinator, AI developers, and lean production system coaches. Goal was to generate ideas.</td>
</tr>
<tr>
<td>Observations</td>
<td>2 hours, 2 times per application project at the shop floor, involving quality engineers, production process owners, AI initiative coordinator, and AI developers. Goal was to understand current processes.</td>
</tr>
<tr>
<td>Informal conversations and e-mails</td>
<td>As much as needed, hard to quantify. Information exchange related to the applications and feedback.</td>
</tr>
<tr>
<td>Documents</td>
<td>Historical customer complaints for axles and gearboxes, drawings, supplier information, production equipment specifications, internal reports, organizational chart, meeting notes, software applications, and e-mail conversations.</td>
</tr>
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</table>

### Table 3.2. Quantitative data collection

<table>
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<tr>
<th><strong>Technique</strong></th>
<th><strong>Description</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Tests</td>
<td>Tests coming from the axle cleaning cell, the transmission quality evaluation, and the drive gear assembly. Several thousand files were available in the form of vibration’s raw and processed measurements, audio files (raw and processed) and images.</td>
</tr>
<tr>
<td>Experiments</td>
<td>Experiments were made to first build the defect and then to evaluate the built-in defect in the axle cleaning cell.</td>
</tr>
<tr>
<td>ML model metrics</td>
<td>Different performance metrics from various models were employed to assess and compare their effectiveness in ensuring progress for each implementation.</td>
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</table>
ensure that different data sources provided the same insights. Quantitative data analysis, such as AI performance metrics, were also compared to conclusions from qualitative data analyses and vice versa, as two distinct phenomena were under investigation: organizational factors and technical factors (Sale et al., 2002).

3.6 Research quality

Research methods are valuable tools for drawing conclusions and they are essential to ensuring the validity and reliability of results. However, according to Maxwell (2012), the key is to identify potential threats and develop strategies to ensure research quality.

With 16 years of experience as a product development engineer, the researcher identified the challenge of relying solely on initial impressions (Lincoln et al., 1985) and projecting personal values and judgments onto situations (Maxwell, 2012). Other issues in applied research within an industrial setting include the availability of people and information, the risk of confirming rather than disconfirming instances, and concerns about data reliability and consistency. Data overload is not a significant threat as the researcher focused on a single company and a consistent group of people within that organization. Applying suggestions from Maxwell (2012) to enhance research validity, the researcher engaged deeply and for an extended period (over two years), prioritizing a thorough understanding over quick judgments and exploring causative processes. As the research is centered on one company with an insider collaborative research approach, it facilitated the gathering of empirical data, which mainly consists of qualitative information such as descriptions, narratives, and contextual insights from diverse sources. This method yielded rich data, providing a comprehensive perspective that contributed to a thorough investigation aimed at addressing the research questions (Karlsson, 2016). Throughout the research process, continuous communication with the case company’s employees validated the findings, ensuring that interpretations and conclusions were clearly established (Karlsson, 2016). As an insider researcher, the researcher intervened positively in the situation, taking on dual roles and occasionally conducting self-interviews during data collection. The ethical considerations section of this thesis goes into more detail about this issue, highlighting the careful steps that were taken to ensure the validity of the research.

To enhance study reliability, the researcher prioritized honesty and detailed explanations of how results were obtained. Comprehensive records of data collection steps, methods, and analysed results were maintained to facilitate replication and verification by others (Säfsten et al., 2020). Also the findings can hardly be generalized due to the single-company focus, the researcher aimed for high-level results applicable beyond the specific case. Comparisons
with similar research, such as by J. Lee (2020), revealed parallels, and discussions with another organization in the process industry highlighted surprising similarities in AI adoption.

3.7 Ethical considerations

Imagine a scenario: a revolutionary AI system designed to optimize factory processes. Initially complimented for its efficiency, the system later reveals a hidden bias, as it unfairly allocates resources and jeopardizes worker safety. This possible scenario emphasizes the vital need for ethical considerations in AI development, particularly in private companies, where potential conflicts of interest are common.

This section describes my approach to implementing ethical principles throughout an academic–industry collaboration project focused on accelerating AI adoption in the manufacturing sector. The project aimed to find a delicate balance: encouraging innovation while preserving ethical standards and ensuring a positive societal impact.

The foundation of our approach was value co-creation. We established regular meetings with diverse stakeholders, including industrial partners and academics. This ensured that potential biases were identified and minimized, diverse perspectives were included, and the project remained grounded in real-world needs.

Furthermore, we supported total transparency. Project findings were communicated through various channels, including academic journals, industrial conferences, and open-format seminars. This promoted open communication, facilitated constructive discussions, and allowed for the proactive expression of ethical concerns.

Beyond transparency, we actively cultivated a culture of shared responsibility and accountability. Researchers were not just responsible for their findings, but also for ensuring that potential biases were minimized and the technology ultimately served the greater good. This involved ongoing dialogues with stakeholders and a commitment to continuous learning and adaptation.

The success of this collaborative approach depended on mutual respect. We actively avoided the pitfalls of viewing industry partners as "case studies" or academics as "cheap consultants" (Melin et al., 2007). Instead, we fostered a collaborative environment where both parties were valued for their unique expertise and perspectives. This approach fostered trust and facilitated the open exchange of ideas crucial for navigating the complex ethical landscape of AI research.

In conclusion, this research project demonstrates the necessity and feasibility of implementing ethical principles within collaborative AI research, even within a private company setting. By prioritizing transparency, shared responsibility, and open communication, we can ensure that AI development not only
drives innovation, but also serves the greater good and safeguards against unexpected consequences.
4. Summary of appended papers

The following section presents an overview of the findings of the appended papers and how they contributed to the thesis.

4.1 Paper I

**Title:** "Toward Zero Defect Manufacturing with the support of Artificial Intelligence—Insights from an industrial application" is a result of the development of the application "Axle".

**Research gap:** There is a lack of research in industrial plants for implementing ZDM.

**Purpose:** To apply AI to an industrial application in order to develop application insights and identify the necessary prerequisites for achieving ZDM.

**Methodology:** A real-time case study was followed for nine months (from September 2021 to May 2022), allowing for comprehensive and detailed findings. The paper describes an approach in which AI was utilized to detect defects in transmission axles.

**Findings:** Training AI models to inspect transmission axles presented two challenges. First, subjectivity and uncontrollable external factors can lead to misclassification in the labeling of approved transmission axles. This makes training AI models harder and lowers the accuracy of detection. Second, the data from the two cleaning cells used to clean the axles cannot be combined due to inconsistencies. This lack of consistent data makes training the AI models more difficult in two ways: there is less data overall, which slows down development, and unique models must be developed for each cell, increasing workload and making the system less adaptive. The inconsistency in the data appears to be due to the design of the cleaning cells. They were not designed for quality control.

The paper further demonstrates that, to achieve the expected benefits of using AI for ZDM, four prerequisites need to be in place. Among these prerequisites, the adoption of lean manufacturing practices, particularly standardization through the 5S framework, emerges as a crucial factor. This emphasis on standardization is grounded in the recognition that a standardized and stable assembly process plays a vital role in facilitating data-driven methodologies and ensuring the validity of statistical conclusions. Another prerequisite is the existence of a core problem to secure support. The organization, driven by a
The first insight underscores that AI not only facilitates ZDM, but also complements traditional quality methods. It details how AI, despite the complexity of vibration transfer issues in a vehicle, identified important features and a defect-detection solution could be developed, allowing for improved manufacturing processes when combined with established quality methods. The second insight emphasizes the importance of quickly modeling and analysing data to ensure data availability and quality. The paper highlights the significance of a data-centric approach, data management policies, and proper equipment calibration for effective AI-driven ZDM application development. The third insight addresses the need for business input to balance defect detection against reworking costs for optimal decision-making. It discusses the challenge of compromising between false positives (false alarms) and false negatives (missed defects) in defect detection, emphasizing the role of business expertise in evaluating solutions and making trade-offs between reworking and delivering faulty products. The fourth insight focuses on the evolution of ZDM toward prediction and preventative capabilities. It outlines how implementing ZDM with AI may initially increase the defect rate but lead to lower defect rates in subsequent assembly stages and with the end-customer, highlighting the importance of considering production scheduling and flow adjustments. The paper also mentions the 1–10–100 rule, emphasizing early defect detection and prevention.

**Implications:** The results from this paper collectively contribute to the understanding of AI’s role in ZDM, emphasizing its potential for improving manufacturing processes, decision-making, and the long-term evolution of ZDM strategies.
Contribution to the licentiate thesis: The paper contributes to answering RQ1 by describing the current situation and the desired situation. The paper also offers insights into the impacts of adopting AI-driven ZDM in the production system. The paper partially contributes to answering RQ2 by presenting some hinders to the application of AI-driven ZDM. Finally, the paper also contributes to answering RQ3 by presenting the prerequisites that need to be in place in order to facilitate the adoption of AI-driven ZDM in the production system.

4.2 Paper II

Title: "Enabling an AI-based defect detection approach to facilitate Zero Defect Manufacturing" is also a result of the development of the application "Axle".

Research gap: Numerous process models exist in the field of AI deployment that answer distinct business needs across various applications. The industrial sector, on the other hand, poses particular problems that inhibit the seamless integration of AI. Factors such as poor data accessibility and quality, the requirement for domain expertise to identify key data measurements, and the need for significant customization to align AI solutions with specific industrial requirements have gotten little attention.

Purpose: Identify key enablers required for the development of an AI-based defect detection solution in an industrial context.

Methodology: The paper relies on a case study conducted at a transmission axle factory, where the use of this approach revealed five critical enablers that facilitate the use of AI in the field of industrial defect detection.

Findings: The paper identifies five key enablers for defect detection in complex products. First, unsupervised learning algorithms within AI significantly streamline defect detection. This approach eliminates the need for pre-labeled data, accelerating development and effectively addressing imbalanced datasets where defects are rare compared to approved products. Second, domain expertise is crucial for understanding controlled parameters affecting quality characteristics, leading to an informed experiment design, sensor selection, and data processing. The third enabler is designed experiments. These experiments help build a robust defect model, learn about the domain, and help build plausible defects on a product. This, in turn, helps ensure the measurement system can distinguish between normal and defective products. The fourth enabler stresses the importance of repeating tests with a built-in defect to ensure the sustained effectiveness of the entire system, including sensors and AI models. The fifth enabler highlights open-source programming languages and file formats. An open-source programming language, backed by a supportive community, significantly eases data exploration and modeling. Adopting open
file formats for storing measurements improves data accessibility and manipulation.

**Implications:** These enablers collectively contribute to a comprehensive defect detection solution, emphasizing efficiency, domain understanding, experimental rigor, system reliability, and the adoption of accessible tools.

**Contribution to the licentiate thesis:** Paper II explores technical challenges relevant to RQ2 and identifies enablers for developing an AI-driven ZDM application, thereby contributing to answering RQ3.

4.3 Paper III

**Title:** "Addressing challenges in implementing AI-driven Zero Defect Manufacturing: Insights from industry" is a result of the development of all four applications.

**Research gap:** The study addresses a gap in the existing literature by focusing on the practical challenges encountered when implementing AI-driven ZDM in production systems and gives recommendations on how to mitigate them. Although previous research has explored the theoretical aspects of ZDM and AI adoption in manufacturing separately, there is a lack of empirical studies providing insights from applications in real-world industrial settings.

**Purpose:** The purpose of the study was to identify and analyse the challenges and recommendations associated with the adoption of AI-driven ZDM in production systems. By examining these factors, the study aimed to provide practical insights that can guide organizations in successfully implementing AI-driven ZDM, thereby enhancing product quality and efficiency in their production systems.

**Methodology:** To achieve its objectives, the study employed a case study methodology, focusing on a heavy-duty automotive industrial case. Data was collected through various methods, such as interviews, observations, workshops, open discussions and document analyses. The guiding theoretical framework for analysis was the TOE framework, which allows for a holistic examination of the technological, organizational, and environmental factors influencing AI adoption in production systems. Thematic analyses were used to identify common themes and patterns in the data, providing insights into the challenges and opportunities encountered during the development of four AI-driven ZDM applications.

**Findings:** The study identified ten challenges regarding the adoption of AI-driven ZDM in production systems. Technological challenges such as data access, quality, and deployment were identified. Data access issues were addressed by using standardized tools and skilled IT personnel. Data quality challenges were mitigated by using unsupervised learning and iteratively improving data collection methods. Deployment
challenges were overcome by starting with a simple model and using modular architecture with cloud services.

The paper also highlights organizational challenges such as adapting to new development approaches (e.g., shifting from linear stage-gate to iterative development), fostering collaboration, and managing change for successful AI implementation. Iterative development, collaboration with external partners, and user education were found to be helpful. Finally, the paper emphasizes the need to integrate AI seamlessly into existing processes while maintaining human control and trust. This can be achieved through explainable AI models, user feedback mechanisms, and a focus on human–AI collaboration.

Justifying the use and effectively scaling AI-driven ZDM within a broader environmental context can be difficult. This difficulty comes from the inherent challenges of identifying high-impact applications and securing funding for solutions that may be perceived as unproven. In addition, relying solely on external partners to design and implement such solutions might not be suitable due to the inherent uncertainty of AI and the limited expertise within existing production teams. To overcome these challenges, the company adopted an alternative approach that focused on internal development with university partnerships. This strategy not only helped them reduce costs by leveraging internal resources, but also fostered valuable AI expertise through collaboration with students. Furthermore, internal development provided the company with greater control over the development process, allowing them to adapt to unforeseen challenges with greater flexibility.

In addition, the study highlighted the importance of an iterative implementation strategy throughout the adoption process to empower the users by integrating feedback collection. This ensures that the applications meet evolving needs and empower users. The study highlights the importance of human-centered design and continuous feedback, suggesting a support for continuous value creation and learning. This suggested support aligns with established theories and emphasizes an iterative approach for continuous improvement of the AI-driven ZDM application.

Implications: Paper III offers practical guidance for organizations seeking to implement AI-driven ZDM. The study emphasizes the importance of balancing automation with human expertise, empowering employees through upskilling, and fostering collaboration to ensure the continued centrality of human workers in the manufacturing process. To facilitate the adoption of AI-driven ZDM in production systems, an iterative approach to addressing technological, organizational, and environmental challenges is proposed.

Contribution to the licentiate thesis: Paper III contributes to answering RQ2 by identifying challenges and RQ3 by describing their associated recommendations.
5. Adopting AI-driven ZDM in production systems

The purpose of this licentiate thesis is to investigate the adoption of AI-driven ZDM in production systems. This chapter fulfils this purpose by synthesizing and discussing the empirical findings. Answers to the research questions are also provided.

5.1 Identifying the impacts of adopting AI-driven ZDM in production systems

Research Question 1 in this thesis is: What are the impacts of adopting AI-driven ZDM in production systems? The following text synthesizes and discusses the results of Research Question 1.

In Paper I, the current process and issue were described (see Figure 5.1), illustrating a sequence from supplier to end customer. In this figure, the production system, with multiple locations, faces challenges in assessing one component’s quality characteristics earlier than once the final product is assembled.

![Figure 5.1. Current process for handling quality complaints (adapted from Paper I).](image)

Paper I describes a typical production system with some quality issues that are hard to resolve, which makes it suitable for applying ZDM. Implementing a "firewall" at the component site is vital to prevent defect introduction into the final product. Leveraging AI in ZDM enhances component testing and defect identification, aiming to improve customer satisfaction. Key metrics for evaluating its impact include reduced product defects at the final product assembly site and fewer customer complaints. In a survey, Fragapane et al. (2023) show that the respondents believed that ZDM strategies have a strong positive impact on throughput time, product quality, waste reduction, and production cost per unit performance. Of course, all those aspects are linked together, but...
in this study, the main focus was to capture defects at the component site to reduce waste at the final product assembly site.

Paper I shows that AI not only facilitates ZDM, but also enhances traditional quality methods by enabling multivariate analysis, simplifying quality characteristics analysis, and facilitating the identification of critical parameters through traditional tools like Design of Experiments and Pareto analysis.

Companies collect vast amounts of data, which often remain unprocessed, hindering the discovery of useful insights and the reduction of defects, reflecting a low emphasis on utilizing AI in traditional quality management systems (Fragapane et al., 2023).

Complex product default detection is difficult due to component variety, size, and function. Deficiencies in data quality impact AI model accuracy, necessitating a balance between false positives (false alarms leading to extra rework) and false negatives (missed defects). Paper I explains that business expertise is essential for assessing the AI-driven ZDM applications, navigating the dilemma of strict zero-defect policies versus minimizing rework. The optimum level of quality has two main streams: on one hand, an optimal cost model was introduced in the fifties to explain how to balance the failure cost versus the cost of appraisal plus prevention to find an optimum quality level in order to reach the lowest cost per good unit produced (Juran et al., 2010). On the other hand, Schneiderman (1986) suggests that the optimum quality level is zero defects, as the cost of appraisal will still be lower than the cost of defects. In this study, we focused on the first approach, followed by continuous improvement of the detection method, leading to proactive strategies, in order to achieve the zero defect vision of the second approach.

Implementing consistent detection strategies and continuously improving AI-enabled ZDM applications are essential for early defect detection and prevention, ultimately optimizing quality in manufacturing processes. Paper I discusses the potential increase in rework at the component plant due to the new AI-driven ZDM detection strategy. It requires the component plant to carefully assess its impact on production scheduling and flow to avoid any negative responses from the impacted people. ZDM defect detection is the most explored strategy among the different ZDM strategies in the current literature (Fragapane et al., 2023; Caiazzo et al., 2022). However, Caiazzo et al. (2022) showed that ZDM detection strategy is an enabler for prevention and prediction strategies. Indeed, implementing a feedback loop from the rework operations helps identify parameters causing defects, which enables more proactive ZDM strategies.
5.2 Challenges hindering the adoption of AI-driven ZDM in production systems

Research Question 2 in this thesis is: What challenges hinder the adoption of AI-driven ZDM in production systems? The following text synthesizes and discusses the results of Research Question 2. The research question aimed to establish the current landscape and identify the challenges that companies face when integrating AI technologies into their production systems. It laid the foundation for understanding why adoption may be slow or difficult in some cases. The thesis presents a summary of the challenges related to AI-driven ZDM adoption, sorted by the technological, organizational, and environmental aspects associated with a production system.

Technological challenges

Papers I and II discussed technical problems related to data quality and availability. Paper I showed that inconsistent test cell measurements and subjective quality judgments hinder the development of data-driven models, while difficulties in correlating component properties to product quality and constraints on testing methods impede thorough analysis and quality evaluation (Paper II). However, given the data-dependent nature of AI-driven ZDM, it may not be surprising that data is at the source of many technological challenges. In a literature review, Peres et al. (2020) identified data availability, data quality and AI model selection as key challenges to be addressed for AI implementation.

The production system cannot benefit from an AI model as long as it remains on local computers and only the developer sees the results. As noted in Paper III, three out of four applications faced significant challenges in deciding the next steps due to limited data or model performance. Although isolation of the AI-driven ZDM applications ensures control, it comes at the cost of hindering broader value creation. Therefore, it is critical to develop a workflow for deploying the AI-driven ZDM application and gather user feedback for continuous improvement. In a literature review of AI for Industry 4.0, Jan et al. (2023) identified that 67% of the papers addressed challenges related to the development phase, which were divided into three categories (i.e., data acquisition/validation, data processing/fusion and model training/testing) while the actual value-adding phase, or operationalization of the AI solution, called "model interpretation" represented the remaining 34% of the papers. The authors summarized the challenges as "how to properly interpret the ML model" and "how to drive business value from the model". This shows that the current state of the art is still focused on finding out how to resolve data issues and obtain satisfying AI models rather than integrating AI models into the manufacturing process. This is also reflected in the literature, with many papers explaining how a low digitalization level and a low IT infrastructure impeded the implementation of ZDM (Magnanini et al., 2020; Pombo et al., 2020).
Organizational challenges
The field of quality evaluation is undergoing a paradigm shift. Traditionally, expert systems with predefined rules governed the process. Now, AI offers a new approach: we feed AI algorithms with data, allowing them to learn and develop their own quality evaluation rules by uncovering hidden patterns. This paradigm shift demands not only the right data for the AI to learn effectively, but also a whole new approach to development. Peres et al. (2020) also identified this as a need to transition from experience-driven to data-driven production in operations technology.

Traditional project management methods, as highlighted in Paper III, struggle with the iterative nature of AI development. AI is an ongoing process of training and refinement, requiring a more flexible approach. Collaboration across departments is key. To tackle the technological challenges mentioned earlier, clear ownership of tasks and efficient resource allocation are crucial for successful AI implementation. Fragapane et al. (2023) found that the main barrier to implementing ZDM is the low knowledge and training in ZDM and the lack of familiarity of the employees with how to effectively use digital technologies.

Change management is essential. We need to address employees’ worries about AI potentially replacing them. Educating operators about the role and limitations of AI is vital to building trust and ensuring a smooth transition. Peres et al. (2020) also takes on some governance aspects and explains that interpretability and trust are two main issues that need to be addressed so that the solution can be adopted into an existing process, particularly if the decisions have an impact on human workers.

Finally, adopting AI-driven ZDM into existing decision-making processes presents a unique challenge. Introducing the new technology while balancing human control and earning operators’ trust is a key challenge. Reiff et al. (2018) recognized that the machine operator’s expertise and ability to spot nonconformances play a critical role in achieving ZDM. This reinforces the fact that the new technology needs to augment operators, empowering them in their tasks.

Environmental challenges
To motivate the time and resources required to develop an AI-driven ZDM application, a convincing use case must be established. This use case ought to concentrate on a scenario where there is increased customer demand, which might result from changes in the external market.

However, finding a high-impact application is difficult due to the inherent uncertainties surrounding this innovative approach. Even if a promising use case is identified, expanding it to other processes proves to be another challenge. Furthermore, leveraging external companies can be expensive with no guarantee of success. The difficulty lies in defining the requirements in advance. Traditional methods, where vendors provide quotes based on specifi-
cations, are inadequate in this case. The very nature of AI makes it hard to
predetermine the exact design, as it relies heavily on the specific product, pro-
cess, and sensors used. This makes it challenging for production engineers,
who may not be AI experts themselves, to write detailed technical specifica-
tions. Although they can describe the desired outcome, the specifics of how
to achieve it remain difficult. This places a significant challenge on the AI
vendor who, lacking a clear roadmap and the ability to thoroughly test before-
hand, might struggle to provide accurate quotes based on estimations. Escobar
et al. (2021) explain that the success of Quality 4.0 initiatives heavily relies on
proper project selection, as evidenced by the fact that a significant percentage
(80-87%) of AI projects fail to reach production due to improper selection,
despite initial vision, investment, and team formation. Wan et al. (2023) show
that the adoption of new technology for ZDM is hindered by substantial costs
associated with obtaining, incorporating, training, and maintaining these tech-
nologies.

5.3 Facilitating AI-driven ZDM adoption in production systems

Research Question 3 in this thesis is: *How can we facilitate the adoption of AI-
driven ZDM in production systems?* This research question addresses the sup-
port needed to select and integrate digital technologies in a resource-efficient
way. The following text synthesizes and discusses the results of Research
Question 3.

As seen in Section 5.2 and in Paper III, in order to find a way to facilitate
the adoption of AI-driven ZDM, a holistic approach needs to be taken. The
prerequisites presented in Paper I, the enablers presented in Paper II, and the
recommendations encompassing technological, organizational, and environ-
mental aspects presented in Paper III form an insightful path towards adoption.

Paper I shows the critical prerequisites for the adoption of AI-driven ZDM
in production systems. Among these prerequisites is the existence of a core
problem to secure support. The organization, driven by a longstanding issue of
random noise in the cabin, exhibited a strong organizational interest in develop-
ing an AI solution, leading to a motivated staff and their support during the
study, aligning with the notion that industrial AI applications are most suitable
for addressing advanced problems that conventional approaches cannot solve.
J. Lee (2020) also discusses that a core problem needs to be found; otherwise,
the project members will vanish when challenges arise. Another prerequisite
is the adoption of lean manufacturing practices, particularly standardization
through the 5S framework, which emerges as a crucial factor. This emphasis
on standardization is grounded in the recognition that a standardized and stable
assembly process plays a vital role in facilitating data-driven methodologies
and ensuring the validity of statistical conclusions. Furthermore, good collab-
oration among diverse experts, spanning product development, manufacturing, IT, and AI specialists, is crucial in developing successful AI solutions for industrial challenges, emphasizing the need for a broad range of competencies to navigate complexities in data identification, extraction, model development, and validation. Finally, the organization’s ability to effectively manage digital and information technology was deemed critical for the development of successful AI solutions, as demonstrated by a skilled team adept at implementing Industry 4.0 technologies, including the independent setup of vibration measurement equipment and associated data systems, emphasizing the importance of adaptability, cybersecurity, and efficient data utilization and sharing. Peres et al. (2020) explain that clear definitions, semantics, and the grammatical structure of the information are vital for interpreting information and ensuring good cross-collaboration between people from different departments. Regarding AI, Peres et al. (2020) mentions that it is crucial to unambiguously define functions and consequences, validating knowledge with domain experts. Integration with legacy IT systems, alongside standardization and a data-driven culture, is key for deploying AI applications effectively (Peres et al., 2020).

Paper II develops important enablers to facilitate the development of an AI-driven ZDM application. Using AI to detect anomalies in complex datasets requires expertise to identify relevant features and set appropriate thresholds for classifying anomalies as defects. Paper II showed that experimenting with the products to create a plausible defect can support unsupervised AI models to define a threshold for identifying defects. Furthermore, creating a defect on purpose can support ensuring data acquisition system repeatability and monitoring model performance over time which are two crucial aspects of effective defect detection. Unsupervised learning and anomaly-detection models are not new concepts for quality detection. However, in most studies, they are employed in applications with huge production numbers, such as the electronics sector, where there are many defects, allowing the model’s performance to be assessed (Abdelrahman et al., 2020). It might also use images, where manual labeling is time-consuming but easy (Zipfel et al., 2023). In the case of Application "Axle", the challenge was to evaluate the performance of anomaly detection with only a few defects. Manufacturing a defective product on purpose was identified as a strategy to develop trust in the AI model.

Paper II recommends addressing data quality and algorithm selection through unsupervised learning, and Paper III recommends achieving scalable solutions via a modular architecture. Paper III emphasizes the importance of upskilling the workforce in AI fundamentals, alongside the adoption of iterative development practices, proactive user education, and a careful balance between automation and human expertise. This balance can be further strengthened by implementing explainable AI models. To optimize resource allocation, Paper III suggests partnering with universities and developing AI applications internally, all while utilizing an iterative approach that prioritizes continuous user feedback and human-centered design principles. This holistic approach aims
to ensure the successful adoption of AI-driven ZDM by evaluating adoption factors at each iteration. This continuous improvement approach facilitates AI-driven ZDM adoption in production systems by integrating user feedback to directly address:

- Technological challenges related to data and deployment;
- Organizational challenges related to employee concerns, collaboration, and upskilling; and
- Environmental challenges related to smooth process integration, project selection, and cost control.

This approach prevents common pitfalls, such as getting stuck in the development phase without creating value due to models remaining on local machines awaiting improved data quality.

Jan et al. (2023) and Nakagawa et al. (2021) discuss continuous improvement initiatives for AI applications and compare them with continuous integration and deployment (CI/CD). CI/CD is a key aspect of DevOps practices that automates the integration of code changes into production, enabling rapid and seamless software updates. Finally, Peres et al. (2020) and Jan et al. (2023) discuss the benefits of transfer learning for efficiently transferring knowledge from one use case to another similar one. This recommendation has not been addressed in this thesis, but could be a valuable suggestion for future research.

Leveraging the learnings from the development of four real-world applications of AI-driven ZDM, we proposed in Paper III a support for facilitating AI-driven ZDM adoption in production systems (see Figure 5.2). Similar to the Plan-Do-Check-Act (PDCA) cycle used in lean manufacturing management, this support emphasizes continuous improvement through iteration.

The proposed support consists of four phases:

1. Plan: The planning stage focuses on defining the specific improvements to be implemented during the iteration. This may range from a sketch to the development of entirely new AI models.
2. Do: This stage involves carrying out the plan and introducing it to the target users. This could involve running a workshop, deploying a new technology, or any other activity that brings the plan to life.
3. Check: This stage involves evaluating the effectiveness of the implemented changes by gathering feedback from the people affected. This can involve observations, interviews, surveys, open discussions, etc.
4. Act: This stage involves analysing the data collected during the check step. It also involves assessing the adoption rate of the changes (using DOI factors) and pinpointing any challenges encountered (using the TOE framework). This analysis helps shape the approach for the next iteration.

By repeating these steps over and over, the support encourages constant improvement and adaptation, which is in line with the maturity model for implementing smart factory initiatives (Sjödin et al., 2018). It also follows the idea of continuous improvement from lean manufacturing, stating that lean
Figure 5.2. Support for facilitating AI-driven ZDM adoption in production systems, adapted from Paper III.

manufacturing is not a one-time fix but rather a philosophy that encourages ongoing evaluation and improvement of processes (Juran et al., 2010). Therefore, to facilitate AI-driven ZDM adoption in production systems, an iterative and user-centric continuous improvement approach is recommended.
6. Discussion and conclusion

This chapter provides a discussion of the findings and conclusions of the licentiate thesis. Furthermore, potential future research is emphasized.

6.1 Summary and conclusion

The purpose of this licentiate thesis was to investigate the adoption of AI-driven ZDM in production systems. This suggests the research aimed to explore, understand, and analyse the phenomenon rather than provide definitive solutions or answers. To fulfil that purpose, three research questions were addressed and answered.

Research Question 1: What are the impacts of adopting AI-driven ZDM in production systems?

This research question provided the context and established the potential benefits of adopting AI-driven ZDM.

Ensuring product quality is a complex endeavor with many linked problems. The thesis looked at these complexities, highlighting how factors like production processes and quality evaluation all play a role in the final product’s quality. To address these challenges, the thesis proposed an innovative solution: an AI-driven ZDM approach. This approach focused on the "firewall" concept at the component production stage, leveraging AI to identify and prevent defective components from reaching the final assembly line.

Although AI-driven ZDM can improve defect detection, the thesis acknowledged that consistent detection strategies and continuous improvement are needed to reach truly proactive capabilities. However, although defect detection is traditionally seen as a reactive approach, catching defects early in the production process can be highly proactive. This can prevent a domino effect of errors, saving time, materials, and resources by stopping faulty components from moving through multiple production stages.

To measure the success of this approach, the thesis suggests monitoring two key metrics: a reduction in product defects at the product assembly site directly reflecting the positive impact on component quality and a decrease in customer complaints, which might take longer to show significant changes due to the nature of customer feedback cycles. Both metrics are crucial for evaluating the long-term success and sustained benefits of adopting AI-driven ZDM. An increase in component defects might be seen at the beginning until proactive approaches can be developed thanks to feedback from the rework operations.
Research Question 2: What challenges hinder the adoption of AI-driven ZDM in production systems?
This research question explored the roadblocks that might hinder the realization of the impacts discussed in RQ1.

AI-driven ZDM brings exciting possibilities, but there are challenges to overcome. These challenges fall into three main categories: technological, organizational, and environmental. Ensuring data quality, algorithm selection, and seamless deployment is complex. Culturally, transitioning to data-driven evaluation requires education and collaboration. Economically, justifying AI investments is challenging due to uncertainty. Overcoming these challenges requires organizational alignment and strategic planning. Adopting AI-driven ZDM is not as easy as buying a plug-and-play solution. To reach its full potential—to improve, deploy, maintain, and scale across processes—a profound cultural shift is needed across the organization.

Research Question 3: How can we facilitate the adoption of AI-driven ZDM in production systems?
This research question aimed to develop facilitators to address the challenges identified in RQ2, potentially paving the way for successful adoption.

Although many manufacturing companies recognize the potential of AI-driven ZDM to revolutionize production, some might find the prospect scary because of too many unknowns. The key takeaway from the thesis is to get started and embrace an iterative and user-centric continuous improvement approach with collaboration across departments. Adopting AI-driven ZDM can be compared to climbing a mountain: perseverance is key. Here are some recommendations to ensure a smooth ascent:

- Seek external support: Partner with other industrial partners or universities to gain valuable insights and maintain momentum.
- Invest in employee training: Provide the workers with the necessary expertise to understand and utilize the new AI tools effectively.
- Pilot project feasibility study: Conduct workshops to identify challenges and assess your infrastructure and data collection capabilities, determining your readiness for AI-driven ZDM.

By taking these steps and adopting an iterative approach to overcome technological, organizational, and environmental challenges, manufacturing companies can leverage the potential of AI-driven ZDM to gain a significant competitive advantage in today’s landscape.

However, AI-driven ZDM opens doors to several other benefits. By having a much better quality process, we can imagine many different implications, such as the possibility of integrating circular production into the production system and ensure that quality remains at the desired level. It could also support changing suppliers more easily by having the possibility to evaluate component quality at a very early production stage, resulting in a more resilient production system. Product improvements could also be implemented much
faster by decreasing the validation time thanks to an increased capacity to assess product quality characteristics in the production system.

The DRM provided structure and focus for this licentiate thesis. The DRM helped in several stages. First, it guided the initial research clarification phase by identifying the research gap so the initial research questions could be elaborated. These questions gave the thesis a specific direction and purpose. The main body of the thesis then involved a descriptive study. This study explored the impacts, challenges, and recommendations surrounding the adoption of AI-driven ZDM in production systems. By understanding these factors, the study aims to support successful adoption of AI-driven ZDM. Building on this foundation, the DRM now encourages a natural continuation: a prescriptive study. This next phase will involve a deeper understanding of the current situation in production systems. By exploring various approaches, the prescriptive study will aim to identify the best possible way to achieve AI-driven ZDM adoption. The next section will detail the activities planned for this upcoming prescriptive study.

6.2 Limitations and future work

This licentiate thesis investigated how AI can be leveraged to enhance production systems and achieve ZDM within a specific production system. This system serves as a representative example of a complex mechanical production system for high-precision parts, characterized by an equal balance of machining and assembly processes. Our belief is that the findings are true for many companies with similar operations. However, the fact that this particular production system belongs to a large company presented certain advantages, particularly in terms of accessibility to domain experts. For instance, obtaining assistance from IT specialists might prove more challenging for small and medium-sized enterprises.

Real-world implications of this research include adopting AI-driven ZDM in a production system and checking its impact on product quality. The research also acknowledges the potential of AI-driven ZDM to improve customer value by reducing costs and complaints, although quantifying these benefits might require time due to limited initial data.

This thesis proposes support for AI-driven ZDM adoption that prioritizes continuous improvement through iterative development. Although validation of the support is the next crucial step and several activities are already defined:

- Optimizing sensor data collection and processing: Refining data processing and determining the optimal processing location (on-device vs. cloud) are crucial. The goal is to understand how to easily deploy devices with anomaly detection capacity to other production processes.
- Overcoming data scarcity for AI model training: As highlighted in the thesis, training AI models suffers when data on defective products is limited.
Building defects (like in Paper II) may not always be feasible. Therefore, investigating data augmentation techniques to create simulated defect data from approved products is essential.

Expanding to prediction and prevention ZDM strategies: The first two points pave the way for expanding the implementation of AI-driven ZDM. Studying correlations between different processes along a production flow will hopefully enable proactive defect prediction and prevention, consequently reducing waste and enhancing quality.

Empowering users through explainable AI and user interface design: This may involve implementing explainable AI to provide insights into the decision-making process of the AI model. Additionally, improved visualization and user interface development that allows for users augmentation and empower them in their tasks is seen as a key to adoption.

User feedback and continuous improvement: The user-centric approach extends to collecting and analysing user feedback, a critical factor for successful adoption. Understanding the multifaceted impact of AI on individuals, teams, and the organization as a whole is vital. By analysing user motivations and experiences, the support can be tailored with appropriate training and knowledge-sharing initiatives.

This comprehensive, user-centric approach ensures the support’s continuous evolution and adaptation based on real-world experiences, ultimately unlocking the full potential of AI-driven ZDM.


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