THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Challenges and Solutions for Integrating Artificial Intelligence into Manufacturing Maintenance

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"In theory, theory and practice are the same. In practice, they are not."

- Benjamin Brewster

Abstract

Manufacturing industries recognize the transformative potential of artificial intelligence solutions within manufacturing maintenance, yet successful implementation remains limited despite widespread acknowledgment of their benefits. Although theoretical advantages of using AI such as improved efficiency, cost reduction, and equipment reliability are well-documented, a persistent gap exists between anticipated outcomes and realized value in industrial settings. Many AI initiatives that begin as successful proof-of-concepts struggle to achieve full-scale production deployment, highlighting gaps in understanding the specific socio-technical challenges practitioners encounter.

This thesis addresses this gap by investigating the interconnected challenges of AI integration in manufacturing maintenance and systematically evaluating operational frameworks to identify the most suitable approach for successful deployment. Through a comprehensive multi-method approach within the Design Research Methodology framework, this research provides both theoretical insights and practical solutions for bridging the gap between AI potential and industrial implementation reality.

The research identifies interconnected challenge domains that collectively constrain AI implementation: infrastructure limitations, scalability constraints, workforce skill gaps, and inadequate maintenance strategies for deployed AI systems. The theoretical process model reveals these challenges as an interconnected system rather than isolated barriers. Through systematic evaluation of alternative operational frameworks, MLOps emerges as a particularly suitable approach, with fundamental characteristics that address integration obstacles. In addition, the research demonstrates how containerized monitoring infrastructure combined with human-centric methodology creates a powerful foundation for MLOps implementation. This work presents a network map that guides practitioners by linking identified challenges to suitable MLOps architectural components. By establishing MLOps as the enabling operational framework and providing evidence based architectural guidance, this thesis transforms AI solutions from experimental technology into a reliable support tool for manufacturing maintenance, enabling organizations to benefit from data driven maintenance solutions while contributing to the ongoing evolution toward Industry 4.0 and beyond.

Keywords: Machine Learning Operations, Manufacturing Maintenance, Artificial Intelligence, Predictive Maintenance, Industrial Implementation, MLOps Architecture.

List of Publications

Appended publications

This thesis is based on the following publications:

Paper 1

A Data-Driven Approach to Air Leakage Detection in Pneumatic Systems

Mohan Rajashekarappa, *Johan Lené, Ebru Turanoglu Bekar, Anders Skoogh, Alexander Karlsson*

Presented at 2021 Global Reliability and Prognostics and Health Management (PHM-Nanjing), San Antonio, TX, USA, 10–13 December 2021.
Published in 2021 IEEE Global Reliability and Prognostics and Health Management Conference Proceedings.

`https://doi.org/10.1109/PHM-Nanjing52125.2021.9612973`

Mohan Rajashekarappa developed and performed tasks including study initiation, methodology, literature search, experiments design, data collection, data analysis, investigation, writing, review, and visualization.

Paper 2

Bridging the Gap by Analyzing AI Deployment Challenges and Solutions in Manufacturing

Mohan Rajashekarappa, *Ebru Turanoglu Bekar, Alexander Karlsson, Jon Bokrantz, Anders Skoogh*

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To be published in CIE 52 Conference Proceedings.

DOI: [To be assigned]

Mohan Rajashekarappa developed and performed tasks including study initiation, methodology design, literature review, expert interview design and conduct, qualitative data analysis using Gioia methodology, theoretical model development, writing, and visualization.

Paper 3

Industrial MLOps: A Systematic Review of Architectures and Implementation Challenges

***Mohan Rajashekarappa**, Ebru Turanoglu Bekar, Alexander Karlsson, Jon Bokrantz, Mukund Subramaniyan, Anders Skoogh*

Submitted to Production & Manufacturing Research Journal in May 2025.
Manuscript under review.

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Mohan Rajashekarappa developed and performed tasks including study conceptualization, systematic literature review protocol development, search strategy design, screening and selection of articles, thematic analysis using Braun and Clarke methodology, coding and theme development, challenge-architecture mapping, synthesis of findings, writing, visualization, and manuscript preparation.

Paper 4

Human-Centric CBM Solution for Machine Tools: From Development to Deployment

***Mohan Rajashekarappa**, Ebru Turanoglu Bekar, Alexander Karlsson, Adalberto Polenghi, Anders Skoogh*

Presented at IFAC Conference, 2025.
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Mohan Rajashekarappa developed the human-centric methodology, led the design and implementation of the CBM dashboard solution, coordinated data collection with domain experts, conducted testing with maintenance engineers, and contributed to writing and visualization.

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Acronyms

AI:	Artificial Intelligence
API:	Application Programming Interface
BLE:	Bluetooth Low Energy

CBM:	Condition-Based Maintenance
CD:	Continuous Deployment
CI:	Continuous Integration
CM:	Condition Monitoring
CNC:	Computer Numerical Control
CRISP-DM:	Cross-Industry Standard Process for Data Mining
GDPR:	General Data Protection Regulation
GPT:	Generative Pre-trained Transformer
HMI:	Human Machine Interface
IIoT:	Industrial Internet of Things
IoT:	Internet of Things
IT:	Information Technology
KPI:	Key Performance Indicator
LLaMA:	Large Language Model Meta AI
LLM:	Large Language Model
MES:	Manufacturing Execution System
ML:	Machine Learning
MLOps:	Machine Learning Operations
MTBF:	Mean Time Between Failures
MTTR:	Mean Time To Repair
OEE:	Overall Equipment Effectiveness
OPC UA:	Open Platform Communications Unified Architecture
OT:	Operational Technology
PdM:	Predictive Maintenance
PLC:	Programmable Logic Controller
PM:	Preventive Maintenance
ROI:	Return on Investment

Contents

Part I

Overview

CHAPTER 1

Introduction

1.1 Background

The manufacturing industry is undergoing a significant transformation as companies increasingly embrace Industry 4.0 and smart manufacturing [1]. This digital revolution is empowered by the integration of advanced technologies such as artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT) into traditional manufacturing processes [2]. The significance and promise of these technologies lies in their potential to optimize production efficiency[3], enhance quality control [4], enable predictive maintenance [5], and drive data-driven decision-making. A vital contribution of this transformation, is the evolution of maintenance practices from traditional reactive and preventive approaches toward predictive and prescriptive maintenance strategies. Modern manufacturing maintenance has become sophisticated, which requires the integration of multiple data sources including sensor data from production equipment, historical maintenance records, operational parameters, and environmental conditions. This shift toward data-driven maintenance represents a change in how manufacturing organizations approach asset management, moving from time-based maintenance schedules to condition-based strategies that leverage real-time data analytics and ML algorithms [6].

The maintenance domain in manufacturing environments presents unique characteristics and complexity that distinguish it from other operational domains [7]. Manufacturing equipment usually operates under demanding conditions with high utilization rates, making unplanned downtime particularly costly. The complexity of modern production systems, where interdependent production lines and processes create serial effects from single-point failures, further strengthens the importance of effective maintenance strategies [7].

Despite widespread acknowledgment that data-driven approaches, especially AI, offer significant advantages, their seamless deployment into current manufacturing maintenance processes continues to present challenges [8]. Consequently, many prototype models fail to reach the implementation stage [9]. Manufacturing organizations face specific implementation barriers that are not commonly encountered in other industries [10]. These challenges are due to some of the specific features of manufacturing environment: substantial capital expenditure requirements, extended asset lifecycles, legacy machines, dynamic production environments and rigorous safety and reliability expectations [11].

The maintenance context adds additional layers of complexity to this integration challenge. Maintenance teams often possess deep domain expertise in mechanical and electrical systems but may lack the digital competencies required to effectively implement and manage data-driven solutions. This might lead to a challenge for demonstrating clear return on investment for maintenance technologies, creating substantial barriers to successful implementation [12]. The integration of AI solutions into manufacturing maintenance also faces technical challenges related to data quality, system interoperability, heterogeneous nature of manufacturing environments, and varying data formats that require careful consideration of both technical and organizational factors [12].

Understanding these challenges and developing strategies to overcome them is crucial for manufacturing organizations seeking to realize the full potential of data-driven maintenance solutions. The successful integration of these technologies can lead to significant improvements in equipment reliability, reduced maintenance costs [13], better resource utilization [14], and enhanced overall equipment effectiveness (OEE), ultimately contributing to the competitiveness and sustainability of manufacturing operations [15].While existing research examines the challenges of deploying AI in maintenance solutions in manufacturing systems, there remains a critical gap in understanding how to build scalable, operationalizable solutions that meet the varied requirements of different manufacturing organizations[16]. This thesis addresses this gap by first identifying key implementation challenges and then exploring strategies to enhance the integration of AI maintenance solutions into existing manufacturing infrastructure.

1.2 Vision

This research has a vision where manufacturing environment assets benefit from fully operational AI solutions which are deployed, maintained, monitored, and updated to orchestrate maintenance activities, ultimately enabling more reliable production, reduced downtime, and sustainable manufacturing operations that can adapt to evolving demands.

Manufacturing is one of humanity's oldest industries, developing alongside civilization for thousands of years. Today, it encounters AI, representing the forefront of computational advancement, recently accelerated by significant improvements in computing power. While AI applications have advanced rapidly in domains like finance and e-commerce, manufacturing lags behind in this transformation, despite the substantial value that successful implementation could deliver.

1.3 Aim

The aim of this licentiate thesis is to investigate the challenges associated with integrating AI solutions within maintenance context of manufacturing and equip manufacturing companies with the knowledge and tools to overcome these challenges, To achieve this aim, the research addresses two primary research questions:

RQ1: What are the challenges of integrating AI solutions for maintenance in manufacturing?

This question seeks to identify and characterize the challenges that manufacturing organizations face when trying to implement AI solutions for maintenance.

RQ2: How can the integration challenges of AI solutions for maintenance in manufacturing be addressed?

This question investigates what frameworks, best practice or methodologies, and architectures can systematically address the deployment and integration challenges of AI solutions for maintenance in manufacturing environments.

1.4 Scope and Delimitation

The scope of this thesis focuses on identifying the challenges a manufacturing system faces during integrating of AI solutions in the context of maintenance and exploring the set of practices, principles and culture which enables the successful deployment of AI solutions in a manufacturing system. The research focuses exclusively on manufacturing systems and does not encompass other sectors like healthcare, energy, or transportation, though the findings could potentially be applied more widely.

1.5 Thesis Outline

This licentiate thesis is structured into six chapters following the Design Research Methodology (DRM) framework. Chapter 1 presents the research background, vision, aim, research questions, and scope. Chapter 2 establishes the theoretical foundation covering the role of maintenance in manufacturing, data-driven solutions, and a literature review of AI concepts, operational frameworks, and implementation challenges. Chapter 3 describes the multi-paradigm philosophical approach and DRM framework, detailing data collection and analysis methods for the five studies (A-E). Chapter 4 presents findings addressing both research questions: integration challenges of AI solutions (RQ1) and approaches to address these challenges through MLOps frameworks (RQ2). Chapter 5 synthesizes the findings, discusses contributions, research quality, limitations, ethical considerations, and future work directions. Chapter 6 summarizes key findings and demonstrates how the research objectives have been achieved. The thesis follows a systematic progression from problem identification through theoretical understanding to practical solutions, focusing on AI integration challenges and MLOps frameworks in manufacturing maintenance contexts.

CHAPTER 2

Frame of Reference

This chapter establishes the theoretical foundation for understanding the deployment and integration of artificial intelligence in manufacturing maintenance. As illustrated in Figure 2.1, this research operates at the intersection of five important areas: maintenance in manufacturing context, predictive maintenance, artificial intelligence as an enabling tool, deployment and operational challenges of AI, and AI operational frameworks with specific focus on MLOps.

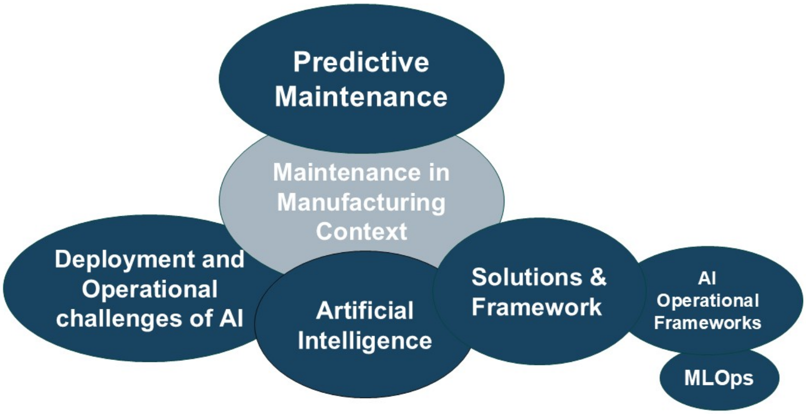

Figure 2.1: Research scope and relevance areas

The chapter begins by examining maintenance as a strategic function in modern manufacturing systems, followed by an exploration of data-driven solutions including predictive maintenance, digital twins, and Industrial Internet of Things integration. This chapter proceeds to explore the exisiting literature to clarify fundamental AI and ML concepts, distinguishes between various operational frameworks and systematically examines the challenges of implementing AI solutions in manufacturing maintenance.

2.1 Role of Maintenance in Manufacturing Industry

Maintenance serves as a critical strategic function in modern manufacturing, directly influencing production quality, quantity, and overall cost structure [17]. The strategic importance of maintenance has evolved significantly, with organizations now treating maintenance excellence as essential for achieving world-class manufacturing status [18]. This shift reflects maintenance's transformation from a cost center to a profit-generating business element, particularly through comprehensive approaches like Total Productive Maintenance (TPM) [19]. Contemporary manufacturing environments employ diverse maintenance strategies, including preventive, opportunistic, and condition-based approaches, each contributing to enhanced manufacturing performance and reduced unplanned downtimes [20], [21]. The integration of maintenance with production planning has become increasingly sophisticated, utilizing advanced algorithms to optimize production stoppages and maximize system availability [22].

Maintenance is formally defined by the European Standard EN 13306:2001 as "the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function" [23]. From a functional perspective, maintenance serves as the systematic function that monitors and keeps plant, equipment, and facilities operational, encompassing activities to design, organize, execute, and verify work that guarantees nominal functioning during uptimes while minimizing downtimes caused by breakdowns or repairs [23]. Contemporary understanding positions maintenance as a comprehensive system operating synergistically with production processes, where maintenance activities combine know-how, labor, spare parts, and resources to maintain equipment in optimal working condition and ensure appropriate production capacity levels [23]. At the strategic level, maintenance has evolved from a reactive cost center into a proactive, value-generating function that encompasses systematic planning, control and supervision, and continuous improvement of organizational methods [23], making it integral to manufacturing operations and overall business performance.

In the systems view of manufacturing, maintenance operates as an integral parallel process alongside production, forming a synergistic relationship where both processes are interdependent and mutually supportive Gits [25]. As illustrated in the figure , the primary production process transforms inputs (material, energy, manpower) into desired outputs (products or services) through technical systems, while simultaneously generating maintenance demand as a secondary output due to system degradation, aging, and operational wear [25]. The maintenance process responds to this demand by combining know-how, labor, spare parts, and other resources to restore or retain technical systems in their required functional state, thereby generating potential production capacity as a secondary input back to the production system. This cyclical relationship demonstrates that maintenance is not merely a support function but an essential component of the production ecosystem, where the state and reliability of technical systems directly influence production capability, and where maintenance activities ensure the continuous availability and performance of production assets [25].

The digital transformation accompanying Industry 4.0 has introduced new complexities requiring maintenance organizations to handle advanced automated systems while supporting sustainability initiatives [26], [27]. Maintenance 4.0 technologies now focus on maximizing equipment lifespan while minimizing resource consumption, aligning with broader sustainability goals

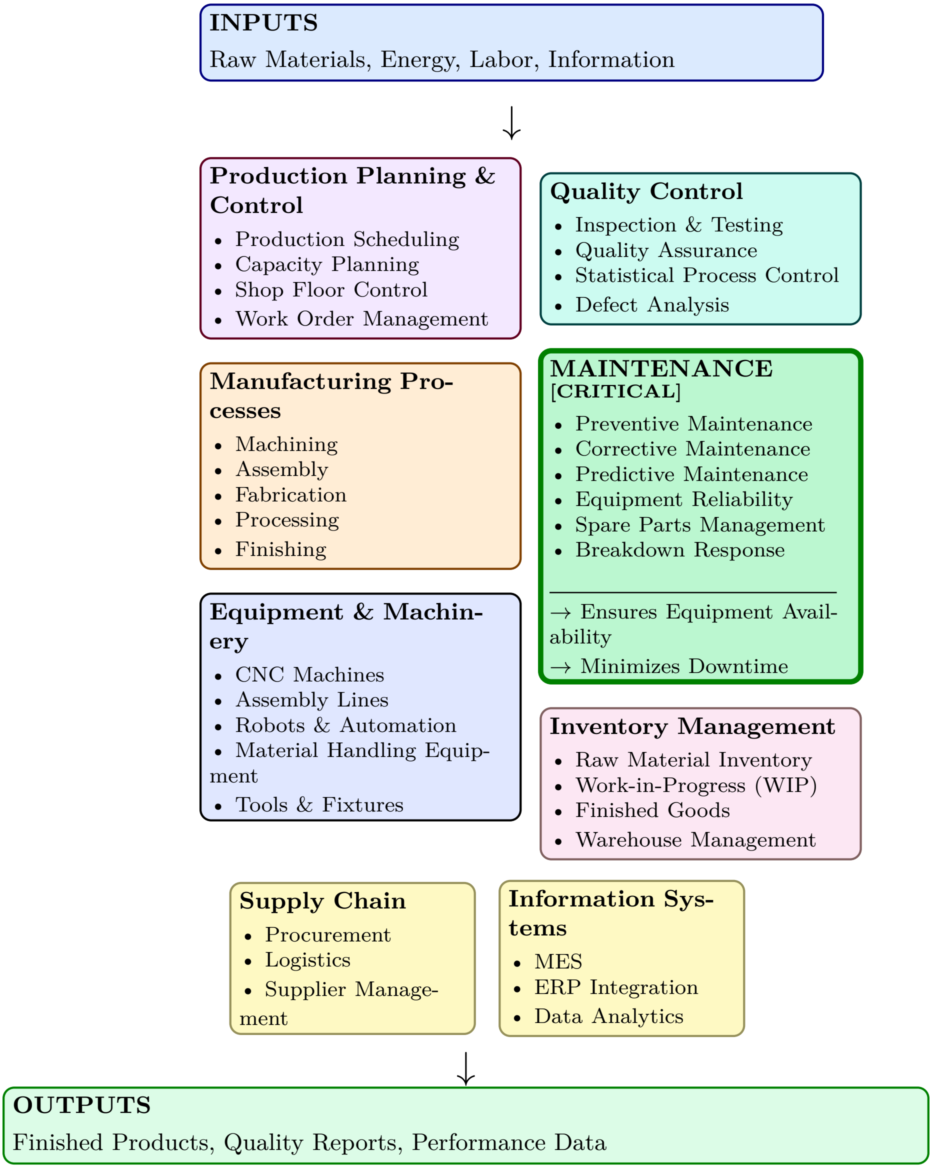

Figure 2.2: Manufacturing system components inspired by [24]

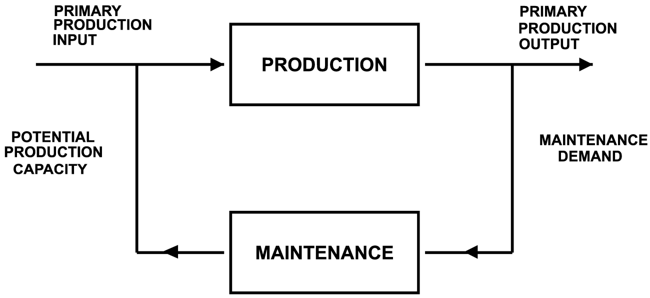

Figure 2.3: The relationship between production and maintenance. (Adapted from [25])

[28].Effective maintenance implementation requires systematic approaches including professional staff training, computerized management systems, and improved spare parts availability [29]. Despite high initial implementation costs, well-executed maintenance programs significantly enhance financial viability and competitive positioning through improved productivity and operational efficiency [30].

The structure and components shown in Figure 2.2 are inspired by the manufacturing system architecture framework developed by Benkamoun et al. [24]. Their work on representing manufacturing systems through functional and physical components, including production units, quality control, material handling, information systems, and maintenance functions, provided the conceptual foundation for this visualization, which helps to demarcate and clearly understand the role and position of maintenance within the broader manufacturing system.

2.2 Data Driven Solutions and Enablers for Maintenance in Manufacturing

2.2.1 AI-Enabled Maintenance

Data-driven solutions in manufacturing maintenance represent a transformative approach that leverages advanced analytics, AI, and real-time sensor data to optimize maintenance strategies and enhance operational efficiency. At the core of these solutions lies predictive maintenance, which utilizes AI algorithms and sensor data to forecast equipment failures before they occur, enabling just-in-time maintenance interventions that significantly reduce downtime and operational costs [31], [32]. This approach extends to specialized applications such as tool condition monitoring in manufacturing environments, where edge AI technology processes complex algorithms locally to monitor tool wear in real-time, thereby ensuring product quality while reducing latency and improving data privacy [31].

Complementing predictive maintenance, condition-based maintenance strategies rely on continuous monitoring of equipment through in-situ tests and operational measurements, enabling maintenance decisions based on actual equipment condition rather than predetermined schedules [33]. The integration of manufacturing execution systems and computerized maintenance management systems creates sophisticated decision support frameworks that prioritize maintenance activities through machine criticality assessments, ultimately increasing productivity [34]. Full-stack data analytics solutions that encompass data collection, storage, processing, and visualization have demonstrated substantial improvements in factory uptime while eliminating unexpected equipment breakdowns [35].

The implementation of predictive maintenance strategies involves multiple analytical techniques, including advanced signal processing, statistical analysis, and deep learning approaches such as neural networks [36], [37]. The effectiveness of these systems relies heavily on the integration of diverse ML algorithms, including decision trees, k-nearest neighbors, support vector machines, random forests, and deep learning models [38], [39]. ML techniques, including support vector machines and gradient boosting algorithms, enhance predictive capabilities by identifying potential equipment issues before they manifest into failures [40].

2.2.2 Digital Twin Technology and Virtual System Modeling

Digital twins represent a crucial component of AI for maintenance, functioning as virtual replicas of physical systems that utilize real-time data streams to simulate and predict system behaviors [41], [42]. These virtual models serve multiple critical functions, including fault diagnosis, predictive maintenance optimization, and maintenance schedule planning through the simulation of various failure scenarios [41], [43]. The implementation of digital twin technology significantly enhances system resilience, improves failure prediction accuracy, and provides actionable insights into overall system performance characteristics [41], [42].

2.2.3 Industrial Internet of Things

The Industrial Internet of Things (IIoT) serves as the foundational infrastructure that enables continuous equipment monitoring through interconnected sensor networks and intelligent devices, facilitating comprehensive real-time data collection and analysis capabilities [37], [44]. The strategic integration of IIoT with artificial intelligence and big data analytics substantially enhances predictive maintenance capabilities by providing comprehensive insights into equipment health status and operational patterns [37], [45].

2.2.4 Edge Computing and Real-Time Processing

Edge computing plays a pivotal role in AI maintenance systems by processing data locally at network edges, thereby reducing latency and bandwidth requirements while enabling real-time monitoring and decision-making capabilities that are essential for effective predictive maintenance implementation [46], [47]. This distributed computing approach ensures that critical maintenance decisions can be made instantaneously, without dependence on centralized cloud processing systems.

However, successful implementation of these data-driven approaches requires addressing significant challenges including data quality and trustworthiness issues, system integration complexities, and organizational adaptation barriers such as management competency and trust in data-driven decision-making processes [39], [48], [49]. The synchronization of maintenance goals with production and logistics functions, coupled with cloud-based systems for real-time monitoring and analytics, creates an integrated ecosystem that optimizes maintenance coordination throughout the entire asset lifecycle [32], [50].

Future developments in this field focus on collaborative prognostics approaches that adapt maintenance plans based on real-time machine behavior and the establishment of standardized taxonomies for recurring data analysis problems, which will create reusable knowledge bases to enhance the efficiency and effectiveness of data-driven maintenance solutions [51], [52]. This convergence enables organizations to achieve unprecedented levels of operational efficiency, equipment reliability, and cost optimization while positioning them for future technological advancements in Industry 4.0 and 5.0 paradigms [41], [53].

2.3 Artificial Intelligence

This section intends to clarify the terminologies, relationships and conceptual demarcation related to AI.

2.3.1 Understanding Artificial Intelligence

Artificial Intelligence represents a comprehensive field within computer science dedicated to creating systems capable of performing tasks that typically require human intelligence. AI is defined as a technique that makes machines mimic human behavior, with the foundational concept positing that human intelligence can be sufficiently defined for machines to emulate [54]. The scope of AI encompasses various sophisticated techniques and methodologies aimed at developing such intelligent systems [55].

2.3.2 Machine Learning

ML constitutes a specialized subset of AI that focuses on enabling software programs to enhance their predictive accuracy without explicit programming [54]. ML uses historical data to forecast new output values and identify patterns present in datasets [55]. The main objective of ML is to design programs that can access data and learn autonomously, making systems work independently without human intervention [54].

The methodological approach of ML centers on pattern recognition and data-driven learning. In order to obtain better decisions, the procedure is started by inspecting the data and searching for patterns, with the aim of making systems work independently without human intervention while identifying patterns present in data [54]. ML techniques are classified into four categories: Supervised learning, Unsupervised learning, Semi-Supervised learning, and Reinforcement learning [54].

2.3.3 Deep Learning as a Specialized Domain

Deep Learning represents a more specialized subset within the ML hierarchy. Deep learning, a subset of ML, involves training models to organize sounds, text, or images using neural networks and substantial labeled data [55]. Deep learning is based on the anatomy and physiology of the human brain, using artificial neural networks to analyze data and make predictions [55]. The

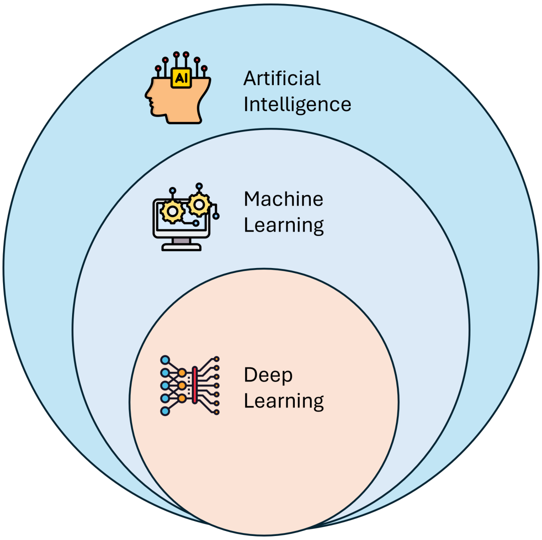

Figure 2.4: Position of AI, ML and DL inspired by [55] (These icons has been designed using resources from Flaticon.com)

performance capabilities of deep learning can be remarkable, as in some cases, deep learning models surpass human performance, achieving state-of-the-art accuracy [55].

2.3.4 Conceptual Demarcation and Hierarchical Relationships

The relationship between these technologies follows a clear hierarchical structure that is visualized in 2.4. AI serves as the overarching field, with ML as a subset within AI, and deep learning as a specialized area within ML [55]. This hierarchical arrangement demonstrates that while all ML techniques are part of AI, not all AI techniques constitute ML, and similarly, while deep learning is part of ML, it represents only one approach within the broader ML domain. AI encompasses a broad range of techniques for creating intelligent systems. Non-ML AI includes rule-based systems that follow pre-programmed instructions, search algorithms for optimization and pathfinding, symbolic reasoning systems for logic and theorem proving, and traditional computer vision techniques using mathematical formulas rather than learned patterns. These systems demonstrate intelligence through sophisticated problem-solving and decision-making capabilities, but unlike ML systems, they operate using fixed rules and algorithms rather than learning and adapting from data over time.

The technical distinctions become apparent in their methodological focuses.

Supervised learning makes use of previous data and knowledge to forecast events with the help of labels, requiring human input and feedback to predict accuracy in the training process [54]. Unsupervised learning is contrary to supervised learning technique with the absence of training process, exploring hidden patterns in unlabeled data [54]. Semi-supervised learning uses both labeled and unlabeled data, lying between supervised and unsupervised learning [54].

2.4 Operational Frameworks in AI and ML

This section dives in deep to understand the various operational frameworks in AI and ML. While these terms are often used interchangeably in literature, each represents distinct operational approaches with specific focus areas and applications.

DevOps (Development Operations) is the foundational methodology that combines software development (Dev) and IT operations (Ops) to shorten the development lifecycle while delivering features, fixes, and updates frequently and reliably [56]. DevOps emphasizes collaboration between development and operations teams, continuous integration and deployment (CI/CD), infrastructure as code, and automated testing and monitoring practices DevOps. The paradigm emerged in the years 2008/2009 and aims to reduce issues in software development with the goal of eliminating the gap between development and operations [56]

MLOps (Machine Learning Operations) extends DevOps principles specifically to ML workflows, encompassing the end-to-end lifecycle of AI models from development through deployment and maintenance [9]. MLOps addresses unique AI challenges such as data versioning, experiment tracking, model drift detection, and automated retraining pipelines that are not present in traditional software development. MLOps is aimed at productionizing ML systems by bridging the gap between development (Dev) and operations (Ops), facilitating the creation of ML products by leveraging principles such as CI/CD automation, workflow orchestration, reproducibility, versioning of data, model, and code, collaboration, continuous training and evaluation, metadata tracking and logging, continuous monitoring, and feedback loops MLOps [9].

MOdelOps (Model Operations), is a set of practices and tools designed to manage and streamline the deployment, monitoring, and maintenance of ML and AI models in production environments[57]. It aims to ensure that models are efficiently and effectively integrated into operational systems, providing continuous value and adapting to changing data and conditions [57]. While MLOps and ModelOps are often used interchangeably, they represent distinct operational approaches with different scopes and focus areas. MLOps specifically targets ML models and their entire lifecycle, emphasizing technical automation, data preparation, model training, and AI-specific challenges like data drift and experiment tracking. In contrast, ModelOps encompasses a broader range of analytical models including traditional statistical, rule-based, and business logic models, with a stronger focus on governance, regulatory compliance, enterprise model management, and business value measurement, typically involving business analysts, risk managers, and compliance teams. The key distinction lies in their approach: MLOps is more technical and automation-focused, while ModelOps is more governance and business-focused. In practice, many organizations implement both approaches, using MLOps for technical pipeline management and ModelOps for enterprise wide model governance, with some companies adopting "ModelOps" as an umbrella term that includes MLOps, depending on their organizational focus and the types of models they primarily manage [9], [57].

DataOps (Data Operations) applies DevOps principles to data pipeline management, focusing on improving the speed, quality, and reliability of data analytics through automated data integration, testing, and deployment processes [58]. DataOps is defined as "a set of practices, processes, and technologies that combines an integrated and process-oriented perspective on data with automation and methods from agile software engineering to improve quality, speed, and collaboration and promote a culture of continuous improvement" [58].

AIOps (Artificial intelligence for IT operations) is an advanced approach to managing and automating IT operations by leveraging AI [59]. It integrates big data analytics to enhance various aspects of IT operations, including event correlation, anomaly detection, root-cause analysis, and predictive modeling. AIOps automates routine and complex tasks, such as incident management, remediation, and optimization.

LLMOps (Large Language Model Operations) is a specialized framework designed to manage the lifecycle processes of large language models (LLMs) such as GPT, BERT, and LLaMA [60]. While building on the foundational principles of MLOps, LLMOps addresses the distinct operational challenges that emerge from the scale, complexity, and unique characteristics of large language models. This framework provides tailored tools and methodologies to optimize LLM deployment, monitoring, and management, ensuring these powerful models operate efficiently and reliably in production environments across diverse real-world applications[60].

The evolution of operational practices in software and AI has given rise to various "Ops" methodologies, each addressing specific operational challenges. DevOps serves as the foundational paradigm that bridges software development and IT operations through continuous integration and deployment practices. MLOps extends these principles specifically to ML workflows, focusing on the technical automation of AI model lifecycles including data versioning, experiment tracking, and model drift detection. ModelOps takes a broader enterprise approach, encompassing all types of analytical models with emphasis on governance, compliance, and business value management across the organization. DataOps applies DevOps principles to data pipeline management, emphasizing data quality, reliability, and automated data integration processes. AIOps leverages artificial intelligence to automate and enhance IT operations management through intelligent monitoring, anomaly detection, and predictive analytics. LLMOps represents the newest specialization, addressing the unique operational challenges of large language models including their scale, complexity, and deployment requirements.

However, by closely studying [57]–[59], it can be deduced that DataOps, AIOps, and ModelOps address complementary operational aspects, none specifically focus on the end-to-end ML model lifecycle management that is critical for successful AI deployment. DevOps, while foundational to operational practices, targets general software development rather than the specialized requirements of ML models [56]. LLMOps, though ML-focused, addresses only the specific operational challenges of large language models rather than general ML applications [60]. While other 'Ops' methodologies such as FinOps [61], InfraOps [62], ETLOps[63] exist to address operational concerns outside the AI domain. There are still other "Ops" terms which are predominantly industry coined concepts and practitioner terminology that lack substantial peer reviewed academic literature, distinguishing them from academically established methodologies such as DevOps and MLOps. This research therefore centers on MLOps as the primary operational framework capable of addressing the complete deployment and integration challenge for AI solutions in manufacturing, providing the necessary tools and practices for managing models from development through production deployment and ongoing maintenance.

2.4.1 MLOps in Manufacturing Maintenance

MLOps represents a critical evolution in the integration of ML capabilities into industrial production environments. At its core, MLOps is a systematic approach that combines ML model development, deployment, monitoring, and maintenance to ensure continuous operation and improvement of AI systems in production settings [64]. This discipline encompasses the entire lifecycle of ML models, from initial development through deployment, ongoing monitoring, and iterative refinement.

In the context of manufacturing maintenance, MLOps serves as the backbone for implementing predictive maintenance strategies that leverage data-driven insights to optimize equipment performance and maintenance schedules [65]. The framework addresses the complexities of managing large-scale ML deployments across diverse manufacturing environments, ensuring that predictive models remain accurate, relevant, and operationally effective over time. The integration of MLOps in manufacturing maintenance addresses several fundamental challenges. First, it provides robust data management capabilities to handle the vast amounts of sensor data, operational logs, and historical maintenance records generated by modern manufacturing systems [66]. Second, it establishes systematic procedures for model training, validation, and deployment that ensure predictive maintenance algorithms can reliably anticipate equipment failures and optimize maintenance interventions [67]. Furthermore, MLOps platforms enable continuous monitoring and automated retraining of ML models, ensuring they adapt to changing operational conditions and maintain predictive accuracy [68]. This capability is particularly crucial in manufacturing environments where equipment behavior, operational parameters, and maintenance requirements evolve over time due to factors such as equipment aging, process modifications, and changing production demands. The operational benefits of MLOps in manufacturing maintenance are substantial. By enabling systematic deployment and management of predictive maintenance models, MLOps contributes to significant reductions in unplanned downtime, optimization of maintenance schedules, and extension of equipment lifecycles [69].

2.5 Implementation Challenges of AI Solutions for Maintenance in Manufacturing

The implementation of AI solutions for maintenance in manufacturing faces many challenges that span from technical, organizational, to societal dimensions.

Technical Infrastructure and Environment: The foundational technical challenges center on data quality and management, where effective predictive maintenance systems require high-quality, accurate, complete, and consistent data from various sensors and monitoring devices [70]–[72]. Managing and processing large volumes of heterogeneous data in real-time presents significant complexity and resource demands [73], [74]. The computational intensity of AI implementations creates substantial barriers, particularly for small and medium-sized enterprises, as these systems require considerable processing power for real-time data analysis, pattern recognition, and decision-making [75], [76]. Additionally, establishing robust network infrastructure and ensuring reliable connectivity between distributed sensors, edge devices, and centralized systems remains a critical technical prerequisite [73].

Model Management and Maintenance: The complexity of model selection and performance evaluation represents a significant challenge, encompassing feature engineering, algorithm selection, hyperparameter tuning, and ensuring model robustness across diverse operational conditions [75], [77], [78]. Models must demonstrate the ability to generalize effectively to new, unseen data while maintaining predictive accuracy over time [75]. Continuous model monitoring, retraining, and updating procedures are essential to address concept drift and maintain performance as manufacturing processes evolve [74]. The challenge extends to developing appropriate validation frameworks and establishing metrics that accurately reflect real-world performance in dynamic manufacturing environments [77].

Human Factors and Adoption Organizational challenges significantly impact implementation success, beginning with the critical shortage of skilled personnel capable of developing, implementing, and maintaining sophisticated AI systems [72], [79]. The need for comprehensive training programs to upskill existing workforce and attract new talent with expertise in data science, ML, and industrial applications creates substantial human resource challenges [72], [79]. Organizational culture and resistance to adopting new technologies can severely hinder implementation progress, requiring effective change management strategies and clear demonstration of tangible benefits from AI-driven maintenance solutions [72], [79]. Cross-functional collaboration between data scientists, domain experts, and operational staff is essential but often difficult to achieve [72].

Security and Privacy: Data security and privacy concerns present challenges in manufacturing environments where sensitive operational data must be protected while enabling AI system functionality [80], [81]. Ensuring algorithmic transparency and accountability while maintaining competitive advantages creates tension between openness and proprietary protection [80], [82]. The implementation of robust cybersecurity measures to protect AI systems from adversarial attacks and data breaches requires specialized expertise and ongoing vigilance [74]. Additionally, compliance with evolving data protection regulations and industry standards adds complexity to system design and deployment [82]. Integration to Existing Infrastructure The challenge of integrating AI-driven predictive maintenance solutions with existing manufacturing systems and workflows requires seamless communication between legacy machines, modern sensors, and AI models [72], [73]. Compatibility issues between different system architectures, communication protocols, and data formats create significant technical hurdles [73], [74]. The need to maintain operational continuity during system integration phases while minimizing disruption to production schedules presents logistical challenges [79]. Furthermore, scaling AI solutions across diverse manufacturing environments with varying equipment types, ages, and configurations requires flexible and adaptable system architectures [72].

Domain Challenges: Manufacturing-specific challenges include addressing the unique characteristics of industrial environments, such as harsh operating conditions, electromagnetic interference, and varying operational modes that can affect sensor performance and data quality [70], [75]. The heterogeneity of manufacturing processes, equipment types, and operational parameters across different facilities creates complexity in developing generalizable AI solutions [77]. Societal and ethical considerations, including concerns about algorithmic bias in decision-making processes and the potential for AI technologies to exacerbate economic inequalities through uneven access to advanced maintenance capabilities, must be carefully addressed [80]–[82]. The economic justification for AI implementation, particularly in terms of return on investment and long-term value creation, remains a persistent challenge for manufacturing organizations [79].

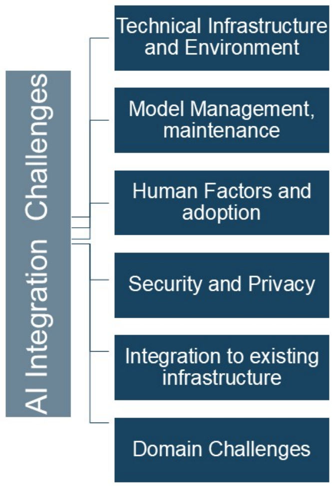

Figure 2.5: Category of AI implementation challenges from the literature

CHAPTER 3

Methodology

The research design for this thesis is structured according to the DRM framework, which provides a systematic approach for addressing complex problems in design and engineering contexts. This section explains the DRM stages, their application to this research, and the sequential progression of studies conducted within this framework.

3.1 Philosophical Worldview

My approach to this research is influenced by my background as an engineer with five years of industrial experience before starting my PhD. This practical foundation influences how I identify research problems, design studies, and evaluate solutions. I focus on challenges that exist in real manufacturing environments and solutions that can be implemented in practice.

Working closely with industrial partners throughout my PhD has strengthened a pragmatic perspective. I believe research should connect theoretical possibilities with practical realities. When investigating AI integration challenges in manufacturing maintenance, I consider not just what could work under ideal conditions, but what works with real constraints like limited data, existing systems, workforce skills, and organizational conditions.

This pragmatic approach is reflected in my research design: conducting experiments in actual production facilities, gathering insights from experienced practitioners, and developing solutions that address real deployment challenges. My engineering background provides a structured approach to problem-solving, while my industry experience keeps the research focused on the practical realities of manufacturing operations.

3.2 Research Design

Design Research Methodology (DRM) represents a systematic framework for conducting research in design and engineering contexts, providing structured approaches to understanding complex problems and developing effective solutions. Originally developed by Blessing and Chakrabarti [83], DRM offers a comprehensive methodology that bridges the gap between theoretical understanding and practical implementation through its systematic four-stage approach.

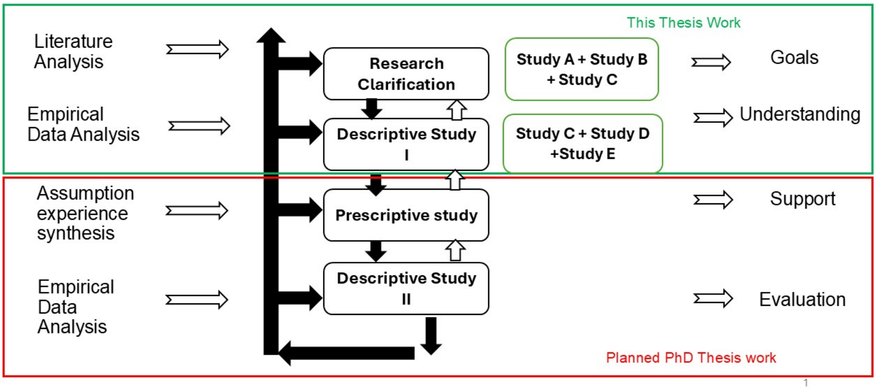

Figure 3.1: - Design Research Methodology stages [83]

DRM framework provides a systematic approach for conducting design research that emphasizes both understanding existing situations and developing improved solutions. As illustrated in figure 3.1, the DRM framework consists of four interconnected stages: Research Clarification (DS1), Descriptive Study I (DS2), Prescriptive Study(DS3), and Descriptive Study II (DS4), each serving distinct but complementary purposes in the research process. First two phases of DRM highlighted in green is in the scope of this thesis and the final two stages highlighted in yellow is planned for the PhD work. The literature analysis and empirical data analysis provide inputs to the Research Clarification phase (DS1), Study C, Study A, and Study B. The framework then progresses to Descriptive Study I (DS2), which includes Study C, Study D, and Study E focusing on understanding existing solutions and analyzing current approaches.

The DRM framework was selected for this research due to its particular suitability for addressing complex, varied problems that require both theoretical understanding and practical solutions. The methodology's emphasis on iterative refinement and validation aligns with the research objectives of understanding AI deployment challenges in manufacturing and exploring practical frameworks to address these challenges.

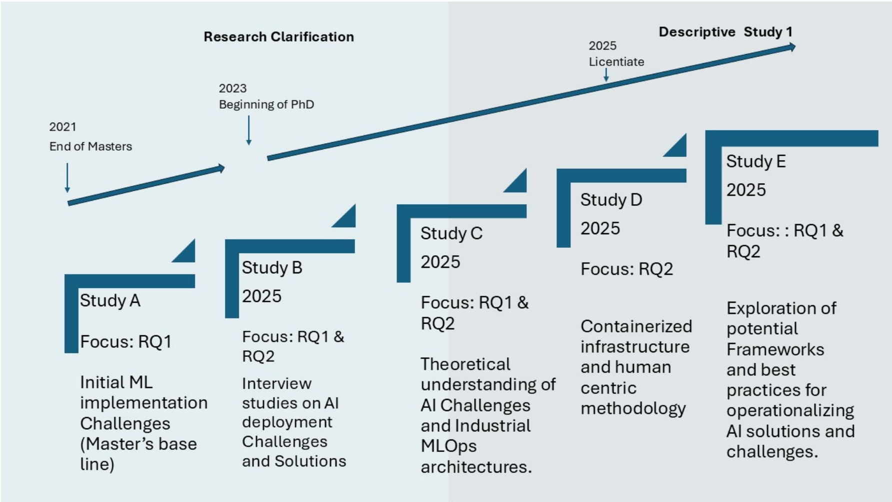

Figure 3.2: Research progression timeline

As shown in figure 3.2, the studies were strategically sequenced to build upon each other's findings. In the research clarification stage, multiple methods were used for the purpose of defining the the research scope. Initially, Study C, which was a systematic review of the literature, was a focus of providing a theoretical understanding of challenges and MLOps basics and exploring the state of the art of industrial MLOps architectures. In addition, this study provides a comprehensive understanding of MLOps architectures that aid in the successful implementation of the AI solution in the manufacturing maintenance context. This study contributes to both DS1 and DS2. Study A (Air Leakage Detection) was conducted in 2021 as an initial AI implementation challenge investigation, forming part of the Research Clarification phase. Study B (Expert Interviews) was planned for 2025 to provide industry validation of AI deployment challenges, also contributing to DS1. Study D (CBM Implementation) was conducted in 2025 to demonstrate deployment using containerized infrastructure and human interface requirements, within the DS2 phase. During the planning and writing of this licentiate thesis, Study E, which included narrative literature review, was planned to explore the frameworks for operationalizing the AI solutions documented within the academic publications and AI integration challenges.

The systematic progression through the DRM stages ensures that research outcomes are theoretically grounded and practically applicable. The Research Clarification stage establishes clear understanding of the problem domain and formulates precise research questions. The stage of descriptive study I provides a comprehensive analysis of existing approaches and current practices. This systematic progression ensures that each study contributes meaningfully to the overall research objectives while maintaining methodological rigor throughout the investigation. The iterative nature of the DRM framework, evident in the interconnections shown between studies, allows for continuous refinement of research questions and methodology based on emerging insights from each stage. This approach ensures that the research maintains both academic rigor and practical relevance throughout the investigation process.

3.3 Research Methods, Data Collection and Data Analysis

The research methodology employed a multi-method approach within the DRM framework, ensuring complementary insights across all studies. The combination of single case studies (Studies A and D), qualitative interview research (Study B), and systematic literature review (Study C) and Thematic literature review (Study E) enabled triangulation of findings across multiple data sources and methodological approaches, providing comprehensive coverage of the research questions within the systematic DRM structure. The summary of research methods, Data collection & Data analysis is presented in the table 3.1.

3.3.1 Study A: Air Leakage Detection - Single Case Study with Experimental Design

Study A employed a single case study methodology with a data-driven experimental approach to investigate air leakage detection in pneumatic systems at a Swedish bearing manufacturing company during 2021. The study utilized the CRISP-DM methodology as a systematic approach for the ML project, following its six top-level phases in an iterative process. The methodology involved artificially inducing anomalies to address the challenge of limited historical fault data, representing a novel approach for data labeling in manufacturing contexts where historical failure records are scarce. The single case design focused on one manufacturing facility's wrapping and packaging machines located at the end of a highly automated flow production line. Two separate experiments were designed and conducted to understand machine behavior under different operational conditions. The first experiment was performed during a planned maintenance period, where a small hole was deliberately drilled in an external plug using a 1mm drill, connected to a pneumatic tee tube-to-tube adapter to simulate leakage conditions. The second experiment was conducted during normal production operations with a 0.8mm hole to simulate early-stage leakage over an extended period. The experimental methodology involved systematic data collection using sensors measuring pressure (bar), air flow (l/m), and temperature (°C) of compressed air systems at one-second intervals. The collected data underwent systematic preprocessing including outlier detection and removal using box plot analysis, idle time detection and removal through algorithmic approaches, and data grouping based on processing time dimensions. Feature extraction was performed using MATLAB's Diagnostic Feature Designer App to identify significant time-domain features, with Kruskal-Wallis feature ranking employed to identify the most discriminative features. A RUSBoost bagged trees model was developed as the supervised ML approach, combining random undersampling with AdaBoost algorithm to address class imbalance challenges inherent in the experimental design.

Table 3.1: Research methods, data collection, and data analysis

Study	Paper	Research Method	Data Collection	Data Analysis
A	[**Paper 1**]	**Single case study with experimental design**	Sensor data (pressure, air flow, temperature) at one-second intervals from artificially induced anomalies using 1mm and 0.8mm drill holes	CRISP-DM methodology, MATLAB's Diagnostic Feature Designer App, Kruskal-Wallis feature ranking, RUSBoost bagged trees model
B	[**Paper 2**]	**Qualitative interview study (Gioia methodology)**	Semi-structured interviews with 4 participants (Solutions Architect, Business Developer, Automation/IT Manager, IoT Specialist) over one month, 50 minutes each	NVivo software, inductive coding with first-order concepts, second-order themes, aggregate theoretical dimensions
C	[**Paper 3**]	**Systematic literature review**	Scopus database search with TITLE-ABS-KEY strategy, 186 initial documents filtered to 12 final papers through inclusion/exclusion criteria	Thematic analysis following Braun and Clarke's [84] approach using Rayyan [85] software for systematic analysis
D	[**Paper 4**]	**Single case study with human-centric design**	Built-in circularity test data, iterative discussions with maintenance engineers, user feedback collection	Flask web framework development, statistical preprocessing, Docker containerization, comprehensive user manual validation
E	[**Licentiate Thesis**]	**Narrative Literature Review**	Literature search across multiple databases (academic journals, conference proceedings, industry reports) using keyword combinations related to AI operational frameworks and manufacturing maintenance	Synthesis and organizing sources into conceptual categories (AI definitions, operational methodologies, implementation challenges), narrative analysis for terminology clarification and framework distinction

3.3.2 Study B: Expert Interviews - Qualitative Interview Study

Study B employed the Gioia methodology [86] to conduct qualitative research investigating AI deployment challenges in manufacturing. The study utilized purposeful sampling to select four highly knowledgeable participants: a Solutions Architect, a Business Developer, an Automation and IT Manager, and a Senior IoT and Edge AI Specialist. Semi-structured interviews were conducted over a one-month period in February 2025, with each session lasting approximately 50 minutes. The interviews covered current state of AI implementation, successful deployment examples, primary technical and organizational challenges, workforce skill gaps, infrastructure requirements, and future outlook. The analytical approach employed NVivo qualitative data analysis software following the Gioia methodology structure. The analysis began with an inductive approach identifying first-order concepts directly from participant language. These concepts were systematically grouped into second-order themes through dimensional analysis, exploring relationships between categories. Finally, second-order themes were consolidated into aggregate theoretical dimensions representing the highest level of abstraction.

3.3.3 Study C: MLOps Systematic Literature Review

Study C employed systematic literature review methodology following established guidelines to analyze MLOps architectures in industrial contexts. The search strategy utilized Scopus database with the search string: TITLE-ABS-KEY (("ML OPS" OR "MLOps" OR "ML-OPS" OR "machine learning operations") AND ("factory" OR "manufac*" OR "maintenance" OR "industr*")). The initial search yielded 186 documents, systematically refined through inclusion and exclusion criteria. Filters were applied based on subject areas (Engineering, Computer Science, Mathematics, Decision Sciences) and language restrictions (English). Following title and abstract screening, 33 documents were selected for full-text review, with final selection comprising 10 documents supplemented by 2 additional documents through backward snowballing. Thematic analysis was performed following Braun and Clarke's [84] structured approach, utilizing Rayyan [85] software for systematic analysis. The analysis involved thorough familiarization with selected articles, initial coding to categorize data into architectural characteristics and implementation challenges, and systematic grouping into themes and patterns.

3.3.4 Study D: CBM Dashboard Development - Single Case Study with Human-Centric Design

Study D employed a single case study methodology using a human-centric design approach to develop and deploy a condition-based maintenance dashboard at a Swedish heavy-duty vehicle powertrain facility. The single case design focused on establishing foundational infrastructure components necessary for future MLOps implementation, though no ML models were developed in this study. The methodology consisted of six phases: problem understanding through discussions with maintenance engineers, data collection utilizing existing built-in circularity tests, data preprocessing and standardization, CBM application development using Flask web framework through iterative discussions with domain experts, deployment using Docker containerization, and validation through comprehensive user manual creation and feedback collection from domain experts.

3.3.5 Study E: Narrative Literature Review - Operational Frameworks and AI Implementation Challenges

Study E employed a narrative literature review to systematically examine and synthesize existing knowledge on AI operational frameworks and AI implementation challenges in manufacturing and maintenance contexts. The review approach focused on clarifying terminologies related to AI technologies, operationalizing AI concepts, and distinguishing between various "Ops" methodologies that have emerged from the foundational DevOps paradigm. The methodology consisted of comprehensive literature search across multiple academic databases and industry sources using targeted keyword combinations regarding AI definitions and hierarchical relationships, operational frameworks (DevOps, MLOps, AIOps), and AI implementation challenges in manufacturing environments. The analysis employed narrative synthesis techniques to develop conceptual clarity around terminologies and frameworks, enabling systematic exploration of challenges that impact successful AI deployment for maintenance and manufacturing applications. This study was documented within the Frame of Reference chapter of this thesis and the results are analyzed in the Results chapter.

3.4 Research Quality

Research quality in DRM is established through systematic evaluation of how well the research addresses its stated aims and generates credible, dependable knowledge [87]. Following Blessing and Chakrabarti [83] and design science validity principles [88], this research is evaluated through criterion validity, methodological rigor, and context considerations adapted to each study type.

Criterion validity addresses whether research outcomes demonstrate utility relative to existing approaches or established standards [88]. Study A achieved 98.67% accuracy in air leakage detection, outperforming traditional threshold-based methods, with the artificial anomaly induction approach validated against domain expert knowledge. Study B's identified AI implementation challenges were validated through triangulation across four domain experts with diverse roles, ensuring findings represented multiple manufacturing industry perspectives. Study C followed PRISMA [89] guidelines for systematic review with transparent thematic analysis using Rayyan software across 186 initially identified documents, grounding findings in peer-reviewed literature from multiple manufacturing contexts. Study D's dashboard utility was validated through iterative feedback from maintenance engineers, with practical applicability demonstrated through comprehensive user manual and Docker containerization. Study E's conceptual framework synthesizing AI operational frameworks was validated through consistency with established literature and its ability to clarify terminology confusion in manufacturing contexts.

Methodological rigor was maintained through established research methods appropriate to each study's objectives [90]. Studies A and D followed Yin's [91] case study recommendations, establishing construct validity through multiple data sources, documented evidence chains, and domain expert feedback. Study B employed the Gioia methodology [86] with systematic first-order concept identification, second-order theme development, and aggregate dimension formation, supported by NVivo software for transparent analytical procedures [92]. Studies C and E employed systematic procedures with documented search strategies, explicit inclusion/exclusion criteria, and structured analysis appropriate for systematic and narrative synthesis respectively.

Context validity considerations address how findings apply across different settings [88]. Studies A and D conducted in authentic Swedish manufacturing settings provided high ecological validity, while Study B's expert perspectives across multiple organizations enhanced generalizability. The single case studie's generalizability is strengthened through connection to broader theoretical frameworks (e.g., CRISP-DM, MLOps) and triangulation with literature-based studies. Study C's examination of MLOps implementations across diverse industrial contexts supports broader applicability. The sequential study progression from 2021 to 2025 captures the evolving state of AI integration in manufacturing during this critical Industry 4.0 adoption period.

This research acknowledges characteristic limitations of DRM studies in early stages [93], [94]. Studies A and D involved single manufacturing facilities, limiting immediate generalizability, though this is mitigated through the multi-study design where literature-based studies provide broader context and Study B incorporates multiple expert perspectives. This licentiate thesis covers DS1 (Research Clarification) and DS2 (Descriptive Study I), with DS3 and DS4 planned for PhD work, appropriately focusing on descriptive accuracy and problem understanding rather than solution validation. The research addresses rapid AI technology evolution by focusing on fundamental challenges and architectural principles that remain relevant despite technological changes. Methodological triangulation through the combination of experimental case study, qualitative interviews, systematic literature review, single case study with human-centric design, and narrative review strengthens confidence in conclusions through convergence of findings across different methods.

Quality assurance measures were implemented throughout the research process to ensure transparency and rigor [87], [95], including regular supervisory review, peer review through conference presentations and journal submissions, stakeholder validation from practitioners, systematic documentation of research procedures and analytical decisions, and use of established analytical tools (e.g., MATLAB, NVivo, Rayyan). The research followed ethical guidelines including informed consent from interview participants, confidentiality protection for sensitive company information, secure data management according to institutional policies, and industrial partnerships governed by mutual agreements respecting intellectual property and confidentiality requirements. The multi-method approach within the DRM framework, combined with systematic attention to quality criteria appropriate for each study type, ensures this thesis generates credible knowledge about AI integration challenges in manufacturing maintenance [88], [96] while maintaining appropriate scope and depth for a licentiate-level investigation.

CHAPTER 4

Results

This chapter presents the findings from the five studies conducted within the Design Research Methodology framework, addressing the research questions formulated in Chapter 1. As a reminder, the research questions are: RQ1- What are the challenges of integrating AI solutions for maintenance in manufacturing? and RQ2- How can the integration challenges of AI solutions for maintenance in manufacturing be addressed? Table 4.1 provides an overview of how each study contributes to these research questions. The chapter is organized into two main sections: the first section examines the integration challenges of AI solutions in manufacturing maintenance contexts (RQ1), while the second section discusses potential approaches and frameworks to address these identified challenges (RQ2).

Table 4.1: Summary of contributions of appended papers

Paper	**Study**	**Research Question**	**Key Contributions**
Paper 1	Study A	RQ1	**Historical Data Limitations:** Demonstrates how manufacturing environments lack sufficient fault occurrence records.
Paper 2	Study B	RQ1, RQ2	**Theoretical Process Model:** Developed interconnected challenge framework showing dependencies between infrastructure, scalability, skills, and maintenance. **Infrastructure Barriers:** Identified communication systems, legacy integration, IT/OT convergence, and data collection issues. **Scalability & Skills Analysis:** Revealed point solution limitations, ROI challenges, and multi-level skill requirements. **Lack of AI solution maintenance:** revealed the lack of comprehensive ML life-cycle management and maintenance frameworks like MLOps within manufacturing. **Solutions:** Expert recommended solutions for identified challenges.
Paper 3	Study C	RQ1, RQ2	**Architectural Framework:** Identified fundamental MLOps characteristics which makes it suitable for addressing AI integration challenges in manufacturing maintenance. **Challenge-Architecture Mapping:** Systematic mapping between integration challenges and corresponding recommendations. **Recommendation System:** Practical framework enabling manufacturers to select appropriate MLOps components based on specific challenges.
Paper 4	Study D	RQ2	**Containerized Architecture:** Demonstrated Docker-based deployment with docker-compose configuration providing MLOps infrastructure foundation. **Interactive Processing Framework:** Automated pipelines with user-adjustable parameters demonstrating flexible management capabilities **Human-Centric Integration:** Iterative development with domain experts ensuring operational alignment and user acceptance.
Literature review in Licentiate thesis	Study E	RQ1, RQ2	**Operational Framework Comparison:** Established MLOps as the most suitable framework providing complete AI lifecycle coverage (development through maintenance) while identifying critical gaps in alternative frameworks. **Challenges:** Explored the challenges of AI integration documented in literature using narrative literature review.

4.1 Integration Challenges of AI Solutions

This section describes the findings regarding the integration challenges of AI within manufacturing maintenance. This section attempts to contribute to RQ1.

4.1.1 Infrastructure Related Challenges

The narrative literature analysis performed in this licentiate thesis (Study E) summarizes technical infrastructure and Environment challenges as a key implementation challenge. This encompasses data quality management issues, computational resource requirements, and network infrastructure limitations and security and privacy related challenges. Manufacturing environments present heterogeneous data formats, real-time processing demands, and legacy system integration complexities that require specialized technical solutions. Security and privacy concerns involve data protection requirements, algorithmic transparency needs, cyber security measure implementation, and compliance with evolving regulations while maintaining competitive advantages.

Adding on, Study A primarily contributes to understanding of implementation challenges. This study validates an experimental approach for generating training data when historical failure records are unavailable. The developed classification model achieved high performance metrics (>98 % accuracy) in detecting early-stage leaks, demonstrating the viability of controlled fault induction for model development in maintenance contexts. This research demonstrates how manufacturing environments often lack sufficient fault occurrence records, making traditional supervised learning approaches impractical for maintenance applications. This study reveals the difficulty of obtaining properly classified datasets in operational manufacturing settings, where fault conditions may not be well-documented or readily available.

Study B identifies infrastructure challenges through expert interviews, revealing that manufacturing facilities typically lack adequate connectivity systems, proper communication infrastructure, and server capabilities necessary for AI deployment. The study highlights difficulties in data collection from legacy machines with unique formats, challenges in IT/OT convergence for synchronized data access, and complexities in managing edge infrastructure across numerous intelligent devices requiring regular updates. Additionally, experts emphasized concerns regarding data quality issues, particularly the lack of structured failure data storage, and security challenges in balancing data accessibility with protection requirements.

In Study C, each reviewed article identifies specific problems or limitations in AI or automated ML implementation, which motivates their proposed MLOps or automated ML architectures. Specifically, "Challenge 1", "Challenge 2" and "Challenge 5" in this study talk about infrastructure related challenges. "Challenge 1" discuses about manufacturing systems being diverse, involving different technologies, machines from multiple vendors, and varied processes. This heterogeneity in the OT layer introduces challenges due to the coexistence of multiple communication protocols, devices, and data formats. In modern industrial settings, seamless machine-to-machine communication is essential, yet protocols like OPC UA, MODBUS, and BLE use distinct data structures, complicating integration and automation. These differences create barriers to building efficient data pipelines for MLOps. "Challenge 2" in this study discusses data-related challenges such as poor data quality, limited availability, complex preprocessing, and feature engineering are common, especially when dealing with inconsistent formats and imbalanced datasets from multiple sources. In specialized areas like additive manufacturing, collecting sufficient high-quality data for training ML models remains difficult. Unlike data-rich sectors such as e-commerce, manufacturing often lacks adequate production data, particularly in processes with infrequent operations. The limited availability of ground-truth data in applications such as vacuum pumping further restricts model training and validation, increasing the risk of overfitting and reducing robustness. Additionally, managing both structured and unstructured data formats adds another layer of complexity to data handling, model training, and overall AI implementation in industrial environments. This study discusses "Challenge 5" which states that deploying ML on industrial IoT edge devices faces major technical barriers due to severe resource constraints - limited processing power, memory, and bandwidth compared to cloud environments. Industrial edge devices are often basic embedded systems lacking standard computing interfaces, making AI implementation particularly challenging. Scaling across multiple devices is complicated by diverse hardware architectures and inadequate development tools for industrial IoT.

4.1.2 Model Management and Maintenance

The narrative literature analysis performed in this licentiate thesis (Study E) discusses challenges regarding model management and AI solution maintenance which include feature engineering complexity, algorithm selection difficulties, hyperparameter tuning requirements, and model performance evaluation across diverse operational conditions. The dynamic nature of manufacturing processes necessitates continuous model monitoring, retraining procedures, and validation framework establishment.

Study B finds critical challenges in maintaining AI systems in manufacturing environments. In manufacturing perspective, the AI solutions are just viewed as traditional equipment, overlooking the continuous maintenance requirements that AI systems demand. Unlike conventional equipment with long lifecycles and predictable maintenance schedules, AI systems require ongoing monitoring, frequent retraining with new data, and adjustment as production conditions evolve. This study finds absence of effective maintenance and AI lifecycle frameworks, like MLOps as a prominent challenge for adoption of AI solutions in manufacturing maintenance context.

In Study C, the authors of each reviewed article highlight particular challenges or gaps in AI or automated ML implementation, which serve as the rationale for their proposed MLOps or automated ML architectures."Challenge 3" of study C quotes that the success of ML models is closely tied to their training environment, and any alterations in production processes or manual adjustments can impact their performance, requiring frequent updates and continuous monitoring. Model operations and maintenance in manufacturing setup face challenges around performance degradation over time through model drift and data drift, requiring both technical and business level monitoring of deployed models, and the need to continuously train and retrain models as new data becomes available to maintain optimal performance.

4.1.3 Scalability Challenges

In Study B, experts who were interviewed consistently emphasize that value for investment is typically realized only when solutions are scaled beyond a single use case or machine. This finding is strongly supported across the dataset in this study, with 26 coded references distributed across multiple expert interviews. The high frequency and consistency of these references talks about the critical importance of scalability considerations in industrial AI implementations and suggest this is a fundamental rather than peripheral challenge in the field.

Manufacturing companies commonly adopt a point solution mindset, targeting specific issues on individual machines rather than taking holistic approaches. This machine-centric thinking severely limits ROI potential, as the financial equation rarely works for isolated implementations. Experts provided examples where solution costs for development, production, and maintenance exceeded the generated savings, and noted that platform costs make single-machine implementations financially unfeasible.

The prototype-to-production gap presents another major hurdle. Solutions that perform well with prototype data often encounter unexpected issues during production deployment. Many projects succeed in limited deployments but fail during broader implementation, with numerous initiatives stalling after single factory line deployments.

In Study C, each reviewed article describes challenges or gaps in AI or automated ML implementation, which serve as the motivation to propose the respective MLOps or automated ML architectures. "Challenge 4" in this study discusses scalability related challenges. This study discusses that Industrial automated AI systems must rapidly scale to accommodate sudden data volume spikes while managing diverse AI frameworks across heterogeneous software environments. This scalability demand is critical in manufacturing where continuous data processing is essential. Industrial expansion compounds these challenges when new hardware differs from existing machinery. Integrating different equipment into established processes creates significant scalability barriers. This "Challenge 4" also discusses that Digital twin implementations face additional complexity as system instances multiply. Managing numerous concurrent AI workflows escalates resource demands and infrastructure costs while requiring coordination of multiple data streams and models across simultaneously operating digital twins.

4.1.4 Skill Gaps Related Challenges

Study E dives into challenges represented by organizational barriers including skilled personnel shortages, comprehensive training program requirements, cultural resistance to technological change, and cross-functional collaboration difficulties between data scientists and domain experts.

In Study B, the interviewees discuss that manufacturing AI adoption faces significant skill gaps affecting both operators and technical specialists. This research identified substantial skills deficits hampering AI implementation in manufacturing. Floor operators lack training in ML algorithms and computer vision applications, with some organizations having no personnel trained in these technologies. Training operators closest to machines proves effective for identifying AI errors, though implementing AI requires different expertise than traditional automation. Unlike robot implementation which follows established procedures, AI deployment lacks standardized approaches and demands specific personnel types. Manufacturing organizations typically lack data scientists with analytics expertise, creating dual skill gaps between operational and technical domains. Contrary to expectations, worker resistance was not identified as a significant implementation barrier when handled appropriately. Successful implementations focus on making work easier and more effective rather than replacing workers. Companies achieved adoption success by targeting AI solutions at most tedious tasks of employees and involving operators from project initiation by clearly explaining implementation rationales. Implementations succeed when they improve work quality or increase job satisfaction.

In Study C, each reviewed article discusses various issues or limitations in AI or automated ML implementation, which form the basis for their proposed MLOps or automated ML architectures. "Challenge 6" and "Challenge 7" of this study discuss human factors and adoption related challenges. Especially "Challenge 6" documents that understanding and explaining AI model decision-making processes is fundamental for building confidence in outputs, particularly in manufacturing environments where prediction errors carry serious consequences. While interpretability and explainability enable informed model validation and selection by domain experts, these initiatives require significant time investment. Building transparent model architectures and integrating domain knowledge with contextual explanations is essential for improving AI solution trustworthiness in industrial processes. "Challenge 7" documents that skill gap and lack of technical know-how regarding AI implementation poses as a challenge especially for SMEs. Enterprise AI adoption faces organizational challenges from unclear data science role definitions, cultural conflicts between data science and software team's workflows, practices and tools.

4.1.5 Interdependency of Deployment Challenges

The theoretical process model (Figure 2, Paper 2), from study B, reveals that AI implementation challenges in manufacturing environments operate as an interconnected system rather than isolated barriers, creating complex dependencies that significantly impact overall implementation effectiveness. The manufacturing context, characterized by long equipment lifecycles, isolated solutions, physical production environments, and established operational technology infrastructure, serves as the foundational driver that simultaneously generates both infrastructure and skill gap challenges. These contextual factors create a sequential progression where traditional manufacturing approaches fundamentally misalign with the dynamic requirements necessary for successful AI deployment, establishing the conditions for subsequent implementation difficulties.

Infrastructure and skill challenges demonstrate bidirectional influence relationships that compound implementation complexity beyond their individual impacts. Infrastructure limitations directly constrain the development of technical expertise, as inadequate connectivity, legacy system incompatibilities, and insufficient edge computing capabilities prevent workforce members from gaining hands-on experience with AI technologies. Conversely, skill gaps perpetuate infrastructure deficiencies, as organizations lacking AI expertise struggle to make informed decisions about necessary technological investments and system architecture designs. This cyclical relationship creates a reinforcing pattern where addressing one challenge domain inadequately leaves organizations vulnerable to continued difficulties in the complementary area, emphasizing the necessity for integrated solution approaches rather than isolated intervention strategies.

The model demonstrates how infrastructure and skill challenges collectively influence scalability considerations, creating a hierarchical dependency structure that determines implementation scope and economic viability. Organizations facing significant infrastructure barriers and workforce capability gaps typically default to point solution approaches, as comprehensive platform implementations appear overwhelming given existing constraints. This scalability limitation subsequently impacts maintenance capabilities, as point solutions lack the systematic monitoring, retraining protocols, and organizational processes necessary for sustainable AI operations. The connection between scalability and maintenance reveals that organizations achieving broader implementation scope develop more sophisticated support systems, while those constrained to limited deployments struggle to establish adequate maintenance frameworks due to insufficient scale economies and organizational learning opportunities.

Critical feedback mechanisms emerge from maintenance challenges back to infrastructure and skill requirements, creating ongoing dependencies that extend throughout the AI lifecycle. Maintenance activities reveal previously unrecognized infrastructure needs, such as additional monitoring capabilities, data storage requirements, and computational resources necessary for model retraining and performance evaluation. Similarly, effective maintenance demands continuous skill development as AI systems evolve and production conditions change, requiring workforce members to adapt their expertise and develop new competencies over time. These feedback relationships establish maintenance as both a consequence of earlier implementation decisions and a driver of future infrastructure and skill investments, highlighting the dynamic nature of AI deployment challenges. Implementation effectiveness emerges as the central outcome influenced by the dynamic interplay of all challenge domains, positioning successful deployment as dependent on managing interconnected relationships rather than sequentially addressing individual barriers. The model illustrates that organizations achieving high implementation effectiveness must simultaneously address infrastructure modernization, workforce development, scalability planning, and maintenance preparation in coordinated approaches that recognize mutual dependencies. This systems perspective challenges traditional manufacturing technology adoption frameworks that typically focus on discrete implementation phases, instead requiring organizations to conceptualize AI deployment as a continuous cycle of interdependent activities. The theoretical framework thus provides manufacturing organizations with a comprehensive understanding of how implementation challenges interact, enabling more effective planning and resource allocation strategies that address systemic rather than symptomatic issues in AI adoption efforts.

4.2 Addressing Integration Challenges of AI Solutions

This section discusses potential recommendations and solutions to address the integration challenges discussed in the previous section. This section attempts to contribute to the RQ2.

4.2.1 Comparative Analysis of Operational Frameworks for AI Implementation

The comparative analysis of operational methodologies, 4.2, coming from the narrative literature analysis, demonstrates that MLOps is uniquely positioned to address AI operationalization challenges in manufacturing contexts. MLOps provides complete AI lifecycle coverage spanning development, deployment, and maintenance phases, coupled with high manufacturing AI suitability. This comprehensive approach directly addresses the operationalization requirements that other frameworks fail to meet. DevOps, while foundational to operational practices, shows low manufacturing AI suitability as it targets general software development rather than the specialized requirements of AI models. ModelOps offers only partial AI lifecycle coverage with its primary focus on governance rather than technical implementation. DataOps demonstrates medium manufacturing AI suitability but limits its scope to data preparation phases, providing no support for model deployment or maintenance. AIOps focuses on IT infrastructure automation rather than model operationalization, while LLMOps addresses only specialized large language model scenarios rather than general manufacturing AI applications. The AI lifecycle coverage analysis 4.3 reveals critical gaps in alternative frameworks. MLOps stands as the only methodology providing full end-to-end support across development, training, deployment, monitoring, and maintenance phases. ModelOps provides governance-focused maintenance, but lacks technical development and training capabilities. DataOps supports only data-related aspects of development and monitoring. AIOps offers no AI-specific lifecycle support, focusing instead on IT systems monitoring. LLMOps, while comprehensive for its specialized domain, does not address the broader spectrum of AI applications required in manufacturing environments. The manufacturing AI suitability in Table 4.2 is a subjective analysis based on the findings coming from the narrative litertaure analysis.

Table 4.2: Comparison of Operational Methodologies: Focus Areas and ML Lifecycle Coverage

Methodology	**Primary Focus**	**Target Domain**	**ML Lifecycle Coverage**	**Manufacturing AI Suitability**
DevOps	Software development and IT operations integration	General software	Not applicable	Low
MLOps	**End-to-end model lifecycle management**	**Machine Learning**	**Complete (Dev → Deploy → Maintain)**	**High**
ModelOps	Enterprise model governance and compliance	All analytical models	Partial (governance focus)	Medium
DataOps	Data pipeline management and quality	Data engineering	Partial (data preparation only)	Medium
AIOps	IT operations automation using AI	IT infrastructure	Not applicable	Low
LLMOps	Large language model operations	Specialized LLMs	Complete (for LLMs only)	Low-Medium

Table 4.3: AI-Related Operational Methodologies: Lifecycle Coverage Analysis

Methodology	**Development**	**Training**	**Deployment**	**Monitoring**	**Maintenance**
MLOps	✓	✓	✓	✓	✓
ModelOps	Partial	Partial	✓	✓	Governance only
DataOps	✓	Data only	×	Data only	Data only
AIOps	×	×	×	IT systems only	×
LLMOps	LLM only	LLM only	LLM only	LLM only	LLM only

4.2.2 MLOps Framework to address integration challenges

Study C provides a comprehensive systematic review that addresses RQ2 by demonstrating how MLOps frameworks can effectively address the integration challenges of AI solutions in manufacturing environments. The study makes several key contributions toward answering this research question:

- **Architectural Framework for Challenge Resolution**:

Study C's systematic review identifies fundamental themes that characterize effective MLOps architectures in manufacturing:

End-to-End ML Lifecycle Management and DevOps Integration: Integration with DevOps practices along with the establishment of end-to-end ML lifecycle management is an important aspect in modern MLOps architectures in industrial applications. However, the review reveals that architectures exhibit a high degree of automation throughout the end-to-end lifecycle while still requiring manual intervention and oversight at various stages. This finding aligns with Study D's emphasis on human-in-the-loop approaches.

Edge Computing and IoT Integration: The MLOps architecture described in six out of twelve reviewed articles in study C, incorporate edge devices within an IoT setup, highlighting their suitability for deploying AI models in an industrial environment. This distributed approach addresses the real-time requirements typical in manufacturing while managing computational constraints.

Microservices and Containerization: Seven out of twelve reviewed architectures in study C, incorporate the concept of containerization and microservices as part of its proposed architecture for implementing MLOps in manufacturing settings. This architectural pattern enables modular, scalable deployments that can adapt to the heterogeneous nature of manufacturing environments. Solution building and containerizing it with a human centric methodology which facilitates implementation, is demonstrated in study D, thus finding synergy with this MLOps architectural characteristic.

Monitoring and Maintenance: All reviewed articles in Study C adopts various steps for monitoring and maintenance across different stages of the MLOps lifecycle. This portrays the importance of this aspect within a MLOps architecture. Adding on, the core of study D is to build a monitoring and maintenance solution with a human centric methodology to enhance its adoption, trust and usage. This creates a direct bridge between theoretical framework understanding and practical solution development.

Version Control and Digital Twin Integration: Study C identifies version control as critical for managing AI artifacts, while digital twin integration emerges as an important feature for bridging physical and virtual manufacturing systems.

- **Challenge-Architecture Network Map**: The study develops a systematic mapping between identified integration challenges and corresponding MLOps architectural solutions, directly answering how MLOps frameworks address specific integration obstacles (Figure 6 in Paper 3, Study C). For instance, the research demonstrates how containerized microservices and hybrid edge-cloud architectures address scalability and resource constraint challenges, while comprehensive monitoring systems with human-in-the-loop approaches tackle model drift and trust-related integration barriers. Adding on, The research reveals that MLOps frameworks address integration challenges through hybrid automation approaches that combine automated CI/CD pipelines with strategic human oversight, edge-cloud resource distribution for time-sensitive versus computational-intensive tasks, and modular, containerized deployments that enable flexible scaling and maintenance in dynamic manufacturing environments.

- **Evidence-Based Recommendation System**: The paper contributes a practical decision-making framework that enables manufacturing practitioners to select appropriate MLOps architectural components based on their specific integration challenges. This includes recommendations for protocol-level integration solutions to address manufacturing environment heterogeneity, data management components to handle data quality issues, and modular architectural approaches to overcome scalability limitations.

The study provides concrete evidence of how MLOps frameworks transform theoretical AI capabilities into production-ready manufacturing solutions by addressing both technical challenges (through architectural design patterns) and organizational challenges (through structured team approaches and cost-effective implementation strategies). This directly answers RQ2 by showing the mechanisms through which MLOps frameworks bridge the gap between AI development and manufacturing deployment, ultimately enabling successful integration of AI solutions in industrial contexts.

4.2.3 Containerized Deployment Infrastructure

Study D demonstrates the development and successful deployment of a human-centric CBM dashboard that addresses practical integration challenges for data-driven maintenance solutions in manufacturing environments. Though ML models are not implemented in this study, the established Docker-based deployment architecture, automated data processing pipelines, and user-accepted interface provide essential MLOps infrastructure components in a real-world manufacturing scenario. Notably, the containerized deployment of monitoring dashboards represents a critical MLOps capability, as continuous monitoring forms the backbone of any robust MLOps framework. The modular design and containerized approach create the necessary foundation that could seamlessly accommodate future AI model integration while maintaining operational continuity and user trust established through this human-centric approach. This way, the study contributes to RQ2.

The solution utilizes Docker containerization with docker-compose.yml configuration, enabling consistent deployment across different environments. The combination of containerized monitoring infrastructure with human-centric methodology creates a particularly powerful foundation for MLOps implementation, as it addresses both the technical scalability requirements and the critical human acceptance factors that often determine deployment success. The development process involved Human Centric methodology (Figure 1 in Paper 4, Study D) with iterative discussions with domain experts regarding visualization requirements, design explainability, monitoring scope, user interface elements, and scaling factors for micrometer-level deviation display. This approach ensured the solution aligned with actual operational needs and gained user acceptance.

4.2.4 Integration Solutions from Expert Interview

Study B discusses the solutions coming from the interviewed experts regarding the integration challenges of AI in manufacturing context.

- **Infrastructure and Connectivity Solutions**

  Manufacturing organizations can effectively address infrastructure barriers through comprehensive modernization strategies that bridge the gap between legacy systems and modern AI requirements. Expert recommendations emphasize implementing centralized server systems with cloud integration to create unified databases, as demonstrated by successful deployments where one server can efficiently serve multiple machines while maintaining connection to common cloud environments. Companies should adopt flexible connectivity solutions that accommodate both legacy equipment and newer technologies, utilizing specialized integration platforms that can easily connect to diverse machine types across different technological generations. Container infrastructure implementation, particularly Kubernetes deployments, has proven successful in major manufacturing facilities, though organizations must invest in the necessary expertise and change management processes. Security considerations require balanced approaches that provide quick accessible data while maintaining appropriate protective controls, ensuring that IT and OT systems can synchronize effectively without compromising operational security or data integrity.

- **Scalability Implementation Strategies**

  Overcoming scalability limitations requires a fundamental shift from point solution thinking to comprehensive platform approaches that enable meaningful return on investment across multiple use cases. Manufacturing organizations must develop platform-centric strategies that apply ML and computer vision technologies across entire factory operations rather than focusing on isolated machine-specific problems. This transition involves careful selection of initial use cases that demonstrate clear scalability potential and can serve as foundation projects for broader implementation. Companies should address the critical operations gap by ensuring that technical teams developing AI prototypes collaborate closely with operations personnel who understand production realities and infrastructure constraints. Successful scalability also demands bridging the prototype-to-production transition through systematic approaches that anticipate and resolve implementation challenges before they impact full-scale deployment. Organizations must invest in multi-use case planning from project inception, ensuring that AI initiatives are designed with expansion capabilities and can deliver economic benefits that justify platform-level investments.

- **Workforce Development and Skills Integration** Addressing skill gaps requires comprehensive upskilling programs that transform existing workforce capabilities rather than replacing personnel with external expertise. Manufacturing organizations should implement systematic training initiatives that prepare floor operators to work with ML algorithms and computer vision applications, focusing on practical skills that enhance rather than complicate their existing responsibilities. Cross-functional team formation proves essential, combining ML specialists, software developers, data engineers, and domain experts to create collaborative environments where knowledge transfer occurs naturally. Successful implementations involve operators closest to production equipment in AI system management, training them to identify errors and participate in model improvement processes. Organizations can enhance engagement through gamification approaches that reward workers for contributing to model training and improvement activities. Crucially, companies must frame AI implementation as work enhancement rather than job replacement, targeting applications that eliminate repetitive tasks and create more engaging responsibilities for existing personnel. This approach reduces resistance while building internal expertise necessary for long-term AI success.

- **Maintenance and Monitoring Solutions** Establishing sustainable

AI maintenance requires implementing comprehensive monitoring systems that treat artificial intelligence solutions as ongoing processes requiring continuous oversight rather than static equipment installations. Manufacturing organizations must develop systematic retraining protocols that create clear organizational processes for evaluating AI performance metrics and implementing data-driven maintenance decisions. Unlike traditional manufacturing equipment with predictable maintenance schedules, AI systems demand dynamic monitoring dashboards that track model performance, detect drift, and trigger maintenance activities based on real-time performance indicators. Companies should integrate human oversight into automated systems, creating feedback loops where experienced operators validate AI decisions and prevent systems from developing in problematic directions. Effective maintenance strategies require establishing dedicated expertise banks and infrastructure investments that support ongoing AI system evolution. Organizations must recognize that AI maintenance differs fundamentally from traditional equipment servicing, requiring specialized knowledge, tools, and processes that enable continuous model improvement and adaptation to changing production conditions. Success depends on creating organizational capabilities that view AI maintenance as an integral operational function rather than an occasional technical intervention.

CHAPTER 5

Discussion

This chapter presents the key findings that address the research questions posed in this thesis and discusses how this work contributes to both academic knowledge and industrial practice. The chapter also examines the study's limitations, assesses the quality of the research approach, and considers the ethical and sustainability aspects of the work. The chapter concludes by identifying opportunities for future research.

5.1 Answers to Research Questions

5.1.1 The Answer to RQ1

RQ1: What are the challenges of integrating AI solutions for maintenance in manufacturing?

The integration of AI solutions for maintenance in manufacturing faces challenges that spread across technical, organizational, and operational dimensions. These challenges can be categorized into: scalability challenges where manufacturing companies typically adopt a point solution mindset, focusing on solving specific issues on individual machines rather than thinking holistically about factory-wide implementation; infrastructure and technological barriers including inadequate connectivity infrastructure, IT/OT convergence complexities, data quality issues, and lack of historical fault data necessary for training ML models; maintenance and sustainability challenges where manufacturing companies treat AI solutions like traditional equipment, overlooking their need for ongoing maintenance, frequent retraining, and MLOps frameworks; and skills and organizational challenges including skilled personnel shortages, significant skill gaps, and cultural conflicts between data science and software teams.

Study B reveals that the identified challenge domains are highly interdependent, creating a web of barriers that must be addressed holistically rather than in isolation. Infrastructure limitations directly constrain scalability efforts, these scalability constraints then grow into maintenance challenges, and skill gaps create feedback loops that reinforce both infrastructure and maintenance challenges. This interconnected nature means that addressing any single challenge in isolation is unlikely to succeed; instead, organizations must develop comprehensive strategies that simultaneously tackle infrastructure development, workforce upskilling, scalable platform thinking, and robust maintenance frameworks to achieve effective AI implementation in manufacturing environments.

5.1.2 The Answer to RQ2

RQ2: How can the integration challenges of AI solutions for maintenance in manufacturing be addressed?

The comparative analysis of operational frameworks reveals that MLOps emerges as a suitable approach for addressing AI integration challenges in manufacturing environments. Alternative methodologies like DevOps, DataOps, and AIOps demonstrate significant limitations when applied to manufacturing AI contexts, lacking the specialized requirements for AI model management or offering no support for model deployment or maintenance phases. In contrast, MLOps provides complete lifecycle coverage from development through maintenance while specifically addressing the unique requirements of manufacturing AI applications, making it the most suitable framework for overcoming the integration challenges identified in this research.

The research identifies fundamental architectural characteristics of MLOps frameworks that specifically target integration challenges: End-to-End AI Lifecycle Management with DevOps Integration, Version Control systems, comprehensive Monitoring and Maintenance capabilities, Edge Computing and IoT Integration, Digital Twins and Cyber-Physical Systems integration, and Microservices with Containerization.

The combination of findings from studies C and D reveals that successful MLOps architectures must integrate technical sophistication with human-centric design. The emphasis on human-in-the-loop approaches and domain expert integration builds the essential trust and acceptance needed for successful deployment, while technical features such as edge computing integration, microservices architecture, and continuous monitoring ensure that AI systems can operate effectively within the demanding real-time constraints and heterogeneous infrastructure typical of manufacturing settings.

This research identifies challenges in AI implementation and provides architectural recommendations for each through its systematic architecture recommendation network map. This network map serves as a practical decision-making tool that connects manufacturing challenges to appropriate architectural solutions, enabling practitioners to identify suitable MLOps architectures for overcoming particular challenges they encounter during AI implementations.

5.2 Contributions of this thesis

This thesis examines the practical challenges encountered when implementing AI solutions for manufacturing maintenance, compares and investigates how MLOps is uniquely positioned and suitable to address AI deployment and operationalizing challenges. The research identifies challenges through empirical analysis of actual use cases (Study A) and direct consultation with industry practitioners (Study B), thereby establishing strong empirical foundations. To address the identified challenges, the thesis examines key MLOps characteristics that transform traditional model-centric AI approaches into process-centric, end-to-end frameworks (Study C). Study C further develops practical implementation guidance for industry practitioners, enabling them to select appropriate MLOps architectures for specific operational challenges. Given that MLOps relies heavily on continuous monitoring of data streams and model performance, Study D investigates human-centered approaches for deploying CBM dashboards. The research draws extensively from industrial case studies, yielding practical contributions for industry implementation. Academic contributions include the development of theoretical process models and frameworks, which are examined in detail in the following subsections.

5.2.1 Academic Contributions

This thesis makes several significant contributions to the academic understanding of ML integration challenges and MLOps frameworks in manufacturing contexts. From a theoretical perspective, the research develops a comprehensive theoretical process model that conceptualizes AI implementation challenges as an interconnected system of tensions rather than isolated barriers, throwing light on dependencies between infrastructure limitations, scalability constraints, skill gaps, and AI solution maintenance inadequacies. This interconnected systems view contrasts with existing literature that tends to examine challenges in isolation [70], [72]–[74], [79], failing to capture the bidirectional influence relationships and feedback mechanisms revealed in this research. While previous studies have identified individual technical [70], [73], [74], organizational [72], [79], and model management challenges [75], [77], [78] separately, this thesis advances understanding by demonstrating how these challenges create reinforcing patterns and hierarchical dependencies that determine implementation effectiveness.

The systematic literature review provides the first comprehensive mapping of MLOps architectural characteristics specifically for industrial contexts, identifying fundamental architectural themes and establishing a challenge-architecture network map that connects integration obstacles to corresponding technical solutions. This contribution addresses a critical gap in the existing body of knowledge, as prior research has focused primarily on general MLOps principles [9], [11], [64], [65] without systematic investigation of how these frameworks translate to manufacturing-specific requirements.

Additionally, the research validates experimental approaches for generating training data when historical fault records are unavailable, contributing to the growing body of knowledge on data-driven maintenance in data-scarce environments. This methodological contribution directly addresses the data quality and availability challenges extensively documented in manufacturing AI literature [70], [72], [73], where lack of historical fault data represents a persistent barrier to predictive maintenance implementation. Unlike previous approaches that primarily rely on existing historical datasets, this research demonstrates artificial anomaly induction as a viable alternative, extending practical options for organizations facing the data scarcity challenges identified by [70], [72].

The qualitative analysis using the Gioia methodology provides deep insight into practitioner perspectives, bridging the gap between theoretical AI capabilities and real-world implementation challenges through empirically grounded theory development [86]. This methodological approach complements existing quantitative and technical studies [73]–[75], [77], [78] by capturing the subtle organizational and human factors that influence AI adoption success, aspects often under emphasized in technically-focused literature. Where previous research has acknowledged skill gaps and organizational resistance as implementation barriers [72], [79], this research reveals the specific mechanisms through which these factors interact with technical constraints, providing richer understanding of the socio-technical nature of AI deployment in manufacturing.

5.2.2 Industrial Contributions

The industrial contributions of this thesis provide practical frameworks and solutions that address real-world challenges faced by manufacturing organizations implementing AI solutions for maintenance. The research provides an evidence-based recommendation system that enables manufacturing practitioners to systematically select appropriate MLOps architectural components based on their specific integration challenges, reducing the trial-and-error typically associated with AI adoption in industrial settings. This practical contribution directly addresses the integration complexity and lack of systematic implementation guidance identified in prior industrial research [72], [73], where organizations struggle to navigate diverse technical options without clear decision frameworks. Unlike the general MLOps implementation guidance found in existing literature [9], [64], [65], this research provides manufacturing-specific architectural recommendations linked to empirically validated challenge domains. Adding on, this thesis provides manufacturing organizations with concrete strategies for overcoming the challenges in specified domains identified: infrastructure limitations, scalability constraints, workforce skill gaps, and maintenance inadequacies of AI systems. This integrated approach contrasts with existing literature that typically addresses these challenges separately [70], [72]–[75], [77]–[82], without recognizing their interconnected nature. Through its comprehensive analysis of industry practitioner experiences, documenting and Analyzing their perspectives as solutions, the research offers actionable insights.

The human-centric CBM dashboard development demonstrates a proven approach for building trust and acceptance among domain experts, showing how containerized deployment architectures with Docker can provide the essential infrastructure foundation while maintaining operational continuity. This contribution extends existing work on human factors in AI adoption [72], [79], which identifies trust and acceptance as critical barriers but provides limited guidance on concrete implementation strategies. Where previous research acknowledges the importance of user acceptance [72], [79], [80], this work demonstrates specific design principles and deployment approaches that facilitate practitioner engagement, complementing theoretical discussions with validated implementation methods.

The experimental validation of artificial anomaly induction provides manufacturing companies with a practical methodology for generating labeled training data in scenarios where historical failure records are limited, enabling the development of predictive maintenance systems even in newly installed or fault-free environments. This methodological contribution directly resolves a critical practical barrier documented extensively in manufacturing AI literature [70], [72], [73], where data availability constraints prevent organizations from implementing predictive maintenance despite clear operational benefits. While existing research identifies data scarcity as a persistent challenge [70], [72], this work provides a validated alternative approach that expands practical options for organizations facing this barrier, thereby enabling broader adoption of data-driven maintenance strategies.

These contributions collectively enable manufacturing organizations to make informed decisions about AI implementation strategies while avoiding common pitfalls that lead to failed deployments, complementing the theoretical understanding provided by existing literature [70], [72]–[75], [77]–[82] with validated practical guidance developed through empirical investigation in real manufacturing settings.

5.3 Ethical Considerations

Researchers who want their work to be both scientifically credible and socially beneficial must follow established ethical guidelines and professional standards[97]. This thesis examines research ethics by drawing on the principles and recommendations found in Good Research Practice guidelines [98], exploring how these standards shape responsible scientific conduct.

This licentiate research adheres to established ethical principles for academic research involving industrial collaborations and data collection. All data collection activities during interviews were conducted with explicit consent from participating manufacturing companies, with formal agreements ensuring confidentiality and data protection in accordance with GDPR regulations. The industrial case studies presented in this work involved close collaboration with domain experts and maintenance personnel, where their expertise and insights were incorporated through voluntary participation, ensuring that all human subjects were treated with respect and their contributions properly acknowledged. No personally identifiable information was collected or stored during the research process, and all industrial data was anonymized to protect proprietary information and trade secrets. The research methodology emphasized transparency and reproducibility, with clear documentation of data sources, analysis procedures, and limitations.

5.4 Limitations

The research presented acknowledges several methodological and contextual limitations that should be considered when interpreting the findings. The empirical studies conducted, particularly the air leakage detection system and CBM dashboard development, were constrained by limited data collection periods of only 10 weeks each, which may not capture the full spectrum of operational conditions and seasonal variations typically encountered in industrial environments. The qualitative research component, specifically the expert interviews examining AI deployment challenges, involved only four participants, which may not adequately represent the diversity of perspectives across different manufacturing sectors, organization sizes, and geographical regions. However, purposeful sampling was adopted to shortlist candidates for the interview who had knowledge in depth regarding the topic discussed. Additionally, the systematic literature review was limited to 12 selected articles, reflecting the relatively nascent state of industrial MLOps research, and may not comprehensively cover all relevant architectural approaches and implementation strategies across the broader manufacturing domain.

The validation approaches employed throughout this research also present inherent limitations that affect the generalizability of the results. The time and resource savings estimations for the CBM dashboard were primarily based on end-user evaluations and experiences rather than rigorous quantitative validation studies, potentially introducing subjective bias into the reported efficiency improvements. The contextual anomaly detection approach implemented in the pneumatic leakage detection system may fail to identify anomalies of other different types for which it has not been specifically trained, limiting its broader applicability. Furthermore, the usability testing conducted during the CBM dashboard development phase was largely unstructured, and the selection criteria for user input parameters such as tolerance and threshold values lacked comprehensive documentation of the underlying decision-making rationale. The expert perspectives gathered in the qualitative studies, while valuable, may reflect particular organizational experiences and individual biases.

5.5 Future Work

The foundation established in this licentiate thesis through the Research Clarification (DS1) and Descriptive Study I (DS2) phases provides a platform for advancing toward comprehensive MLOps implementation and validation in manufacturing maintenance contexts. The future research encompasses empirical validation through industry collaboration, theoretical development through prescriptive frameworks, and validation through multi-case studies.

Building upon the fundamental MLOps characteristics identified in this research, future work will empirically validate these architectural elements with collaborative initiative with industrial partners that provide opportunity to test and refine the theoretical frameworks within real manufacturing environments. The ongoing case study implementations will systematically test each architectural characteristic, documenting implementation barriers, adaptation requirements, and performance outcomes.

The third phase of the Design Research Methodology (DS3: Prescriptive Study) will synthesize insights from the foundational studies completed in this thesis and the ongoing empirical validation work to develop comprehensive MLOps implementation frameworks tailored for manufacturing maintenance. This work will create detailed architectural blueprints that translate the identified MLOps characteristics into implementable system designs, providing manufacturing organizations with concrete specifications for data pipeline architectures, model development and deployment workflows, monitoring infrastructure, edge computing configurations, containerization strategies, and version control systems adapted to manufacturing contexts.

Recognizing that manufacturing organizations differ significantly in their technical maturity and resource availability, DS3 will also develop modular MLOps components that organizations can adopt incrementally. These modules will range from basic monitoring and alerting systems for organizations beginning their MLOps journey, to automated retraining pipelines for organizations with established AI models, to comprehensive orchestration platforms for factory-wide AI deployments. Each module will be designed to address specific challenge domains identified in this research, with clear guidance on implementation pathways suited to different organizational contexts.

The fourth phase (DS4: Descriptive Study II) will conduct comprehensive validation of the developed frameworks through systematic multi-case industrial studies across diverse manufacturing sectors. This validation work will implement and evaluate the developed MLOps frameworks in organizations spanning different sectors, company sizes, and technological maturity levels. Each case study will systematically assess implementation feasibility, effectiveness in addressing the challenge domains, performance improvements in maintenance outcomes, and adaptations required for specific manufacturing contexts. The multi-case approach enables identification of generalizable MLOps principles that apply across manufacturing contexts while documenting context-specific considerations that organizations must address during implementation.

CHAPTER 6

Conclusion

The digital transformation of manufacturing through Industry 4.0 has positioned AI as critical enablers for predictive maintenance and operational excellence. While the theoretical potential of AI solutions in manufacturing maintenance is well-established, the practical implementation of these technologies continues to face challenges. Previous research has primarily focused on technical algorithmic development or isolated case studies, leaving a gap in understanding the systemic challenges that hinder successful AI integration and the operational frameworks necessary to overcome them.

This thesis addresses this gap by investigating the interconnected challenges of AI integration in manufacturing maintenance (RQ1), systematically evaluating alternative operational frameworks, suggesting MLOps as a particularly suitable framework for successful deployment, and mapping potential solutions (RQ2). Through a multi-method approach within the Design Research Methodology framework, this research provides insights and practical solutions for bridging the gap between AI potential and industrial implementation.

The research identifies interconnected challenge domains: infrastructure limitations, scalability constraints, workforce skill gaps, and inadequate maintenance strategies for deployed AI systems. The theoretical process model developed reveals these challenges as an interconnected system rather than isolated barriers.

To address these challenges, the thesis compares operational frameworks in literature, suggesting that MLOps is uniquely positioned through its comprehensive lifecycle management capabilities and manufacturing-specific architectural features. Fundamental characteristics of MLOps architetcure are identified: end-to-end ML lifecycle management with DevOps integration, version control systems, monitoring and maintenance capabilities, edge computing and IoT integration, digital twins integration, and microservices with containerization. The challenge-architecture network mapping provides guidance for selecting appropriate MLOps components. The experimental approach for generating training data addresses the challenge of insufficient historical fault records, while the containerized monitoring infrastructure combined with human-centric methodology addresses technical scalability requirements and human acceptance factors.

By providing systematic frameworks and actionable MLOps architectures, this research empowers manufacturing organizations to move beyond pilots and into reliable, scalable AI operations. It lays a foundation for future academic inquiry into operational frameworks for industrial AI, while giving maintenance leaders and technical teams practical roadmaps that accelerate value, and build lasting capability. Above all, this work aspires to transform AI from experimental promise into trusted industrial reality, enabling factories to operate smarter, safer, and more sustainably. In doing so, it advances the journey toward maintenance excellence and brings Industry 4.0's vision closer to the shop floors where its impact matters.

AI Writing Assistance Declaration

In preparing this thesis, the author has employed ChatGPT 4o as a writing assistance tool for proofreading and readability enhancement only. The authors have thoroughly reviewed and revised all AI-assisted content and assume complete responsibility for the work presented.

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