Master Thesis: AI-Driven Business Model Innovation in Manufacturing Industry: An In-Depth Look at Siemens

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Abstract

Operational efficiency, innovation, and maintenance in the manufacturing industry have stepped into a new era with artificial intelligence integration. This thesis analyses Siemens AG and how three core technologies, MindSphere IoT Platform, Predictive Maintenance, and Digital Twin, impacted Siemens's business model. Comprehensive analysis indicates how AI impacts Siemens strategy, operational efficiency, and customer relationships using the Innovation Impact Analysis Model (IIAM), Business Model Canvas (BMC), Cost-Benefit Analysis, and System Thinking and Casual Loop Diagrams (CLDs). The findings show that Siemens' key activities, key resources, customer engagement and revenue streams are impacted by AI integration. This demonstrates how AI can help drive innovation and efficiency, offering a competitive edge in the industry. This thesis adds to the understanding of AI-driven business model innovation and provides strategic recommendations for manufacturing industry companies to better adopt AI technologies into business models.

Contents

1. Introduction

The beginnings of AI can be traced back to the mid-20th century when computing pioneers like Alan Turing envisioned machines that could think. His seminal 1950 paper, "Computing Machinery and Intelligence," proposed the idea of machines simulating human intelligence, a concept that laid the very foundation of AI. (TURING, 1950) This paper marked the beginning of decades of AI research and development.

Early AI research was marked by enthusiasm and significant breakthroughs, such as creating the first neural networks in the 1960s and developing ELIZA, one of the earliest natural language processing computer programs.(“Artificial Intelligence for the Real World,” 2018) However, the journey was not without its challenges. Periods of decreased interest and funding tested the resilience, showcasing its determination to push forward despite setbacks. The main challenge was computational power, and as a result, the research has experienced what is commonly referred to as “AI winter.” Reducing funding and a drop in optimism in the field reduced advances.(Crevier, 1993)

AI research revived in the late 1990s and early 2000s, fuelled by advances in algorithmic design, computational power increases, and data availability explosion. During this period, machine learning techniques were developed that moved the study from a rule-based approach to a learning-based one, allowing machines to learn and improve from experience without being explicitly programmed.(Russell and Norvig, 2021) The development of deep learning was particularly transformative as it enabled image and speech recognition and processing.(LeCun et al., 2015)

The increase in computational power that occurred in the last twenty years, exemplified by Moore's law(Reid, 2001), allowed the processing of large data to be more efficient and less time-consuming. In addition, the rise in big data has offered more material needed to train machine learning models. (Goodfellow et al., 2016)

Ais's reach has influenced various industry sectors, including healthcare, finance, transportation, and manufacturing. Applications are diverse, ranging from diagnostics to prediction of design outbreaks, from financial fraud detection to automated trading to autonomous driving systems. (Blanco et al., 2016; Davenport and Kirby, 2016; Ngai et al., 2011; Topol and Verghese, 2019)

AI in Manufacturing

The integration of AI into the manufacturing industry starts with the appearance of Industry 4.0. This new industrial revolution is a new step of manufacturing, a merge of physical and digital technologies. This allows the development of smart factories, where communication and data analysis provide insights to optimise production processes. AI technologies allow manufacturing operations to run more efficiently and flexibly and offer more customisation. Hence, the growing adaptation resulted in a predicted annual growth of over 50% in the next years. An example of that prediction is made by MaketsandMarkets, which predicted the market to grow from 1.1 billion

USD in 2020 to over 16 billion by 2026.(“Artificial Intelligence in Manufacturing Market Size, Share, Industry Report, Growth Drivers, Opportunities - 2032,” n.d.)

Integrating AI with other emerging technologies further enhances the impact on the manufacturing industry. Where a combination of AI and technologies like IoT, 5G and blockchain offers solutions for existing problems. These combinations allow better communication between two instances, generate large amounts of data, and provide secure and transparent data sharing. An example is the Bosch Connected Industry solution; combining those three technologies with AI resulted in a solution that provides better quality products while gaining on efficiency and trust of its suppliers and customers. (“Bosch Connected Industry,” n.d.)

This thesis will focus on the application of three technologies implemented into Siemens. Those are the MindSphere IoT platform as a production optimisation solution, Siemens Predictive Maintenance, and Siemens Digital Twin. Those technologies have been chosen due to their widespread applications and foundational role for Siemens. Siemens has been chosen as a reputable brand with a history of innovation and the creation of something new. By looking into those innovations, this thesis aims to look into how the implementation of AI has affected Siemens's business model and what patterns can be identified.

In summary, the evolution of computational performance has led to developments in AI, which have resulted in various applications in different industries. For example, developments in manufacturing have allowed businesses to enhance product quality and reduce costs while bettering their relationships with customers. This thesis focus is relevant as Siemens has been active in their initiatives “Vision 2020” and “Simenes Vision 2020+”, which have focused on implementing industry 4.0 technologies into operations.(Kaeser, 2018)

2. Literature review

This literature review attempts to critically assess the state of the literature from some authoritative sources, including peer-reviewed journals, industry reports, and case studies. The following sections will attempt to report the use of AI technologies within the manufacturing industry and how that has resulted in change or innovation in business modelling. This paper will, therefore, take themes across sectors to compare and contrast those with common and uniquely characteristic characteristics to provide an all-encompassing view of the transformative potential of AI to business innovation.

Introducing Artificial Intelligence (AI) into business practice is not a process change but an absolute remodelling of business models in all industries. Machine learning, natural language processing, robotics, and other AI technologies are transforming and revolutionising industries today. (David Olanrewaju Olutimehin et al., 2024) This literature review explores the impact of AI on business model innovation within the manufacturing industry. Therefore, this paper will aim to synthesise existing research, look for patterns of AI use, and identify critical gaps that indicate opportunities for further investigation.

Recent developments in AI allow businesses to enhance their value propositions and strategies to better engage with customers and generate more revenue.(Kumar et al., 2024) For example, AI-driven analytics give insights that could develop strategies to better target customers and their needs, while AI automation would offer savings costs by improving efficiency.

AI in Manufacturing

Context and significance

AI in manufacturing is an important part of what is popularly termed Industry 4.0. It represents a basic shift in the optimisation and management of production processes. This industrial revolution is not only about expanding present operations but also includes a redesign in the very landscape of manufacturing. AI deals with increasing accuracy and efficiency and creates new business models; thus, it is at the forefront of such transformation.(Skilton and Hovsepian, 2018)

Uses of AI in Manufacturing:

- **Predictive maintenance**
  AI systems monitor the equipment's real-time performance, predicting failures before they occur and scheduling maintenance that reduces downtime. This approach extends machinery life and reduces operational costs attributed to unscheduled repairs.(Kostolani et al., 2019)
- **Production optimisation**
  AI optimises the production line for efficiency, analyses production data, and finds potential bottlenecks and improvements. It also drives robots that work in teams with humans to enhance safety and productivity. Production optimisation impacts the bottom line by increasing productivity, reducing waste, and better-utilizing resources.(Lee et al., 2018)

- **Quality control**
  At any point in production, the products are checked using advanced imaging, sensor technologies, and artificial intelligence. The AI is trained to detect any inconsistency or defect with precision far exceeding human capacity to maintain high-quality standards, thereby improving customer satisfaction and brand reputation(Villalba-Diez et al., 2019)
- **Digital Twin**
  Digital Twin is a copy of a real object, system, or process in a virtual world. The aim is to use a digital twin to simulate, optimise, and predict performance in a virtual environment. Thus, changes in the production process can be tested without stopping production. This results in higher uptimes and cheaper improvements on products or production lines.(Malik et al., 2022)
- **Edge AI**
  This technology runs on local devices, ”at the edge,” rather than in centralised data centres. This allows the implementation of AI into processes that require real-time data processing and decision-making. Edge AI improves response times and reduces dependency on cloud infrastructure.(Dr. D. Sivaganesan, 2019)
- **Cognitive Computing**
  Cognitive Computing systems simulate human thought processes. These systems use natural language processing(NLP), data mining, and self-learning algorithms to enhance decision-making and problem-solving in manufacturing. They tackle complex production challenges and make informed decisions based on real-time analysis.(Varadarajan et al., 2020)
- **Generative Adversarial Networks (GANs)**
  GANs are two neural networks, a generator and a discriminator, producing realistic data samples. GANs are used to enhance AI model training, increase product design efficiency and improve quality control(Zong and Wang, 2022)
- **Augmented Reality (AR) with AI**
  AR offers real-world environments with computer-generated graphics overlay. When combined with AI, it could be used for immersive training, quality inspections, and improving accuracy and efficiency. It provides real-time information to a user, enhancing efficiency and reducing human errors.(Koontawee et al., 2023)

This paper will focus on predictive maintenance, digital twins, and production optimisation technology. Reasons to focus on that are that those technologies are the most commonly used across industries and also that those technologies have been basis of implementation the other solutions for the chosen case company, Siemens.(Carvajal Soto et al., 2019; “Digital Enterprise – Infinite opportunities from infinite data-Siemens,” n.d.; Guerra-Zubiaga et al., 2020)

Business Model Transformation

Mass Customization

One of the groundbreaking features of AI in manufacturing is that it allows mass customisation. Customised products can be manufactured with the help of AI systems using customer data at almost the same rate and price as mass production. This allows manufacturers to reach individually specified customer preferences without necessarily leading to inefficiencies or cost premiums.(Du and Ge, 2024)

Supply Chain Integration:

AI optimises supply chain management by predicting patterns of demand and inventory levels and planning logistics. Systems of this kind provide easy material and product flows without interruption, reducing waste and improving manufacturers' time to market.(Aishwarya Shekhar, 2023)

Conclusion of Industry Exploration

Research and practical implementations reveal that AI's role in manufacturing is not just a game-changer but foundational for the next era of industrial innovation. AI further develops with its ability to enhance all aspects of the manufacturing process. At this point, AI becomes a foundational technology upon which modern industry operates.

Innovation in Business

Innovation is the lifeblood of competitive advantage and survival in business. According to Schumpeter (Sweezy, 1943), innovation can take the form of new products, production methods, markets, sources of supply, or industrial reorganisation. It is not just creating a new idea but also innovation in commercialisation and application that transforms industries and propels economic growth.

While innovation needs to be maintained not only in the product and technology context, it is also necessary for the company to develop new business models and strategies that might change along with the shifts happening in market dynamics and consumer preferences, especially in the modern business context. Effective innovation, therefore, requires a holistic approach that considers organisational and process, besides technological advancements, that can sustain business growth.(Teece, 2010)

The Role of AI in the business environment

Artificial Intelligence (AI) represents a new paradigm in how businesses conduct operations and compete. AI technologies, such as machine learning, deep learning, and robotics, rank among today's leading disruptive technologies. They offer capabilities ranging from predictive analytics and automated decision-making to state-of-the-art robotics and cognitive technologies. As (Porter and Heppelmann, 2014) Observe that AI is not just a powerful way to automate routine activity but, in fact, a set of technologies that opens up new possibilities for being transformative and recasting industries.

In business, AI goes further to help improve decision-making, refine customers' experiences, optimise operations, and bring about new value propositions. It can analyse data and make some patterns and insights that human analysts fail to interpret, giving it an advantage over more informed and strategic decision-making in business.(Zhu, 2023)

Business modelling and artificial intelligence integration

Business modelling is how organisations create, distribute, and capture value. In the AI era, traditional business models are under siege by advanced technologies that act as crucial value chains and customer interface disruptors. AI integration touches on all nine building blocks of a business model canvas. These AI technologies can improve business models through the possibility of even more personalised services, optimal supply chain logistics, better design of products with data analytics, and the automation of all the interactions in customer service. This integration improves efficiency and creates new business opportunities that were impossible before AI emerged.(Von Garrel and Jahn, 2021)

Business Model Innovation Directed by AI

Business model innovation is a new way of thinking about the existing business model, building new value for the customer at times with differentiations from competitors and other times for greater profitability. Several ways show that AI is instrumental in accelerating business model innovation by allowing firms to use data in real-time, develop customer engagements more quickly, and enter new markets more quickly. Recent studies have found, in one form or another, that companies able to harness AI effectively in their business models are bound to perform better, whether in terms of revenues or profitability, than their counterparts. However, with such huge potential in AI for driving business model innovation, ethical considerations related to technology adoption and long-term sustainability still come across challenges, and overcoming these demands an approach that is strategic and cuts across one side of AI technologies and another, aligning with organisational objectives and market demands.(Hahn et al., 2020)

Theories and Models

The following section will cover the models and theories used for this research. This paper will base itself on established theories and models to systematically examine the interactions between AI and business model components. This will result in insights into how businesses can use AI to achieve an advantage over the competition.

Innovation impact analysis model (IIAM)

The innovation impact analysis model represents innovation's direct and indirect impacts on business. The primary purpose of the IIAM model is to quantify potential benefits and risks associated with innovation and to supplement decision-making processes. The components of the IIAM model are:(Goffin and Mitchell, 2017)

- Identification of innovation- Determination of what innovation is looked at.
- Business model components – Define the impact of innovation on Business model components
- Impact metrics/analysis – evaluate the impact of each innovation.
    - Financial, Operational, Market, Customer impacts
- Scenario analysis- develop different scenarios based on future innovation.
- Strategic recommendations – Develop strategies based on analysis.

IIAM results in recommendation strategies based on executed analysis. This model offers a structured approach to understanding and leveraging innovation while looking at the business model. Businesses can strategically align their innovation efforts by integrating the mentioned components. (Goffin and Mitchell, 2017)

Business Model Canvas (BMC)

Business model canvas is a business modelling tool that enables a holistic overview of business operations. The business model canvas comprises nine building blocks, divided into 3 categories: desirability, feasibility and viability. And are as follows:(Osterwalder et al., 2010)

- Desirability- Focus on what customers want and need:
    - Value Propositions: AI has enriched products and/or services to better serve customers.
    - Customer Segments: Expanded and diversified target markets due to AI capabilities.
    - Channels: Explain how each business developed to reach and engage with customers.
    - Customer Relations: From standardised, reactive customer engagement to proactive and personal customer interaction.
- Feasibility-Focuses on operational and technical aspects of business:
    - Key resources: those of great value in creating an AI initiative, like a technological infrastructure and expertise.
    - Key Activities Include core activities fuelled by R&D and digital innovation using AI.
    - Key Partnerships: Strategic collaborations that have enriched AI capabilities at each company.
- Viability- Focuses on the financial aspect of a business model:
    - Revenue Streams: Unique and recurring revenues that AI empowers.
    - Cost structure: cost efficiency and innovation with AI.

The proposed BMC is a structured way to visualise and understand how AI has impacted the core components of each firm's business model. In doing so, it outlines the structural changes incurred upon adopting AI and compares the business model before and after AI integration.(Osterwalder et al., 2010)

Cost Benefit analysis

Cost-benefit analysis is a financial assessment tool used to evaluate projects or decisions by comparing costs and benefits. The purpose of this analysis is to quantify the efficiency of investments. The key components are:(Boardman et al., 2018)

- Costs
    - Direct
    - Indirect
    - Intangible

- Benefits
    - Direct
    - Indirect
    - Intangible

To conduct a cost-benefit analysis, it will be necessary to identify and quantify costs, compare the costs and benefits and make decisions or recommendations. (Boardman et al., 2018)

Systems Thinking Theory

System thinking is an approach to analysis that looks into the way system components interact with each other. It focuses on the system's connections and dependencies, focusing on holistic perspectives. This is useful in analysing complex systems, like business models, where components interact dynamically.(Meadows and Wright, 2008)

The key concepts of system thinking theory:

- Interconnectedness
    - Everything is connected to everything else. System thinking looks at the bigger picture of the system and portrays how system elements interact.
- Feedback Loops
    - Basic mechanisms by which the system regulates itself
        - Reinforcing loops: They amplify changes and move the system away from its past state
        - Balancing loops: They counteract changes and help maintain system stability
- Causality
    - The emphasis of System thinking theory is on cause-and-effect relationships within the system.
- Dynamic Complexity
    - Addressing the complexities of interactions of multiple system components.
- Emergence
    - Focus on properties or behaviours that are not visible on the individual component level while it is visible on the system level

Causal Loop Diagrams (CLDs)

Casual Loop Diagrams (CLDs) are tools used in system thinking to visualise the interconnections of components within a system and understand their complex relationships.(Meadows and Wright, 2008)

Components of Casual Loop Diagrams:

- Variables
    - Elements or components of the system that are susceptible to change. They can be anything from physical things to abstract concepts.
- Arrows (links)

    - Indicators of component relationships. An arrow between components A and B means that the A component influences the B component
- Polarity
    - Positive polarity (+) indicates that the relationship causes an increase in a component
    - Negative polarity (-) indicates that the relationship causes a decrease in a component
- Feedback Loops
    - Reinforcing Loop
    - Balancing Loop

This literature review showcases the importance and potential of AI within the manufacturing industry, and it also shows how AI can significantly improve product customisation, quality control, maintenance, and production optimisation. By synthesising existing research, it became obvious that there has been a lack of a holistic overview of artificial intelligence technology's impacts on business model innovation, and there has also been a lack of comprehensive Frameworks to analyse this transition. This results in the opportunity to address challenges that manufacturing industry enterprises face when implementing AI. In conclusion, this literature review serves as a foundation for this research and helps give a starting point for the analysis of the data available.

3. Problem Description

Significance of the study

Integrating artificial intelligence into business processes is an incremental improvement and a revolution. AI integration enhances operational efficiency, improves customer relationships and experiences, and enables new business models. However, it's not only affected individual applications but a change in the entire business model.(McAfee and Brynjolfsson, 2018) This research will attempt to address existing gaps identified in the literature review. Besides the lack of a holistic overview of changes and comprehensive frameworks, the dynamic nature of AI development, with the complexity and uncertainty that this technology brings, is making this research more valuable and relevant. Understanding these existing gaps will help enterprises looking to integrate AI into their operations to better leverage AI to gain competitive advantage and growth.

Aim of the thesis and problem formulation

While reviewing the published research and literature, the common occurrence was the lack of available research on the impact of AI on business models and business model innovation, resulting in a potential lack of understanding on how to effectively implement AI into a business and how to adjust all core business segments. This research will attempt to give answers to the following questions:

1. What business model building blocks are affected by the implementation of AI in the manufacturing industry?
    - The aim is to better understand AI's impact on each building block of the Business Model Canvas of a company in the manufacturing industry.
2. What patterns can be identified in changes in business model building blocks?
    - Aims to identify patterns of impact over building blocks of Business Model Canvas
3. What strategic recommendations can be made for manufacturing businesses implementing AI?
    - Aim to offer strategic suggestions for the industry on how to implement AI into operations.

With answers to these questions, this paper would contribute to both academic and corporate strategies by providing a holistic analysis of how AI technologies impact business model components, identifying strategic patterns that can guide future research, and offering practical recommendations for developing strategies for integrating AI innovations into business operations.

4. Methodology

This section will outline how this study employs data collection methods, analytical techniques, theoretical considerations, and research design. This approach also ensures the reliability and validity of sources, methods, and findings. By applying both qualitative and quantitative data, this research will offer a detailed understanding of artificial intelligence's impact on business models.

Data Collection

A comprehensive and structured search of different databases of academic journals, industry reports, conference papers, and case company publications was used to collect secondary data. Some of the most notable are EBSCO, Aalborg University Library, and Google Scholar, and its website has been used for case company publications.

Research Design

The research used a mixed methods approach, using both qualitative and quantitative data to analyse the paper's topic. This approach allowed the best in-depth approach for the examination of AI integration and its impact on a real-world case, allowing us to answer all of the research questions. he design of this research is as follows (Figure 1.):

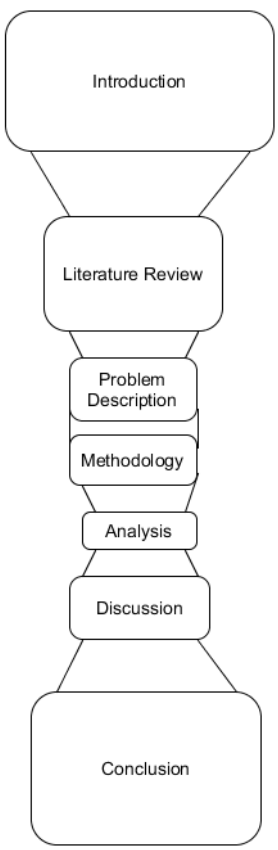

Figure 1 Research Desing

Introduction
This section sets the stage for the thesis by providing an overview, explaining the significance of the study, and presenting the research.

Literature review

This section summarises the existing research on AI technology, Business Models, Business Model Innovation, Impact of Innovation, Impact of AI, and Siemens. It also identifies the key theories and models used in previous research, showing the gap in the current literature. This section provides academic context to the topic and justification for the study's need.

Problem Description

This section dives deeper into the specific issue, explains the relevance and defines research questions.

Methodology
This section details the research design, data collection methods, and analytical approach to the study. It also addresses its validity and reliability.

Analysis
This section presents the case company and analysis of this study, connects it with the research questions, and answers those questions. It also provides a detailed exploration of the impact of AI on Siemens' Business model.

Discussion
This section provides an in-depth analysis of the results' implications, examining both strengths and limitations. It also answers the last research question by offering strategic recommendations based on the analysis of Siemens's business model transformation.

Conclusion
The key findings and overall contributions of the study, both academic and practical, are summarized in the conclusion. The conclusion also suggests further research and explorations of the topic in different contexts.

Data Analysis

Several analytical frameworks were used; the basic framework for the whole analysis section was the Innovation Impact analysis model, of on it was taken an analysis of the chosen innovations, an analysis of the impact of chosen innovation through a business model canvas and a cost-benefit analysis, and there the relevancy of the framework stops. Further, the analysis uses Systems thinking and causal loop diagrams (CLDs) to understand interactions and loops within case company operations. Additionally, the Business model canvas has been duplicated into “Before AI” and “After AI” because of its limitation, as it captures the state at one point.

Reliability and Validity

The research will use data and method triangulation and peer reviewing to maintain the results' validity and reliability. Therefore, detailed data collection and analysis will be conducted to ensure that the discussion regarding AI's impacts on business models is exhaustive and presents a balanced and rounded perspective. Documenting data collection and analysis ensures reliability, enabling other researchers to replicate this study.

Limitations

The limitations would be secondary data from available sources, as no primary data research had been conducted. The scope of the data may limit the inclusive nature of covering all nine building blocks equally across different industries.

By applying a mixed methods approach and using multiple robust analytical frameworks, this study provides a comprehensive and credible analysis of AI technologies' impact on Siemens' business model. The consideration of validity and reliability further strengthens the value of this research.

5. Analysis

This section will systematically evaluate the impact of artificial intelligence technology on the business model of manufacturing industry leader Siemens. The focus innovative technologies will be Siemens MindSphere IoT Platform, Predictive Maintenance and Digital Twin technologies. This analysis aims to answer research questions one, “What Business model building blocks are affected by the implementation of AI?” and two,” 2. What patterns can be identified in changes in business model building blocks?”. Understanding artificial intelligence's impact on business modelling is crucial for manufacturing companies to stay competitive today. The goal is to provide insight into how Siemens has implemented AI technology and propose a framework for future AI adoption in the manufacturing industry.

This section will be based on the Innovation Impact Analysis Model (IIAM). The IIAM model will be used as a framework for this analysis. It will be slightly adjusted as the prime purpose of this model is to look forward and analyse the future, while this model will be used to look at what already happened and analyse the business model as is. These adjustments are the usage of Business Model Canvas to identify the impacts of innovation on the business model and to look into operational and customer impacts. Each of the nine building blocks will be divided into before and after AI integration, and the latter will be divided into each innovation technology and describe their impact on a building block. This allows the elimination of separate sections/analyses for operational and customer impacts. Meanwhile, market impacts are not of interest as the analysis aims to determine the impact of technology on the business models and internal aspects. To cover financial impacts, a cost-benefit analysis will be conducted, and scenario analysis is not important to this analysis as the technology is already implemented. Identification of innovation will be made through the Siemens case description, as Siemens has already determined it in their publications. The analysis section will conclude with an application of Systems Thinking theory and causal loop diagrams to each of the innovation technologies with the goal of determining impact patterns.

5.1. Siemens

Historical Background and Evolution

Siemens AG, a global industrial manufacturing giant, has a rich history that traces back to its founding by Werner von Siemens and Johann Georg Halske on October 12, 1847, in Germany. From its humble beginnings as a telegraph company, it was obvious that innovation is in company culture, as its first innovation was a significant improvement over existing telegraph technology. Throughout the late 19th and early 20th century, Siemens swiftly diversified its technological portfolio and expanded its product range while continuing its innovation achievements like: (“SIEMENS Historical Institute– a technology company since 1847,” n.d.)

- 1881. – First public electric railway in Berlin by Siemens (“First public electric railway,” 1881)
- 1881 - First street lights in the United Kingdom, in a town of Godalming (“Godalming & Electricity,” n.d.)

- 1920s-1930s: Siemens became a leading manufacturer of radios, household appliances, and electric motors (“SIEMENS Historical Institute– a technology company since 1847,” n.d.)

During World War II, Siemens factories were heavily damaged. Siemens managed to overcome those challenges and rebuild its factories, contributing to the reconstruction of Germany. (“SIEMENS Historical Institute– a technology company since 1847,” n.d.)

In the 1980s and 1990s, Siemens expanded into the semiconductor manufacturing and information technology industries. In the 21st century, Siemens has heavily invested in research and development projects, with its programs named “Siemens 2014,” “Siemens Vision 2020,” and “Vision 2020+.” Those programs included investments in streamlining operations, electrification, automation, digitalisation, digital industries, smart infrastructure, and energy systems.(Kaeser, 2018; “SIEMENS Historical Institute– a technology company since 1847,” n.d.)

Core Business Areas

Siemens is involved in so many core business areas, and the impact on corporate reputation as an industrial manufacturer and leader in digitalisation goes way beyond these highlights:

- **Energy**
  Siemens is a leading supplier of energy-efficient technologies and solutions for renewable energy systems, power generation, transmission, and distribution. With its innovative products, it supports the transformation of energy systems around the world to serve a sustainable future.(“Sustainable Energy & Infrastructure,” n.d.)
- **Healthcare**
  Siemens Healthineers drives medical technology for the company, providing its services with imaging systems, diagnostics, and laboratory diagnostics. Innovations are on top of medical innovations, helping healthcare providers realise better patient results and operation efficacy better.(“Innovations with impact,” n.d.)
- **Infrastructure and Cities:**
  Smart infrastructure solutions from Siemens include a broad portfolio of buildings, transportation systems, and utility service solutions for increasing urban living gains in energy efficiency, safety, and sustainability.(“Smart Infrastructure,” n.d.)
- **Industrial Automation and Digitalization:**
  Siemens is at the forefront of industrial automation and digitalisation with state-of-the-art technologies that make factories flexible, efficient, and intelligent. These solutions range from automation systems to IoT platforms, including MindSphere and digital twin technology.(“Future of Manufacturing,” n.d.)

Commitment to innovation

Siemens adheres to innovation with its heavy investment in research and development. The company devotes a significant portion of its revenues to emerging technology, particularly artificial intelligence, machine learning, and digitalisation. As part of its commitment to creating a culture of innovation and continuous improvement, Siemens has many research centres spread across the globe. Key milestones in Siemens' digital transformation journey include the MindSphere IoT Platform, Predictive Maintenance technology, digital twin technology, and AI technologies, which will be analysed in this paper.(“Future of automation | Siemens,” n.d.)

About MindSphere IoT Platform

MindSphere IoT Platform is Siemens’ cloud-based open operating system for industrial IoT devices. The platform enables businesses to use data generated by their products, plants, systems and machines to analyse that data and make informed decisions. Key features of the MindSphere platform are: (“Siemens MindSphere Whitepaper,” n.d.)

- Connectivity:
    - Offering simple and seamless connectivity, including different manufacturers of IoT devices. Support for standardised protocols like HTTP, OPC, and MQTT allows greater platform versatility. (“Siemens MindSphere Whitepaper,” n.d.)
- Data Management
    - The platform offers security and scalability of data, enabling users to use the platform as a centralised repository for IoT data from all different sources, no matter the volume of data produced. (“Siemens MindSphere Whitepaper,” n.d.)
- Analytics and AI
    - MindSphere offers many prebuilt tools based on AI and/or machine learning for data analysis and better decision-making. Users can use the platform to check the operation of their devices, and tools enable the possibility of reacting to the detection of anomalies in data. (“Siemens MindSphere Whitepaper,” n.d.)
- Application development
    - MindSphere includes APIs and SDKs that help developers integrate MindSphere with their existing monitoring software. Besides that, MindSphere allows developers to build their tools with the capabilities of the MindSphere platform. (“Siemens MindSphere Whitepaper,” n.d.)
- Marketplace and Ecosystem
    - The MindSphere platform has an ecosystem of third-party developers who offer their applications. This creates the possibility for users to find solutions instead of developing them.(“Siemens MindSphere Whitepaper,” n.d.)

MindSphere IoT platform is classified as part of the Production Optimisation technology category. Although its ability to transform an enterprise process is impressive, it is a product innovation for Siemens. Although free, a free account offers limited functionality, and subscription fees are based on individual needs. (“Siemens MindSphere Whitepaper,” n.d.)

About Predictive Maintenance

Predictive Maintenance is a combination of technology and actions to maintain equipment. Siemens uses and offers predictive maintenance as part of its MindSphere IoT Platform. Predictive maintenance's main benefit is reducing downtimes for manufacturing lines by using an array of sensors to detect abnormalities in production equipment. By doing that, it is possible to detect whether a piece of equipment is close to malfunctioning and needs service or not. Key features of Siemens Predictive Maintenance are:(“Maintenance,” n.d.)

- Data Collection and connectivity
    - Siemens predictive maintenance solution collects data from sensors, control systems and machines and transmits them to an Edge device or towards the MindSphere platform for processing. (“Maintenance,” n.d.)
    - This solution supports a wide range of protocols, enabling compatibility with a wide range of equipment and different manufacturers. (“Maintenance,” n.d.)
- Advanced analytics and Machine learning
    - Predictive maintenance uses machine learning algorithms in order to analyse collected data. These analyses can indicate equipment failures based on anomalies in data patterns. (“Maintenance,” n.d.)
    - Machine learning algorithms are always learning on new data and, as such, offer higher reliability as time goes on. (“Maintenance,” n.d.)
- Diagnostic and Prognostic analytic capabilities
    - Based on received data, diagnostic analytics offer a better understanding of the current state of equipment, while prognostic analytics offers the remaining useful life of equipment components. (“Maintenance,” n.d.)
- Scalability and Flexibility
    - Siemens predictive maintenance is scalable in order to meet the needs of a specific operation and is flexible, allowing integration into existing IT and operational technology systems while allowing integration with Computerised Maintenance Management Systems (CMMS) and Enterprise Asset Management (EAM) systems (“Maintenance,” n.d.)

As the name suggests, Siemens Predictive Maintenance is classified as a part of Predictive Maintenance technology. It offers another way of maintaining equipment, which is classified as a process innovation, even though Siemens also offers its technology as a product. (“Maintenance,” n.d.)

About Digital Twin Technology

Siemens Digital Twin is a technology capable of creating virtual representations of physical assets or systems. This allows Siemens to simulate and predict the performance of its production lines more accurately without implementing changes in the production line. This technology reduces the risk of solutions that will be less effective or not suit the rest of the production line. Digital Twin technology offers Siemens a better way to test and optimise its innovative solutions. The key features of Siemens Digital Twin technology are:(“Digital Twin,” n.d.)

- Virtual Representation
    - Offering an accurate digital model that accurately reflects the physical properties and behaviour; this also involves the geometry, physical characteristics and operational data. (“Digital Twin,” n.d.)
    - Siemens Digital Twin can represent anything from a product to an entire facility.

- Data Integration
    - Siemens Digital Twin can leverage its MindSphere IoT Platform to integrate data into a virtual model. Besides, MindSphere Digital Twin can also incorporate data from CAD models, sensors and enterprise management systems. (“Digital Twin,” n.d.)
- Simulation and Analysis
    - Siemens Digital Twin uses a combination of different technologies, like finite element analysis, computational fluid dynamics, and multi-body dynamics, to simulate operations accurately and to give a better understanding of product behaviour. (“Digital Twin,” n.d.)
- Lifecycle Management
    - Siemens Digital Twin can simulate a product's whole lifecycle, enabling continuous improvement and innovation. This is done with Siemens Product Lifecycle Management software that is integrated with Digital Twin(“Digital Twin,” n.d.)
- Collaboration and Visualisation
    - Digital Twin serves as a single source of truth platform where designers, engineers, and operators can collaborate and visualise the product, resulting in better understanding and communication. (“Digital Twin,” n.d.)

As the name suggests, Siemens Digital Twin is part of the Digital Twin technology category. This innovation can also be classified as both product and process innovation. As a product, it represents a new offering that presents virtual models of real-world products, and as a process, it enhances and optimises manufacturing operations through simulations and monitoring. (“Digital Twin,” n.d.)

A commitment to innovation has backed the evolution of Siemens from a telegraph company to an industrial leader. With its initiatives, Siemens, like “Siemens 2014”, “Siemens 2020”, and” Siemens 2020+”, has made big steps into digitalisation and automation. These initiatives brought innovations like Predictive Maintenance, Digital Twin, MindSphere Platform, and many more to life. This paper will focus on the three innovations because they are the basis for most other AI-based innovations within Siemens's product range. This innovation also allows us to look into different types of innovations, products, process and both product and processes.

5.1.1. Business Model Canvas

The Business Model Canvas will create an image of Siemens's business model and emphasise the impact of the MindSphere platform, Predictive Maintenance, and Digital Twin technologies on it. This analysis will start with the Feasibility part of the Business Model Canvas, as the product and process type of innovation will be the most affected.(Osterwalder and Pigneur, 2010) This analysis will go through each building block and provide insight into how they looked in and around 2015, before and after implementing artificial intelligence into Siemens operations. The analysis will be segmented into each technology.

Feasibility

Key Activities

Before AI implementation

Siemens key activities were research and development, manufacturing, and engineering. Siemens invested heavily in research and development to remain an industry leader. The manufacturing efforts had focused on ensuring that high standards of reliability and performance were met while engineering teams focused on adapting solutions to the specific needs of Siemens customers. Siemens has also put efforts into servicing its products and offered training to customer personnel to efficiently work with the products sold.(Ades et al., 2013; Dörner et al., 2011; Kikolski, 2016)

After AI Implementation

- **MindSphere IoT Platform**
  Siemens, with MindSphere, has introduced a way to collect and use advanced data analysis for enhanced research and development efforts. It has also created a platform for internal purposes. MindSphere has developed an obligation to maintain the platform for the benefit of Siemens and its customers, who can access and use it.(Kulawiak, n.d.; "Siemens MindSphere Whitepaper," n.d.)
- **Predictive Maintenance**
  Using advanced analytics and machine learning, Siemens has been able to predict equipment failures, resulting in a less disruptive manufacturing process. Siemens is using data from its production to refine machine learning and improve early failure detection. (Carvajal Soto et al., 2019; Langarica et al., 2020)
- **Digital Twin**
  The introduction of Digital Twins has enabled Siemens to find more efficient and sophisticated ways of dealing with research, development, and manufacturing. Using this technology, Siemens can run its production in a virtual environment and create and test optimisations in virtual environments without stopping production, allowing it to test more and then implement only the best solution. ("Digital Twin," n.d.; Guerra-Zubiaga et al., 2020; Latsou et al., 2024)

Key resources

Before AI implementation

Siemens's crucial asset is employing a highly skilled workforce, including engineers, technicians, and researchers. These workers offered Siemens knowledge and expertise that enhanced the quality of its products. Other important assets are production facilities, state-of-the-art facilities that can produce high-quality products at scale, and intellectual property, which enabled Siemens to protect its innovation and keep a competitive edge.(Neely, 2008; “Siemens annual report 2015.,” n.d.)

After AI Implementation

- **MindSphere IoT Platform**
  For Siemens, this platform becomes a resource on its own, giving access to data, performing data analytics, and offering a platform for internal IoT devices. (“Siemens MindSphere Whitepaper,” n.d.)
- **Predictive Maintenance**
  This technology has enabled Siemens to use advanced analytics, machine learning, and IoT capabilities in its resources. Data collection and analysis are crucial for this technology, and predictive maintenance brings new resources. (Falekas and Karlis, 2021)
- **Digital Twin**
  Siemens can use Digital Twin as a new resource for testing its innovations and research and development project results. By using advanced simulation and analytic capabilities, Siemens can better develop and maintain its equipment while offering its customers customised solutions.(Guerra-Zubiaga et al., 2020)

Key Partners

Before AI implementation

Siemens relies on a robust network of suppliers and partners to operate. It needs high-quality components and raw materials suppliers to produce its products. Siemens also collaborates with research institutions and universities to conduct research and development and integrate the latest technological advancements into its offerings to customers. Furthermore, Siemens works closely with system integrators to help deliver and integrate its solutions for end customers. (Meyer et al., 2015; “Siemens annual report 2015.,” n.d.)

After AI Implementation

- **MindSphere IoT Platform**
  MindSphere, a cloud-based platform by design, requires a lot of computational power. This resulted in Siemens partnering with Google Cloud. This partnership ensures that MindSphere runs off well-developed infrastructure and has failovers for downtime. (Patrizio, 2021)
- **Predictive Maintenance**
  Predictive maintenance has not directly influenced new collaborations or partnerships, but MindSphere establishes collaborations with Google Cloud.(Patrizio, 2021)
- **Digital Twin**
  The implementation of Digital Twin technology has not resulted in new partnerships. Still, the use of current partnerships with academic institutions has been strengthening to develop better digital twin models and increase the efficiency of technology.(Falekas and Karlis, 2021)

Desirability

Value Proposition

Before AI

Siemens was providing robust and dependable industrial solutions. The focus of those solutions was on high-quality electrical and mechanical systems. Products were made to fit industry standards, and the possibility for customisation was low. Maintenance was mostly reactive or scheduled, where equipment could break "ahead of schedule, " resulting in downtime and increased operating costs.

After AI Integration

- **MindSphere IoT Platform**
  MindSphere IoT platform offers customers a way of communicating between a centralised IoT platform and IoT devices while offering real-time data analysis. The main benefit of this technology is data processing, as the platform can process collected data and notify customers of anomalies or different metrics. Applications of this technology are diverse, from industrial production to Smart City solutions.(Kazuyuki and Javid, 2024; Okonta and Vukovic, 2023)
- **Predictive Maintenance**
  With Predictive maintenance technology, Siemens continuously monitors data using a combination of sensors. Received data from sensors is processed in a central system, where AI detects anomalies. This application's benefit is the ability to detect early and schedule maintenance accordingly, minimising wear and tear on equipment and ultimately leading to higher equipment longevity. Besides having equipment functional longer, downtimes are also lower as the equipment is being serviced in a planned fashion.(Lu and Gong, 2023; Morandi and Jüngling, n.d.)
- **Digital Twin**
  With Digital twin technology, Siemens uses virtual simulations and real-time data to simulate real-world conditions of physical assets, systems or production processes. This technology allows engineers to run simulations and predict outcomes regarding increasing production efficiency. Digital twins are one of the main reasons why customised solutions are possible. Using digital twins, it is possible to simulate the production process with a new setting, and once optimised, it can be applied more efficiently. Besides simulation, this technology can also be used for predictive maintenance by comparing real-world data to the data in the digital twin. (Falekas and Karlis, 2021; Ruppert and Abonyi, 2020)

Customer Segments

Before AI integration

Siemens customer segments were predominantly in the energy, healthcare, infrastructure, and heavy manufacturing sectors. Siemens' standardised, robust, and reliable equipment attracted these sectors. (“Siemens annual report 2015.,” n.d.)

Customers of Siemens before AI integration:

- Energy sector: Power generation, transmission, distribution companies(Tenfält and Bäckman, 2015) (“Siemens annual report 2015.,” n.d.)
- Healthcare sector: Hospitals and medical facilities with imaging and diagnostics equipment (“Siemens annual report 2015.,” n.d.; Tenfält and Bäckman, 2015)
- Infrastructure sector: Building technology, urban development projects and smart city initiatives (“Siemens annual report 2015.,” n.d.; Tenfält and Bäckman, 2015)
- Heavy Manufacturing sector: Automotive, Aerospace, machinery manufacturing (“Siemens annual report 2015.,” n.d.; Tenfält and Bäckman, 2015)

After AI Implementation

- **MindSphere IoT Platform**
  MindSphere allows Siemens to enter new markets by creating custom maid solutions for different customers. With this platform, Siemens met the specific needs of a wider variety of customers. Opening access to data-centric customers and high-tech industries (Okonta and Vukovic, 2023)
- **Predictive Maintenance**
  Due to predictive maintenance technology, Siemens can enter better into maintenance agreements with its customers or achieve new customers by offering predictive maintenance even if they are not existing customers. (“Transform your operations with predictive maintenance,” n.d.)
- **Digital Twin**
  Siemens Digital twin technology allows Siemens to increase its presence in already established customer segments, offering additional value. It also allows Siemens to tap into a new customer segment in the high-tech industries. (Falekas and Karlis, 2021)

Customer Relationships

Before AI

Siemens customer relationships were mostly transactional and reactive. Siemens had focused on direct interactions with dedicated account managers and through support channels and service visits. Siemens developed an extensive network of sales and service representatives, allowing them to cooperate closely with its customers. Siemens maintained most customer relationships via face-to-face, telephone, and email communications. Customer support was also based on the same form of communication, while Siemens organised educational and training programs. (“Siemens annual report 2015.,” n.d.)

After AI Implementation

- **MindSphere IoT Platform**
  Using this platform, Siemens can offer continuous support for its customers. From proactively addressing equipment issues to offering predictive maintenance, Siemens's customer relationships strengthened.("Siemens MindSphere Whitepaper," n.d.)
- **Predictive Maintenance**
  The customer relationship does not change when looking at the type of relationship, but it changes slightly. Siemens is now more proactive and uses data collected as a lead to provide maintenance service instead of being reactive or scheduled.("Transform your operations with predictive maintenance," n.d.)
- **Digital Twin**
  For Siemens Digital, twin technology offers the ability to develop proactive customer relationships. This means that Siemens can now offer its customers better engineering services, and with more data collected and analysed, Siemens can continuously improve its customer operations.(Falekas and Karlis, 2021)

Channels

Before AI Implementation

Siemens relied on a combination of distribution channels. Depending on the type of customers and their importance, there would be either direct sales, where Siemens would do it themselves or employ their partners and distributors to handle sales. Siemens would also actively participate in trade shows and industry conferences, where it would be possible to reach out to customers and expand its customer base. Although present online, Siemens was not as developed as some other businesses, but the main focus was on direct sales, not online sales.(Czinkota et al., 2021; Kulawiak, n.d.)

After AI Implementation

- **MindSphere IoT Platform**
  Siemens MindSphere platform offers a new way of engaging with customers through digital channels. Siemens Solutions customers can access, monitor, and receive insights for solutions remotely. This means that Siemens is moving beyond its traditional sales and support channels.("Siemens MindSphere Whitepaper," n.d.)
- **Predictive Maintenance**
  For Siemens, Predictive Maintenance does not change the channels of interaction with customers.
- **Digital Twin**
  Siemens Digital Twin technology does not affect customer interaction channels.

Viability

Cost Structure

Before AI implementation

Siemens' key cost components could be divided into production costs, research and development costs, maintenance and customer support costs, and administrative and marketing costs. (“Siemens annual report 2015.,” n.d.)

- Costs of production include raw materials, components, labour and maintenance. (“Siemens annual report 2015.,” n.d.)
- Research and development costs include prototyping, researchers' and engineers' salaries, innovation testing and validation, and legal costs related to protecting intellectual property.(“Siemens annual report 2015.,” n.d.)
- Maintenance and customer support costs are related to technical support teams, maintenance staff, and service centres.(“Siemens annual report 2015.,” n.d.)
- Administrative and marketing costs include salaries for administrative staff, office expenses, direct sales forces, distributor partnerships, and marketing campaigns.(“Siemens annual report 2015.,” n.d.)

After AI Implementation

- **MindSphere IoT Platform**
  Excluding one-time investments for the development and implementation of MindSphere, the MindSphere platform brings new operational and maintenance costs. These costs involve the operating cost of the platform on Google Cloud, maintaining the platform, and minor innovations and performance optimisations. This platform also impacts Siemens' whole operation, as using it, Siemens can reduce costs in other areas, such as improving the overall performance of its production lines and running data analysis of its equipment to predict maintenance. (Patrizio, 2021; “Siemens MindSphere Whitepaper,” n.d.)
- **Predictive Maintenance**
  Excluding one-time investments for developing and implementing Predictive maintenance, Siemens's cost includes additional computational capabilities for machine learning and new high-skilled employees. However, reductions in maintenance costs and higher productivity offset those costs.(“Maximizing Operational Efficiency with Predictive Maintenance Tools,” n.d.)
- **Digital Twin**
  Excluding a one-time investment for developing and implementing Digital Twin, Siemens has new expenses in maintaining supporting hardware and software and newly hired specialists that work with that technology.(“Digital Twin Cost for Development | Toobler Blog,” n.d.)

Revenue Streams

Before AI implementation

Siemens's revenue streams could be divided into Product sales, Service contracts and maintenance, Engineering Services, Training, Software, and licensing.("Siemens annual report 2015.," n.d.)

- Product sales: sales of products produced by Siemens, such as PLCs, sensors, actuators, and control systems. ("Siemens annual report 2015.," n.d.)
- Service and maintenance: Siemens provides service and maintenance to its customers with long-term contracts, providing a recurring revenue stream("Siemens annual report 2015.," n.d.)
- Engineering services: Offered to customers that require customisable solutions, this revenue stream is often part of large industrial projects. ("Siemens annual report 2015.," n.d.)
- Training: Siemens offers its customers training on implementing and operating its products. This is a supplementary service to its products, and customers must pay for it. ("Siemens annual report 2015.," n.d.)
- Software and licencing: Sales of software connected with hardware products. ("Siemens annual report 2015.," n.d.)

After AI Implementation

- **MindSphere IoT Platform**
  Although MindSphere Platform is open to the public, it offers Siemens new revenue streams. Customers pay for the platform's services, like additional storage, more users, and advanced analytics tools. Siemens profits more from bigger customers and offers accessible pricing for smaller customers.("Upgrade - Developer Documentation," n.d.) Also, MindSphere platform introduces a new type of revenue stream by subscription, as on the platform, bigger customers are paying a monthly subscription.
- **Predictive Maintenance**
  For Siemens, Predictive Maintenance offers an opportunity for new service contracts but not a new revenue stream.
- **Digital Twin**
  Using digital twin technology, Siemens is increasing its Engineering, training, and Software revenue.("Digital Twin Cost for Development | Toobler Blog," n.d.)

Conclusion

This analysis using Business Model Canvas reveals what changes did Siemens experienced integrating AI technology into its portfolio. Siemens' business model from before AI integration (Figure 2.) hints at how traditional manufacturing companies look, offering products and infrastructure solutions, dealing with customers in a reactive manner, and not relying on automated communication processes. Also, having activities focused on industrial equipment while using manufacturing facilities and a skilled workforce. Siemens focused on making profits from its skills and knowledge.

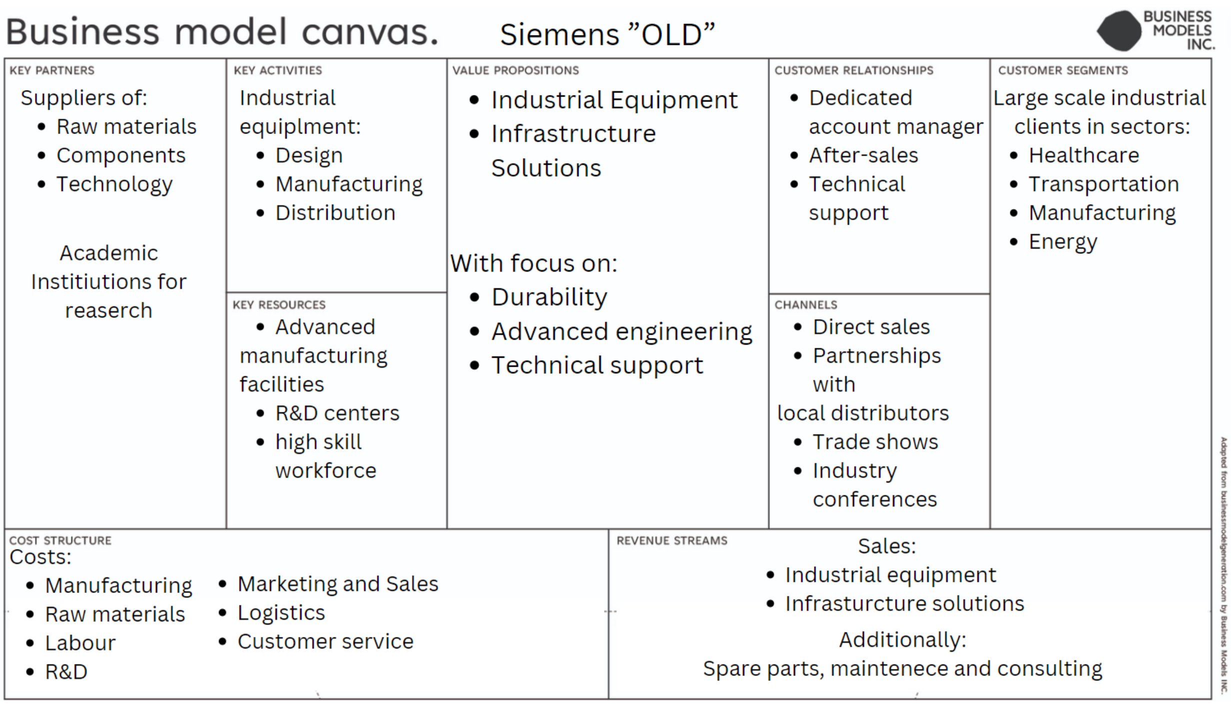

Figure 2 Representation of Siemens Business Model Canvas before AI integration- BMC image form ("Business Model Canvas – Download the Official Template," n.d.)

Siemens' Business Model after AI integration (Figure 3.) is leaning more towards a mix of manufacturing and high-tech industries. Siemens started offering personalised services and using data to enhance its products. Siemens also started using technology in the form of automatisation to keep feeding customer data into machine learning algorithms, thereby enhancing its products' value. Investments and partnerships grew towards IT infrastructure to support AI, and a subscription model was used.

Each of the three technologies has significantly impacted and nudged Siemens towards the high-tech industry by offering software solutions. This movement continues to develop as there are constant investments and developments with AI technology, and Siemens is continuing to expand and further develop its products using that technology. Partnerships like Google only ensure that Siemens stays at the forefront of its industry. Their products continue to revolutionise how things are done within the industry.

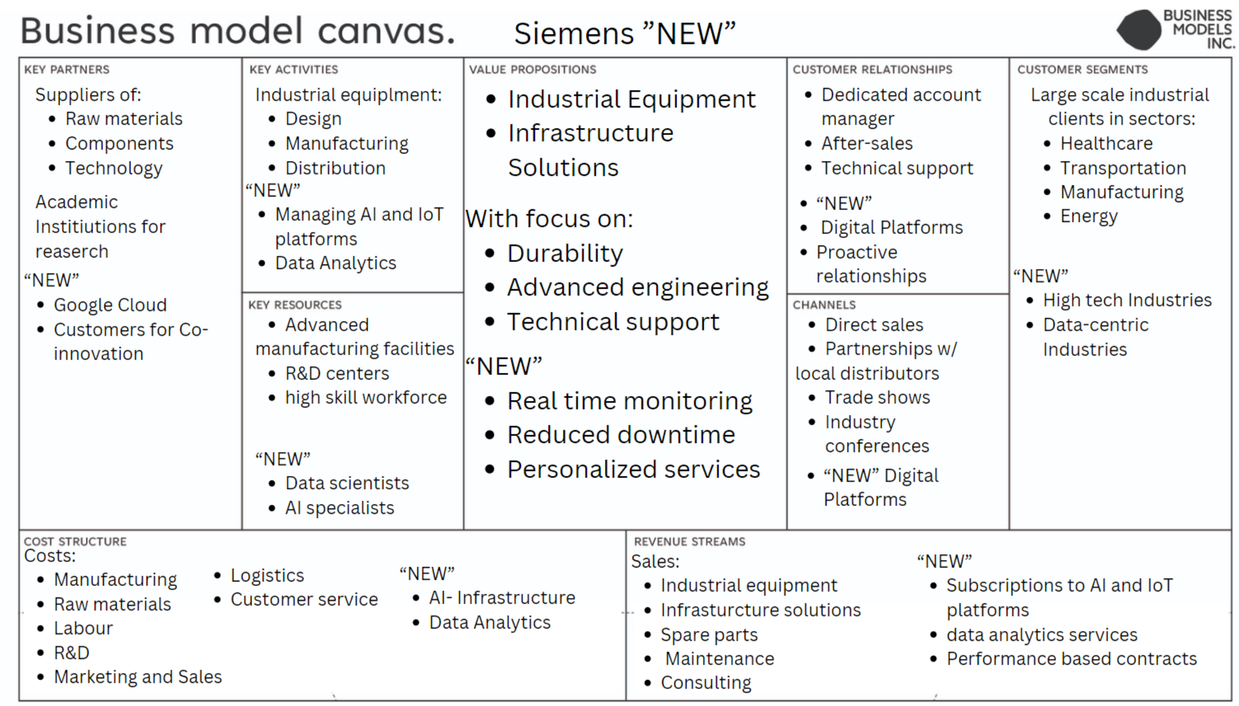

Figure 3 Representation of Siemens Business Model Canvas after AI integration- BMC image form ("Business Model Canvas – Download the Official Template," n.d.)

5.1.2. Cost Benefit Analysis

MindSphere IoT Platform

Cost Factors

Development costs of the MindSphere IoT Platform are speculated to be between 10 and 20 million euros. Ongoing expenses are unknown but related to the Google Cloud platform. Maintenance and updating are on the lower side due to the platform's many users, around 10000, and its operational history of more than seven years.("Siemens Annual Reprot 2023," n.d.)

Benefits

Mindsphere has introduced a new revenue model allowing users to pay monthly subscriptions. It also offers the ability to train its machine-learning models and provide powerful advanced analytics for its customers.("Siemens MindSphere Whitepaper," n.d.)

Predictive Maintenance

Cost Factors

Estimates for spending on predictive maintenance technology are around 150 million euros. The costs of operations and training are also unknown but considered high, as are the maintenance and updating costs due to the continuous development of this technology.("Siemens Annual Reprot 2023," n.d.)

Benefits
Siemens Predictive Maintenance offers a 70-75% reduction in downtime and a 15-30% reduction in maintenance costs. Continuous equipment monitoring and regular and timely machinery servicing will prolong the machinery's life and provide long-term cost savings. ("Maximizing Operational Efficiency with Predictive Maintenance Tools," n.d.)

Digital Twin

Cost Factors

The cost of development and implementation for digital twins is not publicly available. Digital Twin technology is part of a broader 2 billion Euro strategy plan, and speculations put the cost at around 20 million Euros. The cost of training and operating is also unavailable (Guerra-Zubiaga et al., 2020) The costs of maintaining and updating Digital Twin will increase as technology develops. ("Digital Twin Cost for Development | Toobler Blog," n.d.; "Digital Twin," n.d.)

Benefits
Siemens benefits from Digital Twin technology include Improved R&D efficiency, prototyping in a virtual environment, Optimized production, higher efficiency at lower cost, processes, and offerings to Siemens Customers like customisation by simulation of customer-specific scenarios.("Digital Twin," n.d.)

5.1.3. Systems Thinking and Casual Loops Diagrams

This part of the analysis will focus on defining the patterns of effect Siemens AI Innovation had on its business model. Using Systems thinking theory, an already finalised Business Model Canvas analysis, and the analysis of Artificial intelligence technology's impact on Siemens' Business model, it will be possible to offer a holistic overview of changes and emphasise interactions between business model building blocks. The structure of this section will be separated into three sections, each for one of the analysed AI technological innovations. Diagrams will be used to visualise findings and indicate patterns.

MindSphere IoT Platform

When looking at MindSphere Platform's effects on Siemens's business model, three loops can be determined: the Data collection and Usage Loop, the Research and Development loop, both reinforcing loops and the Operational efficiency loop, as a balancing loop. (Figure 4.)

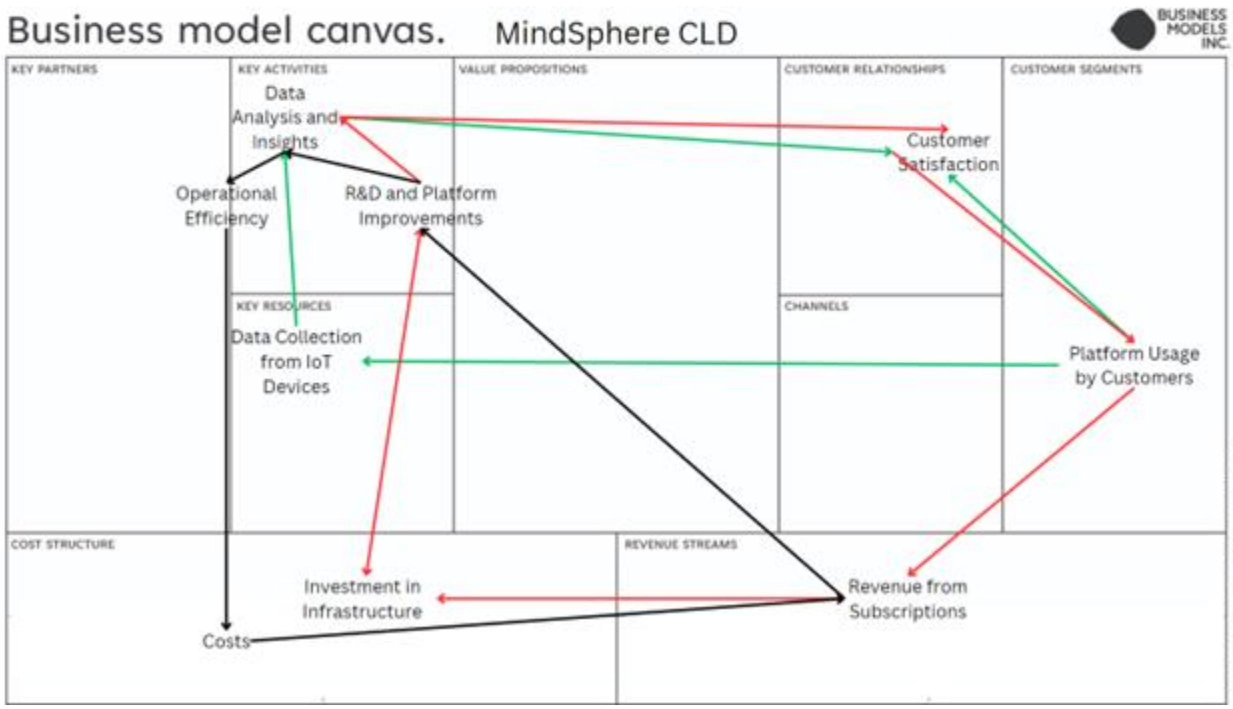

Figure 4 MindSphere CLDs, Green - Data Collection, Red- R&D, Black - Operational Efficiency- BMC image form ("Business Model Canvas – Download the Official Template," n.d.)

Data Collection Loop

Connecting a wide array of IoT devices to the MindSphere platform allows Siemens to gather data from industrial operations. These data are transformed into insights. With more data to analyse, the platform can provide Siemens and its customers with better, more precise and actionable insights, allowing the MindSphere platform to be a decision-making tool. As a result, this generates better customer satisfaction and adds more value for customers. If insights are more precise and accurate, customers will continue to use this platform; if not, implement it in more operational processes, increasing the platform usage and, in the end, increasing the data generation and collection.
This loop, in turn, looks like this: Increased Data Collection from IoT Devices enhances Data Analysis and Insights, which improves Customer Satisfaction. This leads to increased Platform Usage, which leads to more Data Collection.

Research and Development loop

Customer satisfaction and usage must grow to increase the MindSphere platform's revenue. This revenue will allow Siemens to Invest back into infrastructure and updates to the platform, allowing better data processing capabilities, better security, and quicker results. Ultimately, this will create more customer satisfaction and Usage, increasing the revenue the platform generates.

This loop, in turn, looks like this: increased subscription revenue allows for greater Investment in Infrastructure, which boosts R&D and Platform Improvements. This leads to better Data Analysis and Insights, which increase Customer Satisfaction and Platform Usage, driving more Revenue.

Operational efficiency loop

This loop examines efficiency gains and cost savings. The insights generated by the platform influence operational efficiency. Siemens and its customers satisfaction from the usage of the platform are boosted by improved operational efficiency. Operational efficiency also reduces costs associated with operations. This loop also offers better insights into why customers would adopt this platform, and the better and higher value of adopting this platform is that more businesses will recognise it as an option and, in turn, adopt it.

The Casual Loop Diagrams for the MindSphere platform show how Siemens uses IoT and advanced analytics to create a system that increases customer satisfaction, revenue, and continuous platform development. Siemens' increased data generated from usage reduces the efforts needed to develop a better platform, as machine learning capabilities are improving independently.

This analysis showcases a pattern of how the MindSphere platform influences Siemens's Business Model. Its value is stronger customer relationships, enhanced key resources (data and infrastructure), and better key activities (data collection, analysis, R&D). This platform also brings new revenue streams and a new subscription-based pricing model.

Predictive Maintenance

When looking at Siemens Predictive Maintenance and its effects on Siemens's business model, three loops can be identified. Reinforcing loops of Data Analytics, improvement, and customer satisfaction can also be identified, as can a cost management balancing loop. Figure 5.)

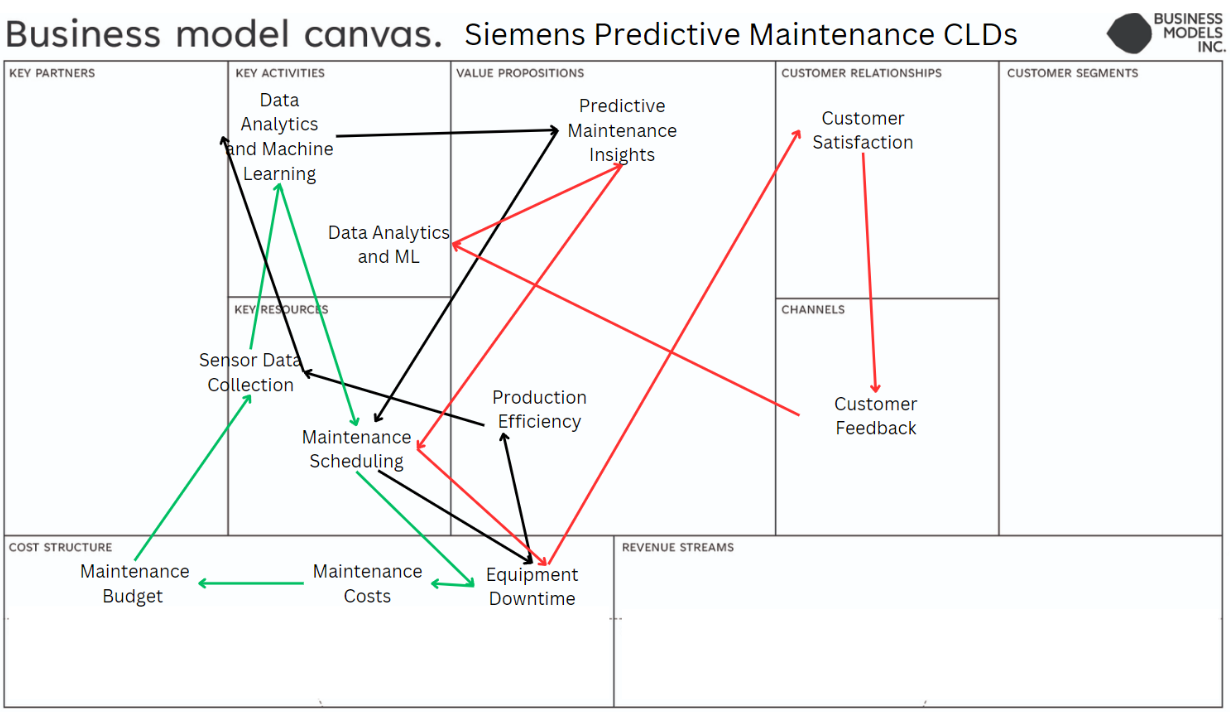

Figure 5 Predictive Maintenance CLDs, Data analytics - Black, Customer satisfaction- Red, Cost management - Green- BMC image form ("Business Model Canvas – Download the Official Template," n.d.)

Data analytics and improvement loop

With predictive maintenance, sensor data collection becomes the main technology resource. It enhances data analysis and allows machine learning to provide better insights into maintenance. This results in more efficient maintenance scheduling and lower downtimes, offering increased production efficiency, bigger dataset collection, and better data analytics.

Customer Satisfaction loop

Predictive maintenance and its insights are needed to develop better maintenance schedules. This will reduce equipment downtime, resulting in better customer satisfaction and more data being fed back to data analysis. This will give better insight into maintenance scheduling and result in lower downtimes.

Cost Management Loop

For Siemens, predictive maintenance offers the ability to better manage its costs and maintenance budget. To do so, it is necessary to schedule maintenance more accurately to reduce equipment downtime. Reducing downtime will result in lower maintenance costs and a lower maintenance budget. It will offer more data to be fed into predictive maintenance data analytics and machine learning models.

The casual loop diagrams for Siemens predictive maintenance show how the system of continuous improvements is made by integrating real-time data, advanced analytics, and customer feedback. These loops allow the system to evolve and create cost savings for Siemens and its customers. They show enhancements in maintenance efficiency, downtime reductions, and increased customer satisfaction.

This analysis offers insight into patterns of how predictive maintenance impacts Siemens's business model. Predictive maintenance drives key activities(data collection, analysis, maintenance planning), introduces key resources (sensor data, machine learning models) and offers proactive customer relationships. The system also offers Siemens a cost reduction in its operations and the ability to increase its market with customers looking for advanced and reliable maintenance solutions.

Digital Twin

When looking into Digital Twin technology's effects on Simens's business model, two reinforcing loops, Continuous improvement and Customer Customization, and one balancing loop regarding Cost management can be identified. (Figure 6.)

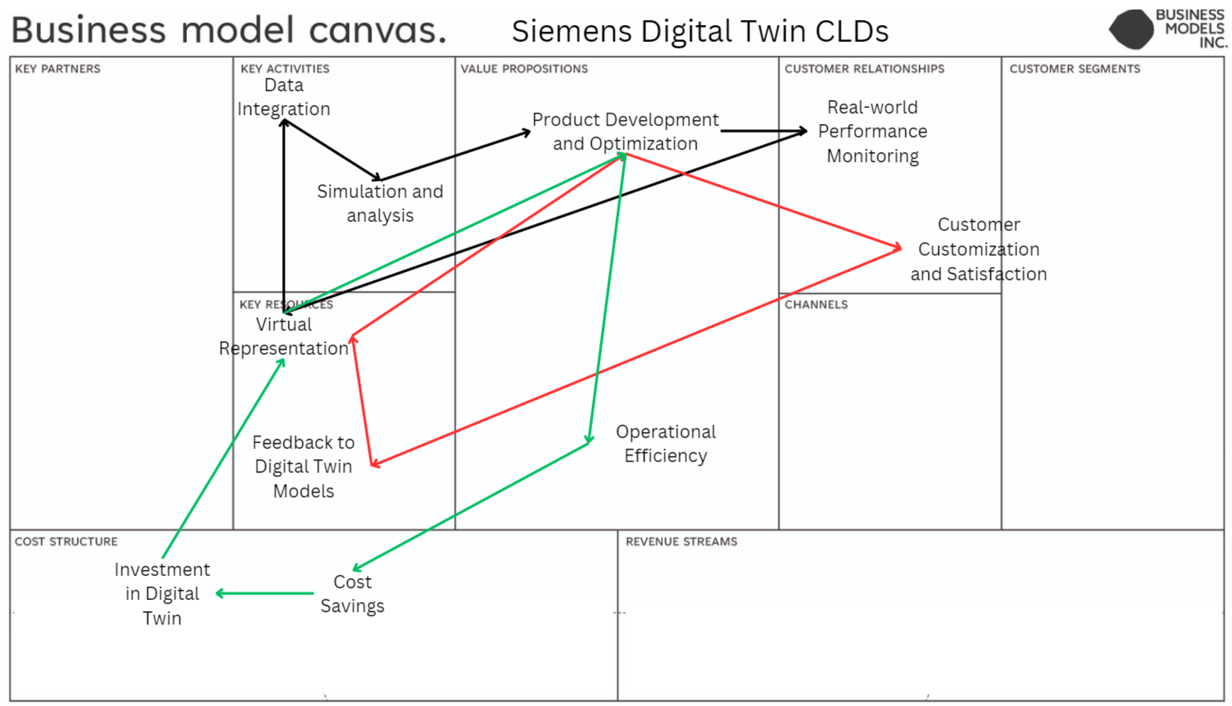

Figure 6 Siemens Digital Twin CLDs, Continuous improvement- Black, Customer satisfaction- Red, Cost management- Green

Continuous Improvement loop

The core of this technology is the virtual representation capabilities of digital twins. When included in that there is integration with real-time data, it allows the digital twin to run different simulations and analyse different scenarios, giving insights on potential improvements and performance. This insight could be used to optimise current real-world operations or to develop new manufacturing processes. The ability to compare real-world data to virtual representation is used to better enhance the ability to create virtual representations.

Customer Satisfaction Loop

Digital Twin technology provides customised solutions for every virtual representation, leading to better alignment with customer needs and, in turn, increasing customer satisfaction. Customers who are better satisfied with the technology will use it more and keep feeding it metrics from the real world, resulting in better virtual representation and performance optimisation.

Cost Management Loop

Siemens Digital Twin technology offers possibilities to enhance product development and optimise operations. This results in more effective production and, in turn, operational cost savings. When cost savings are made, additional funds are available to invest in digital twin technology, giving better virtual representation and operational efficiency.

The Casual Loop Diagrams of Siemens Digital Twin technology show how certain systems are made to ensure continuous technology improvement by integrating real-time data, simulations, and customer feedback. These reinforcement loops offer insight into how to keep developing technology while ensuring Siemens and its customers benefit from operational efficiencies. This analysis showcases Siemens' importance of digital twin technology. It allows Siemens to offer highly customised solutions and strengthen customer relationships while enhancing key resources (data, digital models) and driving key activities (simulation, optimisation, R&D). This technology also allows Siemens to create a new revenue stream and expand its market reach. This integration of CLDs into the business model canvas offers a pattern of digital twin technology's impact on Siemens's business model.

Applying CLDs allows us to conclude how interconnected Siemens AI technologies are. The reinforcing loops highlight the ability for systematic and continuous improvement of technologies, while the balancing loop offers a framework of cost-effectiveness and sustainable innovation. Using CLDs in Siemens's example gives a deeper understanding of how AI technology innovation could impact the business model, allowing better and more informed decision-making and strategy planning.

5.2. Conclusion

A combination of models has been used to answer research questions 1. ("What business model building blocks are affected by the implementation of AI in the manufacturing industry?") and 2. ("What patterns can be identified in changes in business model building blocks?").

The Innovation Impact Analysis model was used as a framework to shape the analysis process, where innovation identification was the first step and the classification of MindSphere, predictive maintenance, and digital twin was done. Afterwards, the impact on the business model was analysed with a business model canvas, and to conclude, the search for patterns was done in the form of Casual loop diagrams for each of the technologies. Although this model is meant to study an innovation's impact on the business model, it is meant to be done in different periods. It should be done after the innovation process and before implementing it into business. This and the aim of the thesis have resulted in the modification of IIAM to suit it better.

The Business Model Canvas was used to compare Siemens's business model before and after the integration of artificial intelligence. It shows how the business model looks after integrating advanced AI technologies, the MindSphere IoT platform, Predictive Maintenance, and Digital Twin. The main limitation of this model is that it captures the business model at one specific time and can analyse the transition from one point to another. There is also an oversimplification of financial analysis, ergo the need for cost-benefit analysis. To analyse this transition better, a modification to the process was made, where each building block was analysed separately, and the impact of each innovation was analysed separately. and afterwards, all the insights were considered into one, answering "What business model building blocks are affected by the implementation of AI in the manufacturing industry?".

System thinking theory and Casual loop diagrams focused on answering the "What patterns can be identified in changes in business model building blocks?". The goal was to represent the holistic impact of every individual innovation and to detect the patterns of how it impacts. The diagrams defined patterns of effect using business model canvas findings. This model captures interactions and interdependencies of this innovation with the business model. The downside of this model is that when creating these diagrams, analysts' experiences and opinions have a bit more effect, producing a subjective outlook on these patterns.

The analysis section shows how innovative AI technologies like MindSphere, Predictive Maintenance, and Digital Twin reshape Siemens' business model. Integrating these innovations has offered Siemens better operational efficiency, improved customer relationships, and new revenue streams, all of which allow Siemens to gain a competitive advantage.

In conclusion, while adopting these AI technologies has driven significant benefits for Siemens, it has also allowed Siemens to get indirect collaboration with its customers, allowing easier refinement and development of technology. This approach will allow Siemens to remain at the forefront of industrial innovation and maintain its competitive edge in the market.

6. Discussion

This paper analysis has shown how AI integration has significantly transformed Siemens's business model. The MindSphere IoT Platform has changed Siemens's key activities to provide more data-driven actions, like data-driven decision-making and data analytics. This platform serves as a new resource for Siemens, as it can provide data that will fuel the activities. Customer relationships are more proactive due to the use of the platform, and Siemens can offer better services more effectively, resulting in longer-term higher customer satisfaction and loyalty. Furthermore, the revenue model has become more diversified. An integral part of the platform is the subscription model.

Siemens' proactive maintenance, on the other hand, has changed the maintenance processes and strategies. Going from reactive to proactive reduces operational downtime and gives Siemens greater control over the production process. By utilising sensors, data analysis, and machine learning, Siemens can predict the future of its equipment and can, in turn, control the way schedule maintenance is executed, evading ad hoc repairs when something stops or breaks. This change has also allowed Siemens to provide predicted maintenance and offer more flexible service, increasing customer trust and satisfaction.

Integrating Digital Twin technology into its process and product lineup changed internal product development, operational processes, and how Siemens produces solutions for its customers. Integrating real-world data into digital twins allows Siemens to utilise AI in identifying future product or operation behaviour and, in turn, allows accurate data on efficiency. This offers the additional ability to "thinker" with variables and develop more efficient products or production processes, resulting in lower expenditures and improved customer satisfaction.

The findings of this study confirm previous studies about AI-driven business model innovation. They support the finding of artificial intelligence's potential to enhance operations and customer engagement. However, this research gives a complete overview of how AI technologies affect business models. This research demonstrates the symbiotic relations between AI technologies and Siemens' overall business strategy and operation.

This research extends the understanding of the integration of AI into operations. The findings highlight how Siemens AI technologies are within the positive reinforcing feedback loops, resulting in a push for improvement and innovation. For example, the MindSphere platform is not only a product that feeds data into data analysis and then back to the customer. It can also enhance the predictive maintenance and digital twin with the insights it gathers. This analysis of insights broadens the theories about how AI can create self-enforcing innovation systems that support sustainable business model transformation.

Strengths and limitations

The strength of this study is the use of multiple analytical frameworks, the case of the successful and innovation-oriented company Siemens and providing holistic overviews of three technologies' impact on the business model. The limitations are reliance on secondary data and the complexity and subjectivity of some used frameworks, like CLDs. Additionally, focusing on only one case could limit the application of the results to other cases and industries.

7. Conclusion

The integration of AI technologies transformed Siemens's business model. Due to increased data collection and analytics, key activities have become more efficient. Key resources, simulation tools, and data management capabilities have been added as an IoT platform. Customer relationships have become more proactive and personalised, and revenue streams have been diversified.

The findings of this research elevate knowledge in AI and business model innovation. They highlight how transformative AI can be for business models and its impact on operations, value proposition, revenue generation, costs, and customers. The broader implications of AI's impact on business models suggest that AI technology drives digital transformation within the industry.

This paper highlights the importance of continuous innovation and adaptation of new technology in maintaining a competitive edge. Siemens has positioned itself as a digital transformation leader by enhancing its operations using AI, and that could be a sign to the rest of the world that commitment to innovation ensures technological advancements and a competitive edge. On the other hand, when looking into the impact of business models, the integration of AI for Siemens has enforced some strategic changes to use AI's potential. MindSphere analytics, predictive maintenance reduction in downtimes, and Digital Twins capability to run precise simulations and optimisations all bring potential that can be used. It is on the company that integrates them into its operations to adjust, just like Siemens did, showing the world that it is possible and profitable. When examining how Siemens customer interactions are impacted, AI technologies provide an opportunity to create additional value. With reduced downtimes, research and development and maintenance costs, improved operational efficiency, and better data analysis, Siemens, by its mindset of delivering high-quality solutions, will always bring more value to the customers, building stronger customer relationships.

However, while there are benefits, there are also some challenges. First, data privacy and security concerns are important to address, especially due to new rules and laws like GDPR. Integration with older systems and equipment might require additional complex and/or costly efforts. Also, the dynamic nature of AI technology and its exponential growth over the last few years have set the demands for a more adaptive approach to implementing and managing innovation.

Practical implications

This study also involves practical solutions for integrating AI technologies seamlessly into the manufacturing industry. To answer research question 3. “What strategic recommendations can be made for manufacturing businesses implementing AI?” three strategic suggestions will be made. The first and most difficult suggestion is to encourage a culture of continuous learning, technology adaptation, and innovation. This will offer a solid base for what AI integration brings. The second suggestion relates to, when integrating AI, adopting a holistic approach containing models like IIAM, BMC, and CLDs will offer a solid framework to use, giving insights into what to adjust. Lastly, the last suggestion is that implementing scalable and flexible solutions will ensure a gradual transition into a data- and AI-operated enterprise.

Further Research

Further research on this topic could explore the impact of AI on business models in other cases, industries, environments, and AI technologies, including primary data. This would validate the findings of this study. Also, looking into longer-term effects can provide better insights into the sustainability of AI innovations. Developing a new framework for this type of analysis would be beneficial, as the existing ones are subjected to complexity and analyst subjectivity. This would, in turn, offer more accurate and actionable insights.

In conclusion, Siemens's implementation of AI technologies has been successful, and it gives a blueprint for the rest of the industry, which aims to leverage AI technologies. As the manufacturing industry evolves, there are indications that there will be more shifts towards AI and digitalisation; it is just left to see who will be left behind.

8. References

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