CHALMERS

Leveraging AI to Enhance Innovation Efficiency in the MedTech Sector

AI Applications and Strategies for Enhancing Innovation Efficiency: A Case Study in the MedTech Sector

Bachelor's thesis in Industrial Engineering and Management

Hanna Blomström
Emil Broqvist
Emil Halvordsson Johansson
Fred Kylevik
Tilda Qvist
Oskar Uhlmann

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF ENTREPRENEURSHIP AND STRATEGY

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2025
www.chalmers.se

Bachelor's thesis TEKX18-25-01

Bachelor's thesis TEKX18-25-01

Leveraging AI to Enhance Innovation Efficiency in the MedTech Sector

AI Applications and Strategies for Enhancing Innovation Efficiency: A Case Study in the MedTech Sector

Användning av AI för att öka innovationseffektiviteten inom MedTech-sektorn

Strategier och applikationer för att förbättra innovationseffektivitet med AI: En fallstudie inom MedTech-sektorn

HANNA BLOMSTRÖM
EMIL BROQVIST
EMIL HALVORDSSON JOHANSSON
FRED KYLEVIK
TILDA QVIST
OSKAR UHLMANN

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
Division of Entrepreneurship and Strategy
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2025

Leveraging AI to Enhance Innovation Efficiency in the MedTech Sector
AI Applications and Strategies for Enhancing Innovation Efficiency: A Case Study in the MedTech Sector

HANNA BLOMSTRÖM
EMIL BROQVIST
EMIL HALVORDSSON JOHANSSON
FRED KYLEVIK
TILDA QVIST
OSKAR UHLMANN

Bachelor's thesis TEKX18-25-01

Department of Technology Management and Economics
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone + 46 (0)31-772 1000

Gothenburg, Sweden 2025

Leveraging AI to Enhance Innovation Efficiency in the MedTech Sector
AI Applications and Strategies for Enhancing Innovation Efficiency: A Case Study in the MedTech Sector

HANNA BLOMSTRÖM
EMIL BROQVIST
EMIL HALVORDSSON JOHANSSON
FRED KYLEVIK
TILDA QVIST
OSKAR UHLMANN

Department of Technology Management and Economics
Chalmers University of Technology

SUMMARY

The MedTech industry is experiencing rapid technological change and facing evolving healthcare needs, which puts pressure on actors to innovate efficiently and stay competitive. At the same time, Artificial Intelligence (AI) is emerging as a transformative tool with the potential to enhance efficiency. However, despite its potential, the adoption of AI within the MedTech sector remains limited. The aim of the thesis is therefore to examine how MedTech companies can leverage AI to enhance innovation efficiency. The main research question is explored through the lens of an innovation process framework, consisting of the three phases: Idea, R&D, and Commercialization. Within this framework, four key areas have been identified with the potential to improve overall efficiency by the integration of AI, namely: Knowledge Management, Patent Analytics, Market and Customer Analysis, and Resource Allocation. In addition, the study addresses important aspects of implementing AI within organizations to optimize the possible outcomes.

A single case study has been conducted analyzing a MedTech company, which was selected as it constitutes a suitable case to explore the research question. The methodology consists of a literature review followed by an interview study. The literature presents the current state of AI applications in the four focus areas defined and reviews opportunities and challenges regarding implementation. The interview study included participants both working at the company studied, to depict its current practices and needs, and individuals at other organizations who are at the forefront of AI adoption, to gain best-practice perspectives and expert insights.

The results show that AI technologies have great potential in enhancing innovation efficiency in the MedTech industry. AI helps to improve the flow of information inside the organization, strengthen intellectual property strategies, enhance market and customer insight, and optimize resource allocation between projects. However, to achieve those benefits, a highly coordinated strategy with top-down support is necessary. Thus, the thesis concludes that a structured and human-centered approach to AI adoption is essential for companies in the complex and highly regulated MedTech landscape to remain competitive and achieve long-term innovation success.

Keywords: Artificial Intelligence, AI, Innovation Efficiency, MedTech, Knowledge Management, Patent Analytics, Market and Customer Analysis, Resource Allocation, Machine Learning, ML, Natural Language Processing, NLP, AI Implementation.

Note: The report is written in English.

SAMMANFATTNING

MedTech-branschen genomgår snabba tekniska förändringar och står inför föränderliga hälsovårdsbehov, vilket sätter press på aktörer att effektivt driva innovation för att förbli konkurrenskraftiga. Samtidigt framträder Artificiell Intelligens (AI) som ett transformativt verktyg med potential att öka effektiviteten. Trots sin potential är dock implementeringen av AI inom MedTech-sektorn fortfarande begränsad. Syftet med arbetet är därför att undersöka hur MedTech-företag kan nyttja AI för att förbättra sin innovationseffektivitet. Den huvudsakliga forskningsfrågan utforskas genom perspektivet av ett innovationsprocessramverk bestående av Idé-fasen, FoU-fasen och Kommersialiseringsfasen. Inom detta ramverk har fyra nyckelområden identifierats med potential att förbättra den totala effektiviteten genom integration av AI, nämligen: Kunskapshantering, Patentanalys, Marknads- och Kundanalys samt Resursallokering. Dessutom tar studien upp viktiga aspekter av att implementera AI inom organisationer för att optimera möjliga resultat.

En enskild fallstudie har genomförts med ett MedTech-företag, vilket valdes ut eftersom det utgör ett lämpligt fall för att utforska forskningsfrågan. Metoden består av en litteraturgenomgång följt av en intervjustudie. Litteraturen presenterar det nuvarande läget för AI-tillämpningar inom de fyra definierade fokusområdena och granskar även utmaningar gällande implementering. Intervjudeltagarna inkluderade både anställda, för att beskriva företagets nuvarande praxis och behov, och individer i andra organisationer som ligger i framkant när det gäller AI-implementering, för att få bästa praxis-perspektiv och expertinsikter.

Resultaten visar att AI-tekniker har stor potential att förbättra innovationseffektiviteten inom MedTech-branschen. AI bidrar till att förbättra informationsflödet inom organisationen, stärka strategier för immateriella rättigheter, förbättra marknads- och kundinsikter och optimera resursallokeringen mellan projekt. För att uppnå dessa fördelar krävs dock en välkoordinerad strategi med stöd uppifrån organisationshierarkin. Avhandlingen drar slutsatsen att en strukturerad och människocentrerad strategi för AI-implementering är avgörande för att företag i det komplexa och högreglerade MedTech-landskapet ska förbli konkurrenskraftiga och uppnå långsiktig innovationsframgång.

Nyckelord: Artificiell intelligens, AI, Innovationseffektivitet, MedTech, Kunskapshantering, Patentanalys, Marknads- och Kundanalys, Resursallokering, Maskininlärning, ML, Naturlig språkbehandling, NLP, AI-implementering.

Notera: Rapporten är skriven på engelska.

Table of Contents

1 Introduction 1
1.1 Background 1
1.2 Purpose 2
1.3 Problem Analysis 2
1.3.1 The Innovation Process Framework 2
1.3.2 Problem Breakdown 3
1.3.3 Research Questions 5
1.4 Scope and Limitations 6
1.5 Structure of the Report 6
2 Literature Review 7
2.1 Knowledge Management 7
2.1.1 The SECI Model 7
2.1.2 AI in Everyday Knowledge Management Tasks 9
2.2 Patent Analytics 9
2.2.1 Natural Language Processing in Patent Analytics 10
2.2.2 Patent Classification 10
2.2.3 Emerging Technology Identification 11
2.2.4 Novelty Analysis 11
2.2.5 White Space Identification 12
2.2.6 Patent Valuation 12
2.3 Market and Customer Analysis 12
2.3.1 Cluster Analysis for Market Segmentation 13
2.3.2 Customer Sentiment Analysis 13
2.3.3 Predictive Analytics 14
2.4 Resource Allocation 14
2.4.1 Limitations to Traditional Resource Allocation and Project Selection 15
2.4.2 How AI can Improve Resource Allocation 15
2.5 Implementation of AI into the Innovation Process 16
2.5.1 Risks and Implementation Challenges 16
2.5.2 Importance of Clear Leadership 17
2.5.3 Process Redesign 17
3 Methodology 18
3.1 Ethical Considerations 18

3.2 Case Study 18
3.2.1 Evaluation of Single Case Study as a Methodology 19
3.2.2 Literature 19
3.2.3 Interviews 20
3.2.4 Analysis Method 22
4 Results 23
4.1 Results for Knowledge Management 25
4.1.1 The Role of AI in Knowledge Management 25
4.1.2 Applications for AI in Everyday Tasks to Improve Efficiency 25
4.1.3 Challenges of AI and the Need for Human Interaction 26
4.2 Results for Patent Analytics 26
4.2.1 Invention Harvesting and Innovation Support 27
4.2.2 Prior Art Search and Novelty Analysis 28
4.2.3 Competitive Landscape Analysis 28
4.2.4 Data Security and Regulatory Compliance 29
4.3 Results for Market and Customer Analysis 29
4.3.1 Segmentation and Forecasting 29
4.3.2 AI Workflow for Sales and Market Insights 30
4.3.3 Market and Competitor Analysis 30
4.4 Results for Resource Allocation 30
4.4.1 Application for Project Planning 31
4.4.2 Application for Project Valuation 31
4.5 Results for Implementing AI 31
4.5.1 Strategic AI Integration 32
4.5.2 Developing AI-tools Internally 32
4.5.3 Managing Data Quality, Uncertainty, and Sensitivity 32
4.5.4 Importance of AI Education 33
4.5.5 Human-Centric AI Adoption 33
5 Discussion 34
5.1 Knowledge Management 34
5.1.1 Improving Efficiency in Everyday Tasks 34
5.1.2 Efficient Information Structuring 35
5.1.3 Information as the Driver of Innovation 36
5.1.4 The Importance of Human Interaction 36
5.2 Patent Analytics 37

5.2.1 AI-Driven Patent Analytics and Innovation Efficiency 37
5.2.2 Early Identification of Emerging Technologies 38
5.2.3 Competitive Monitoring and Strategic Response 39
5.2.4 Further AI Patent Research 40
5.3 Market and Customer Analysis 40
5.4 Resource Allocation 41
5.4.1 Optimize Resource Allocation Using AI 41
5.4.2 AI-Driven Project Planning and Resource Forecasting 42
5.4.3 AI's Role in Project Evaluation 42
5.5 Implementing AI 43
5.5.1 Technology Selection and Development strategy 43
5.5.2 Organizational Readiness 44
5.5.3 Strategic AI Integration 46
6 Conclusions 48
7 References 49

1 Introduction

Innovation efficiency is increasingly recognized as a critical success factor in industries characterized by rapid technological change and regulatory complexity. In the MedTech sector, this need is especially urgent, as companies face rising demand for affordable, high-quality care alongside escalating innovation costs and compliance requirements. Although Artificial Intelligence (AI) offers significant potential to enhance innovation processes, its integration into MedTech companies' internal operations remains limited. This study explores how AI can be leveraged to improve innovation efficiency, aiming to identify practical implementation opportunities and provide actionable recommendations for MedTech firms navigating this technological shift.

1.1 Background

The MedTech industry is highly dynamic and driven by rapidly evolving healthcare needs, technological advancements, and an increased demand for cost-efficient and high-quality healthcare (Choen, et al., 2020). These qualities became evident, not least during the COVID-19 pandemic, which highlighted the urgent need for innovative and flexible solutions to meet large uncertainty and surging demands. In this environment, Choen et al. (2020) suggest that innovation that is systematic, efficient and adheres to market needs becomes not just an advantage, but a prerequisite for creating and maintaining one’s competitive advantage.

At the same time, rising competition from newer, sometimes state-backed manufacturers put additional pressure on MedTech companies to remain competitive. According to Alagazy et al. (2022), these newer MedTech organizations can often, at least in the short term, outcompete more established actors on price. Competitive pricing forces these established companies to instead build competitive advantages through innovation and trust.

Thus, the primary challenges for MedTech companies lie in their ability to innovate efficiently, adapt flexibly to meet market demands, and respond to fierce competition while simultaneously maintaining a trustworthy and ethical brand. Doing this necessitates the implementation of an effective innovation process encompassing all stages, from idea inception to commercialization. Alagazy et al. (2022) highlight that one of the most transformative tools in enabling such innovation efficiency is AI.

To address these challenges, recent literature increasingly emphasizes managing innovation as an end-to-end process, from ideation through R&D and on to market introduction (Garcia et al., 2024). Understanding this full pathway is crucial for strategic decision-making, as inefficiencies can emerge at any point: in generating the right ideas, executing R&D projects, or commercializing new products. Each stage, therefore, demands tailored strategies to enhance innovation efficiency.

While AI has illustrated significant promise for enhancing innovation efficiency in the MedTech sector and has seen some adoption, its widespread use remains relatively limited. A 2023 survey of medical device professionals revealed that only 32% currently utilize AI-tools in their work, though 85% expressed interest in exploring its applications further (Greenlight Guru, 2023). The low degree of adoption suggests that, despite AI’s recognized potential to

drive operational efficiency, its integration into MedTech innovation processes is still in its early stages. However, the potential impact is predicted to be significant, Schroer et al. (2023) projects that the market for generative AI will experience an 85% compound annual growth rate in healthcare through 2027**,** reaching a total market size of $22 billion.

These findings indicate both a strong willingness to adopt AI in the MedTech sector and a significant economic opportunity in doing so. Even though adoption remains low, this is not indicative of low potential. Focusing on the innovation process, AI can be leveraged to enhance data-driven decision-making, optimize resource allocation, and streamline innovation processes. As explained by Alagazy et al. (2022), AI enables companies to process vast amounts of data, identify trends, and make informed decisions faster and more accurately than ever before.

As the demand for affordable and reliable healthcare continues to grow, MedTech companies are well-positioned to capitalize on technological advancements of AI. By integrating AI into the innovation process with the ambition of improving patient outcomes and operational efficiency, companies in the MedTech sector could continue to meet the evolving needs of the healthcare sector while driving meaningful operational change within the industry.

1.2 Purpose

Despite the widespread recognition of AI's capability, the adoption within the MedTech sector remains low. The limited degree of implementation indicates that there is a lack of knowledge on where and how this powerful technology could create the most value. Through analyzing the case of a MedTech company, this study aims to address this gap in knowledge and investigate how MedTech companies could leverage AI-driven processes to enhance the efficiency of their innovation processes.

1.3 Problem Analysis

To identify the key drivers that enable AI to enhance efficiency within MedTech companies' innovation process, this report outlines a relevant analytical framework. The following section introduces this framework, breaking down the problem of AI driven innovation efficiency into key subareas and formulating research questions.

1.3.1 The Innovation Process Framework

The innovation process, as defined in this report, refers to a series of activities through which ideas are generated, developed, and transformed into market-ready solutions. This process consists of three main stages: the *Idea Phase,* the *R&D Phase,* and the *Commercialization Phase*, each of which represent key decision points and challenges with effects on efficiency and quality of outcome of the innovation process (Granstrand, 2018). This widely recognized framework illustrates the thesis in a comprehensive way, providing an avenue to systematically identify areas where AI could be applied to improve efficiency.

The Idea Phase is where ideas are created and evaluated (Granstrand, 2018). Effectiveness at this stage requires internal knowledge sharing and external awareness, leveraging cross-functional insights while monitoring market and competitive trends to identify promising opportunities and risks.

In the R&D Phase, activities include research and patent applications (Granstrand, 2018). At this stage, companies must navigate complex challenges such as meeting resource requirements, understanding market needs, and addressing existing patents that may pose barriers. These challenges highlight the importance of staying informed about the technical landscape and ensuring that limited development resources are directed toward the most impactful projects.

The final phase, known as the Commercialization Phase, involves market introduction, establishing distribution channels, and setting marketing strategies (Granstrand, 2018). Being aware of both market and customer opportunities is key for making informed decisions and ensuring efficacy at this stage.

By examining these three stages, Idea, R&D, and Commercialization, through the lens of AI applications, key areas can be identified where AI-tools and best practices create efficient processes.

1.3.2 Problem Breakdown

This study is concerned with how AI applications can improve efficiency within the three stages of the innovation process, thus requiring a definition of what innovation efficiency entails. Therefore, this report will adopt the European Innovation Scoreboards (EIS) definition of innovation efficiency as the ratio between inputs, the resources invested in the innovation process, and the outputs, the outcomes achieved (Hollanders & Celikel-Esser, 2007). Attaining higher innovation efficiency thereby means achieving a larger output given the same input. Innovation inputs are the investments and resources allocated to innovation activities. Outputs refer to the results generated from such innovation activities.

An initial scan of the literature through the lens of the innovation process framework described in section 1.3.1 revealed four subareas particularly relevant for improving innovation efficiency using AI. This set of subareas consists of: *Knowledge Management, Patent Analytics, Market & Customer Analysis, and Resource Allocation*. These domains span across different phases of the innovation process, as visualized in Figure 1, and represent key leverage points where AI can drive efficiency gains. Overarching all three innovation stages is the way in which organizations go about implementing AI. The remainder of this section examines each sub-area in detail to clarify their role in the innovation process and how AI applications can enhance efficiency.

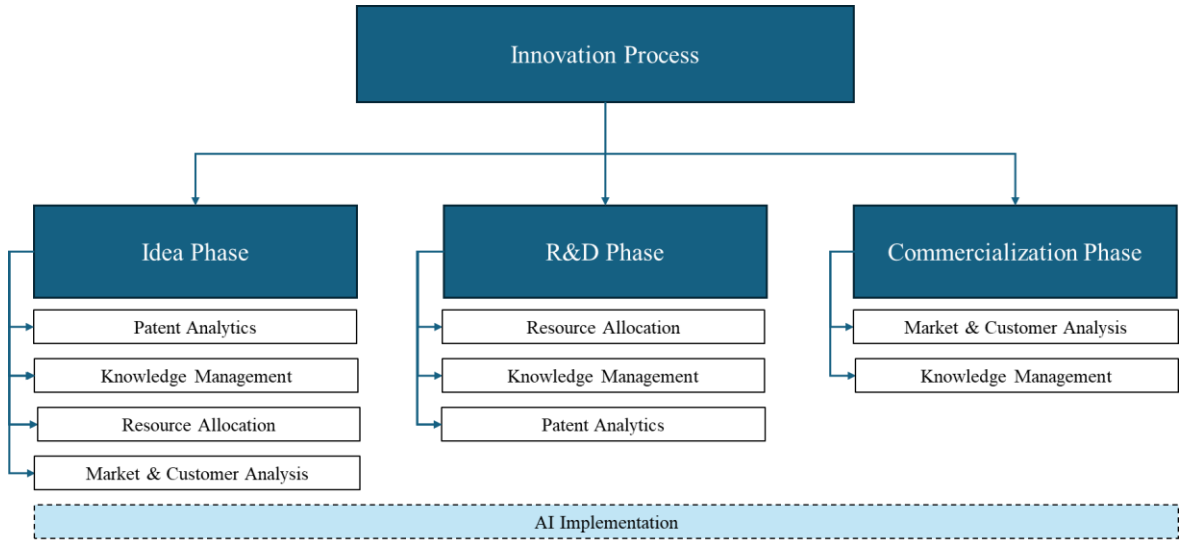

Figure 1: Conceptual framework illustrating how AI implementation spans the entire innovation process — enhancing efficiency in Knowledge Management, Patent Analytics, Market & Customer Analysis, and Resource Allocation across the Idea, R&D, and Commercialization Phase.

In large multi-national corporations, especially those operating in R&D-intensive sectors such as MedTech, effective information sharing is critical for a productive innovation process, thereby highlighting the importance of knowledge management (Chen & Huang, 2009). According to Salem et al. (2024), knowledge management enables centralized and standardized data storage facilitating the implementation of AI-tools to give seamless access to internal knowledge and technical documentation. Managing data in this way can enhance the diffusion of know-how, improve cross-functional collaboration, and reduce the risk of overlapping work (Böhm & Durst, 2024). Moreover, research from Yue et al. (2024) indicates that AI can handle repetitive and time-consuming tasks, such as summarizing meetings and report generation, thereby allowing employees to focus on higher-value activities. These capabilities are particularly valuable in the Idea and R&D phases, where rapid access to prior knowledge, technical documentation, and internal expertise is essential for identifying and developing opportunities. As noted by Jarrahi et al. (2023), sharing knowledge effectively during early-stage innovation is a prerequisite for informed decision-making and problem-solving, both of which are crucial for translating ideas into viable R&D projects.

In technology-intensive industries like MedTech, patent analytics plays a crucial role throughout the Idea and R&D Phase of the innovation process. At these stages, analyzing patent landscapes helps identify emerging trends, avoid duplication, and assess freedom-to-operate. Since patents often signal future technological developments, early insights can guide R&D direction before products reach the market (Garcia, et al., 2024). Kerstel et al. (2021) explain that with the increasing volume and complexity of patent filings, AI-powered tools, particularly those using natural language processing (NLP), are increasingly used to convert unstructured patent text into actionable intelligence. Such mapping of patent data is especially relevant in MedTech, where rapid product cycles demand quick and informed innovation decisions (MedTech Europe, 2024).

Another area where AI can support innovation is in market and customer analysis. According to Breuer et al. (2023), the technological complexity of the MedTech industry constitutes a

high barrier to entry, limiting the number of actors capable of entering and competing on the market. Moreover, once established, companies must maintain a reputation of technical excellence and trustworthiness to retain their market share. When a competitor exits the market due to financial or operational challenges, an opportunity arises for other actors. AI could support such strategic evaluations by continuously monitoring competitor behavior and market dynamics, enabling firms to identify gaps, anticipate shifts, and capitalize on emerging opportunities more effectively (Cekuls, 2024). This area is therefore critical both in the validation of new ideas and in being able to enter the market efficiently.

Resource allocation within R&D is another strategic area where AI can improve decision-making. With large volumes of ongoing projects and complex product development processes, AI-tools support a more data-driven approach to identifying high-impact projects (Jang H. , 2019). This data-driven approach would enable companies to accelerate the most promising initiatives while reallocating resources away from less effective ones, thereby increasing overall R&D efficiency.

While AI holds significant potential to increase innovation efficiency across all three stages of the innovation process, these benefits cannot be fully realized without thoughtful and strategic implementation. Poorly integrated AI-tools risk creating inefficiencies or being underutilized by employees. In this sense, effective implementation becomes a prerequisite for achieving the innovation gains that AI can enable. For MedTech companies operating in a complex and competitive environment, a structured approach to AI implementation is therefore essential for securing long term innovation efficiency in all three phases of the innovation process.

1.3.3 Research Questions

Building on the identified opportunity for AI integration in the MedTech sector, this study aims to explore the central question:

How can MedTech companies leverage AI-driven processes, tools, and methodologies to enhance the efficiency of their innovation process?

This question is addressed by analyzing the five key sub areas derived from the analytical framework and problem breakdown. Each sub-area is explored through a dedicated research question, targeting a specific dimension where AI can improve efficiency in the innovation process:

1. *In what ways can AI-tools in knowledge management improve information sharing within MedTech companies?*

2. *How can the use of AI-driven patent analytics influence MedTech companies' ability to innovate efficiently and respond to competitive threats?*

3. *In what way could the application of AI in customer and market analysis increase the likelihood of innovations successfully reaching the market in MedTech?*

4. *How can AI be applied to optimize resource allocation within the innovation process in MedTech companies?*

5. *How can MedTech companies implement AI to effectively enhance innovation efficiency?*

1.4 Scope and Limitations

This report focuses exclusively on how AI can be utilized to improve efficiency in the innovation process within the MedTech industry. It does not address AI applications embedded in medical products, as such implementations require deep technological understanding of the devices themselves as well as consideration of regulatory requirements. Notably, product-related AI applications are subject to the European Artificial Intelligence Act (European Parliament, 2025), under which the healthcare sector is classified as high risk. This places strict regulatory demands on AI used in MedTech products, requiring advanced legal and technical expertise, areas that fall outside the scope of this study.

In addition, a comprehensive review of all AI techniques would be too extensive for the purposes of this report. Therefore, the study focuses on practical applications of AI that are relevant for enhancing innovation efficiency. Innovation is examined through the framework presented in section 1.3.1, using the previously defined concept of efficiency and concentrating on five key subareas. By limiting the scope to innovation-related applications and excluding product-level regulation, the analysis remains targeted on areas where AI can deliver measurable gains without necessitating extensive regulatory or technical assessment.

Limiting the scope in this way, focusing on the innovation process and on practical applications within said processes, ensures that the analysis remains focused on areas where AI can drive efficiency without requiring in-depth regulatory assessment or deep technical knowledge.

1.5 Structure of the Report

The subsequent chapter will provide a brief overview of the current literature, specifically focusing on the potential of artificial intelligence within the areas identified in section 1.3.2. Thereafter, a section outlining the methodologies used and a case description will follow. Thereafter, the results from the conducted case study will be presented and subsequently analyzed from the perspective of the selected literature, addressing both areas where the findings are in conflict, and in line with the underlying research. Lastly, the conclusions that have been derived from the findings will be presented.

2 Literature Review

The following literature review explores how AI can be applied to enhance innovation efficiency across the three phases of the innovation process: the Idea Phase, the R&D Phase, and the Commercialization Phase, see Figure 1. The review is divided into five main sections, each corresponding to one of the identified sub-areas: Knowledge Management, Patent Analytics, Market and Customer Analysis, Resource Allocation, and AI Implementation. It focuses on how AI can transform the first four domains and, importantly, how AI should be implemented within MedTech companies to drive innovation efficiency.

2.1 Knowledge Management

Knowledge management refers to the processes of creating, capturing, organizing, and sharing an organization's knowledge, improving innovation capability and decision-making (Taherdoost & Madanchian, 2023). Grant (1996) argues that a firm's competitive advantage stems from its ability to create, store, and apply knowledge effectively. Unlike physical assets, knowledge tends to increase in value with use, and it is hard for competitors to imitate. Additionally, Chen and Hung (2009) state that effective knowledge management can improve innovation performance by encouraging creative and innovative ideas. Jarrahi et al. (2023) further highlight that sharing knowledge across the organization is a prerequisite for using it effectively in performing tasks such as problem-solving and decision-making essential to the innovation process.

MedTech companies operate in knowledge-intensive environments where intellectual capital is central to competitive advantage (Grant, 1996). Traditional knowledge management practices have long supported the management of both explicit knowledge and informal, experience-based tacit knowledge. However, these approaches increasingly struggle to keep pace with the scale and complexity of today's digital information. Recent advances in AI significantly enhance the flow of information, allowing organizations to efficiently assimilate extensive scientific findings, navigate evolving regulatory requirements, and swiftly integrate new clinical data under high-pressure conditions (Taherdoost & Madanchian, 2023).

2.1.1 The SECI Model

To better understand how AI can support knowledge creation and sharing in MedTech firms, it is useful to analyze this through the lens of a foundational model in knowledge management literature, namely Nonaka and Takeuchi's (1995) SECI model. As visualized in Figure 2, this model describes four modes of knowledge conversion between tacit and explicit knowledge. The four modes include: *Socialization, Externalization, Combination*, and *Internalization*. In essence, individuals share tacit knowledge through Socialization, articulate it into explicit form via Externalization, Combine diverse explicit knowledge sources into new knowledge, and Internalize that back into tacit understanding, a spiral that drives innovation in firms (Nonaka & Takeuchi, 1995).

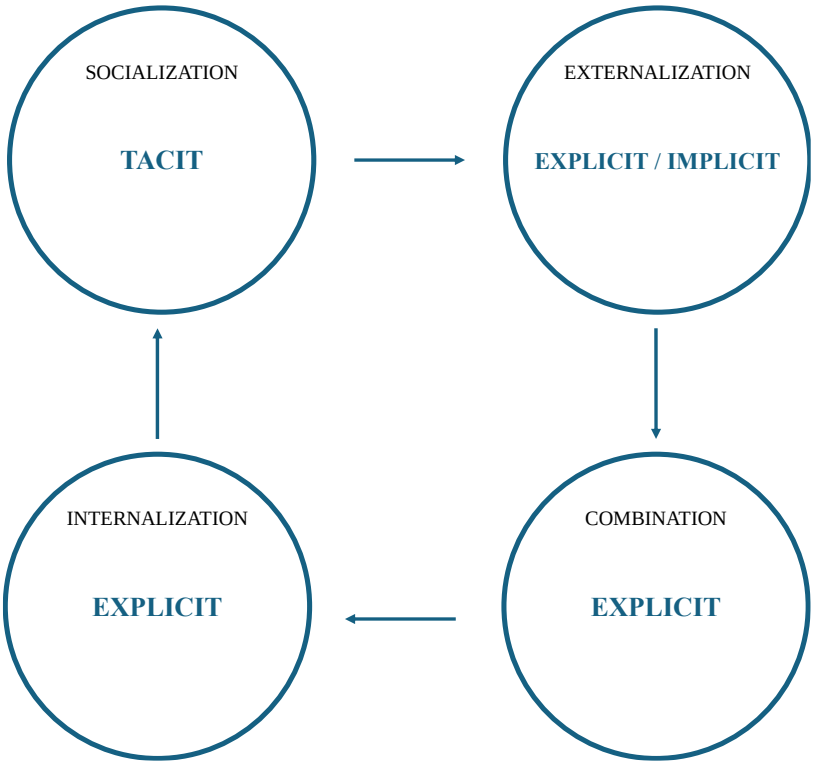

Figure 2: An interpretation of the SECI model of knowledge conversion, illustrating the dynamic flow between tacit and explicit knowledge (Nonaka & Takeuchi, 1995).

Recent advances in AI offer new opportunities to enhance each stage of the SECI model. For instance, generative AI systems can assist in Externalization by helping capture experts' tacit knowledge and turning it into explicit documentation (Böhm & Durst, 2024). The authors observe that large language models (LLMs) now participate in human-like dialogue and can represent implicit knowledge in text form, suggesting that generative AI is becoming capable of tasks historically reliant on humans. The authors further suggest that AI-driven systems could, for example, listen to oral discussions or analyze project notes and then generate structured reports or lessons learned, effectively externalizing tacit insights. AI can also facilitate Combination of knowledge by integrating diverse information sources. According to Jarrahi et al. (2023), an intelligent knowledge platform might automatically gather and synthesize research papers, clinical trial data, and internal reports on a given topic, providing R&D teams with a consolidated knowledge view. In their analysis, Böhm and Durst (2024) highlight that generative AI aligns especially well with the Externalization and Combination modes of SECI, by converting tacit inputs to explicit outputs and integrating heterogeneous knowledge bases. Even Socialization, the tacit-to-tacit sharing through interaction, can be supported by AI-driven tools, for example, NLP algorithms can match and connect employees with complementary expertise or interests, encouraging peer knowledge exchange across an organization (Böhm & Durst, 2024). Finally, AI can aid Internalization by personalizing knowledge delivery, such as recommending relevant documents or training when an employee encounters a new problem, thereby helping individuals absorb and apply explicit knowledge in their work context.

In summary, while the SECI model was developed before the AI era, modern AI technologies can act as accelerators or enablers for each SECI process, amplifying an organization's ability

to create and mobilize knowledge. Thus, understanding how AI supports each SECI mode offers a valuable lens for examining how AI can enable greater efficiency across all stages of the innovation process, from idea generation to commercialization, by ensuring that, at decision-points, employees have access to the right knowledge at the right time.

2.1.2 AI in Everyday Knowledge Management Tasks

Yue et al. (2024) suggest that AI can help automate low-level routine tasks such as collecting and analyzing data from meetings, generating ideas, and creating content. This automation would not only enhance employee efficiency but also frees up resources for other value generating tasks and thus increases productivity. The authors further state that AI technologies, such as chatbots, are always accessible, thereby improving the flow and accessibility of information within organizations.

Fahad et al. (2024) highlight that the implementation of AI chatbots into the organization's digital workplace could help improve knowledge management processes and boost overall efficiency. Chatbots interact with users and provide them with personal assistance using NLP and machine learning (ML), meaning that they could learn over time and adapt their responses to be more personalized and relevant. Fahad et al. (2024) further highlight that this interactive nature of chatbots promotes an environment where employees can continuously learn and share knowledge. Jarrahi et al. (2023) mention the fact that chatbots can offer information through a natural conversation with its user, which can help lower the social barriers that may prevent equal access to the organization's knowledge.

Salem et al. (2024) further state that utilizing AI to enhance storage and retrieval of explicit information is the most useful application in knowledge management. AI is highly proficient in the process of searching, organizing and summarizing information and can therefore revolutionize the management of large data volumes in organizations. The authors add that the capabilities of AI such as offering personal solutions, identifying important documents, and collecting relevant information can greatly improve productivity for knowledge workers. However, Pimentel and Palomino (2024) note that storing and making knowledge accessible does not automatically improve productivity and performance, since the application of knowledge is what generates value inside organizations.

2.2 Patent Analytics

The MedTech industry is highly innovation-driven, generating a constant flow of new devices and solutions, reflected by an intense patent activity (MedTech Europe, 2024). Notably, MedTech patent filings have nearly tripled at the European Patent Office (EPO) over the past two decades. A large share of these innovations comes from Europe and the U.S., with 40% of MedTech EPO filings originating from European countries and 38% from the U.S. Additionally, products generally have short life cycles, often only 18-24 months, before improved versions appear, underscoring the rapid pace of change (MedTech Europe, 2024). In this competitive global landscape, patents serve as early indicators of innovation, signaling emerging technologies and competitor activities before products reach the market (Garcia, et al., 2024).

However, analyzing the ever-growing volume of patent documents is a formidable challenge. Traditional patent analytics, manually tracking new filings, extracting relevant information, and analyzing competitor patents, is a labor-intensive and costly process (Garcia, et al., 2024). Companies employing this method risk missing "weak signals" of disruptive innovation if they cannot efficiently scan patent data. As a result, they risk, amongst other things, failing to notice competitors' patents, which can lead to costly infringement lawsuits or missed opportunities to secure freedom-to-operate. To contextualize, patent litigation in the U.S. costs an estimated $3.5 million on average per case (Thomson Reuters, 2022). These risks, both strategic and economic, underscore a strong incentive for MedTech companies to enhance their patent analysis capabilities, not only to respond more effectively to competitive shifts and reduce legal compliance costs, but also to accelerate invention rates, particularly during the early Idea Phase of innovation.

Patent tools utilizing AI have emerged as a possible solution to these challenges. Krestel et al. (2021) suggest that by leveraging AI, companies can automate and enhance the analysis of patent information. To better understand how these technologies are applied in practice, the following sections provide a more detailed overview.

2.2.1 Natural Language Processing in Patent Analytics

As outlined by Krestel et al. (2021), the core technique underlying most AI-driven patent analytics applications is NLP. Since patent data is overwhelmingly text-based, NLP enables efficient extraction and contextual interpretation of key information, going beyond keyword matching to uncover deeper technical insights (Garcia, et al., 2024). Modern tools can identify entities like medical devices, translate foreign patents, segment technical sections, and classify documents by technology domain. These capabilities allow MedTech firms to monitor emerging trends, map innovation trajectories, and transform unstructured patent data into actionable strategic intelligence, crucial for making informed decisions early in the innovation process.

2.2.2 Patent Classification

Trappey et al. (2006) describe patent classification as the process of organizing patent documents into categories, a crucial aspect of knowledge management, patent portfolio management, and innovation tracking. Traditionally, patents are classified manually by experts using standardized systems, but this manual approach is slow, costly, and labor-intensive, especially given the large and growing volume of patents (Xiaoyu, 2013). Misclassification or delays in categorizing patents, more common in the manual workflow, can hinder a company's ability to find relevant knowledge, spot technology trends, or conduct comprehensive prior art searches.

AI-powered classification tools address these limitations by automatically assigning patents to relevant categories using ML trained on large patent datasets (Xiaoyu, 2013). These systems can process titles, abstracts, and claims to accurately categorize patents at scale. Importantly, they can adapt to company-specific taxonomies, for example, aligning patents with a firm's strategic focus areas rather than only standard classification codes (Aristodemou & Tietze, 2018).

By enabling fast and consistent classification, AI transforms patent archives into structured, searchable knowledge bases. This structured information provides a critical foundation for strategic applications such as technology scouting, competitor monitoring, and white space analysis. According to Sugjoo et al. (2018), patents are particularly valuable in these contexts, as they offer detailed technical disclosures and early signals of emerging innovations across industries, making them vital for efficient innovation.

2.2.3 Emerging Technology Identification

Another key strategic application of AI-powered patent analytics is the early identification of emerging technologies. As noted by Aristodemou and Tietze (2018), forecasting next-generation technologies is essential for innovation planning, as it enables organizations to seize early opportunities and prepare for potential disruptions. As highlighted by both Kyebambe et al. (2017) and Lee et al. (2019), AI models can detect subtle patterns in patent data, such as novel keyword combinations, rising citation trends, and cross-domain classifications, three indicators of future technological breakthroughs. By analyzing these indicators systematically, companies can gain early insights into where innovation is heading.

For MedTech firms, this capability is particularly relevant given the industry's fast innovation cycles and regulatory complexity. Patent-based forecasting can help firms not only anticipate technological shifts but also align internal R&D strategy with external trends. As highlighted by Benjamens et al. (2023), such tools have already been applied to predict developments in AI-driven healthcare solutions. This type of forecasting illuminates how AI could promote knowledge-driven decision-making in the early phases of innovation, allowing MedTech firms to act faster, reduce uncertainty, and improve the efficiency of their innovation processes.

2.2.4 Novelty Analysis

According to research by Ali et al. (2024), AI is increasingly employed to assist in determining the patentability of new technologies, primarily by enhancing prior art searches and novelty analysis. Traditional patent searches rely on keyword queries and expertise within the field, but modern NLP and semantic search techniques allow AI systems to comprehend the context and intent behind queries, retrieving more conceptually relevant prior art. As a result, thoroughness and precision of novelty searches can be improved, helping organizations and patent examiners ensure that an invention is truly novel before a patent application is filed. Research conducted by Hyejin et al. (2023) noted that as the technology development cycle accelerates, novelty analysis becomes ever more critical both for R&D planning and during the patent application process. Overall, AI-driven patentability analysis empowers inventors and decision-makers with faster and more reliable insights into whether a proposed innovation meets the criteria of novelty and inventive step in a crowded global innovation landscape.

2.2.5 White Space Identification

Building on the information extracted through NLP, research by An et al. (2018) indicates that AI algorithms can rapidly analyze large patent databases to identify technology whitespaces, areas with little prior patent activity. Knowledge of these areas can then be utilized to map out unsaturated domains, guiding R&D investments toward high-opportunity areas. The authors further explain that patents often appear before new products reach the market, so they provide a forward-looking window into R&D activities globally. By applying ML to patent text and metadata, firms can detect weak signals of technological change that would be hard to spot manually (Garcia, et al., 2024). Moreover, An et al. (2018) emphasize that the true value of patent analysis lies in describing the content of technology and relationships between technical concepts. This intelligence assists R&D managers in the process of deciding where to allocate resources or which research collaborations to pursue. With clearer insights into untapped areas, firms can more effectively steer their efforts toward idea development in unsaturated domains, increasing the potential of breakthrough innovations.

2.2.6 Patent Valuation

Efficient innovation requires strategic allocation of resources to projects with the highest impact. Recent research highlights that significant progress has been made using AI-based patent valuation models. For instance, a study by Hsu et al. (2020) utilized neural networks that integrated full patent text analysis via NLP with structured patent data, employing forward citations as proxies for economic value. This method improved prediction accuracy by more than 46% compared to traditional regression-based valuation models, highlighting the substantial advantages of incorporating comprehensive textual data over bibliographic metrics alone.

Vázquez et al. (2013) further reinforce the critical economic impact of patent portfolios. The same paper further demonstrates a direct correlation between robust patent assets and financial performance, revealing that a 10% increase in a patent value index correlates to an approximate 10% increase in market capitalization. Additionally, enhancements in patent quality and protection correlate with an estimated 8% rise in overall market value, underscoring patents as foundational drivers of economic success within MedTech firms.

2.3 Market and Customer Analysis

AI is transforming industries and has important implications for allowing the right innovations to successfully reach the market at the right time. In the MedTech sector, where innovation cycles are rapid and market entry is highly regulated, Kumar et al. (2024) state that AI has the potential to enhance market strategies and improve competitive positioning. The authors further describe AI's ability to swiftly process vast amounts of data, find patterns and trends, provide analysis and insights, which can aid in the evaluation of both market segments and competitors. However, much of the existing literature focuses on business-to-consumer contexts. There is limited research addressing how these approaches translate to highly regulated sectors like MedTech, suggesting a potential area for future investigation.

While AI thrives on large datasets, the regulatory frameworks that MedTech operates within, such as GDPR and HIPAA can severely limit access to relevant data (U.S Department of Health and Human Services, HHS, 2000). Further, as pointed out by Breuer et al. (2023), the market is multifaceted and involves many stakeholders, which requires an understanding of not just procurement organizations in hospitals, but also of regulatory bodies, clinicians, and patients. Therefore, in contrast to consumer markets, where sentiment and purchasing trends are more directly shaped by consumer preferences, MedTech decision-making is more complex.

Despite these limitations, AI-applications can provide valuable insights into market segmentation, customer sentiment, and industry trends. Promising techniques for this are cluster analysis, sentiment analysis, and predictive analytics, which can help companies navigate complex markets and gain competitive advantage. These subject areas will be further explored in the following sections.

2.3.1 Cluster Analysis for Market Segmentation

One area that AI excels in is cluster analysis, where ML algorithms can identify patterns or structures in data in order to group similar entities into clusters based on similarities without any prior knowledge of the data (Migliore, 2023). These clusters can then be analyzed and used to segment markets. As outlined by Huang and Rust (2021), segmentation is the process of dividing markets and customers into distinct groups with unique needs, which can enable better targeting. The authors further highlight that being able to focus on and understand the needs of specific groups instead of using a one-size-fits-all approach can lead to competitive advantages. Additionally, it can help identify niche markets and emerging opportunities.

With clustering it is possible to generate insights and provide business value, despite limited access to data (Arunachalam & Kumar, 2018). By leveraging cluster analysis, companies can make more informed decisions about market positioning and resource allocation, which contributes to innovations reaching the market more effectively.

2.3.2 Customer Sentiment Analysis

Another area where AI is useful is in sentiment analysis. According to Sahoo et al. (2023), sentiment analysis is the process of using NLP and ML in order to identify and classify the emotional tones of a text. Companies can use these techniques to gain insights into how different customers, stakeholders, and industry stakeholders perceive products, competitors, and market trends. According to Sahoo, et al. (2023) data can be monitored from several different sources such as social media, conference discussions, reviews, regulatory reports, and forums to understand both public and professional attitudes toward products and competitors. Furthermore, Lee et al. (2019) emphasize that sentiment analysis can also be used to track emerging trends and uncover customer pain points, enabling companies to identify market gaps, improve existing solutions, and tailor marketing strategies to specific audiences.

Cooper (2024) references a case study where AI was successfully used for voice-of-customer research on patients to develop new medical devices. Using AI, unmet needs were identified

by analyzing text data from social media, online forums, and e-commerce. A prioritized set of customer needs were identified, which provided valuable insights for the innovation team, allowing them to focus on the most important needs. The insights from this process allowed the company to redirect their R&D resources, transforming their product development strategy, ultimately improving innovation efficiency.

2.3.3 Predictive Analytics

According to Kumar and Garg (2018), predictive analytics leverages historical data and ML to forecast future trends, risks, and opportunities. In the MedTech industry, predictive analytics can be applied in several areas, including demand forecasting, risk assessment, and regulatory compliance. Regression models are mainly used for this purpose. These applications can help companies anticipate the future market developments and find opportunities to successfully launch new innovations.

Accurate demand forecasting has important implications for understanding the market and market entry strategies. The most common ML models for this purpose are time series forecasting models and regression-based models as these can analyze historical data, seasonal patterns and external factors (Xu & Chan, 2019).

2.4 Resource Allocation

Resource allocation is a strategic process in which an organization distributes its limited resources, such as capital, personnel, and time, between competing innovation projects and activities (Klingebiel & Rammer, 2014). The objective is to optimize innovation outcomes while aligning with organizational goals and managing the inherent uncertainty of innovation.

According to Klingebiel and Rammer (2014), the success of innovative projects depends on both the quality and quantity of resources committed to the project. However, dealing with the uncertainty of innovation introduces significant risk, thus making it difficult to predict which projects will succeed. Particularly, firms with high innovative ambition often engage in projects beyond their established knowledge domain, resulting in increased uncertainty when predicting successful projects.

A common response to uncertainty is to adopt a portfolio-based approach where innovation projects are organized into diversified portfolios (Klingebiel & Rammer, 2014). The process of selecting projects for a project portfolio is a structured, recurring workflow that involves the systematic evaluation and approval of projects that align with the organization's objectives while being compliant with resource limitations and preexisting constraints (Archer & Ghasemzadeh, 1999). This selection process ensures that investments are made in projects that maximize value, while balancing risk and time to completion. The outcome of this process is a well-structured project portfolio, comprised of approved projects that the organization commits to perform in order to achieve its overarching goals.

Resource allocation and project selection are closely correlated, and their effectiveness is crucial due to its direct influence on innovation performance (Heidenberger & Stummer, 1999). Often, a large quantity of resources is invested in R&D projects and if not properly

managed, may lead to large inefficiencies and resource waste which could be detrimental to the firm. Several techniques have been developed, and the authors describe a number of quantitive modelling approaches to support decision makers in selecting projects and allocating resources effectively.

2.4.1 Limitations to Traditional Resource Allocation and Project Selection

The objective of project portfolio selection is to pick a set of projects that align with the business strategic objectives while also being compliant with existing resource limitations. However, Blichfeldt and Eskerod (2008) highlight in their report that many small projects fall outside the project selection process but still consume valuable resources. Since these projects are not part of the formal selection process, they are not subject to project portfolio management and undermine the efficiency of the portfolio and planned resource allocation. This inefficiency may increase the likelihood of delays as important resources are being consumed by other projects.

On the other hand, Blichfeldt and Eskerod (2008) emphasize that these smaller projects have a positive effect on the employees as they facilitate creativity. Nevertheless, organizations should acknowledge and account for these projects to ensure an effective project portfolio and resource allocation strategy. A solution suggested by the authors is to expand the scope of project selection to include all projects, no matter their size, to reduce resource drains from other projects. However, the authors also highlight that considering the number of projects in an organization, this approach would be impossible in practice. Another proposed solution to improve resource allocation is to create a pool of loosely controlled resources that projects too small to be included in the formal project portfolio, could draw resources from. Such a solution would eliminate the unintentional competition of resources from larger projects.

2.4.2 How AI can Improve Resource Allocation

Artificial Intelligence has become an important tool for project management, and it shows great promise of being able to outperform traditional methods for resource allocation (Sravanthi, et al., 2023). Techniques such as ML, linear programming, and neural networks enable optimizations in resource allocation across projects using AI. These techniques are capable of accounting for numerous interdependent variables and constraints, including personnel and equipment availability, task-specific competence, and project schedule. As a result, AI offers an effective tool for project managers, particularly for the management of large-scale and intricate projects. There are several potential areas of application, some of which are described in greater detail in the following paragraphs.

With the capability to process substantial quantities of data, AI can forecast future resource requirements by analyzing historical data, team performance metrics, and external variables (Mohite, et al., 2024). Furthermore, ML algorithms can analyze data from previous projects to identify patterns and obtain insights into how previous resource allocation decisions have impacted project outcomes. The authors emphasize that these abilities enable AI-tools to predict future resource requirements, which can support the development of optimized resource allocation strategies, and to detect potential bottlenecks in projects.

Moreover, the integration of AI in resource allocation can lead to significant efficiency improvements (Mohite, et al., 2024). AI can enhance the allocation of personnel and material resources by analyzing availability of personnel and equipment, work demand, and team capabilities, thereby ensuring that activities are scheduled optimally and assigned to appropriate team members. Further, by analyzing historical data, AI can identify resource wastage, cost-saving opportunities, and reduce the risk of under- or over-allocating resources, resulting in more efficient use of the organization's limited resources. Additionally, AI supports more informed decision-making enabling increased return on investment and contributes to overall project success.

Furthermore, AI-tools enable adjustments to resource allocation strategies during project execution by being able to quickly analyze real-time data (Mohite, et al., 2024). Therefore, AI can respond effectively to changes in project conditions, including changes in resource requirements, modifications to the project scope, and external events. This adaptability increases the projects' overall resilience and reduces the risk of bottlenecks, thereby reducing the likelihood of delays.

In summary, with its great potential within predictive analytics, optimization, and real-time adaptability, AI can be utilized by decision-makers to optimize resource allocation among the projects in their project portfolio. Using this approach, one could decrease costs and resource waste, reducing the risk of delays, and increasing ROI on the selected projects.

2.5 Implementation of AI into the Innovation Process

Recent research underscores that the implementation of AI in MedTech organizations depends not only on the technical capabilities of the tools but also on organizational factors such as internal skill levels, cultural alignment, and regulatory constraints. Salwei and Carayon (2022) emphasize that successful AI adoption in healthcare settings requires alignment with existing workflows and investment in staff training, as these elements influence system usability and safety. Similarly, Yue et al. (2024) highlight the importance of addressing employee concerns, data governance, and user trust, noting that resistance can emerge when the role of AI in daily tasks is unclear. These studies suggest that AI implementation should be understood as a socio-technical process, where organizational conditions shape the extent to which efficiency gains, particularly in innovation-related processes, can be realized.

2.5.1 Risks and Implementation Challenges

Organizations face notable challenges during AI implementation, particularly resistance to change, often driven by job security fears. Yue et al. (2024) highlight concerns regarding job losses due to automation, particularly affecting administrative and tactical roles. Mitigating these fears involves promoting collaboration between AI systems and employees, ensuring AI supports rather than replaces human roles, thereby freeing employees for higher-value tasks (Callari & Puppione, 2025). Such collaborative approaches necessitate employee reskilling and competency development to effectively engage with AI.

Another significant challenge, outlined by Yue et al. (2024), is the lack of AI proficiency among employees, leading to resistance, misunderstandings, and ineffective AI use.

Addressing this issue requires comprehensive education and training programs, fostering a culture of continuous learning and unified corporate standards for AI usage (Tymoshenko, 2024). These training initiatives reduce resistance, promote effective interaction with AI, and ensure consistent AI practices within organizations.

Ethical and privacy concerns, especially prevalent in sensitive fields like healthcare, also complicate AI adoption (Corvello, 2025). As pointed out by Yue et al. (2024), employees often fear security breaches, biases, and lack of transparency from AI systems. Transparent communication, pilot projects demonstrating ethical AI applications, and establishing clear governance frameworks are recommended solutions to build trust and mitigate ethical concerns. Ethical guidelines and accountability measures thus become critical to fostering a trustworthy environment during AI adoption.

2.5.2 Importance of Clear Leadership

Academic studies consistently highlight that MedTech organizations require robust internal AI governance frameworks and active leadership support to ensure successful implementation of AI systems. According to Nair et al. (2024), clear internal policies and management-led guidelines, addressing data governance, algorithm validation, privacy, and ethics, provide a structured approach that reduces staff uncertainty and resistance. Without such formal strategies, Hassan et al. (2024) explain that employees often hesitate to trust or adopt AI-tools, whereas strong executive sponsorship and oversight have been shown to foster trust and smoother integration of AI into workflows. The authors identify dedicated governance structures and visible leadership engagement as critical enablers that align AI initiatives with organizational goals, ensuring new technologies are embraced rather than feared. In essence, clear internal strategies and leadership-endorsed AI policies emerge as best practices for facilitating AI adoption in healthcare technology settings, directly contributing to higher adoption rates and more effective use of AI innovations.

2.5.3 Process Redesign

Recent literature emphasizes that MedTech AI integration must entail fundamental re-engineering of operational workflows, rather than merely layering AI onto legacy processes. According to Sriharen et al. (2024), AI transformation involves systematic changes in organizational processes and business models to identify and operationalize value-creating AI use-cases. By this account, AI-tools must either be fit to processes, or the processes must be adapted with new AI capabilities in consideration. Commentators warn against superficial AI adoption, noting that hype can distract decision makers from the many non-technical factors such as culture, training, governance, and workflow redesign, which are determining factors for success (Sriharan, et al., 2024). Consistent with this caution, scholars call for clear implementation-roadmaps to guide responsible AI deployment. For example, a recent health-systems survey by Guleria et al. (2024) underscore an “urgent need for a comprehensive roadmap” to ensure safe, ethical, and effective AI use.

3 Methodology

To address the research questions defined in section 1.3.3, a single case study has been conducted using a qualitative research method. This approach combines a case study framework with interviews and literature review to gain in-depth insights. As described by Bell et al. (2019), a qualitative research strategy focuses on descriptive, rather than numerical, methods when gathering and analyzing data. The authors further state that another notable feature of the strategy is the inductive development of theories, where findings emerge from the research process rather than being predefined.

3.1 Ethical Considerations

For confidentiality purposes, the company in this report is referred to as MedCo, which is a pseudonym and not a reference to any actual companies with the same name. MedCo's request for anonymity in the study necessitated careful handling of data throughout the research process, particularly in interview documentation, analysis, and presentation of findings. To ensure confidentiality, all transcripts and notes have been anonymized, avoiding specific references to proprietary projects, locations, or internal strategies that could identify the company. While anonymization can limit the ability to discuss company-specific AI implementation strategies, this study focused on generalizable trends, best practices and broader MedTech industry challenges to maintain relevance.

This study's recommendations and observations may have significant implications for employees, requiring careful consideration from an ethical perspective. While AI has the potential to streamline repetitive tasks and improve efficiency, it may also lead to changes in job roles, raising concerns about job security that must be appropriately considered. To address this, the perspectives of multiple different stakeholders, such as employees and managers, has be incorporated to ensure that the recommendations have a human-centric view.

3.2 Case Study

The MedTech industry is currently undergoing a significant transformation, driven by the fast development of AI and other digital technologies. However, the implementation of AI in this sector is particularly complex to navigate, partly due to strict regulatory requirements and high demands for data security (MedTech Europe, n.d.). These industry factors make the MedTech sector a particularly relevant candidate for investigating how to successfully coordinate the implementation of AI.

MedCo stands out as a suitable case due to the company's strategic focus on innovation and its willingness to explore emerging technologies, while still being subject to the common limitations of a highly regulated industry. As a MedTech company, MedCo places strong emphasis on quality, patient safety, and meeting strict regulatory standards, factors that are central to the industry's operations and significantly influence how technologies like AI can be adopted.

Conducting a case study with a company that is in the early stages of AI implementation has allowed for examination of the real-time decision-making processes, internal capabilities, and external pressures that shape AI adoption. In this regard, the company aligns with what Bell et al. (2019) describe as a typical case, as it faces challenges that are representative of broader industry trends. Thus, the case not only illustrates existing challenges but also highlights actionable opportunities for other companies in similar contexts.

By focusing on MedCo, this study aims to generate insights that are both practically applicable and theoretically relevant, contributing to a deeper understanding of how AI can be integrated into innovation processes within the MedTech industry.

3.2.1 Evaluation of Single Case Study as a Methodology

According to Denscombe (2010) one of the key strengths of case studies is their ability to capture complexity and context of real-world situations. By focusing on a single company, this study enables a deeper understanding of how AI can improve efficiency and how it should be implemented in innovation processes within the MedTech sector. This depth would be difficult to achieve through broader but more superficial methods such as large-scale surveys.

Another advantage is the methodological flexibility of case studies, which enables the use of multiple data collection methods (Denscombe, 2010). In this study, for example, both interviews and literature review were conducted, drawing on a diverse range of sources within each method. Denscombe further argues that this increases the reliability of the insights and strengthens the overall credibility of the conclusions drawn.

However, it is also important to acknowledge the limitations of the single case study approach. One key concern is the limited generalizability of the findings (Denscombe, 2010). Since the study is based on one company's specific context the conclusions may not automatically apply to other MedTech firms or industries. According to the author's suggestions, the study explicitly compares its findings with previous research and highlights contextual similarities and differences where relevant.

Another limitation is the reliance on qualitative data rather than quantitative measures. While qualitative insights provide depth and richness, they are less suited for producing statistically significant results or drawing causal inferences (Creswell & Creswell, 2018). Ultimately, the single case study method is well-aligned with the explorative nature of this thesis and the goal of developing a deeper understanding of how AI can enhance innovation efficiency in MedTech companies.

3.2.2 Literature

The literature review examines the established theory available about the five subareas defined in the problem breakdown. The review compiles reports from consulting firms, scientific peer reviewed articles, and other similar sources to gain an understanding about how AI can be utilized to enhance efficiency in the innovation process. Literature has been identified through the selection of keywords for each of the five subareas, and a relevant publication timespan depending on the subject at hand. Moreover, to ensure reliability and

quality of the sources, primarily articles from databases accessible through Chalmers Library have been cited.

3.2.3 Interviews

To get a deeper understanding of how AI can strategically enhance innovation efficiency in the MedTech industry, primary data was collected qualitatively using interviews. In line with the recommendations of Denscombe (2010), semi-structured interviews were conducted with specialists in the field to obtain detailed information and insights into relevant areas. To be able to correctly portray the current situation at MedCo, half of the participants were employees at MedCo. To get a deeper understanding of the widespread adoption of AI technology, the other half consisted of professionals with relevant expertise within the area of study. The main criterion for these participants was that they had experience from strictly regulated industries with high innovation intensity.

In line with the recommendations by Parker et al. (2020), the selection of specialists followed a snowball sampling approach, where initial interviewees were identified based on their expertise and relevance to the study. These selected participants were then asked to recommend other specialists in the field who could provide additional insight. In turn, these individuals suggested further participants until a saturation point was reached, as suggested by the authors. This method leverages participants' social networks and creates sampling momentum while maintaining flexibility throughout the research process.

Once the participants had been selected, semi-structured interviews were conducted to maximize the depth and value of the collected data. According to Gill et al. (2008), this interview format consists of predefined key questions in selected areas, allowing both interviewers and participants to be dynamic and get deeper insights into the relevant topics through open discussion and follow up questions. This approach enables discovery and exploration of information that may previously not have been considered, ensuring a comprehensive understanding of AI's role and ability to drive innovation efficiency within the MedTech industry.

The interviews were conducted both online and in person, depending on the participants' availability. Chalmers' AI portal tool was used for transcription which made the process of extracting valuable insights from the interviews more efficient and enabled methodical review and structuring of the results. In Table 1, each of the interviewees have been assigned a number that is used to reference any results derived from that interview. The table further contains the date on which the interview was conducted and what role they have in their organization.

Interviewee Reference	Date of Interview	Interviewee's Role
Interviewee 1	2/14/2025	Researcher
Interviewee 2	2/26/2025	Head of Innovation
Interviewee 3	2/28/2025	Purchasing Director
Interviewee 4	3/12/2025	HR Director
Interviewee 5	4/7/2025	Director of AI
Interviewee 6	4/7/2025	Product Manager
Interviewee 7	4/9/2025	Founder & CEO of a Patent Analytics Platform
Interviewee 8	4/11/2025	Software Engineer
Interviewee 9	4/14/2025	Embedded Design Manager
Interviewee 10	4/16/2025	Patent Consultant
Interviewee 11	4/19/2025	IP Partner
Interviewee 12	4/23/2025	IP Specialist
Interviewee 13	4/24/2025	Innovation Professor
Interviewee 14	4/25/2025	Innovation Professor
Interviewee 15	5/1/2025	Founder & CEO / Engineer / Patent Attorney
Interviewee 16	5/2/2025	Head of Strategy

Table 1: Mapping and Short Description of Interviewees

3.2.4 Analysis Method

To analyze the data collected from the interviews, a coding approach has been employed. As described by Bell et al. (2019), coding is a procedure where the transcripts from the interviews are decomposed into elements and then assigned labels, using a three-level approach. The first level of coding aims to make a summary of the interviewee's responses and construct codes. The goal of the second level is to further break down these labelled elements and generate concepts by comparing and consolidating the codes. The final level aims to find broad analytic themes by looking at the characteristics and relationships between the codes.

As previously described, the interviews in this case study were recorded, then transcribed using the AI tool accessible through Chalmers. The transcriptions were then analyzed collaboratively using an iterative approach to avoid bias and broaden perspective. First, each of the transcripts were read through, and any statements and quotes that were deemed as relevant to the case were extracted into a Microsoft Excel workbook. The entailing step consisted of identifying any common sentiments amongst these extracts, and then summarizing them into central ideas, commonly referred to as first order concepts. Thereafter, common overarching topics among these first order concepts were pinpointed and formulated into second order themes. Lastly, the second order themes were classified as pertaining to specific aggregated dimensions, in this case representing subareas of the innovation process.

4 Results

This chapter presents the empirical findings derived from the conducted interviews and is structured around the five central thematic areas identified in the analysis: Knowledge Management, Patent Analytics, Market and Customer Analysis, Resource Allocation, and AI Implementation. Each of these themes emerged as critical dimensions in understanding how the innovation process can be enhanced using AI and forms the foundation for the analytical categories used throughout the chapter.

To facilitate clarity and coherence, Figure 3 visually outlines the structure of the results within each domain. This hierarchical structure is used to illustrate how subthemes and findings branch from broader categories, helping to guide the reader through the layered insights presented in each section. Structuring the results in this manner allows for systematic exploration of the data and reflects the interconnectedness and complexity of the themes investigated.

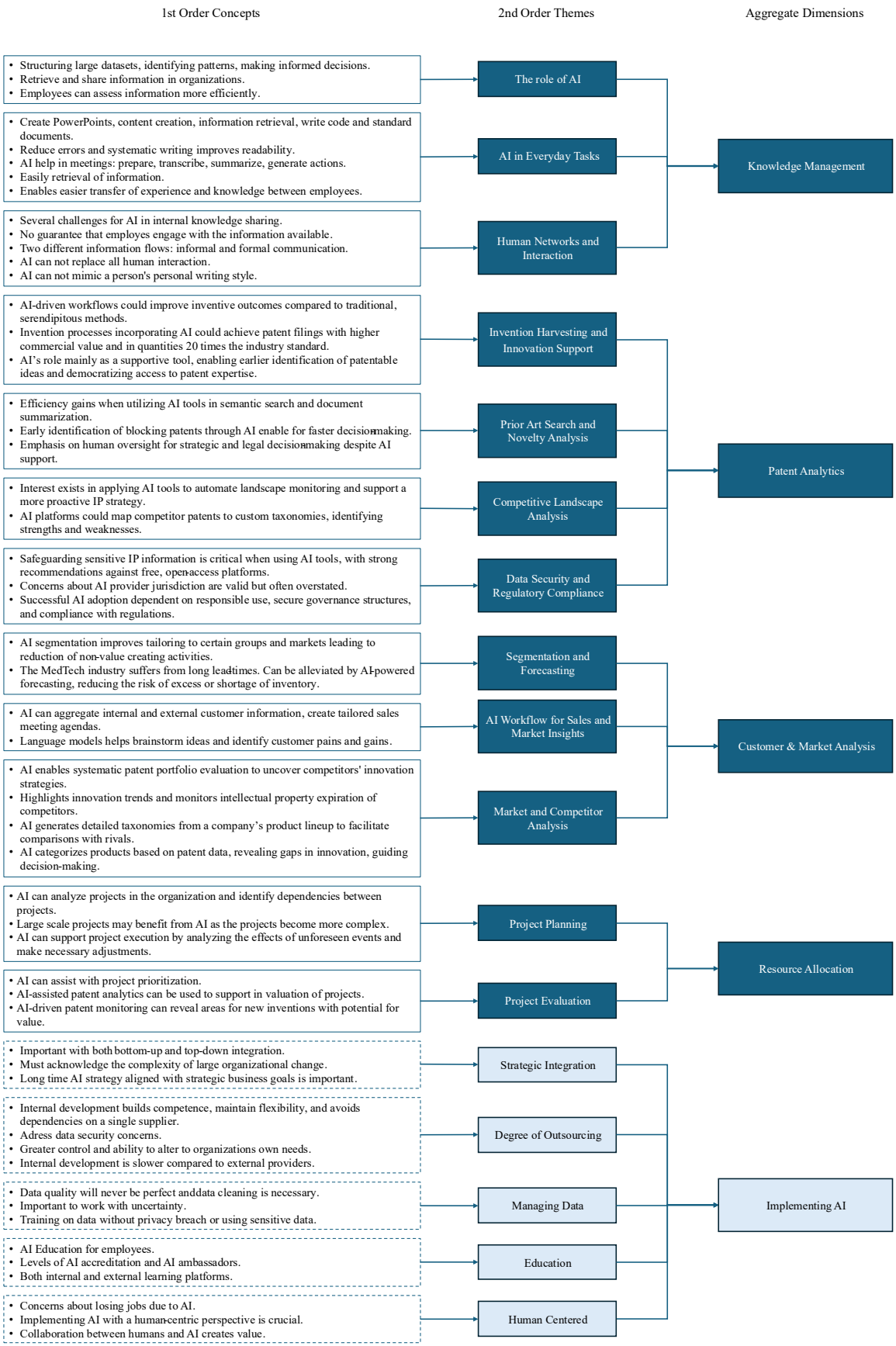

Figure 3: Thematic Coding of Findings from Interviews

4.1 Results for Knowledge Management

At MedCo, knowledge management currently relies heavily on manual processes. Although the organization has implemented an internal chatbot intended to support information retrieval, interviewees consistently described its performance as poor and its use as limited. Instead, information is typically spread through monthly meetings, where departments share updates and align on ongoing projects. While this approach ensures a degree of communication and transparency, it is time-consuming and does not fully meet the needs of a fast-paced, innovation-driven environment. Even though they have had negative experiences, some employees at MedCo expressed a positive attitude towards AI's potential to improve knowledge management, particularly by automating routine tasks and enabling staff to focus on more creative and value-adding activities.

4.1.1 The Role of AI in Knowledge Management

Throughout the interviews, AI was repeatedly brought up as a tool to enhance knowledge management within organizations. Respondents highlighted that AI could assist in structuring large datasets, identifying relevant patterns, and supporting employees in making informed decisions. Many of the interviewees agreed that AI plays a significant role in improving how organizations retrieve and share information. Some organizations have built and seamlessly integrated an internal technology infrastructure for efficient data management that enables users to easily find and manage information. Interviewee 7 emphasized the importance of information as the true driver of invention, stating that *"You don't necessarily need the biggest brain to make the best inventions if you've got the right information".*

4.1.2 Applications for AI in Everyday Tasks to Improve Efficiency

At many organizations, AI supported tools are integrated into daily knowledge management tasks, assisting both in content creation and information retrieval. One possible use-case that was mentioned was that AI can help generate and prepare simple PowerPoints based on a selected topic. In addition, AI-tools are also used for translating standard documents and providing a supportive function to streamline daily work. Another participant also emphasized how AI aided in the preparation, execution, and follow-up of meetings by gathering relevant information, transcribing discussions, and generating action items. Furthermore, organizations have implemented AI-tools that can partially or wholly automate tasks to enhance productivity, such as writing extensive reports. One interviewee estimated that this integration could potentially automate about 70-80% of the writing process and thus liberate time for more value creating activities. Another notable feature of these tools is that these documents can be written to be more readable and reduce errors.

While MedCo currently does not utilize AI applications for automating everyday tasks, several interviewees at MedCo expressed a strong interest in implementing such tools in the future. They saw potential for MedCo to increase efficiency by reducing time spent on routine work, allowing employees to focus on more strategic and value-creating activities.

Several of the respondents shared their experiences of implementing chatbots into their organizations, with notably mixed results. At MedCo, one interviewee explained that they

personally avoid using the internal AI chatbot tool because of varying performance and an initial negative experience, noting that the tool occasionally provides incorrect information and therefore cannot be fully trusted. In contrast, another organization reported clear benefits of their chatbot, one being that having a chatbot available in the organization was that employees could retrieve information in an efficient way. Additionally, interviewees described AI-tools as a way to democratize the access and availability of information, regardless of complexity, which in turn has a positive effect on the dynamics in the organization.

4.1.3 Challenges of AI and the Need for Human Interaction

A recurring theme in the interviews was the challenges associated with internal communication and knowledge sharing. As pointed out by one MedCo employee, even though more information is made readily available, this does not guarantee that individuals will engage with or absorb it. However, consolidation and ease of access to information through the use of AI-tools was highlighted as an important factor in encouraging greater employee engagement.

One interviewee mentioned a distinction between two different information flows that both are a part of the daily flow of information in the organization. The first type, formal communication, often takes place via the intranet. The second type, informal communication, occurs when individuals talk across departments to investigate specific questions or clarify unusual issues. These informal networks and personal exchanges across departments were emphasized as crucial for effective information flow, particularly within large organizations. The participant elaborated this by highlighting that open networks, a network where information is shared freely between individuals, facilitates a creative and productive environment. The interviewee further elaborated that networks that encourage open information sharing tend to outperform those where information is restricted. Additionally, it was emphasized that while AI can support access to documented knowledge, it cannot replace the importance of human networks, openness, and transparency in ensuring effective information flow. Another aspect is the difficulty of having AI mimic an individual's personal communication style. A possible solution for AI to do so effectively is to train the model on the employee's own data to learn how they communicate, although this poses some privacy concerns.

4.2 Results for Patent Analytics

In MedCo's current workflow, patent analysis activities, including monitoring and document creation, are characterized by a high degree of manual work and reliance on individual initiative. The Intellectual Property (IP) department identifies opportunities for new patents through continuous coordination with business units and manual monitoring of ongoing projects. However, they currently do not have any formalized processes or systems in place for detecting potential patent infringements.

While some AI-tools are already in use, such as the internally developed chatbot, AI has not yet been integrated into the core workflows of patent analytics or legal assessments. One of the employees at the IP department estimated that current AI usage has led to productivity

gains in the reviewing process of approximately 10-25%, although broader improvements have not been realized due to limited domain-specific integration. However, subjects working with IP expressed interest in adopting AI solutions that could screen project documentation for potential inventions or match internal functionalities against external patents, functions that could significantly improve current workflows.

4.2.1 Invention Harvesting and Innovation Support

To support invention identification, MedCo has implemented an invention harvesting process, where departments submit ideas to the IP department for evaluation. However, in complex areas such as software development, continuous facilitation by IP specialist remains necessary to recognize patentable inventions, but there is no tool specifically for supporting innovation practices.

A contrasting approach was provided by an expert who specializes in the patent analysis field. They described a workflow that utilizes a structured, data-driven model for supporting innovation. Traditional invention processes were further described as inefficient and serendipitous, often relying on informal, chance-based idea generation. The data-driven approach tries to address this by delivering relevant insights, grounded in patent data, to the inventors when the strategic value of that information is highest. This specialist further stated that successful utilization of such a tool has historically improved the efficiency and reliability of the inventive outcomes significantly. The interviewee elaborated on this by quoting case studies that they had conducted in collaboration with several multinational innovative organizations, where patent filings 20 times that of the industry standard were achieved. Furthermore, data from the same studies suggested that inventions created through this AI-assisted method are twice as likely to contain new patentable subject matter and were more likely to lead to commercially valuable outcomes.

Interviewee 11 further emphasized the transformational role of AI in IP processes, suggesting that "*AI will not only create new insights and enhance efficiency but also lead to entirely new workflows*", particularly in how infringement is detected and how innovation is scouted and supported. They noted that while the legal domain is slightly ahead of MedTech in AI adoption, IP professionals within the sector are beginning to integrate tools for search, landscape creation, and even drafting.

Currently, all patent drafting and litigation within MedCo is outsourced to external parties. However, this is not due to a lack of expertise, as the team possesses the necessary competency and experience, rather, the findings explain that this is due to resource constraints caused by the manual nature of other tasks.

The findings further show a consensus that AI does not constitute a replacement to inventors and patenting professionals but rather functions as a supportive tool, providing insights into the patent landscape, identifying competitive threats, and facilitating collaboration within the organization. Moreover, the interviews highlighted a broader potential of AI in enabling earlier action in the innovation cycle. Empowering inventors to act earlier in the innovation cycle, something that could maximize competitive advantage by reducing exposure to prior art. Another interviewee similarly highlighted the significant early-stage efficiencies achievable through AI applications, where one such use case could be quickly identifying

patentable ideas from informal discussions using semantic tools, greatly reducing the time traditionally associated with initial patent analytics.

4.2.2 Prior Art Search and Novelty Analysis

Freedom-to-operate (FTO) searches are currently conducted manually at MedCo. These are done at various stages of product development, requiring careful interpretation of the external patent claims. While effective, this method is labor-intensive and limits scalability, as noted by interviewees. It was noted that early-stage AI applications, such as semantic patent search tools and AI-driven document summarization, could significantly reduce the time and effort required for FTO analyses.

Interviewees with expertise in FTO searches utilizing AI noted efficiency gains of 20-40% when AI-tools were sporadically applied, compared to fully manual methods. Furthermore, early identification of blocking patents through AI-driven analysis was seen as critical for enabling faster go/no-go decisions in R&D projects. However, experts emphasized that human oversight remains crucial for making strategic and legal decisions, stressing that AI should be viewed as a tool that helps ensure decisions are based on the best and most accurate information.

Patent experts also emphasized that AI-driven summarization of patent documents allows for rapid pinpointing of relevant pre-existing innovations, reducing the burden on inventors during manual document reviews. Another participant echoed this sentiment, suggesting that AI will eventually shift the focus from traditional pre-set workflows to dynamic, data-fueled discovery, blending patent intelligence with business, technology, and financial insights. Several experts further pointed out that early use cases, such as automated prior art searches and IP landscape monitoring, are already being implemented by smaller, agile firms, with larger organizations awaiting further validation and integration into enterprise systems.

4.2.3 Competitive Landscape Analysis

MedCo currently does not conduct systematized competitor monitoring, instead relying on observations made by sales and marketing personnel, resulting in a primarily defensive patent strategy. Although the company employs a system to track patent deadlines and filings for its own applications, the detection of competitive threats remains entirely manual and largely depends on the employees to report any suspected breaches. Several interviewees highlighted that relying on manual approaches could put firms at risk of missing emerging threats or opportunities and may present a significant challenge in maintaining a strong competitive position.

Moreover, the findings indicate that the perception of AI technology is that it levels the playing field from the perspective of patent expertise, enabling inventors unfamiliar with the legal field to quickly map the area of domain with minimal input from patenting professionals. Several of the participants envisioned a future where AI-tools act autonomously as "agents" that proactively monitor competitors, technologies, and market shifts.

4.2.4 Data Security and Regulatory Compliance

Employee trust in AI-tools for patent analytics and legal processes is closely tied to data security and regulatory compliance, both of which emerged as critical concerns in this study. Multiple interviewees emphasized that safeguarding sensitive IP is fundamental for maintaining credibility and protecting competitive advantage. The use of free, open-access AI-tools was strongly cautioned against, as any information inputted into such platforms could be considered public, thereby compromising the patentability of inventions.

Underlying the concern of data security is the broader uncertainty around the ownership and jurisdiction of AI service providers. Particularly considering geopolitical tensions and the dominance of major AI companies based in the United States. Although these concerns have some validity, most businesses already rely heavily on the same providers for enterprise solutions, suggesting that the perceived risks, while real, might sometimes be overstated.

Beyond tool-specific concerns, respondents also pointed to structural inefficiencies. For example, delays in formalizing partnership agreements were mentioned as a source of uncertainty regarding IP ownership. At MedCo, the outsourcing of patent drafting and litigation underscores the need for careful management of sensitive information across external collaborations.

Despite these challenges, there was general agreement among respondents that global patent legislation is relatively consistent, reducing some of the jurisdictional risks associated with AI adoption. However, compliance with new and evolving regulations, such as the European AI Act, will be essential. Interviewees suggested that responsible use, clear internal governance, and careful selection of secure AI-tools will be critical prerequisites for safely integrating AI into MedCo’s IP workflows.

4.3 Results for Market and Customer Analysis

The interview data highlighted AI’s potential to improve the analysis of both markets and customers. It further showed that despite MedCo’s currently restricted leveraging of this potential, there is a growing interest in adoption within the organization. Three particularly important themes emerged from interviews with professionals at the forefront of this subject area. First, segmentation and forecasting were identified as important in aligning product offerings with actual customer demand. Second, AI was shown to streamline various aspects of the sales and marketing workflow. Third, certain AI-tools demonstrated strong capabilities for understanding market trends and the competitive landscape. Collectively, these themes hold important implications for both the Idea and Commercialization Phase in the innovation process.

4.3.1 Segmentation and Forecasting

One interviewee described that an ongoing issue is the oversupply of product ranges in certain markets, where customers only require a subset of what is offered. It was suggested that AI could support the identification and reduction of an excessive product range by tailoring the product assortment to match local demand more accurately. This suggestion was also framed

as a way to not only decrease “Lean waste”, but also as a potential avenue for improving customer satisfaction and performing better in metrics such as Net Promoter Score.

Being able to forecast and predict trends using AI was mentioned as particularly useful in MedTech where certain supply chains have lead times of up to six months. Anticipating customer needs is therefore seen as key to minimizing mismatches between supply and demand, which when optimized could create large productivity gains.

4.3.2 AI Workflow for Sales and Market Insights

A respondent detailed a workflow where LLMs were used from the initial customer research phase through to post-meeting follow-up. AI was used to gather internal customer data from sources such as emails and documentation, as well as public information from the internet. This information was then used to prepare meetings. The AI-tools were also used to transcribe and summarize sales meetings and produce follow-up action points. Additionally, the interviewee mentioned the use of AI in market research activities by using LLMs to brainstorm potential customer pains and gains in preparation for mapping value propositions.

4.3.3 Market and Competitor Analysis

The interviews also demonstrated comprehensive ways to analyze the market and competitors using AI-driven tools. These tools can systematically evaluate an entire patent portfolio in targeted industries or technology areas, allowing for deep insights into competitors’ innovation strategies. By benchmarking these portfolios against one another, organizations can identify where competitors are intensifying or reducing their innovation efforts based on observable trends in their patent activities. For example, a respondent highlighted that AI can show which areas competitors are shifting focus away from and which areas they are ramping up their innovation efforts in. It can also monitor when their IP are nearing expiration.

Additionally, one interview revealed that AI can generate taxonomies from a company’s product line-up. This taxonomy creation enables a side-by-side comparison between a specific competitor’s product areas or across entire markets. Furthermore, the interviewee underscored the value of AI-powered white-space analysis. By creating clusters of product categories based on patent data, these tools can help experts easily identify gaps in innovation, supporting decision-making for entering new markets or redirecting R&D efforts.

4.4 Results for Resource Allocation

Through interviews with representatives from MedCo, a more detailed understanding of the organization’s process for project evaluation and resource allocation emerged. Based on the information gathered, no AI-tools are employed to support decision-making in either process. The interviews revealed that, while their current approach is sufficient for the allocation of material and monetary resources, there are inefficiencies with the distribution of personnel and knowledge among activities within the firm. One of the interviewees stated that while it might not be difficult to locate the individuals within the organization with the appropriate expertise, their involvement in other activities limits their ability to engage in new tasks.

4.4.1 Application for Project Planning

The potential of AI-tools to efficiently assist with complex and time-consuming activities in projects was recognized by several interviewees. AI demonstrates potential for supporting both project planning and execution. During the interviews, it was suggested that AI-tools could be utilized to identify the complex dependencies between projects in the organization and the dependencies between components within individual projects. Therefore, by enabling more informed decision-making, this ensures that activities are completed in an appropriate sequence. It was highlighted that this would be particularly beneficial when planning projects on a larger scale as the number of dependencies can increase rapidly, resulting in increasing complexity. Furthermore, AI could assist during the execution of a project by analyzing and predicting the effects of delays. The process of re-planning in case of delays was explained as a time-consuming task which could be made more efficient with the support of AI.

4.4.2 Application for Project Valuation

The interviews suggested that AI has shown great potential of being able to assist with project prioritization and evaluation. While not capable of determining which of the higher quality options are the best, it has shown itself to be effective in identifying the lowest quality options. By disregarding project ideas with the lowest potential, decision-makers can spend more time and effort into evaluating a smaller quantity of high-quality projects. AI could therefore be able to enhance efficiency in the project selection process, resulting in project portfolios with higher strategic value.

Additionally, the interviews suggested that patent monitoring could be utilized as a tool to evaluate projects and discover new opportunities for innovation. One interviewee explained that patent citations could serve as an indicator of the patent's perceived value and that in general, patents with a high number of citations are considered to have a greater value in their domain. However, the respondent cautioned that citations alone are insufficient for evaluating projects as there are many aspects affecting it, such as prospective litigative and licensing value. Rather than trying to infer a value directly from the citation counts, the focus should instead be on the problem that the patent addresses and its value. By prioritizing high value problems, it is possible to identify opportunities for new inventions.

4.5 Results for Implementing AI

Although MedCo currently does not have a formalized plan for their AI implementation, several interviewees highlighted key aspects that would be important in any future integration. A clear, company-wide strategy was emphasized, ensuring that AI adoption is aligned with overall organizational goals. Additionally, participants stressed the importance of building awareness and competence across the organization to ensure that employees understand how to use AI-tools effectively.

4.5.1 Strategic AI Integration

Several interviews emphasized the importance of integrating AI strategically within organizations. Both top-down and bottom-up integration approaches were regarded as important when incorporating AI, along with acknowledging the complexity of organizational change. One participant shared their experience of an unsuccessful implementation of a big organizational system that nearly jeopardized the company. In this case, an underestimation of the associated challenges resulted in serious disruption. The importance of a structured long-term AI strategy was also underlined, where one company described that they had a five-year transformation program aimed at aligning AI implementation with strategic business goals. The participant further elaborated that AI adoption requires significant changes in operational models and organizational structures.

4.5.2 Developing AI-tools Internally

Several participants emphasized the advantages of developing their own AI-tools. By building internal solutions, companies aim to gain vital experience, maintain flexibility, and avoid becoming dependent on a single supplier's ecosystem. Additionally, internal development helps organizations build valuable competence that otherwise would require external consultants. Developing in-house solutions was also seen as a way to address security aspects, ensuring that sensitive information does not risk leaking to external systems. Moreover, building internal AI-tools provides greater control over the model and can therefore be tailored to the organization's own needs.

On the other hand, one disadvantage mentioned was that maintaining and updating internal AI models demands significant resources and may slow down the adoption of the latest technological advancements compared to external providers. Some interviewees, including MedCo employees, have observed noticeably worse performance and consistency in their internally developed chatbot in comparison to current state-of-the-art models, thus corroborating the notion that companies do not have the resources or capability to keep up with specialized businesses.

4.5.3 Managing Data Quality, Uncertainty, and Sensitivity

Several interviewees highlighted that organizations must accept that data quality will never be perfect. There will inevitably be variation and uncertainty in the data, emphasizing the importance of accounting for this uncertainty and incorporating it into the AI model. Data cleaning was emphasized as a prerequisite for the effective application of AI, despite being a time-consuming process.

Another important aspect discussed was the handling of sensitive data, where several interviewees stressed the need for caution. It was further noted that, due to the MedTech sector being highly regulated, obtaining appropriate training data can be challenging. One important consideration when sourcing an external tool is that data security is ensured. Customers must be certain that any proprietary data inputted into the model is not used for training. In addition, there are strict regulations about how sensitive data can be stored and shared. Sometimes data might not be allowed to be transferred out of the country, or even

outside the company. To protect privacy and align with regulations, sensitive data is often stored by the customer, while only the necessary, cleaned data is being processed centrally.

4.5.4 Importance of AI Education

Education was highlighted by several interviewees as a crucial factor in successfully implementing AI. One company has created platforms where employees can voluntarily engage in learning and earn different levels of accreditation by completing different training modules. In the same organization, about 10 % of their employees have become “AI ambassadors”, and are leading the way by spreading knowledge about AI within the company. Other organizations provide educational resources on both internal platforms and external training platforms like LinkedIn Learning. However, as Interviewee 9 noted “*it is a learning journey”* and therefore it is also important to apply this knowledge in practice to understand how to use AI and when it creates value for the user. Simply distributing an AI tool to everyone without proper training can be counterproductive, as it increases the risk of misuse or unintended consequences if users do not fully understand how to use it.

4.5.5 Human-Centric AI Adoption

Concerns about potential job loss were raised, with internal resistance towards AI based on the fear of being replaced, stressing the need for a human-centered approach to AI implementation. Thus, AI’s role should be to supplement human work rather than replace it, with a focus on collaboration between people and AI systems to create value. However, not all employees share the fear of replacement. For some interviewees, AI was primarily seen as a tool for boosting productivity and freeing employees to focus on more advanced, value-creating tasks by automating routine activities. An important aspect of the human-centric adaptation of AI, echoed by multiple participants, is that AI should not be forced upon employees but rather something that emerges naturally to assist in their work. However, many interviewees also emphasized the necessity for a clear strategy and policy outlining principles, goals, and ethical considerations, employed with a top-down approach. On the other hand, specific use-cases should be defined by the personnel, utilizing a bottom-up approach, as the staff have the experience and knowledge to ensure contextual relevance and operational feasibility. As has become evident from the interviews with MedCo employees, such a policy has yet to be put in place.

5 Discussion

This is one of few studies specifically focused on how innovation efficiency could be increased through the strategic application of AI. Through the case of MedCo, the findings of this study shed light on the implications of introducing AI technology into the innovation workflow within the MedTech industry. The following chapter will discuss these findings by putting them in the context of existing literature and interpreting their practical and theoretical implications. Furthermore, the limitations of this research will be addressed, and further research topics proposed.

5.1 Knowledge Management

The findings show that in companies comparable to MedCo, AI is being used to structure data, streamline daily tasks and improve access to information which significantly improves innovation efficiency. The interviewees shared examples of various tools and strategies for leveraging AI into existing workflows, as well as experiences with AI-based solutions such as chatbots. In addition, the result also highlights challenges related to implementing AI in knowledge management and internal communication, stressing the need for human interaction as one example.

The SECI framework offers a useful lens for analyzing how AI supports the creation, sharing, and internalization of knowledge across teams and subsidiaries. The synergy between AI and SECI reflects a broader trend of "AI-augmented knowledge creation", wherein human creativity and tacit insight are still central, but are more effectively captured and disseminated with AI support. Such synergies are critical for driving innovation in MedTech organizations. The findings show that AI has significant potential to reinforce the Externalization, Combination, and Internalization stages of the SECI model. These stages are essential for enhancing the efficiency and accessibility of knowledge within organizations and are crucial throughout all phases of the innovation process.

5.1.1 Improving Efficiency in Everyday Tasks

Several interviewees described how AI can be used in the Externalization mode to improve efficiency in the innovation process. Transcription software and generative models assist in this process by automatically summarizing meetings and documenting discussions. These tools provide employees with summarized actions, helping them effectively structure and document their work. This, in turn, promotes productivity by freeing up time for more complex tasks. The benefit of Externalization is further supported by Böhm and Durst (2024), who argue that generative AI can participate in and document human dialogue, transforming it into useful, sharable knowledge, readily available to other employees.

Another example highlighted in the result was how generative AI can be used to improve efficiency by writing standard documents and reports. One interviewee estimated that AI could eventually automate 70-80% of certain documentation tasks, like report writing, thereby liberating time for more creative, value-adding activities. This is a clear example of how AI would significantly improve efficiency within organizations like MedCo, where employees

have expressed a desire for their non-complex tasks to be more standardized and supported by AI-driven efficiency tools.

However, MedCo currently does not use such AI-tools extensively, even though some are available. Their internal communication remains reliant on manual methods such as monthly meetings between departments to spread information. This presents a missed opportunity for more efficient Externalization through AI, suggesting a gap between current use and best practice. The reliance on slow, scheduled meetings to transfer important knowledge or insight, hinders agility. Information that is not shared immediately could risk redundancy, misalignment between teams, or missed opportunities. In a fast-paced, innovation-driven environment like the MedTech industry, this is especially important. Moreover, poor Externalization often makes information sharing dependent on individuals or local storage, increasing the risk of data loss over time, which ultimately undermines the innovation efficiency.

5.1.2 Efficient Information Structuring

Regarding Combination, AI systems facilitate the integration of diverse information sources by integrating knowledge and data across various formats and departments, which leads to enhanced innovation efficiency. Different AI powered assistants can gather content from emails, documents, and meeting data to produce synthesized reports or presentations, as shown in the result. These tools therefore help break down knowledge silos, a critical challenge in large organizations that could hinder innovation, and thereby supporting deeper collaboration.

One of the interviewees highlighted that having chatbots available at the company provides a way for employees to retrieve information more intelligently. This aligns with Salem et al. (2024), who identify information storage and retrieval as the most useful application of AI in knowledge management, and therefore important for increasing innovation efficiency. The same interviewee, however, added an insightful aspect of how this changes internal organizational dynamics by democratizing the accessibility of information to employees. Yue et al. (2024), further strengthen this claim by stating that the constant availability of AI enhances the flow of information within the organization and among employees, which is important through all phases of the innovation process. These insights highlight a potential power shift that enables employees, not otherwise having access to the information, to be able to contribute with their ideas and opinions.

As observed by MedCo, the information produced by chatbots must be both high quality and reliable. The principle “garbage in, garbage out” holds especially true in the Combination mode. Errors in AI-generated outputs not only undermine the credibility of reports and recommendations but also risk propagating mistakes and misinformation across the organization, which could be devastating for an information-driven company operating in a fiercely competitive environment.

5.1.3 Information as the Driver of Innovation

AI-tools could contribute to increased innovation efficiency through the Internalization mode by improving how information is presented and understood. Interviewees noted that AI improves access to personalized, readable information that employees can find more easily, contributing to faster learning and application in work contexts. One interviewee estimated that AI could eventually automate 70-80% of certain documentation tasks, such as report writing. This alleviation of resources would liberate more time for creative and higher-value activities, providing a clear example of how AI could be used to increase efficiency. This example illuminates opportunities for organizations to replicate these effects by using AI in other activities, with the potential for similar efficiency improvements across various tasks.

One interviewee, working at MedCo, stated that even though they already have some tools for employees to more easily find and retrieve information, the issue lies in whether employees absorb the information provided. Delivering information in a digestible format is particularly important since, as one interviewee emphasized, information is the true driver of innovation, further highlighting the need for effective knowledge management. In MedCo's case, this implies that easier access to information alone may not be sufficient but might also require incentives and adjustments to ensure effective knowledge absorption. This aspect remains somewhat unexplored in the literature, although Pimentel and Palomino (2024) highlighted that the actual application of knowledge is what generates value. Thus, if AI-tools are not actively utilized, they cannot improve innovation efficiency. One solution to help employees absorb the information available, mentioned in the interviews is to use AI-tools to make documents more readable or translate them into other languages. The literature also brought up that AI can be trained for personalization, and can thus provide expanded explanations to its user to ease absorption. By ensuring that information is both accessible and easily absorbed the innovation process will be enhanced.

5.1.4 The Importance of Human Interaction

Despite its advantages, AI-tools fall short in the Socialization mode of the SECI model, which relies on tacit-to-tacit knowledge exchange through informal human interaction. These human factors, such as trust, shared context, and emotions, are essential for nuanced understanding and co-creation, and cannot be replaced by AI alone.

This limitation was clearly reflected in the result. Many interviewees highlighted the importance of human involvement in knowledge sharing, especially through personal networks and information exchange. Participants noted that human interaction, social structures, and informal conversations are key in ensuring that information is both shared and absorbed. These interactions ensure that information is not only exchanged but also internalized and contextualized. AI-tools cannot fully replace the social and relational dimensions of knowledge sharing in organizations, an important aspect to keep in mind when implementing AI. Efficient knowledge sharing depends on a combination of AI information tools and the informal human driven exchange of information and experiences. Human interaction is therefore crucial for an efficient innovation process.

At MedCo, knowledge sharing continues to rely heavily on these informal human-driven channels. Although monthly interdepartmental meetings offer a structured forum for updates,

employees often rely on informal conversations with experienced colleagues to gain deeper insight. Such examples reinforce the view that even as AI advances, it should complement, not replace, the human-centered dynamics that are the foundation for effective knowledge sharing.

However, emerging research suggests that AI may still have some use cases in the Socialization phase. Böhm and Durst (2024), for instance, describe how NLP tools can connect employees with complementary expertise or shared interests, encouraging spontaneous peer-to-peer knowledge sharing across organizational boundaries. Although such tools cannot replicate the depth of informal, face-to-face interactions, they may enhance the reach of Socialization practices by initiating new connections. Though, this potential was not reflected in the interviews conducted. None of the participants described using AI to support informal knowledge exchange or peer matching, indicating that such tools have yet to be adopted, or recognized, in practice. This gap between theoretical possibilities and current implementation highlights a valuable opportunity for future research.

In summary, AI enhances many structural and operational aspects of knowledge management, but it cannot replace the human dimensions of communication at any stage in the innovation process. For innovation to thrive, MedCo and similar organizations must invest not only in digital tools but also in fostering strong social structures and open communication cultures that allow tacit knowledge to flow freely.

5.2 Patent Analytics

The implementation of AI-driven patent analytics appears to bolster MedTech companies' innovation processes and strategic agility in the face of competition. The findings of this study suggest that AI-enhanced patent analysis can serve as both a catalyst for more efficient innovation and as a radar for competitive threats, aligning with prior research. Key themes include the efficiency gains in innovation, early identification of emerging technologies, improved competitive monitoring, the accompanying risks and limitations, and proposals for future research.

5.2.1 AI-Driven Patent Analytics and Innovation Efficiency

The implementation of AI-driven patent analysis could enhance MedTech companies' capacity to innovate efficiently, particularly in the Idea and R&D phases, by transforming traditional invention identification and support processes. Empirical findings from MedCo illustrate a stark contrast between their current manual, resource-intensive methods and the structured, AI-supported workflows described by experts in patent analytics. MedCo's existing invention harvesting process is heavily reliant on manual submissions and often requires facilitation by the IP department. This approach embodies the broader industry's documented struggles with manual patent analysis, characterized by labor-intensive, error-prone, and costly practices (Garcia, et al., 2024). Given the MedTech industry's rapid innovation cycles and the critical importance of timely patent filings, such manual approaches pose strategic and operational risks. MedCo's current situation falls in line with findings by Perl et al. (2025), stating that many firms within the MedTech industry grapple with fragmented invention workflows,

siloed departments, and the growing complexity of patent landscapes. The sector's fast-paced, compliance-heavy environment makes efficiency in patent analytics not just advantageous but essential for sustaining innovation pipelines.

In contrast, the structured AI-driven workflows highlighted by patent analytics specialists can systematically deliver strategic, data-driven insights directly to inventors, without requiring mediation from the IP department. This structured approach aligns closely with existing literature emphasizing NLP as transformative tool capable of efficiently extracting meaningful insights from vast and complex MedTech patent datasets (Rodriguez-Esteban & Bundschus, 2016; Garcia, et al., 2024). Experts in the field reported measurable improvements, including a twenty-fold increase in patent filings and significantly higher probabilities of generating commercially valuable inventions. Such outcomes directly address resource constraints and capability limitations prevalent within MedCo and reflect broader industry benefits achievable by adopting AI-driven analytics.

Moreover, the adoption of analytical AI-tools further enables earlier action in the innovation cycle, an advantage particularly critical in the fast-moving MedTech sector. Empirical insights from MedCo respondents substantiate claims from prior research that early detection and swift action on patentable inventions enhance competitive positioning and reduce infringement risks, both of which are vital given the industry's aggressive innovation pace (Thomson Reuters, 2022). For example, NLP-powered AI applications capable of automatically detecting patentable ideas from informal invention discussions, as highlighted in interviews, illustrate practical implementations of NLP-based tools. These tools expedite initial patent analysis stages and make intricate patent knowledge more accessible to non-experts, reducing bottlenecks and broadening innovation participation. As noted, NLP-powered AI systems that map informal discussions to existing patent spaces could reduce innovation blind spots while easing the burden on overtaxed IP professionals.

5.2.2 Early Identification of Emerging Technologies

This study offers several insights into the role of early identification of emerging technologies within the innovation processes of MedTech companies. It highlights the critical nature of systematically identifying emerging technologies to sustain competitive advantage in a rapidly evolving industry. This idea aligns with the established understanding that companies lacking structured methods for technology scouting face substantial strategic and operational risks, including delayed responses to disruptive innovation and potential infringement liabilities (Garcia, et al., 2024).

Moreover, the findings emphasize the transformative potential of AI-tools, particularly those employing ML, and NLP, in overcoming these challenges. Patent analytics literature corroborates that these AI methodologies enable systematic and proactive detection of nascent technological shifts, capturing subtle indicators embedded within extensive patent datasets (Aristodemou & Tietze, 2018). Specifically, according to both Kyebambe et al. (2017) and Lee et al. (2019), neural network models that combine patent citation patterns, keyword novelty assessments, and the classification of patents have proven particularly effective in pinpointing emerging technologies at their earliest stages. As pointed out by Benjamens et al. (2023), MedCo could utilize the automation of these activities to strategically position their

R&D efforts by proactively adjusting their innovation agendas in response to anticipated market demands.

Furthermore, the literature touches on the ability of this technology to, based on patent data, indicate future developments within a specific market sector and thus pinpoint whitespaces that are yet to be fully explored. This methodology of identifying undersaturated areas of the market was corroborated by the findings, as patent experts described experiences with tools that employ this functionality. By utilizing such tools, MedCo could lie at the forefront of the MedTech sector, by continuously being one of the first actors that identify and explore new technologies. This would provide them with early mover advantages and give them superior opportunities for IP claims.

Beyond detection, AI-enabled NLP clustering and thematic mapping offer a pathway to align internal R&D trajectories with external technological trends. Tools that cluster patents by concept and link them to unmet market needs could help MedCo prioritize high-impact innovation domains and foster cross-departmental alignment from the earliest stages of development. In a sector increasingly shaped by convergence between software, hardware, and diagnostics, MedTech companies as a whole face rising pressure to anticipate and capitalize on emerging technologies early. AI-enabled mapping tools can offer a systematic method to adapt faster than competitors, particularly in high-stakes domains.

5.2.3 Competitive Monitoring and Strategic Response

The findings further highlight the transformative potential of AI in enabling proactive competitive monitoring and strategic responsiveness within the MedTech sector. Currently, MedCo relies predominantly on manual processes and informal observations from sales and marketing personnel to monitor competitive threats. This reactive and decentralized approach limits the company's strategic agility and increases vulnerability to competitive disruptions and overlooked threats (Thomson Reuters, 2022).

Furthermore, as substantiated by the literature, the strategic adoption of AI-tools systematically enhances competitive intelligence capabilities. AI-driven methodologies, particularly those leveraging ML and NLP, can proactively and continuously analyze large volumes of patent and market data. According to research by both Aristodemou and Tietze (2018) and Garcia et al. (2024), these tools can swiftly identify subtle shifts in competitor activities, technological advances, and market dynamics, thereby enabling early and effective strategic responses.

One such application is automated patent classification. As described by Xiaoyu (2013), the traditional approach of manual classification is slow, resource-intensive, and error prone, qualities that are ill fitted for monitoring the dynamic MedTech landscape. As stated by Trappey et al. (2006), modern systems apply ML techniques to categorize patents based on their textual content, often outperforming manual efforts in both consistency and scalability. AI based tools thus present an opportunity to enable a new way of automatically gathering intelligence by classifying patents to identify any changes in competitor R&D efforts.

Patent experts interviewed envision future developments, where AI-powered systems evolve to include autonomous agents, actively scanning competitor activities, patent filings, and

emerging technologies. These views align with research advocating for proactive innovation management strategies, which leverage AI's predictive and analytical capabilities to substantially shorten strategic response times to competitive threats (Aristodemou & Tietze, 2018). By automating the early detection of potential disruptions, MedCo could proactively reposition resources, adjust R&D directions, or strategically respond through acquisitions and partnerships, enhancing competitive resilience.

5.2.4 Further AI Patent Research

Although AI technologies show considerable promise, the field of patent drafting still requires further research before widespread adoption can be realized. Experts interviewed support the potential implementation of AI in this area; however, the technologies require further refinement before wide adoption is possible. In particular, the reliability, legal validity, and explainability of AI-generated outputs must be thoroughly assessed. Future research should also explore how AI-assisted drafting can be conducted efficiently, as improvements in this area could have a significant impact on the innovation process, not only within the MedTech industry but across broader sectors as well.

5.3 Market and Customer Analysis

The interviews revealed that, although MedCo's incorporation of AI into their market and customer analysis remains limited, they recognize the potential of the technology. Both the literature and interview findings suggest that AI holds significant potential for enhancing both market and customer insights, which could increase the likelihood of MedCo's innovations successfully reaching the market.

The results demonstrate that AI, specifically LLMs, are being used to increase the understanding of customer needs. These findings support the claims of Kumar et al. (2024) and Huang and Rust (2021), who state that AI can reveal patterns and trends in large datasets and segment markets in more granular ways. One interviewee described that product offerings could be optimized to meet local market needs using AI insights, which parallels the role of cluster analysis in identifying under- or over-served market segments (Arunachalam & Kumar, 2018). Here, AI reveals inefficiencies while also guiding resource allocation. A key insight is that AI allows for more responsive and adaptive market strategies, enabling products to enter the market more efficiently. Although segmentation in the MedTech sector could prove more complex compared to the contexts which were studied in the literature, the interviews still highlight its potential.

Sentiment analysis was less explicitly mentioned in the interviews, but its underlying logic, extracting insights from qualitative data was frequently illustrated. Sahoo et al. (2023) describe the use of LLMs to collect and interpret internal documents, emails and internet sourced information prior to sales meetings suggests an operationalization of sentiment analysis. These findings indicate that AI can use both public and professional sentiment to inform strategic decisions. However, the data from interviewees focused less on emotions and more about providing context: understanding pain points, competitive gaps, and unmet needs in more nuanced ways.

The case study highlighted by Cooper (2024) aligns well with how AI is being used to understand customer sentiment, but the interview examples broaden its implications. While Cooper emphasizes AI's role in voice-of-customer research, the interviewees reveal its ongoing use across the sales lifecycle, from prospecting to follow up, which reflects a deeper integration of qualitative analytics into day-to-day sales and marketing operations.

Additionally, predictive analytics were cited as valuable for anticipating customer needs and reducing lead time mismatches. This application speaks directly to the challenges of relatively short innovation cycles in MedTech, where delays or mismatches can have significant consequences. The findings validate the focus of Xu and Chan (2019) on time series and regression based forecasting models, however the interviews also point to a more integrated use of forecasting where market and customer insights feed directly into strategic planning. For example, the reference to reducing lean waste through AI optimized product offerings implies a continuous feedback loop between demand forecasting and operational decision making.

While the literature mostly focused on business-to-consumer contexts, the interviews described powerful applications of AI-tools in market and competitor analysis. The ability of modern tools to simultaneously scan competitors' product line-ups and entire patent portfolios offers unprecedented ability to understand the competitive landscape. By both tracking shifts in innovation focus and looming patent expirations, these AI-tools can help optimize market entry and help screen new ideas, aiding in both the Idea and Commercialization Phase.

In conclusion, the use of AI in analyzing customer sentiment and uncovering unmet needs in combination with comprehensive market and competitor intelligence forms a powerful framework for innovation. A clear understanding of current trends, unexplored technological areas, and customer needs provides a powerful basis for decision-making. This market intelligence is ultimately what allows companies to successfully bring products to the market. However, it should be noted that MedTech has other barriers to market entry, such as strict quality and regulatory compliance, which this study has not touched upon. Taking these into consideration could be an interesting area for further studies.

5.4 Resource Allocation

The results of this study reveal that MedCo currently does not utilize AI for their resource allocation process. Although they are experiencing inefficiencies in the allocation and scheduling of personnel, no significant efforts toward making this adoption have been made, even though there is widespread recognition of the technology's potential. This gap presents a clear opportunity for MedCo to benefit from the integration of AI-based tools, which could significantly enhance the efficiency of resource allocation within the innovation process.

5.4.1 Optimize Resource Allocation Using AI

As revealed by the literature, AI has illustrated great potential of being able to enhance the allocation of both personnel and material resources among different activities. As emphasized by Mohite et al. (2024), AI can analyze the availability of employees and their expertise together with work demand to be able to allocate personnel to appropriate activities. Further

supporting AI's ability to support the allocation of personnel is a study by Amar et al. (2022) on workforce planning with AI. The study showed that the use of AI increased the productivity of both field workers and schedulers. The authors highlighted the importance of efficiently allocating personnel and showed that AI-driven solutions would be able to generate optimized schedules, resulting in employees spending more time with value creating activities and reducing idle-time. Additionally, AI-driven solutions would require less time to schedule the workforce than traditional methods, allowing for more adaptability in case of unforeseen events. These two studies highlight the advantages of integrating AI-driven tools for workforce planning and how it could assist MedCo and the MedTech industry in general to reduce inefficiencies during the R&D phase of the innovation process.

Furthermore, resource allocation plays a crucial role in enabling a more efficient innovation process, as innovation efficiency is the ratio between the quantity of invested resources and the outcome. As highlighted by Mohite et al. (2024), AI has the ability to identify resource wastages and lower the risk of over- or under-allocating resources to projects. Thus, by reducing resource wastage, the quantity of resources invested into a project can be optimized without sacrificing the outcome, resulting in increased innovation efficiency.

5.4.2 AI-Driven Project Planning and Resource Forecasting

Another application of AI in the R&D phase is its ability to assist in the planning process of a project. Both the interviews and the literature agree that one of the most important aspects of AI is its ability to process large volumes of data, thus enabling more informed decision-making. It was highlighted by the interviews that AI was particularly useful during the initial stages of a project for identifying dependencies and resource needs. Mohite et al. (2024) discuss how AI can be utilized to analyze projects within the organization to detect bottlenecks and predict future resource requirements. This predictive ability could be utilized together with dependencies between projects in the organization and between components in a project, to give decision-makers more insight into a project's prerequisites and future resource needs. These insights could enable improved project scheduling, and better knowledge of project dependencies could reduce the consequences of delays.

5.4.3 AI's Role in Project Evaluation

With project evaluation being a critical aspect of the portfolio selection process, increasing effectiveness and accuracy in the project evaluation may therefore result in a better project portfolio that is more aligned with the company's objectives. During the interviews, AI's ability to evaluate projects was discussed, particularly its ability to reject project ideas of low quality that do not meet the portfolio criteria and to instead prioritize projects of greater value. This ability to efficiently prioritize projects is important for the MedTech industry with its rapid innovation cycles, to ensure that they pursue the most promising ideas. AI has demonstrated strong capabilities in predictive analytics, particularly in analyzing large volumes of data while accounting for multiple constraints to forecast future resource needs and costs. These capabilities also extend to supporting project portfolio selection by providing accurate predictions of project value. By leveraging AI in this way, MedCo could increase

efficiency in its project portfolio process, ensuring that limited resources are directed toward the most promising and impactful innovation initiatives.

AI also shows potential in improving project selection by enabling more accurate valuation of projects using patent data, an increasingly important capability in R&D-intensive sectors like MedTech. Recent studies demonstrate that AI-based valuation models, particularly those leveraging full-text patent analysis through NLP, outperform traditional methods in predicting economic value. For example, Hsu et al. (2020) found that neural network models using both structured and unstructured patent data improved prediction accuracy by over 46% compared to regression-based benchmarks. Increased precision allows firms to more effectively prioritize projects with the highest commercial potential. Vázquez et al. (2013) further show that stronger patent portfolios are directly linked to improved financial performance, with a 10% increase in patent value translating to a similar rise in market capitalization. Integrating such AI-driven insights into project evaluation frameworks could significantly enhance MedCo's ability to allocate resources toward innovations with the greatest strategic and economic value.

However, project evaluation is not limited to the Idea Phase, as it could also play an important role during project execution in the R&D phase. As progress is being made on a project, its evaluation may fluctuate due to unforeseen breakthroughs or setbacks. Continuously reevaluating projects during execution may therefore provide valuable insights into the project's status, which can be used for making strategic, data-driven decisions on how to proceed. Similar reasoning was applied by Archer and Ghasemzadeh (1999), who explained that projects are usually evaluated at certain milestones. With the introduction of AI-tools, the decision-makers can get more accurate insights into the projects predicted future value and could make more informed decisions on where the organization's limited resources should be invested.

5.5 Implementing AI

The findings make it clear that AI holds significant potential across all stages of the innovation process, suggesting that effective implementation can substantially enhance efficiency. However, realizing this potential requires a strong foundation, both technically and organizationally. This dual nature of AI implementation calls for a comprehensive strategy that integrates appropriate technology choices, organizational readiness, and an ethical, human-centric approach to AI adoption. Despite the high potential of AI highlighted in both the literature and empirical findings, its adoption within the MedTech sector remains limited. The low rate of adoption indicates the presence of a knowledge gap, either in understanding which tools to use, or in how organizations should implement and integrate them effectively. The remainder of this discussion will explore both dimensions of this gap.

5.5.1 Technology Selection and Development strategy

The findings reveal that it is crucial for organizations to choose the right AI-tools for the specific challenges they aim to address. This is especially true in the MedTech sector, where innovation is tightly linked to regulatory demands and where efficiency is increasingly a

prerequisite for competitiveness. As a result, decisions about which technologies to use, and how to source them play a pivotal role in determining whether AI delivers meaningful efficiency gains across the innovation process.

A key insight from the case study is the interplay between the scope of the tool and the risk of supplier dependence. Broad, enterprise-wide tools, such as AI-powered chatbots or internal knowledge management platforms, typically require deep integration into core systems and are used across multiple functions. In these cases, supplier lock-in poses a significant risk. Committing to a single external vendor for such foundational tools could reduce long-term flexibility and make it difficult to adapt to new technological developments, especially in a rapidly evolving AI landscape. Interviewees frequently raised this point, citing the rapid pace of AI evolution as a strong argument for retaining control over foundational systems. Internal development, while resource-intensive, was seen as a strategic way to mitigate these risks, enabling greater autonomy, stronger compliance control, and the ability to evolve systems over time in line with organizational needs.

However, internal development also requires sufficient technical capacity. The case of MedCo's internally developed chatbot illustrates that while offering full control, shortcomings in quality undermines user trust and ultimately limits adoption. This example illustrates that internal development is only effective when the resulting system meets a high usability and reliability threshold. Otherwise, the expected efficiency benefits are unlikely to materialize.

By contrast, narrowly scoped tools, such as patent and market analytics software, are less embedded in core infrastructure and tend to have a clearer, more specialized use. For such tools, supplier dependence is less problematic, since the risks of lock-in are lower and switching costs more manageable. Moreover, the empirical findings suggest that specialized vendors often offer more advanced and up-to-date capabilities in these domains. Interviews revealed that MedTech firms value these external providers for delivering state-of-the-art functionality that would be difficult or inefficient to replicate in-house. In such cases, the benefits of outsourcing, namely speed, performance, and reduced internal strain, outweigh the risks, even when the tools handle sensitive data such as unpublished R&D.

These findings suggest that MedTech firms should view AI investments not only in terms of technical functionality but also considering scope and supplier lock-in risk. However, as the case of MedCo demonstrates, even well-chosen tools can fall short of delivering efficiency gains if they are not embedded within a coherent organizational strategy. This highlights that technology selection must go together with organizational readiness to unlock AI's potential to improve innovation efficiency. A further critical dimension is therefore organizational readiness.

5.5.2 Organizational Readiness

While selecting the right technology is essential, the findings also reveal that successful AI implementation in MedTech firms hinges equally on organizational readiness. Even when the development strategy aligns with strategic fit, such as MedCo's decision to internally develop a company-wide chatbot, the absence of supporting governance structures, cultural buy-in, and user confidence significantly limits its potential impact, limiting efficiency gains.

At MedCo, the chatbot was designed to support employees across departments by processing sensitive information such as internal procedures and intellectual property. Although its broad, organization-wide scope made internal development a conceptually sound strategy, empirical findings revealed widespread skepticism regarding the tool's reliability. Many employees expressed uncertainty not only about the quality of its output but also about when and how it should be used. This lack of trust significantly limited engagement and undermined its intended role as a productivity enhancer.

These findings align with broader academic literature, which highlights that successful AI implementation in organizational settings depends not only on technical adequacy but also on the presence of clear governance frameworks. According to Salwei and Carayon (2022), a socio-technical approach, where organizational policies, leadership support, and workforce engagement are aligned, is essential for safe and effective AI adoption. Similarly, Nair et al. (2024) emphasize the importance of formal internal policy covering areas such as data governance, algorithm validation, and ethical standards. Without it, employees often lack the structure and confidence needed to trust and consistently use AI-tools, increasing the risk that such initiatives stall.

Leadership engagement also emerged as a decisive factor. Several respondents pointed out the absence of clear executive sponsorship for AI, resulting in fragmented initiatives and inconsistent priorities across teams. This finding is echoed by Hassan et al. (2024), who emphasize that active leadership is not merely a facilitator but a prerequisite for AI transformation. Leadership signals legitimacy and creates alignment with broader strategic goals and fosters the internal momentum necessary for cultural acceptance.

However, as several interviewees stressed, effective leadership does not imply top-down control over every implementation detail. Instead, best practices suggest that strategic direction should be set at the management level, while specific use cases and applications are best defined by end users who understand their operational needs. This hybrid approach, combining top-down strategic alignment with bottom-up engagement, was viewed as essential for unlocking the full efficiency potential of AI-tools. Similar perspectives are supported by Tymoshenko (2024), who advocates for participatory AI design processes that involve users early and continuously to ensure alignment with day-to-day work practices.

This aligns with literature emphasizing that AI adoption often requires rethinking and redesigning existing workflows rather than simply overlaying new tools on legacy systems (Sriharan, et al., 2024). When employees are empowered to help define AI use cases, tools are more likely to fit actual practices and avoid inefficiencies caused by poor integration. As Guleria et al. (2024) note, clear implementation roadmaps that guide both strategic alignment and operational fit are essential to avoid fragmented or ineffective deployments. These observations proved particularly important in a MedTech context, where the limited use of AI appears to stem less from technical shortcomings, as highlighted by previous chapters, and more from user apprehension. As Yue et al. (2024) highlight, concerns about job displacement and skepticism regarding AI transparency can contribute to internal resistance. In this context, fostering a culture in which AI is understood as a supportive tool that users themselves can shape to improve the efficiency of their own tasks is critical. Callari and Puppione (2025) emphasize the importance of framing AI as an enabler that frees employees to focus on

higher-value work. Achieving this requires proactive communication and structured change management to reshape employee perceptions and build trust.

To reduce the hesitancy for using these tools, education and training are indispensable. Lack of formal upskilling initiatives reported by interviews may result in employees feeling unprepared to engage with AI-tools, which mirrors findings by Tymoshenko (2024). A culture of continuous learning, underpinned by clear expectations for AI interaction, is necessary to ensure consistent and responsible use of AI across functions. One company interviewed had established an internal training initiative in which 10% of employees became "AI ambassadors," promoting usage and providing peer support, a tangible benchmark for embedding AI readiness across the workforce.

Beyond internal alignment, external constraints such as data security regulations also shape organizational readiness. Interviews revealed persistent concerns about regulatory compliance and data governance, especially given the MedTech sector's exposure to patient data and intellectual property. These concerns align with Yue et al. (2024), who argue for robust governance structures that ensure privacy, trust, and legal compliance. In addition, several interviewees acknowledged that perfect data quality is unrealistic. Instead, they emphasized the importance of robust cleaning processes and AI models designed to accommodate uncertainty, echoing the need for operational realism over idealized datasets.

Finally, strategic planning emerged as a critical enabler of successful AI adoption. Interviewees stressed that effective AI implementation must be treated as a long-term transformation process rather than short-term technical deployment. Cases where strategic planning was lacking often resulted in fragmented initiatives or failed implementations. These outcomes underline the need for structured, organization-wide AI roadmaps aligned with business goals and operational realities. Equally important is ensuring that AI-tools are implemented as decision-support systems rather than decision-replacing ones. Several interviewees emphasized the continued need for human oversight, particularly when AI-tools are used in complex or strategic contexts. Aligning with findings from Choi et al. (2025), this balance was viewed as essential for ensuring accuracy, maintaining contextual judgement, and fostering user trust in high-stakes environments like MedTech.

5.5.3 Strategic AI Integration

The combined insights from both empirical findings and literature illuminate that effective AI implementation is not merely one of several strategic enablers, it is a foundational prerequisite for unlocking greater innovation efficiency in the MedTech sector. To achieve this, MedTech firms should consider adopting a dual approach that brings together strategic technology selection and deep organizational readiness.

On the one hand, firms must make informed choices about the scope and sourcing of AI-tools, balancing flexibility, supplier dependence, and technical capabilities. On the other hand, even the most advanced tools fail to deliver impact unless accompanied by aligned governance structures, active leadership engagement, and widespread user trust. These two elements are not independent, they are mutually reinforcing. A well-chosen tool, if poorly implemented, will falter; likewise, even a highly prepared organization cannot compensate for misaligned or unsuitable technologies.

Thus, the path forward for MedTech firms is to treat AI implementation as a strategic transformation, not a technical add-on. Success hinges on aligning AI-tools with organizational workflows, ensuring transparent governance and data handling, building internal competencies through training, and fostering a culture where AI is understood as a decision-support asset, complementing human judgement rather than replacing it.

Only when these elements are integrated can MedTech firms shift from fragmented experimentation to sustained efficiency gains across the innovation process. In this sense, the ability to effectively implement AI should be seen not only as a competitive advantage, but as a strategic necessity for innovation-driven performance.

6 Conclusions

MedTech companies are navigating a climate characterized by growing global competition, stringent regulatory demands, and rising expectations for high impact innovation at reduced costs. In this context, AI technologies are maturing rapidly and now offer transformative potential across all three phases of the innovation process, yet adoption remains limited. Findings indicate that this is due to uncertainty regarding where and how to successfully integrate AI. To address these matters, key areas of the innovation process have been identified alongside the preconditions for successful AI implementation. Through the case study of MedCo, this thesis explores how MedTech companies should navigate the adoption of AI into its innovation process.

When strategically implemented, AI offers significant potential to enhance MedTech innovation by improving efficiency in key innovation domains. In Knowledge Management, AI tools can streamline information retrieval and reduce time spent on repetitive tasks, allowing employees to focus more on collaboration and creative problem-solving, activities that are central to a productive innovation process. In patent analytics, AI shifts IP work from reactive to proactive by enabling early trend detection, freedom-to-operate checks, and the identification of invention opportunities. This not only accelerates the patenting process but also empowers innovators to act earlier and with more confidence. AI-driven market and customer analytics provides faster and more accurate insights into customer needs and competitor activity, helping align innovation efforts with real demand, an essential condition for developing viable, market-ready ideas. Finally, in resource allocation, AI tools support more informed project selection and enable smarter distribution of resources, ensuring that the most promising R&D initiatives receive the support they need. Collectively, these applications can relieve staff of administrative burdens, creating space for the type of high-value, collaborative work that drives innovation forward.

Realizing the domain-specific benefits of AI requires more than tool adoption; it calls for integration into a broader organizational strategy grounded in governance, training, and cultural alignment. The findings indicate that this strategy should begin with a strong foundation, clear guidelines, defined policies, and visible top-management support. Such a foundation enables bottom-up practices to emerge, allowing employees with domain expertise to identify high-value AI applications. Actively involving employees in this process not only improves implementation outcomes but also builds internal competence and fosters wider acceptance. The findings indicate three actions of prioritization: establish a comprehensive AI governance framework that defines responsibilities and ensures regulatory compliance; invest in internal capacity through targeted training that empowers staff to effectively use AI tools; and adopt a participatory approach that includes end-users early in defining use cases, ensuring alignment with daily workflows. While these recommendations are drawn from a single case, they provide actionable direction and highlight important areas for future research toward a generalizable model for AI integration in innovation-driven organizations.

7 References

Algazy, J., Le Deu, F., Li, S., Zhang, F., & Zhou, J. (2022, August). *Vision 2028: How China could impact the global biopharma industry.* Retrieved from McKinsey & Company: https://www.mckinsey.com/~/media/mckinsey/industries/life%20sciences/our%20insights/vision%202028%20how%20china%20could%20impact%20the%20global%20biopharma%20industry/vision-2028-how-china-could-impact-the-global-biopharma-industry.pdf

Ali, A., Tufail, A., & De Silva, L. C. (2024). Innovating Patent Retrieval: A Comprehensive Review of Techniques, Trends, and Challenges in Prior Art Searches. *applied system innovation, 7*(5), 91. doi:10.3390/asi7050091

Amar, J., Rahimi, S., von Bismarck, N., & Wunnava, A. (2022, November 1). *Smart scheduling: How to solve workforce-planning challenges with AI*. Retrieved April 28, 2025, from McKinsey & Company: https://www.mckinsey.com/capabilities/operations/our-insights/smart-scheduling-how-to-solve-workforce-planning-challenges-with-ai#/

An, J., Kim, K., Mortara, L., & Lee, S. (2018). Deriving Technology Intelligence from Patents: Preposition-based Semantic Analysis. *Journal of Informetrics, 12*(1), 217-236. doi:10.1016/j.joi.2018.01.001

Archer, N. P., & Ghasemzadeh, F. (1999). An integrated framework for project portfolio selection. *International Journal of Project Management, 17*(4), 207-216. doi:10.1016/S0263-7863(98)00032-5

Aristodemou, L., & Tietze, F. (2018). The state-of-the-art on Intellectual Property Analytics (IPA): A literature review on artificial intelligence, machine learning and deep learning methods for analysing intellectual property (IP) data. *World Patent Information, 55*, 37-51. doi:10.1016/j.wpi.2018.07.002

Arunachalam, D., & Kumar, N. (2018). Benefit-based consumer segmentation and performance evaluation of clustering approaches: An evidence of data-driven decision-making. *Expert Systems With Applications, 111*, 11-34. doi:10.1016/j.eswa.2018.03.007

Bell, E., Bryman, A., & Harley, B. (2019). *Business research methods.* Oxford: Oxford University Press.

Benjamens, S., Dhunnoo, P., Görög, M., & Mesko, B. (2023). Forecasting Artificial Intelligence Trends in Health Care: Systematic International Patent Analysis. *JMIR AI, 2*, e47283. doi:10.2196/47283

Blichfeldt, B. S., & Eskerod, P. (2008). Project portfolio management – There's more to it than what management enacts. *International Journal of Project Management, 26*(4), 357-365. doi:10.1016/j.ijproman.2007.06.004

Böhm, K., & Durst, S. (2024). Knowledge Management in the Age of Generative Artificial Intelligence: Time for Revisiting SECI. *19th International Forum on Knowledge Asset Dynamics* (pp. 1542-1552). Madrid: IFKAD.

Breuer, R., Meuer, M., Neher, K., Passmore, K., & Zurkiya, D. (2023, June 9). *Delivering a stellar experience for all key stakeholders in medtech*. Retrieved from mckinsey.com: https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/delivering-a-stellar-experience-for-all-key-stakeholders-in-medtech

Callari, T. C., & Puppione, L. (2025). Can generative artificial intelligence productivity tools support workplace learning? A qualitative study on employee perceptions in a multinational corporation. *Journal of Workplace Learing, 37*(3), pp. 266-283. doi:10.1108/JWL-11-2024-0258

Cekuls, A. (2024). The Evolution of Competitive Intelligence in a Complex Business Environment. *Journal of Intelligence Studies in Business, 14*(2), 4-5. doi:10.37380/jisib.v14.i2.2546

Chen, C.-J., & Huang, J.-W. (2009). Strategic human resource practices and innovation performance - The mediating role of knowledge management capacity. *Journal of Business Research, Volume 62, Issue 1, 62*(1), pp. 104-114. doi:10.1016/j.jbusres.2007.11.016

Choen, D., Furstenthal, L., & Jansen, L. (2020, November 12). *Healthcare innovation: Building on gains made through the crisis.* Retrieved from McKinsey & Company: https://www.mckinsey.com/industries/life-sciences/our-insights/healthcare-innovation-building-on-gains-made-through-the-crisis

Choi, J., Jang, D., Jun, S., & Park, S. (2025). A Predictive Model of Technology Transfer Using Patent Analysis. *Sustainability, 7*(12), 16175-16195. doi:10.3390/su71215809

Cooper, R. G. (2024). The AI transformation of product innovation. *Industrial Marketing Management, 119*, 62-74. doi:10.1016/j.indmarman.2024.03.008

Corvello, V. (2025). Generative AI and the future of innovation management: a human centered perspective and an agenda for future research. *Journal of Open Innovation: Technology, Market, and Complexity, 11*(1), p. 100456. doi:10.1016/j.joitmc.2024.100456

Creswell, J. W., & Creswell, D. J. (2018). *Research Design - Qualitative, Quantitative, and Mixed Methods Approaches* (5 ed.). Sage Publications Inc.

Denscombe, M. (2010). The Good Research Guid. In M. Denscombe, *The Good Research Guid.* London: Open University Press.

European Parliament. (2025, February 19). *Artificial Intelligence Act.* Retrieved from https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence#ai-regulation-in-europe-the-first-comprehensive-framework-4

Fahad, S., Salloum , S., & Shaalan, K. (2024). The Role of ChatGpt in Knowledge Sharing and Collaboration Within Digital Workplaces: A Systematic Review. In A. Al-Marzouqi, S. A. Salloum, M. Al-Saidat, A. Aburayya, & B. Gupta (Eds.), *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (pp. 259-282). Springer, Cham. doi:10.1007/978-3-031-52280-2

Garcia, S., Pennock, E., Ewedario, O., Green, E., Elgey, J., & Mkwashi, A. (2024). MedTech innovation identification: A rapid scoping review of patent research studies to inform horizon scanning methods. *medRxiv*. doi:10.1101/2024.12.09.24318714

Gill, P., Stewart, K., Treasure, E., & Chadwick, B. (2008, March 22). Methods of data collection in qualitative research: interviews and focus groups. *The British Dental Journal, 204*(6), 291-295. doi:10.1038/bdj.2008.192

Granstrand, O. (2018). *Industrial Innovation Economics and Intellectual Property* (Vol. VII). Gothenburg, Sweden: Svenska Kulturkompaniet.

Grant, R. (1996, December). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109-122. doi:10.1002/smj.4250171110

Greenlight Guru. (2023). *AI in MedTech Trend Report 2023*. Retrieved from Greenlight Guru.

Guleria, S., Guptill, J., Kumar, I., McClintic, M., & Rojas, J. C. (2024). Artificial intelligence integration in healthcare: perspectives and trends in a survey of U.S. health system leaders. *BMC Digital Health, 2*(1), 80. doi:10.1186/s44247-024-00135-3

Hassan, M., Kushniruk, A., & Borycki, E. (2024). Barriers to and Facilitators of Artificial Intelligence Adoption in Health Care: Scoping Review. *JMIR Human Factors, 11*, e48633. doi:10.2196/48633

Heidenberger, K., & Stummer, C. (1999). Research and development project selection and resource allocation: a review of quantivive modelling approaches. *International Journal of Management Reviews, 1*(2), 197-224. doi:10.1111/1468-2370.00012

Hollanders, H., & Celikel-Esser, F. (2007, December). *Measuring innovation efficiency.* Brussels: European Commission. Retrieved from researchgate: https://cris.maastrichtuniversity.nl/ws/portalfiles/portal/1522179/guid-46a68016-6c74-4576-b337-e00c41715756-ASSET1.0.pdf

Hsu, P.-H., Lee, D., Tambe, P., & Hsu, D. H. (2020). Deep Learning, Text, and Patent Valuation. *SSRN Journal*. doi:10.2139/ssrn.3758388

Huang, M., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30-50. doi:10.1007/s11747-020-00749-9

Jang, H. (2019, June). A decision support framework for robust R&D budget allocation using machine learning and optimization. *Decision Support Systems, 121*, 1-12. doi:10.1016/j.dss.2019.03.010

Jang, H., Kim, S., & Yoon, B. (2023). An Explainable Ai (Xai) Model for Text-Based Patent Novelty Analysis. *Expert Systems with Applications, 231*, 3-26. doi:10.1016/j.eswa.2023.120839

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons, 66*(1), 87-99. doi:10.1016/j.bushor.2022.03.002

Klingebiel, R., & Rammer, C. (2014). Resource allocation strategy for innovation portfolio management. *Strategic Management Journal, 35*(2), 246-268. doi:10.1002/smj.2107

Krestel, R., Chikkamath, R., Hewel, C., & Risch, J. (2021). A survey on deep learning for patent analysis. *World Patent Information, 65*, 102035. doi:10.1016/j.wpi.2021.102035

Kumar, V., & Garg, L. M. (2018). Predictive Analytics: A Review of Trends and Techniques. *International Journal of Computer Applications, 182*(1), 31-37. doi:10.5120/ijca2018917434

Kumar, V., Ashraf, A. R., & Nadeem, W. (2024). AI-powered marketing: What, where, and how? *International Journal of Information Management, 77*, 102783. doi:10.1016/j.ijinfomgt.2024.102783

Kyebambe, M. N., Cheng , G., Hu, Y., He, C., & Zhang, Z. (2017). Forecasting emerging technologies: A supervised learning approach through patent analysis. *Technological Forecasting and Social Change, 125*, 236-244. doi:10.1016/j.techfore.2017.08.002

Lee, J., Kim, J., Hong, Y. J., Piao, M., Byun, A., Song, H., & Lee, H. S. (2019). Health Information Technology Trends in Social Media: Using Twitter Data. *Healthcare Informatics Research, 25*(2), 99-105. doi:10.4258/hir.2019.25.2.99

MedTech Europe. (2024, August 18). *The European Medical Technology in Figures: Innovation*. Retrieved from MedTech Europe: https://www.medtecheurope.org/datahub/innovation/#:~:text=In%202023%2C%20more%20than%2015%2C900,originated%20from%20other%20countries

MedTech Europe. (n.d.). *How our sector is regulated*. Retrieved April 2025, from MedTech Europe: https://www.medtecheurope.org/about-the-industry/how-our-sector-is-regulated/

Migliore, A. &.-L. (2023). Cluster analysis. In A. Migliore, & C. Rossi-Lamastra, *Methodological Approaches for Workplace Research and Management* (1 ed., pp. 95-107). Routledge. doi:10.1201/9781003289845-7

Mohite, R., Kanthe, R., Kale, K. S., Bhavsar, D. N., Murthy, N. D., & Murthy, D. R. (2024). Integrating Artificial Intelligence into Project Management for Efficient Resource Allocation. *International Journal of Intelligent Systems and Applications in Engineering, 12*(4S), 420-431. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/3800

Nair, M., Svedberg, P., Larsson, I., & Nygren, J. M. (2024). A comprehensive overview of barriers and strategies for AI implementation in healthcare: Mixed-method design. *PLos One, 19*(8), e0305949. doi:10.1371/journal.pone.0305949

Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-Creating Company: How Japanese companies create the dynamics of innovation.* Oxford: Oxford University Press. doi:10.1080/23735082.2023.2272611

Parker, C., Scott, S., & Geddes, A. (2020). Snowball Sampling. *SAGE Research Methods Foundations*. doi:10.4135/9781526421036831710

Perl, A., Lo, A., Eakins, C., Bartlett, R., & Skov, S. (2025, February 18). *The transformation imperative: Igniting value creation in medtech*. Retrieved from McKinsey & Company: https://www.mckinsey.com/industries/life-sciences/our-insights/the-transformation-imperative-igniting-value-creation-in-medtech?utm_source=chatgpt.com

Pimentel, M., & Palomino, J. C. (2024). The Generative AI Solutions for enhancing Knowledge Management: Literature Review and Roadmap. *Proceedings of the 25th European Conference on Knowledge Management (Vol. 25, No. 1). 25*, pp. 1092-1095. Veszprém: Academic Conference International. doi:10.34190/eckm.25.1.2770

Rodriguez-Esteban, R., & Bundschus, M. (2016). Text mining patents for biomedical knowledge. *Drug Discovery Today, 21*(6), 997-1002. doi:10.1016/j.drudis.2016.05.002

Sahoo, C., Wankhade, M., & Singh, B. K. (2023). Sentiment analysis using deep learning techniques: a comprehensive review. *International Journal of Multimedia Information Retrieval, 12*(2), 41. doi:10.1007/s13735-023-00308-2

Salem, M., Salloum, S., & Shaalan, K. (2024). Exploiting AI's Potential in Knowledge Management. In A. Al-Marzouqi, S. A. Salloum, M. Al-Saidat, A. Aburayya, & B. Gupta (Eds.), *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom* (Vol. 144, pp. 283-299). Springer, Cham. doi:10.1007/978-3-031-52280-2_18

Salwei, M. E., & Carayon, P. (2022). A Sociotechnical Systems Framework for the Application of Artificial Intelligence in Health Care Delivery. *IISE Transactions on Healthcare Systems Engineering, 16*(4), 243-253. doi:10.1177/15553434221097357

Schroer, D., Simon, S., & Trommer, G. (2023, May 8). *Medtech's Generative AI Opportunity*. Retrieved from BCG: https://www.bcg.com/publications/2023/generative-ai-in-medtech

Sravanthi, J., Sobti, R., Semwal, A., Shravan, M., Al-Hilali, A. A., & Alazzam, M. B. (2023). AI-Assisted Resource Allocation in Project Management. *3rd International Conference on Advance Computing and Innovative Technologies in Engineering* (pp. 70-74). Greater Noida, India: IEEE. doi:10.1109/ICACITE57410.2023.10182760

Sriharan, A., Sekercioglu, N., Mitchell, C., Senkaiahliyan, S., Hertelendy, A., Porter, T., & Banaszak-Holl, J. (2024). Leadership for AI Transformation in Health Care Organization: Scoping Review. *Journal of Medical Internet Research, 26*, e54556. doi:10.2196/54556

Taherdoost, H., & Madanchian, M. (2023). Multi-Criteria Decision Making (MCDM) Methods and Concepts. *Encyclopedia, 3*(1), 77-87. doi:10.3390/encyclopedia3010006

Thomson Reuters. (2022, October 27). *Patent litigation 101*. Retrieved Mrach 2025, from thomsonreuters: https://legal.thomsonreuters.com/blog/patent-litigation-101/#:~:text=The%20authors%20estimated%20that%20the,5%20million

Trappey, A. J., Hsu, F.-C., Trappey, C. V., & Lin, C.-I. (2006). Development of a patent document classification and search platform using a back-propagation network. *Expert Systems with Applications, 31*(4), 755–765. doi:10.1016/j.eswa.2006.01.013

Tymoshenko, V. (2024, December 10). *10 Trends In AI Corporate Employee Training As We Move Toward 2025*. Retrieved from Forbes: https://www.forbes.com/councils/forbestechcouncil/2024/12/10/10-trends-in-ai-corporate-employee-training-as-we-move-toward-2025/

U.S Department of Health and Human Services, HHS. (2000, September 10). Standards for privacy of individually identifiable health information. Washington, DC: Federal Register. Retrieved May 4, 2025, from https://www.govinfo.gov/content/pkg/FR-2000-12-28/pdf/00-32678.pdf

Vázquez, G., Juma'h, A. H., Cué, F., & Lloréns, A. (2013). Patent Quality And Company Performance: A Sample within the USA Biotechnology and Pharmaceutical Industry. *Prime Journal of Business Administration and Management (BAM) , 4*(1), 1329-1338. Retrieved from https://www.researchgate.net/publication/368449578_Patent_quality_and_company_performance_A_sample_from_the_US_biotechnology_and_pharmaceutical_industry

Wasden, C. (2013, April 9). *Innovating the way we innovate*. Retrieved February 2025, from MedTech Europe: https://www.medtecheurope.org/medtech-views/policy-views/innovating-way-we-innovate/#:~:text=Regulatory%20reforms%20and%20demographic%20changes,the%20world%20to%20reassess%20their

Xiaoyu, Z. (2013). Interactive patent classification based on multi-classifier fusion and active learning. *Neurocomputing, 127*, 200-205. doi:10.1016/j.neucom.2013.08.013

Xu, S., & Chan, H. K. (2019). Forecasting Medical Device Demand with Online Search Queries: A Big Data and Machine Learning Approach. *Procedia Manufacturing, 39*, 32-39. doi:10.1016/j.promfg.2020.01.225

Yue, C. A., Men, L. R., Mitson, R., Davis, D. Z., & Zhou, A. (2024). Artificial intelligence for internal communication: Strategies, challenges, and implications. *Public Relations Review, 50*(5), 102515. doi:10.1016/j.pubrev.2024.102515

DEPARTMENT OF TECHNOLOGY MANAGEMENT AND ECONOMICS
DIVISION OF ENTREPRENEURSHIP AND STRATEGY

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2025
www.chalmers.se

CHALMERS