LUND UNIVERSITY
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AI for Dementia

A study on the Economic Impact of Artificial Intelligence in the Diagnosis of Dementia in Sweden

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Abstract

The current healthcare system in Sweden suffers from major problems when it comes cost-efficiency and delivery of healthcare services. Unsustainable increase in healthcare cost over the past few decades has led to that Government funding is no longer keeping pace with increasing demand and complexity. There a several ways to address this issue, one is to implement a new healthcare delivery model where healthcare providers better utilize rapidly growing information streams to work with disease prevention supported by advanced technologies such as artificial intelligence to provide more cost-efficient healthcare services. Previous research has explored the possibility of applying artificial intelligence as a tool for clinical decision-making and initial studies and applications deployed has shown promising results in supporting early detection and treatment of different diseases. Since artificial intelligence in healthcare is a relatively new phenomenon and has not been implemented in any wider clinical perspective, research concerning the economic implications is quite scarce, especially results for specific countries and diseases. Hence, the novelty and relevance of the topic makes it interesting for further research.

The purpose of this essay is to examine how the socioeconomic burden of dementia in Sweden could be affected by an implementation of artificial intelligence in the diagnostic process of the disease. Furthermore, this research aims to examine the potential efficiency gains that an implementation would provide.

By considering previous research on the potential economic effects of implementing artificial intelligence as a tool for clinical decision making for various diseases, this research provides estimations of the effects that it may have on the socioeconomic burden of dementia in Sweden.

The finding from this research showed that an implementation of AI-techniques has good potential to decrease the future socioeconomic burden of dementia in Sweden, as well as the potential to increase the quality of life for those affected and their families. An implementation of these techniques can make the diagnostic process of dementia patient more effective and serve as a helpful tool to assist clinicians in their clinical decision making. However, for this to be realized, major initial investments have to made in order to create an environment were AI-technologies can flourish.

TABLE OF CONTENTS

1. Introduction

This part serves as an introduction to the subject of artificial intelligence (AI) as well as the current status and prevalence of artificial intelligence and machine learning in healthcare. This part also includes the problem formulation and the purpose of the thesis. Furthermore, the introduction includes delimitations and the research question that this research aims to answer.

1.1 Background

Artificial intelligence (AI) is the theory and development of computer systems able to perform tasks normally requiring human intelligence, it aims to mimic the cognitive functions of human-beings (National Science and Technology Council [NSTC], 2016). This technology relies heavily on processing large amounts of data, larger volumes than what any human being could possibly manage, as well as recognizing patterns in this data. AI-technologies makes it possible for computer systems to learn from experiences and adjust to new data (IBM, 2018). Although the term AI was coined in 1956, it is still a subject that people and organisations have limited knowledge about, it is difficult to comprehend the actual concept. Well-known practical examples of AI- technology that exist today consist of self-driving cars as well as chess-playing computers (NSTC, 2016). Other more publicly available and used examples of AI consist of SIRI and Alexa.

But AI: s area of use stretches far beyond the examples mentioned above and it is bringing a paradigm shift in operational areas such as banking and financial services. This shift is fuelled by the increasing availability of data and the rapid progress of analytics techniques. Bringing AI out of the lab and into practically all industries and consequently our every-day of living has the potential to benefit quality of life and contribute to tackle some of biggest social challenges that we stand before (McKinsey, 2018).

Recently, new AI techniques has sent waves across the healthcare sector. These new techniques have the possibility to assist clinicians when it comes to making clinical decisions, in some standardized procedures it may even replace the human judgement (Jiang et al. 2017). AI has the possibility to analyse vast amounts of relevant data and therefore, it could be a helpful assistance tool for early detection of illness, as well as diagnosis and treatment plan. Currently, there is only a limited number of examples where AI has been implemented in healthcare systems globally. These examples are also limited in terms of type of diseases and all of them are in early stages of deployment (Jiang et al. 2017).

1.2 Problem Formulation

The total healthcare costs in Sweden and in the rest of the world has been growing in an unsustainable fashion. Healthcare costs are actually growing faster than GDP and has been doing so for the last decades (McKinsey, 2016).

In Sweden, Statistiska centralbyrån has been gathering data of the total health expenditures for many years. According to their data, total expenditures for healthcare as a share of GDP has been growing for some time. As of 2016, healthcare expenditures account for 10,9% of GDP, compared to 8,2% in 2006 (SCB, 2018). If the healthcare costs continue to grow faster than the GDP, this share will be even larger in a few years.

Therefore, the government in Sweden together with the Swedish municipalities and county councils has created the vision of making Sweden the greatest country in the world at e-health by 2025 (Regeringskansliet, 2018). This means capturing the advantages that digitalization brings and consequently achieving a healthier population and thereby lowering the lifetime cost of care.

e-health or digitalization of the healthcare sector carries advantages over and above a healthier population. Digital solutions and the new working methods that they enable may well make the health sector more economically effective and realising a more sustainable cost-growth. Digitalization enable the possibility of using advanced analytical tools when detecting, diagnosing, and treating patients. With these tools, predictions of the best treatment methods for a particular patient can be made as well as identify risk groups. They can also decrease the risk of clinical malpractice and subsequently streamline diagnosis and treatment (McKinsey, 2016).

Despite the increasing volume of AI literature and implementation of AI in the area of healthcare, previous research is concentrated around a few specific areas of diseases (Jiang et al. 2017).

The abilities and features of the AI-technology are developing rapidly and becoming increasingly advanced. It is reasonable to consider the possibility that an implementation of similar technology in detection, diagnostic, and treatment of patients with dementia could have similar effects as in other areas where it has already been evaluated and implemented.

1.3 Purpose

This research seeks to explore how the diagnosis and treatment process of dementia in Sweden could be affected by an implementation of different AI-technologies. Considering previous research on the prevalence of dementia and the cost-efficiency of using different AI-techniques as a clinical decision tool in a more general perspective, i.e. within different disease areas. Furthermore, the intention with this work is by considering existing research, explore potential financial effects associated with a broader implementation of AI enabled clinical decision tools for dementia patients within the Swedish healthcare system. Finally, this thesis aims to give a useful insight on how to better understand and quantify the effects an implementation of AI technologies could have in areas where it has not yet been formally implemented by considering previous research on the topic.

1.4 Delimitations

AI has tremendous potential to impact many industries and government services not least the healthcare sector. It has the potential to positively affect many areas of the healthcare system, including, if not all, at least the treatment of numerous diseases. This research will only examine the impact of using AI-techniques as clinical decision tools when diagnosing people living with or showing early symptoms of developing dementia. Furthermore, this study will be limited to only consist of estimates, analysis and results for Sweden.

1.5 Research Question

What effects on cost-effectiveness will an implementation of artificial intelligence have in the diagnosis process of dementia in Sweden until 2025?

2. Previous Research

This section consists of a presentation and discussion of the existing literature on dementia, digitalization of the healthcare system and artificial intelligence as a tool for clinical decision making. The first part concerns the socioeconomics cost of dementia. The second part discusses the healthcare sector and the demand for digitalization that exist for AI to be compatible. Lastly, research concerning AI is presented including its increasing presence in various industries and operational areas, and its functionality in the diagnosis and treatment process.

2.1 Dementia

Dementia is an umbrella term for a syndrome of progressive nature which is caused by various brain illnesses. Dementia affects the cognitive functions of humans, such as memory, thinking, behaviour and the ability to perform everyday activities (World Health Organisation [WHO], 2017).

Currently, 47 million people worldwide suffer from dementia This number is expected to grow to roughly 75 million by 2030. In 2050, the people living with dementia is expected to have tripled (WHO, 2017).

In Sweden the estimated total of people living with dementia was 158 000 in 2012, which was equivalent to just above 1.5% of the population. This estimate is expected to grow rapidly as a result of an increasingly older population (Socialstyrelsen, 2014).

Although dementia is not a normal part of aging, the disease mainly affects the elderly (WHO, 2017). Out of the estimated 158 000 people living with dementia in Sweden today, 148 000 are 65 years or older (Socialstyrelsen, 2014).

Furthermore, the population in Sweden is becoming older and older. According to estimates the age-class of 80 and above will experience the largest percentage growth in the coming ten years, increasing more than 50 % (SCB, 2018). Therefore, the estimation of the number of people living with dementia in Sweden is expected to grow in line with the increasingly older population. According to Socialstyrelsens report on the socioeconomic burden of dementia, the number of people living with dementia could increase from 158.000 to roughly 250.000 in 2030 (Socialstyrelsen, 2014).

Dementia is a very demanding illness, not only for the people who have it but also for family, caregivers and the entire health system. This, in combination with the lack of awareness and understanding of dementia results in massive costs on the economy (WHO, 2017).

The most common type of dementia is Alzheimer’s disease. It is one of many dementia diseases but roughly half of the people living with dementia suffers from Alzheimer. Alzheimer's disease causes the nerve cells in one or more of these areas of the brain to atrophy and ultimately die.

Different areas of the human brain possess different functionalities. The thinning lobe controls the memory and the head lobe analyses the information that is received from our senses. The head lobe is essential for the functionality of judgment, insight, the ability to concentrate and ability to speak. Although treatment of the disease is possible to prolong the functions of the brain, dementia is a chronic disease and no cure currently exist (1177 Vårdguiden, 2017).

Being able to set a diagnosis in the very early stages of the disease is of high priority. Early diagnosis has the possibility to improve the quality of life of those affected, as well as put up a treatment plan that hopefully can slow down the deuteriation of the dementia patient’s health (WHO, 2017).

Furthermore, most people living with dementia are unaware of their own disease. Approximately 75 % of all people living with dementia has not yet received a formal diagnosis. Consequently, they cannot obtain any medical treatment, care or support that they need (Alzheimer’s Disease International, 2011).

2.1.2 Cost of Dementia

Studies concerning cost of illness (COI) are common in health economic literature. These studies serve the purpose of identifying and measuring all costs related to a specific disease, which include direct, as well as indirect cost. These costs are a measurement of an estimated socioeconomic burden that a disease has. COI-studies is believed to serve as a valuable aid for policy making on where to distributed state funds (Byford, Torgerson & Raftery, 2000).

In 2015 the total cost of illness for dementia was estimated at $818 billion worldwide, which is equivalent to 1,09 % of the global gross domestic product (GDP) (Wimo et al. 2017).

Europe accounted for over one-third of the total socioeconomic burden at $301 billion and the per capita cost of dementia was estimated at about $35.000 (Alzheimer's Disease International, 2015).

The total COI for dementia is expected to experience an exponential growth and according to estimates, this figure is expected to have surpassed the threshold of one trillion dollars worldwide by 2018 (Wimo et al. 2017).

The total socioeconomic burden of dementia in Sweden 2012 was around 63 billion SEK and approximately 398.000 SEK per dementia patient (Socialstyrelsen, 2014). The total socioeconomic burden was equivalent to roughly 1.7 % of GDP (SCB, 2018). Furthermore, the socioeconomic burden is expected to rise as a result of Sweden's increasingly older population (Socialstyrelsen, 2014).

Furthermore, it is important to emphasize that approximately 80 % of the socioeconomic burden of dementia originate from the indirect costs and the costs for social care, such as residential care. The remining 20 % comes from direct medical cost and treatment of patients (Socialstyrelsen, 2014).

This goes to show that early detection must be of high priority. Enabling the possibility to set a diagnosis in early stages of the disease can be of great help for treatment, advanced care planning as well as delaying the need for care homes. Ultimately, early diagnosis does not only affect the efficiency which consequently decreases the direct cost, but it also decreases the indirect cost burden (Alzheimer's Disease International, 2011).

Being able to slow down the deuteriation of one's mental health in the onset dementia will consequently lead to keeping people in the earlier, and milder stages of the disease for longer. There will also be a greater reduction in the severity of the disease. Furthermore, intervening the deuteration would also create greater cost-savings in social and informal care (Alzheimer's Research UK, 2018).

Early diagnosis serves a valuable purpose by delaying the need for residential care. If the need for residential care is delayed for 3-12 months, this could potentially lead to significant cost-savings of 7.6-30.3 % for residential care services (Alzheimer's New Zealand, 2017).

2.2 Artificial Intelligence

The goal of creating a non-biological intelligence has been with us for a long time, even predating the establishment of the field by John McCarthy (Spector, 2006).

The term artificial intelligence dates back to the 1950's. John McCarthy, one of the pioneers in the area of AI, founded the research area together with his colleagues in 1956. They roughly defined artificial intelligence as the science of making intelligent machines (Hamet & Tremblay, 2017).

Numerous of human activities demand some kind of mental intelligence, such as driving a car, reading a book, writing an essay, constructing computer programs, etc. There are several existing computer systems that possess the ability to perform activities resembling these human activities. You may well say that these computer systems hold artificial intelligence (Nilsson, 1980).

With continued progress in electronic speed, capacity, and software programming, computers might someday be as intelligent as humans. Literature on AI is accumulating every day and it is a developing field of research in manufacturing, military, security, transport, and not least medicine (Hamet & Tremblay, 2017).

Recently, machines have progressed into demonstrating abilities that used to be exclusively human, like complex communication and pattern recognition (Brynjolfsson & McAffe, 2014). Much of the recent progress in AI has relied on data-driven techniques, like deep learning and artificial neural networks. When these systems are receiving sufficiently large training data sets and enough calculation, these methods are achieving unparalleled results (Pound et al, 2017). As a result, there has been a rapid ongoing research in AI areas such as computer vision, speech recognition, and language translation.

But the potential drawbacks of AI in the future are uncertain, it might not promise the moon and the stars without any possible repercussions. AI was portrayed as a possible threat to the world economy during the 2015 economic forum held at Davos, where Stephen Hawking even expressed his fear that AI may one day eliminate humanity (Hamet & Tremblay, 2017).

Furthermore, Stephen Hawking together with other artificial intelligence experts signed an open letter accompanied with a document on the research priorities for robust and beneficial artificial intelligence. This document expressed the importance of detailed research priorities on the societal impact that AI has, to avoid major drawbacks. Artificial intelligence has the potential to cure diseases and obliterate poverty, but researcher cannot or rather should not create something that cannot be controlled (Russell, Dewey & Tegmark, 2015).

2.2.1 Artificial Intelligence in the Healthcare Sector

The pressure on healthcare organization, in terms of achieving high-quality care in combination with cost-efficiency in diagnosis and treatment, is increasing. There is a general belief that clinical decision making should be based on clinical evidence in a much larger degree than they have been before (Stefanelli, 2001).

The modern healthcare system is experiencing rapidly expanding costs and complexity. This, in combination with a myriad of treatment options and vast amounts of information available makes it difficult to constantly find the most efficient treatment methods, especially for the individual clinicians at the point of care. But the increase in availability of information also presents future opportunities for evidenced-based clinical decision making. With the expanding use of electronic health records (EHRs) and the growth of large public medical datasets, the healthcare sector is much more prepared for an implementation of applications using artificial intelligence than it previously was. Currently, patients receive a correct diagnosis and treatment only half of the times at first try (Bennet & Hauser, 2013). With the implementation of AI-technologies in the diagnosis process, this proportion will most likely be larger.

A recent study performed on the causes of diagnostic error cases and malpractice showed that 65% of these cases had system-related causes and 75% had cognitive-related causes, some of the cases had both. System-errors were often related to inefficient policies and procedures. Cognitive-errors were mostly due to defective processing of available information. Consequently, there is great demand for better techniques to summarize data which can assist physicians to find the ‘needle in the haystack’ amongst large volumes of unstructured data (Ferrucci et al. 2013).

The number of studies that include quantifiable cost-savings in the healthcare sector as a result of implementing AI are quite limited. Although, in last few years further research has provided knowledge which shows the massive potential of AI.

McKinsey (2016) published a report on the value of digitalizing healthcare in Sweden. According to this report, by implementing digital solutions on a large scale in the Swedish healthcare sector, large cost-saving can be achieved. In a scenario where, digital technologies are completely implemented and used in the healthcare sector by 2025, the total healthcare expenditures will be 25 % smaller compared to a scenario were no digital technologies are implemented and the currently increasing costs continue to grow. All implementations of digital solutions would require initial investments and the report provides estimates on cost-savings that can be made until 2025. According to these estimates, a total of 180 billion in cost-savings can be achieved. The implementation of AI-technologies in clinical decision making for various diseases would account for 29 billion of these cost-savings. Hence, 16.11 % of the total cost-savings made by 2025 would be accounted for by the implementation of AI in the diagnosis of patients. Furthermore, only the direct cost and efficiency effects was included in the research provided by McKinsey. Indirect effects, such as reduced absence due to sickness and consequently the effects on production loss, or the potential effect of future innovations has not been included in these estimates.

According to a report by PwC, AI has the potential to improve the quality and efficiency of care while simultaneously reducing healthcare costs in Europe. Furthermore, this report also specifies the amounts of healthcare cost that could be saved through an implementation of AI-techniques in the diagnosis of dementia patients. They estimate that a total of 8 billion euros can be saved until 2025, these cost-savings will primarily be achieved due to an increased rate of diagnosis. (PwC, 2017).

Another recent study presented the possibility of combining AI-techniques together with magnetic resonance imaging (MRI) to examine blood perfusion in the brain. By doing so they were able to detect and diagnosis early stages of dementia as well as Alzheimer's disease with up to 90 % accuracy (Med Device Online, 2016).

Furthermore, there are explicitly three types of AI techniques that are commonly occurrent in previous research of medical application; classic machine learning (ML), more recent deep-learning, and natural language processing (NPL). The goal with using these applications is initially to make informational data, that may exist in clinical notes and previous medical research, comprehendible and more available to physicians. Secondly, applying techniques such as ML and deep learning so that they can assist physicians in clinical decision making (Jiang et al. 2017).

2.2.1.1 Classic Machine Learning (ML)

Machine learning devices are systems that is represented by mathematical algorithms that can improve learning through experience. With ML algorithms one can examine structured data to find patterns in this data as well as make classification and future prediction (Hamet & Tremblay, 2017).

Input in ML devices consist of data that is of possible interest. ML devices are implemented in the healthcare sector where the process of purpose is detection, diagnosis and treatment. In this case the data of interest is either in form of patient's traits such as age, gender, disease history and other demographical factors. Disease specific data is also of interest, such data consist of diagnostic images, gene countenance, physical examination results, clinical symptoms, medication and so on. The device can then make a predictive model by building a relationship between the input and the output, i.e. a relationship between a patient with a specific set of traits and a specific disease (Jiang et al. 2017).

Popular techniques of ML in medical application are support vector machine (SVM) and neural networks. SVMs are commonly used in classification of subjects into two groups. These two groups often consist of patients having the explicit disease and those who does not (Jiang et al. 2017).

Research on the application of SVMs in medicine is extensive. SVMs have for instance been applied on neuroimaging to be able to identify imaging biomarkers of neurological and psychiatric disease, such as dementia. Evidence also exists suggesting that SVM can be used to distinguish healthy subjects and subjects with dementia, but it can also distinguish various levels of dementia (Orrù et al. 2012).

There has also been research on the application of SVMs for diagnosis of breast cancer. Breast cancer can be detected through cautious studies of a patient's traits as wells as imaging with either mammography or ultrasound. However, definitive and most accurate diagnosis of a breast cancer can only be established through fine needle aspiration (FNA). Applying SVM on this FNA has the ability to identify and classify patients with breast cancer and those whom are healthy (Mu & Nandi, 2006). With this tool the risk of malpractice from the somewhat inexperienced clinicians can be decreased (Sweilam, Tharwat & Moniem, 2010)

Neural networks have re-emerged as powerful machine-learning models, yielding state-of-the-art results in fields such as image recognition and speech processing (Goldberg, 2016)

Neural network is an extension of linear regression that is used to discover complex non-linear relationships between input variables and an outcome. The relationship between the input variables and the outcome are depicted through multiple hidden layer combinations of prespecified functionals (Jiang et al. 2017). Much like SVMs, neural networks have features in medical research that concern detecting and classifying patients with breast cancer (Dheeba, Singh & Selvi, 2014).

2.2.1.2 Deep Learning

Humans are exposed to complex and high dimensional data every second of the day and can interpret this data in a concise way. When we see an object, like for example a flower, our brain has no problem whatsoever to understand that it is indeed a flower.

Imitating the effectiveness that the human brain possesses, regarding understanding and representing information, has been a central challenge for the research of artificial intelligence (Arel, Rose & Karnowski, 2010).

Deep learning is a new era of machine learning. Because of increased computing power, deep learning can examine much more complex and non-linear patterns in data than ordinary ML. Complex and non-linear patterns refers to high dimensional data i.e. data that has a large volume of traits, such as images and videos. Deep learning has become increasingly popular because it works much more effective and accurate when examining images than the classic ML devices. Application of deep learning in the medical research area almost doubled in 2016 compared to earlier years and most of these applications focus merely on image analysis (Jiang et al. 2017).

2.2.1.3Natural language Processing (NPL)

When humans communicate with each other through speech or writing, we use a natural language, such as for example English. The process of understanding and interpreting natural languages is complex and exclusive to intelligent beings (Nilsson, 1980).

A very large portion of clinical information are in form of narrative text that constitutes unstructured data, such as physical examination, clinical laboratory reports, operative notes and discharge summaries. This form of unstructured data is incomprehensible for ML-devices. NPL serve a useful purpose in terms of turning this unstructured data to a form which is comprehendible for machine learning devices that later can be used to assist clinical decision making (Jiang et al. 2017).

NPL can be used to extract relevant information form unstructured data that can be adapted to generate options for diagnosis and treatment. This ability to process unstructured content from new medical research and EHRs allows physicians to work with the most current research and knowledge available. It also reduces the burden associated with reading and comprehending the huge amounts of data that exist (Ferrucci et al. 2013).

3. Theoretical framework

This section will present a theoretical framework that will serve as a basis for the empirical research. An existing framework of cost-effectiveness for medical intervention is reviewed and customized for the purpose of this research.

3.1 Choice of Theory

By examining previous research concerning cost-effectiveness for medical intervention and what implications this has, the Model of Incremental Cost-effectiveness Ratio, or ICER, has been identified. This model incorporates characteristics that are considered vital in several research studies on the topic. The cost in the ICER-model are commonly measured in monetary form but the measurement of the effectiveness differs depending on the type research. The quality-adjusted life-year (QALY) measurement is frequently appearing in previous research on effectiveness of medical interventions. QALY has also been identified as a purposeful measurement for this research and will therefore, together with other measurements of effect, be included.

3.2 Model of Incremental Cost-effectiveness Ratio

The ICER-model is a commonly used mathematical framework for clinical decision problems. The purpose of the ICER-model is to represent the cost-efficiency by using a diversity of sources for estimation of costs and health outcomes (National Institute for Health and Care Excellence [NICE], 2013).

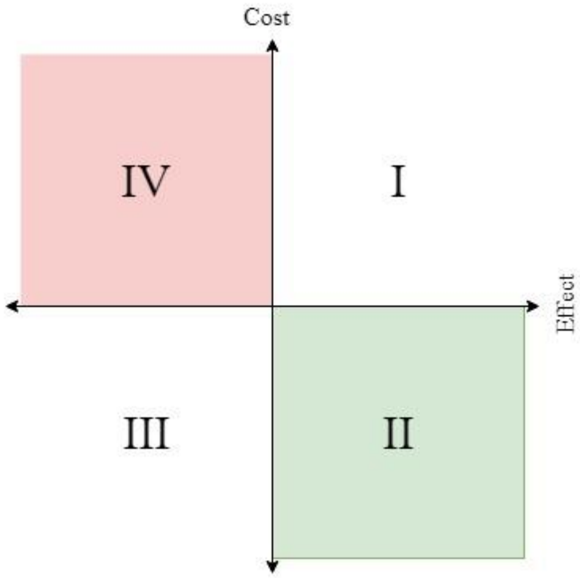
To determine which of two different methods (or solutions) is the most cost-effective, data is needed on both the costs and effects of each method. If a new intervention can achieve better effect as well as require lower investments compared to an older method, the new method is clearly dominant. In this case, the choice of method is simple from a health economic point of view. However, new interventions are regularly costlier than the older and more commonly used methods, but this must not always be the case (Statens Beredning för Medicinsk och Social Utvärdering [SBU], 2017).

The ICER model is often used when presenting results from health economic analyses of two different methods. ICER represents the ratio between the differences in cost and the differences in effect between two methods (SBU, 2017). If we let A denote the new intervention and B denote the older method, ICER is presented as follows:

$$ICER = \frac{Cost\ A - Cost\ B}{Effect\ A - Effect\ B}$$

Furthermore, ICER represent the additional costs for a new intervention to achieve one more unit of effectivity when switching from the older method. The new intervention is cost-superior if the willingness to pay is large enough to cover the costs of implementing this specific method (SBU, 2017).

The result can also be presented with a cost-effectiveness plane. The value of the ICER is placed in the plane and the position describes the incentives to invest in the new intervention.



I: High cost and high effect → The intervention is costly but achieves great effect. A potential implementation should be evaluated based on the extent of cost and effect.

II: Low cost and high effect → The intervention is dominant and cost-efficient. Implementation of the intervention should unquestionably be carried through.

III: Low cost and low effect → The intervention is economical but does not achieve great effect. A potential implementation should be evaluated based on the extent of cost and effect.

IV: High cost and low effect → The intervention is dominated and not cost-efficient. Implementation of the intervention should not be carried through (SBU, 2017).

Effectiveness of a specific treatment is a measurement of the effects that it achieves. In health economics, the effects are frequently measured by quality-adjusted life-years (QALY). QALY represent both the effects on the quality of life, as well as the improvement in lifetime expectancy that a new intervention can achieve (Drummond et al, 2015).

In other words, QALY is a measurement of efficiency that combines two dimensions of a patient's health, their quality of life and their life span. QALY is calculated by multiplying the extended life span with the quality of life that the patient experiences as a result of the treatment. The quality of life (q)has a value of $0 < q \leq 1$, where 1 is equivalent to full health and 0 is equivalent to death (Folkhälsomyndigheten, 2017).

The costs in the ICER-model are often measure in monetary form. The aim is to measure the socioeconomic burden that a specific treatment has compared to the alternative (SBU, 2017). A new intervention may require a large initial investment for implementation but may in the long run result in cost savings.

3.3 Revision of Theoretical Framework

This framework was developed for investigating the comparison of cost and efficiency differences between medical treatments such as different types of drugs (SBU, 2017). However, it could also contribute to a suitable foundation for the understanding and comparison between the effectiveness of two different medical diagnosis processes.

As an alternative of examining the differences between two separate treatment methods, in context of this research, the ICER-model will be used to examine the difference between two different scenarios of diagnosis. One of the scenarios will represent an implementation of AI-techniques in the diagnosis process of dementia, and the other will represent a scenario where no implementation is made.

3.3.1 Revision of Cost

Because of the novelty of the research area, it is tremendously difficult to estimate the costs that an implementation of AI in the diagnosis of dementia would require. Furthermore, AI-techniques have not yet been implemented on large scale. This contributes even more to the difficulty of estimating the costs.

This research aims to examine the cost-effectiveness between two different scenarios. One scenario when AI-techniques is implemented on a large scale in the diagnosis of dementia. The other is when no implementation is made, and diagnosis continues as usual.

Implementation of interventions and new techniques will always require some sort of cost, no gains can be made if there is no initial investment. Therefore, it is more efficient to examine if economic latitude can be created through an implementation of AI-techniques in the diagnosis of dementia, and how large the latitude could be. In the revised form of the ICER-model, costs will be referred to the potential cost-savings that can be made.

3.3.2 Revision of Effect

The effects of a specific treatment or drug is commonly measured by the quality of life that the receiver experiences as a result. OALY is a popular measurement in health economics when measuring the effects of a new treatment. However, in the revised form in the ICER-model, the effects will be considered in three different ways.

Firstly, the common and frequently used measurement QALY will be considered, this will serve as a valuable indication of the possibility that AI has to decrease the morbidity and mortality of dementia. Secondly, the accuracy of AI-techniques in the diagnosis of dementia compared to treatment as usual will be considered. The accuracy of a treatment effects the probability of re-treatment, if the accuracy of a treatment can be improved then the average time spent on diagnosis will be decreased. Lastly, early detection of dementia will be considered as a measurement of effect in this revised form. Early detection of dementia can serve as a valuable purpose for those affected and it might allow for actions in the onset of the disease. Furthermore, at least being aware of your state of health could be a relief that helps patients plan for the future.

4. Methodology & Method

The first part of this section explains the methodology upon which this research was conducted by going through the research philosophy, purpose, approach as well as strategy. The second part describes in what manner the information and data, that is being used throughout this research, was collected.

4.1 Methodology

4.1.1 Research Philosophy

“Methodology is the philosophical framework within which the research is conducted or the foundation upon which the research is based” (Brown, 2006, p.12).

The research philosophy is the belief in what ways the data in a specific research should be collected and analysed. The choice of the most appropriate research philosophy depends on the character of the research (Saunders, Lewis & Thornhill, 2012). An important question to consider is if the research method is of qualitative or quantitative nature.

Pragmatism, positivism and interpretivism are all commonly used philosophies of research, each of which have different characteristics of how data collection is conducted (Wilson, 2010).

The pragmatism research philosophy can be applied for both quantitative and qualitative research, it can be both subjective and objective and it can be both value-free and biased (Wilson, 2010). Pragmatic research philosophy also has the capacity to recognise that no single point of view or way of research can capture the whole picture (Saunders, Lewis & Thornhill, 2012).

Throughout the literature of applications based on different AI-techniques in the healthcare sector, it has been proven that it is a very complex and novel area of research. Consequently, the implications that is may have, on the costs and effectiveness, are difficult to measure. Therefore, this essay will be imprinted by a pragmatic research philosophy.

4.1.2 Research Purpose

One could argue that the purpose of research is simply the reason for why it was conducted. The aim of research can be to explain a certain economic phenomenon, this can be done collecting economic data and analyse it to finally arrive to a conclusion of this phenomenon. Research can be done in many different ways and serve diverse purposes. More specifically, the purpose of research can be; exploratory, descriptive, analytical or predictive (Collis & Hussey, 2014).

Exploratory research is commonly conducted in areas where the previous research of the problem is scarce. The aim of this type of study is to identify patterns and ideas rather than test a hypothesis. Exploratory research is typically applied when the aim is to gain insight and knowledge about a phenomenon that could be valuable for future, more in-depth, research (Collis & Hussey, 2014).

Based on the specific conditions of the research area chosen and for the purpose of this research, an exploratory purpose will be suitable.

4.1.3 Research Approach

Research approaches can generally be divided into three different types; deductive, inductive and abductive. The deductive research approach usually concerns a test of an already known theory or phenomenon. A hypothesis is set, and then the aim is to test the validity of the already know theory under certain circumstances.

The inductive research approach generally begins with detailed observations that later lead to abstract and untested generalisations. Indifferent from the deductive research approach, the inductive approach aims to construct new ideas instead of testing what is already known.

Abductive research approach is virtually a mix of the approaches mentioned above. It is constructed to address the weaknesses of the deductive and inductive approaches. Data collection is performed to explore a phenomenon that is later tested (Saunders, Lewis & Thornhill, 2012).

Generally, inductive research approach is associated with qualitative research and deductive is somewhat related to quantitative research, but this is no law-like scenario. In some researches an inductive approach can be adopted for quantitative research as well. As this research is a form of exploratory data-analysis, an inductive approach will be appropriate.

4.2 Method

4.2.1 Literature Scan

An extensive literature scan was conducted with the purpose of accruing greater knowledge about the existing research area of AI and its potential implications for the healthcare sector. The literature scan also served a valuable purpose of identifying the current gap in the existing research. During this research, information from literature has been collected from various sources. The collection was made using Google Scholars database, as well as other databases for scientific papers, such as ScienceDirect. Publishing company Elsevier was frequently appearing in the literature review as they mostly publish within medicine and science. Articles published by organisations such as IBM, McKinsey & Company, as well as PwC, was also reviewed and used in this paper. Furthermore, reports on the prevalence and effects of dementia was also examined, the reports concerned both country specific data as well as worldwide data of the disease. Moreover, the Statistiska Centralbyrån was also frequently used for the collection of demographic statistics, as well as GDP and the costs for healthcare.

To ensure the quality and creditability of all scientific papers used, the number of citations was taken in consideration. Although, because of the novelty of the research area, the number of relevant papers was quite scarce. Therefore, more recent papers without large numbers of accumulated citations have also been included, and these have been carefully examined based on their publishing company and their relevance.

Furthermore, as relevant literature on the research area was limited, information has been gathered from reports and articles. The reports and articles were also carefully considered based on their creditability and quality. Key-terms, such as Artificial intelligence, Healthcare Sector, Dementia, AI-techniques, was frequently used in the literature scan as it made the search for relevant information more efficient. The literature scan was accomplished in a careful and selective manner, this has consequently led to the use of information with high quality and creditability.

4.2.2 Data Collection

4.2.2.1 Secondary Data

The collection of secondary data being used in the analysis for this research happened somewhat simultaneous with the literature scan. Secondary data is the type of data that already features in books, journals and scientific papers. This type of data tends to be efficient to use for data analysis relative to primary data since it is generally available in an abundance through internet search. However, while it may present opportunities relative to primary data, secondary data may lack some relevant information for the purpose of the specific research. Furthermore, the source of which the selection of secondary data is made from has a significant effect on the reliability and validity of the research (Vartanian, 2011).

Secondary data that was considered valuable for the purpose of this research was collected from reports and articles. Information about the costs and prevalence of dementia in Sweden, in Europe, as well as globally were collected from various reports on the topic.

Data about conditions of dementia in from Sweden was collected from a report published by Socialstyrelsen that describes the number of people with the disease, and the development over time, as well as the socioeconomic burden that it causes (Socialstyrelsen, 2014).

Global and European data of the costs of dementia and the number of people with the disease, as well as the development over time, was collected from a report published by Alzheimer's Disease International, a report that analyses the global impact of dementia (Alzheimer's Disease International, 2015).

Because of the novelty of this research area and the fact that AI-techniques have not yet been implemented in the healthcare sector on a large scale, information about the cost and economic implications that it may have is limited. Few estimations on the economic implications have currently been made. These estimations concern the cost-efficiency of AI-techniques in the diagnosis process of dementia. In this research, estimates from two different sources was used.

In a report regarding how artificial intelligence could improve quality and efficiency and at the same time decrease the healthcare costs in Europe, PwC estimated the cost-savings that could be made in Europe until 2025 by an implementation of AI-techniques in the diagnosis process of dementia patients (PwC, 2017).

In a similar report regarding how digital technology can create value in the Swedish healthcare sector, McKinsey & Company estimated the total cost-savings that could be made until 2025 by implementing digital technology. A significant part of this estimation concerned the implementation of AI-techniques in the diagnosis process of diseases (McKinsey, 2016).

4.2.2.2 Estimations from Data

Methods for data collection can either be quantitative or qualitative. Quantitative methods are based on mathematical calculations and analysis in various kinds or formats. This research serves an exploratory purpose, which means that it tackles problems in areas where little previous research has been done. It also means that the aim of the research is not to reach a conclusive answer to the problem in hand, but to explore the topic and lay ground for future research (Brown, 2006).

The estimation data in this research consist primarily of the estimation of future values of dementia prevalence and cost-savings from AI enabled technologies in the healthcare sector. The data was collected in a careful manner with the aim to reach accurate estimations based on the secondary data. Since the secondary data does not concern both the specific disease area and the specific nation that this research aims to answer, this data has been reconstructed to fit the specifics of this research.

The estimations made by PwC and Mckinsey & Company had the same timeframe, and both of them concerned the possible cost-saving that could be made until 2025. The report from Socialstyrelsen consisted of secondary data concerning the costs and the development of dementia from 2000, 2005 and 2012. Consequently, these values had to be taken into consideration when constructing estimations of the number of people living with dementia in Sweden in 2025.

Furthermore, the report from Alzheimer’s Disease International contained data on the number of people living with dementia in Europe in 2015 and an estimation for 2030. These values were taken into consideration when estimating the value for 2025.

Moreover, the potential cost-savings estimates published by PwC and Mckinsey & Company did not concern either the specific region in question or the specific disease. PwC estimated the effect of an implementation of AI-techniques in the diagnosis of dementia for Europe.

Consequently, this estimate had to be recalculated for Sweden. Mckinsey & Company estimate concerned Sweden but was not disease-specific. Consequently, this estimate had to be reconstructed to fit the question in hand.

4.2.3 Estimation Assumptions

The following assumptions were made when constructing estimates of values for 2025:

- The increase in growth of prevalence of dementia in Sweden will be the same from 2005-2025.
- The estimations of cost-savings in Europe, as a result of the implementation of AI-techniques in the diagnosis of dementia, will be evenly distributed based on number of dementia cases. Cost-saving per capita will be equal.
- The estimation of cost-savings in Sweden, as a result of the implementation of AI-techniques in the diagnosis process of various diseases, will be evenly distributed based on the size of the disease.
- The size of the disease is based on the current socioeconomic burden of the disease.
- The dementia cost per patient will be the same from 2012-2025.

4.2.4 Credibility of Research

The quality of research is an important aspect when conducting studies, ensuring that the research is perceived as credible. This concerns both the trustworthiness of the sources referred to, as well as the consistency in the calculations.

The report conducted by McKinsey (2016), that is used in this research, was based on 500 research articles and studies of the topic. In all of these studies, digital solutions were tested in care environment and quantitative measurement of quality improvements and cost-savings was acquired. The quality improvements were applied on the Swedish healthcare cost base to estimate the effects that they had. Furthermore, assumptions of the Swedish market constructed on over 100 interviews with several actors in the e-health sector in Sweden.

The report conducted by PwC (2017), which is also used in this research, was also based on relevant literature scan concerning the prevalence of dementia and costs related to the disease.

Moreover, the report examines the improvement in quality of care and time consumption in the diagnosis process that could be achieved through an implementation of AI-techniques. Estimations of cost-savings were based on literature scan and interviews with hospitals and clinics, payers and companies active in the AI space.

Since research on the cost-effectiveness of applying AI-techniques in the healthcare sector is almost non-existent, the two reports mentioned above provided the best estimates that exist in this area of research. The lack of estimates of the potential cost-effectiveness of implementing AI-techniques in the healthcare sector and in the diagnosis of various diseases made it difficult to estimate the economic impact of artificial intelligence in the diagnosis of dementia in Sweden. The two reports above are not scientific papers but this does not mean that the reliability of these reports should be disparaged.

4.2.4.1 Validity

Validity is essentially the relevance of the research. There are three types of validity; content, construct and criterion validity. Firstly, content validity is the extent to which the research covers all that it should. Secondly, construct validity is the extent to which the research measure what it was intended. Lastly, criterion validity is the extent to which the research is related to other research that concern the same topic (Heale & Twycross, 2015).

The content validity was ensured by thoroughly considering all aspects that may be included in the analysis. To ensure the construct validity, recalculations of the secondary data was conducted and applied to fit the specifics of this research. This allowed the new estimations to reflect the purpose of this research. Since little previous research has been conducted on this topic, the criterion validity was quite difficult to ensure. However, this work relates to other research on the cost-effectiveness of AI-techniques in the diagnosis of diseases since estimations was made by examining previous research of the subject.

4.2.4.2 Reliability

Reliability is associated with the consistency of the research. If the research is replicated, it should deliver the same result.

Since many people effected by dementia is unaware of their own disease, it is difficult to measure the exact number of people living with dementia. All of the calculations in this research are made with caution from estimations that have been calculated by various well-known organisation that are considered trustworthy. Presumed that this research is replicated with assumptions identical to those made here, and that the same or similar sources are used, the research will deliver the same result. Consequently, the reliability of this research is ensured.

5. Empirical Results

This section presents the empirical findings that were collected in the literature scan and the estimation that was made from the information found from the literature scan.

5.1 Future Estimates of Dementia Prevalence

5.1.1 Dementia Prevalence in Sweden

Data concerning the number of people living with dementia in Sweden was collected from the report from Socialstyrelsen (2014). This report contains estimates of the prevalence of dementia in Sweden, as well as the socioeconomic burden that dementia causes. The following estimates was collected from this report:

Year	**2000**	**2005**	**2012**
Number of Dementia Cases:	133000	142200	158000

Table 5.1

Furthermore, the report estimates that the prevalence of dementia will increase as a result of an increasingly older population. This was incorporated in this research when estimating the prevalence of dementia in 2025. By calculating the annual increase on the prevalence of the disease, as well as the growth that the increase experienced, an estimation of the number of dementia cases for 2025 was constructed.

The average annual growth rate was calculated accordingly:

$$g_i = \left(\frac{y_{t+T}}{y_t}\right)^{\frac{1}{T}} - 1$$

The average annual increase in growth rate was calculated accordingly:

$$g' = \left(\frac{g_{t+T}}{g_t}\right)^{\frac{1}{T}} - 1$$

The estimate for 2025 was constructed as follows. Firstly, the average annual growth rate between 2000-2005 and 2005-2012 was calculated. The annual average growth rate was 1.35 % between 2000-2005 and 1.52 % between 2005-2012. Secondly, the increase in the growth of prevalence was calculated. From the first period, 2000-2005, until the second period, 2005-2012, the annual average growth rate increased by 1.71 % annually:

Year	**2000**	**2005**	**2012**
Number of Dementia Cases:	133000	142200	158000
Annual Growth of Dementia:	0	1,35%	1,52%
Increase in Growth:	0	0	1,71%

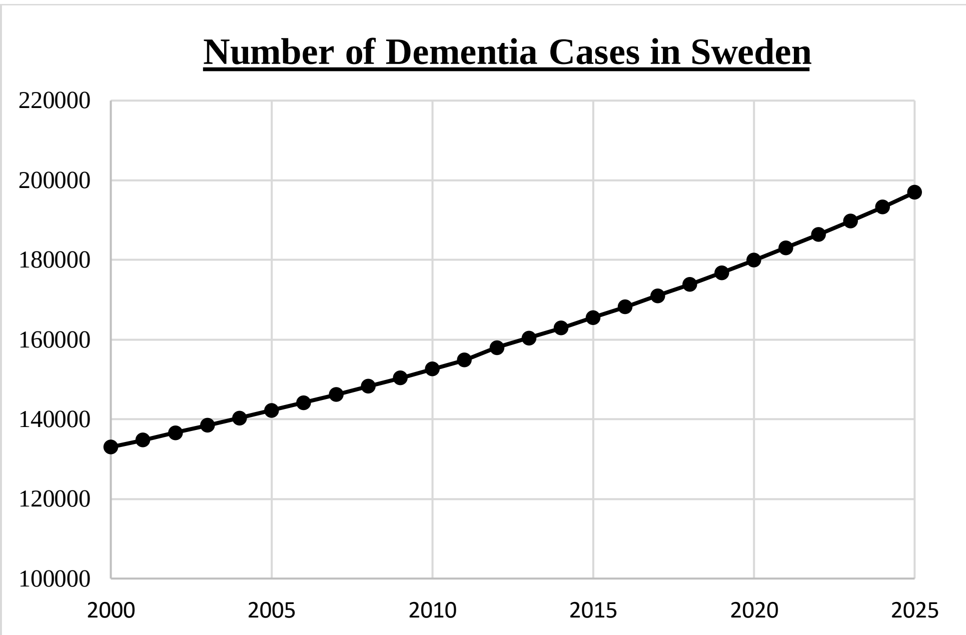
Table 5.2

The assumption was made that this increasing growth would continue in the same rate until 2025. Subsequently, the following estimates for the prevalence of dementia in 2025 was constructed:

Year	**2000**	**2005**	**2012**	**2025**
Number of Dementia Cases:	133000	142200	158000	196942

Table 5.3

As we can see from this graph, the increasing growth of the prevalence of dementia in Sweden is quite noticeable. The number of people living with dementia in 2025 will increase by nearly 50 % between 2000-2025. As mentioned before, this is mainly because of the fact that the population is becoming increasingly older.



Graph 5.1

5.1.2 Dementia Prevalence in Europe

Information about the number of people living with dementia in Europe was collected from Alzheimer's International report from 2015. This report estimates the prevalence of dementia in Europe from 2015-2030, as well as the socioeconomic burden of dementia. The following estimates of the prevalence of dementia in Europe was collected:

Year:	**2015**	**2030**
Number of Dementia Cases:	10460000	13420000

Table 5.4

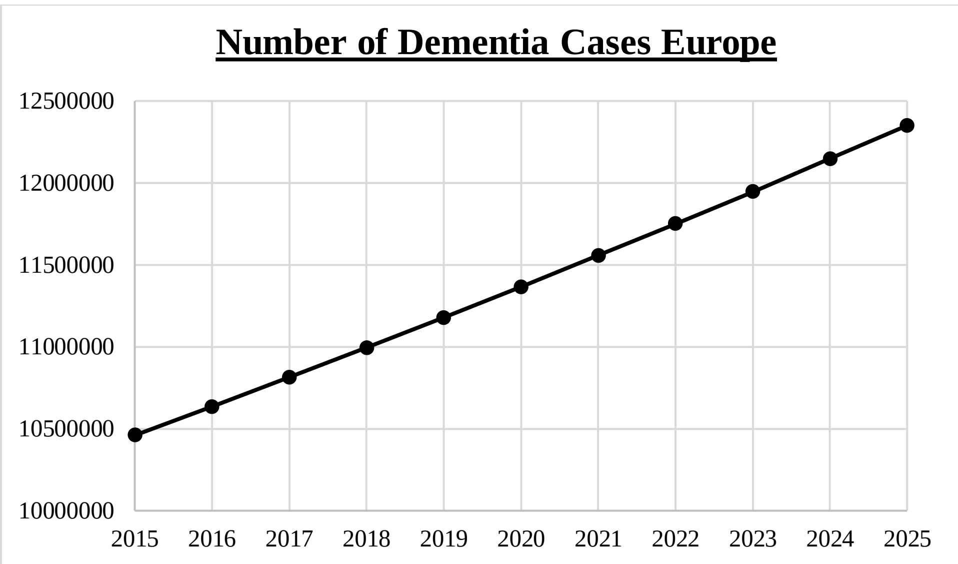
The prevalence of dementia in Europe was estimated by calculating the annual growth of the prevalence of the disease. The annual growth was calculated in the same way as before:

$$g_i = \left(\frac{y_{t+T}}{y_t}\right)^{\frac{1}{T}} - 1$$

Subsequently, the following estimation of the number of dementia cases in Europe from 2015-2025 was made:

Year	**2015**	**2025**
Number of Dementia Cases:	10460000	12350340
Annual Growth of Dementia:	1,68%	1,68%

Table 5.5



Graph 5.2

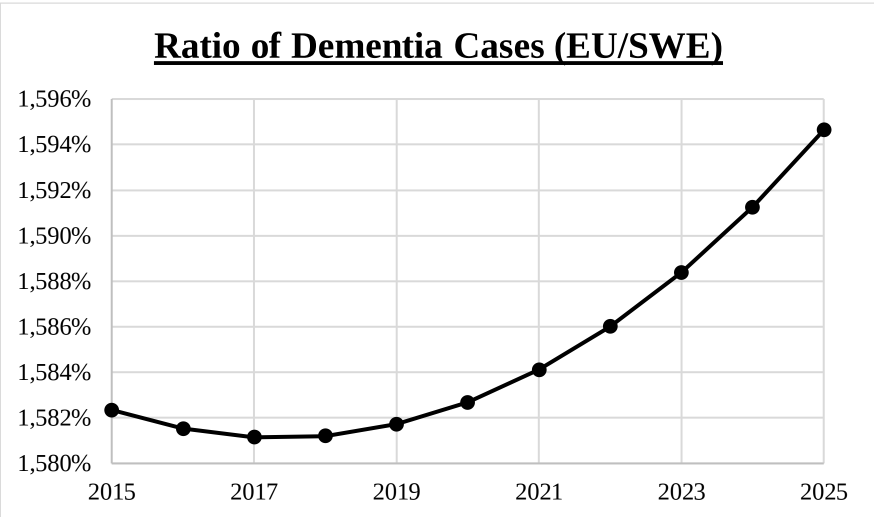
5.1.3 Dementia Prevalence in Sweden vs Europe

Even though it might not be a significant result, it is worthwhile mentioning that the estimated increase in prevalence of dementia in Sweden compared to that in Europe provides us with information that the prevalence of dementia is growing faster in Sweden compared to the rest of Europe.

If we examine the estimated number of dementia cases from 2015-2025, we see a slight increase in the ratio between the number of dementia cases in Sweden compared to Europe:

Year	Europe	Sweden	Ratio(EU/SWE)
2015	10460000	165512	1,582%
2016	10635218	168199	1,582%
2017	10813372	170975	1,581%
2018	10994509	173846	1,581%
2019	11178681	176815	1,582%
2020	11365938	179886	1,583%
2021	11556332	183064	1,584%
2022	11749915	186354	1,586%
2023	11946741	189760	1,588%
2024	12146864	193288	1,591%
2025	12350340	196942	1,595%

Table 5.6



Graph 5.3

According to these estimates, the total dementia population in Sweden will be equivalent to approximately 1.6 % of the dementia population in Europe 2025.

5.2 Estimates of Cost-Savings

5.2.1 Prevalence Based Estimate

In the report published by PwC (2017), they estimated that a total of 8 billion EURO could be saved until 2025 in Europe by implementing AI-techniques in the diagnosis of dementia patients. Furthermore, with the assumption that cost-savings will be equally distributed amongst all dementia cases, the total cost-savings made in Sweden will be roughly 1.3 billion SEK until 2025:

Dementia Prevalence	
Europe(EU):	12350340
Sweden(SWE):	196942
Ratio SWE/EU:	1,59%
Cost-Savings	
Cost-Savings Europe:	8 000 000 000 €
Exchange Rate:	10,23 kr
Cost-Savings Sweden:	1 305 043 689 kr

Table 5.7

The ratio shows the proportion of the estimated European dementia population that lives in Sweden. The estimated number of people living with dementia in Sweden was divided by that of Europe. Furthermore, the estimated cost-savings in Europe was converted from EURO to SEK to make the estimation comparable to the other estimation. This value was then multiplied by the ratio, following the assumption made previously.

5.2.2 Socioeconomic Based Estimate

In the report from McKinsey (2016), they estimated that a total of 180 billion in cost-savings could be made by a large-scale digitalization of the healthcare sector in Sweden. These savings would be a result of the digitalization making the healthcare sector working with more transparency and more smoothly. Out of these 180 billion, 29 billion or 16.11 % will come from implementing AI-techniques for the diagnosis of various diseases. The assumption is made that these 29 billion will be evenly distributed amongst diseases, based on their current relative size. Furthermore, the size of the disease is based on the total socioeconomic burden that the disease cause. Based on these prerequisites, total cost-savings in Sweden until 2025 will be roughly 2.5 billion SEK.

If the assumption is made that the per capita cost for dementia will be the same in 2025 as it was in 2012 if no implementation of AI-technologies is made, then the per capita cost of dementia will be equal to 398.000 SEK according to Socialstyrelsen (2014). Furthermore, according to our estimates, the total dementia population in Sweden will increase by 38.942 people by 2025. Therefore, the increase in the cost of dementia will be equal to the increase in the dementia population multiplied with the per capita cost of dementia. The total cost of dementia will rise by approximately 15 billion SEK if no implementation of AI-techniques is made. However, if an implementation of AI is made in the clinical decision making of dementia then cost-savings of 16.11 % can be made compared to the case where no implementation is made. Consequently, potential cost-savings that can be made will be approximately 2.5 billion SEK.

Cost-Savings Healthcare	
Total Savings	180 000 000 000 kr
Savings from AI-technologies	29 000 000 000 kr
Ratio	16,11%
Cost of Dementia	
COI/Capita	398 000 kr
Number of Dementia Cases 2012	158000
Number of Dementia Cases 2025	196942
Increase in Dementia Cases	38942
Increase in COI	15 498 916 000 kr
Cost-Savings Dementia	2 497 047 578 kr

Table 5.8

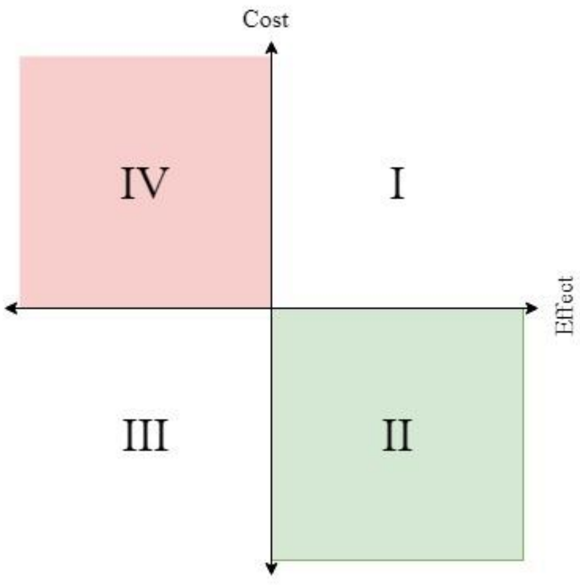
6. Analysis

This section analyses the findings from the empirical data, as well as the findings from previous research. The factors that affect cost-effectiveness of treatment are examined to gain a deeper understanding of the potential cost-effectiveness of using AI-techniques when diagnosis dementia patients.

6.1 Cost-Savings from AI

In the revised form of the ICER-model, the parameter cost was considered as a measurement of the total cost-savings. The cost-savings represent the amount that could potentially be saved by an implementation of AI-techniques in the diagnosis of dementia. According to the empirical data of estimates, the diagnosis of dementia could potentially achieve cost-savings of approximately 1.3-2.5 billion SEK. This might not be a huge amount considering that the socioeconomic burden of dementia in Sweden was equal to about 63 billion SEK in 2012. However, by achieving any sort of cost-savings will in the end mean that the unsustainable growth in the socioeconomic burden of dementia is hindered.

Consider the ICER-model and the cost-effectiveness plane of the ICER-model.



$$ICER = \frac{Cost\ A - Cost\ B}{Effect\ A - Effect\ B}$$

If cost-savings can be attained by implementing AI-techniques in the diagnosis of dementia. This would implicate that the relative cost-effectiveness is in either one of the areas below the X-axis. Furthermore, both of the cases signify that an implementation should at least be considered. If the relative cost-efficiency is located in area II, an implementation should definitely be carried through since the new method is dominant compared to the scenario were no implementation is made. However, if the relative cost-efficiency is located in area III, a potential implementation should be evaluated based on the extent of cost and effect.

The potential cost-savings are defined as relatively small compared to the size of dementia. This is because the estimates of the cost-savings that could be achieved by implementing AI-techniques in the diagnosis of various diseases was based on the technology that exist today. The number of studies that concern estimated cost savings in the healthcare sector are quite scare. But in the last few years, further research has provided knowledge of the tremendous potential to AI to transform the healthcare sector (McKinsey, 2016). Hence, it is possible that these estimates are underestimated and consequently the estimates from this research may as well be underestimated. Although AI-techniques show great potential, a full-scale implementation will take a few years since the digital infrastructure for an implementation to be possible does not currently exist (McKinsey, 2016).

According to estimates in the empirical data, the prevalence of dementia in Sweden appeared to be growing quicker than the prevalence in Europe. Furthermore, Socialstyrelsen (2014) estimated that the dementia population in Sweden will be approximately 250.000 in 2030. Concurrently, the Alzheimer’s Disease International (2015) report estimated that the dementia population will be about 13.420.000. This would mean that the ratio between the two will be roughly 1.86 %, which ultimately supports the estimates represented in graph 5.3 in the empirical results which presents future estimates of the dementia population ratio. Moreover, this could mean that the cost-savings that can be made in Sweden until 2025 are even further underestimated.

6.2 Efficiency Improvements from AI

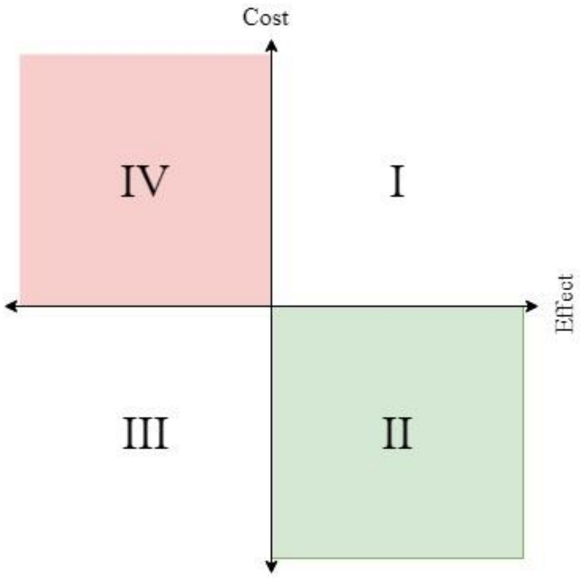
Assessing the efficiency benefits of implementing AI-techniques in the diagnosis of dementia involves examining factors such as differences in the accuracy of AI tools compared to humans, as well as the differences in error rate of diagnosis and the risk of malpractice.

Health-related data will accumulate rapidly over time and result in vast amounts of data. Healthcare data includes personal medical records, radiology images, clinical trial data, FDA submissions, human genetics and population data, etc. Newer forms of big data, such as 3D imaging and videos, as well as sensor readings, are fuelling this exponential growth (Raghupathi & Raghupathi, 2014).

This, in combination with a myriad of treatment options makes it difficult to constantly find the most efficient treatment methods. According to estimates, patients receive a correct diagnosis and treatment only half of the times on the first try (Bennett & Hauser, 2013).

Big analytics such as AI and ML are associated with the three following characteristics; velocity, volume and variety. Hence, AI-techniques can serve a valuable purpose when analysing this data. Future AI-applications of real-time data, such as detecting diseases as early as possible, identifying them swiftly and applying the right treatments could reduce patient morbidity and mortality (Raghupathi & Raghupathi, 2014).

Reducing the morbidity and mortality would affect the quality of life of those affected. QALY measures two dimensions of a patient's health, their quality of life and their life span. QALY is calculated by multiplying the extended life span with the quality of life that the patient experiences as a result of the treatment. If the morbidity and mortality of dementia are reduced, this would subsequently increase the QALY. An increase in QALY means that the cost of achieving one more level of effect is reduced.



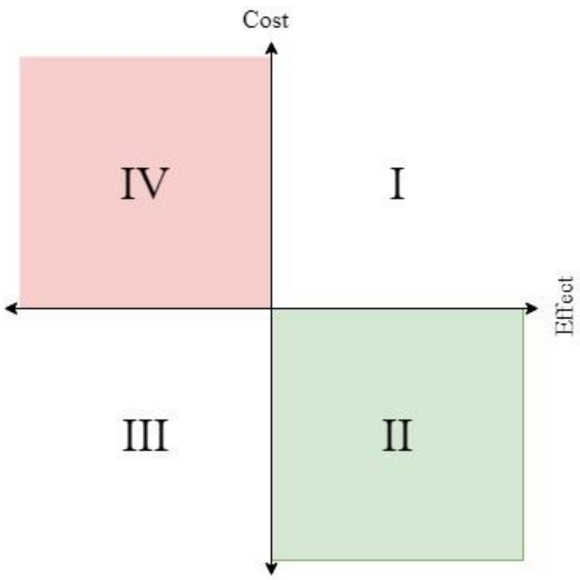
Consider again the ICER-model and the cost-effectiveness plane of the ICER-model. If an implementation of AI-techniques in the diagnosis of dementia increase the efficiency of the process, this would implicate that the relative cost-effectiveness is in either one of the areas to the right of the Y-axis. Both of the cases signify that an implementation should at least be considered. If the relative cost-efficiency, similarly to before, is located in area II, an implementation should definitely be carried through since the new method is dominant. However, if the relative cost-efficiency is located in area I, a potential implementation should be evaluated based on the extent of cost and effect.

6.3 Cost-efficiency of AI

Research on the cost and effects of implementing AI-techniques in the diagnosis of dementia has provided evidence that it could potentially lead to cost-savings as well as efficiency gains. The estimations from this research showed that cost-savings of somewhere around 1.3 – 2.5 billion SEK, depending on the decision basis, until 2025. These values may even be underestimated as a consequence of the increasing prevalence of dementia in Sweden, as well as the underestimation of the effects that AI might have.

If the future proves that AI-techniques in the diagnosis of dementia works more efficiently than current diagnosis process and furthermore, that cost-savings can be achieved, a full-scale implementation of AI-techniques should undoubtably be made.

Consider again the ICER-model and the cost-effectiveness plane of the ICER-model. If an implementation of AI-techniques in the diagnosis of dementia increase the efficiency of the process, as well as achieves cost-savings in terms of cost of illness, the relative cost-efficiency will be located in the area below the X-axis and to the right of the Y-axis. In area II, an implementation should definitely be carried through since the new method is dominant compared to the scenario were no implementation is made.



The previous research featured in this work, as well as the estimated made in the empirical data, has provided evidence that the use of AI-technologies in the diagnosis of various diseases will lead to cost-savings in the long run. Furthermore, previous research has also provided evidence of the potential efficiency that AI-technologies could have in the diagnosis of various diseases.

Moreover, because using AI-technologies is cheaper and operate more efficiently than the treatment as usual, the choice on whether to implement it in the diagnosis of dementia will be an easy decision from an economical point of view. Methods involving AI-techniques in the diagnosis process of dementia are dominant compared to the treatment and diagnosis methods used today. Consequently, they should undoubtably be implemented in the diagnosis process of dementia patients in Sweden today.

7. Conclusion & Discussion

This section contains the key finding of this research and the empirical findings are discussed and interpreted. Furthermore, the limitations of this research are discussed together with implications for future research.

7.1 Conclusion

According to the estimates of this research, somewhere between 1.3 – 2.5 billion SEK can be saved until 2025 by a full-scale implementation of AI-techniques in the diagnosis om dementia patients. The differences in the estimates depends on the assumptions made as well as the calculations basis that these estimates were based on. Perhaps the estimate of 2.5 billion should be considered more reliable since the calculations only consisted of data from Sweden and since the estimations considered Sweden.

However, implementing AI-techniques in the diagnosis of dementia has tremendous potential when it comes to cost-efficiency of treatment. Costs of diagnosis can be reduced by streamlining the diagnosis process and consequently save time, as well as reducing the risk of inaccurate diagnosis. Moreover, AI-techniques also enhances the probability of early detection which consequently might improve the quality of life for those affected.

Early detection of the dementia may serve a valuable purpose for those affected and it might allow for actions in the onset of the disease. Furthermore, at least knowing what is going on could be a relief that helps patients plan for the future, instead of being hastily overwhelmed by the deuteriation of mental health that the disease causes. But there is still a massive problem that remains, even though you might find out what is going on, dementia is chronic disease and there is still no cure. Since the healthcare system is under severe pressure and operates under a strict budget, this is something that will leave policymakers in a tricky situation. They are ultimately going to have to choose a standpoint on whether to invest funds for the implementation of AI at this very moment or, invest the same funds in the research for an eventual cure of dementia. An implementation of AI may increase patient's mental health in the short run through early detection and the inputs of care in the onset of the disease. But in the long run, the consequences of the disease are inevitable. Although, the prerequisites in terms of computing ability for an implementation of AI exist today, there are still hurdles to overcome before a full-scale implementation can become reality. The initial investment will undoubtedly be large, but it will most certainly lead to cost-savings in the long run. These potential cost-savings would liberate funds that would enable future investments in the pursuit of an eventual cure for dementia.

7.2 Digital Base

Although the potential effects from implementing AI-techniques in the diagnosis of dementia may be promising, there is still a question concerning possibility of implementation. If the prerequisites are not in place, a large-scale implementation will not be possible. This is the case because AI builds on other technology and without a digital infrastructure an implementation of AI-technologies will not be possible. Therefore, a solid digital base is essential for the tremendous potential to become reality.

The healthcare sector needs to make digitization a core subject of development and they will need to be supplied with sufficient funds to make this possible. In order for the new services to meet the requirements for efficiency, as well as safety and user-friendliness, it is important that doctors and other healthcare authorities are involved in the e-health initiatives taken at different levels in health care system.

Furthermore, the work concerning integrated medical records is an essential part of the digital infrastructure that needs to be in place for an implementation of AI to be possible. This will require extensive investment and changes in how the healthcare sector operates. Currently, no digital infrastructure with potential for AI implementation exist in Sweden. Therefore, it is crucial that decisionmakers are compelling in the issue, so that the developed system really match the prerequisites that are required for an implementation of AI to be possible.

7.3 Resistance

Even though the population in Sweden is accustomed to technology, the question still remains how AI will be received in a healthcare environment. Will people be able to trust machines and technology when it comes to handling vital data such healthcare data? Furthermore, AI can also pose a risk for doctors and patients. Since AI has not been perfected, doctors cannot fully rely on AI and still need to make decisions based on their knowledge and expertise.

Patients are also at risk for the same reason. If a program provides incorrect information, patients will not be treated properly. Furthermore, who carries the responsibility if malpractice occurs based on the information that the program provides?

Another challenge is training doctors and patients to use AI. Learning how to use technology may be a challenge for some. Likewise, not everyone is open to information given by a “robot.” In other words, accepting AI technology is a challenge that needs to be addressed through education.

Complying with regulations is also a challenge for AI in the healthcare industry. For one, there is the need for approvals from FDA before an AI device or application is applied to health care. This is especially true because AI is at a nascent stage and not a technology that is fully known or understood.

7.4 Limitations

Since there is a large treatment gap in the diagnosis of dementia, many people living with the disease is unaware that they even have it, only 20-50% of dementia cases are identified and documented. Hence, it is difficult to estimate the prevalence and cost of the disease.

Furthermore, a broad implementation of AI-technologies in operational areas has not yet happened. Hence, this research concerned something that is nearly non-existent, therefore it is difficult to examine and estimate the implications that it may have. The previous research was also quite limited which made it difficult to make reliable estimations.

Because of this, it is impossible to know the exact prevalence of dementia. The data of prevalence in this research are based on previous estimates. Consequently, the estimates for potential cost-savings might differ from reality.

7.4 Future Research

The research on cost-efficiency of AI-techniques within the healthcare sector is currently quite scarce. Consequently, more research is essential to improve the understanding of the concept and the potential consequences. Since the use of AI-techniques in the diagnosis of various diseases is in the early stages of development and that no full-scale implementations have been carried through, one could conduct a similar research when, or if, the development reaches the later stages. Consequently, such research would acquire more statistically assured estimates. However, the same purpose and research method used in this research could be applied for future research as well.

Furthermore, future research could consider the potential effects of the new legislation passed by the European Union, the General Data Protection Regulation, GDPR. The purpose of GDPR is to increases the rights and possibilities that consumers have to manage their personal data. GDPR also forces companies oblige rules concerning how this data is being used (European Commission, 2018). These prerequisites may impact the potential use of AI-techniques in the healthcare sector in terms of how the healthcare system are allowed to store and analyse healthcare data. Since healthcare data is of sensitive nature, this legislation may lead to increased demands of security for handling sensitive data. Hence, it would be fascinating to investigate the potential implications that this regulation may have.

8. References

The references follow an alphabetical order.

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