Artificial Intelligence in Psychiatric Healthcare

Exploration of Opportunities and Challenges

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Husni and Mattias

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Abstract

It is shown that when a patient with psychiatric disorder stays on sick leave for a period longer than 180 days, the chance of going back to active life (i.e. studying, working) diminishes. As a result, the Psychiatric Affective (PA) department within Sahlgrenska University hospital seeks an Artificial Intelligence (AI) solution that supports practitioners to make correct diagnosis and treatment and reduces the number of patient long-term seek leaves. This thesis will look deeper into the potentials and the challenges of implementing AI in the PA division to increase effectiveness, where effectiveness is defined as the healthcare practitioner's ability to do accurate actions in the work process. Data was gathered primarily via interviews with employees in the PA department and the Swedish Social Insurance Agency (Försäkringskassan). As well as secondary data from scientific articles and statistics from the PA division. The literature review focussed on finding a theoretical background for the implementation of AI in healthcare and the challenges associated with it. From the qualitative data analysis, the current state and the main problems in the PA department working process affecting the effectiveness were found. The finding showed the accuracy of early patient categorization, in which the referral team decides under what specialization and which practitioner the patient gets treated, have a great influence on the accuracy of diagnosis and treatment further down in the work process. A deep look into AI theories was taken to develop a conceptual AI model illustrating the hypothetical implementation of an AI method in the PA division. Afterward, the conceptual model was evaluated in terms of increasing the effectiveness in the case study; and several challenges at a different stage of implementation were identified. The thesis concludes that there is an opportunity to improve the basis for the practitioners in the PA work process to be able to make effective medical decisions using AI. As a theoretical implication, human bias, the black box effect and automation bias will be the challenges that the PA must be able to overcome to gain the potential benefits that Al can provide.

KEYWORDS: Artificial Intelligence, psychiatric healthcare, sick leave, process improvement

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List Abbreviations

Abbreviation:	Explanation:
AI	Artificial intelligence
PA	Psychiatric Affective
ML	Machine learning
ANN	Artificial neural network
CDSS	Clinical decision support system
RC	Rehab coordinator
ADHD	Attention Deficit Hyperactivity disorder
NLP	Natural language process

List of Glossary

Glossary:	Explanation:
Affective	Relating to, arising from, or influencing feelings or emotions.
Categorization	Involves determining which data is most relevant to solving the problem.
Classification	It is a systematic grouping of observations into categories, such as when biologists categorize plants, animals, and other lifeforms into different taxonomies.
Diagnose	Identify the nature of an illness or other problem by examination of the symptoms
Physician	A medical doctor who has completed graduate training to provide healthcare.
Psychiatrist	A medical practitioner specializing in the diagnosis and treatment of psychiatric disorders.
Psychiatric care	Hospitals or wards specializing in the treatment of serious psychiatric disorders, such as major depressive disorder, schizophrenia, and bipolar disorder.
Practitioner	A person engaged in the practice of a profession, occupation, etc: a medical practitioner
Referral	In medicine, a referral is the transfer of care for a patient from one clinician or clinic to another by request.
Symptom	A physical or psychiatric feature is regarded as indicating a condition of disease, particularly such a feature that is apparent to the patient.

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1 Introduction

This chapter introduces the background to the thesis, a briefcase description, the aim of the research and its delimitations

1.1 Background

During the past decade, medical costs have increased significantly resulting in an alleged lack of quality, universal affordability, and accessibility in many countries (Porter & Teisberg, 2004; Herzlinger, 2006). The worldwide concern about health cost has caused an awareness of the need for greater effectiveness in healthcare (Porter & Teisberg, 2004; Herzlinger, 2006). In response to this phenomenon, healthcare providers are striving to improve outcomes while simultaneously achieving greater efficiency (Rotter et al., 2017). As a result, many stakeholders are turning to industrial- related tools and techniques to solve these problems (Baker, 2001).

Swedish Healthcare Act (Hälso- och sjukvårdslag 2017:30) states that the main goals of healthcare are to provide good health and care on equal terms for the entire population and priority must be given to those with the greatest need. The healthcare system in Sweden is highly decentralized compared to other countries (Molin and Johansson, 2005). The Social Service Act of 1982 states that municipal social services are responsible for integrating long term patients with psychiatric disorders into society (Hans, 2004). However, the act did not stipulate the specific role of social services and psychiatric healthcare. As a result, a psychiatric healthcare reform (The Psychiatric Care Reform) was implemented in 1995 to define the division of responsibilities between social services and psychiatric healthcare. The psychiatric care was given the responsibility of managing and developing good treatment methods while the social services have been given the role of integrating the patients back to normal life (Hans, 2004). To reinforce decentralization, the state has also given the responsibilities to the county councils and the municipalities while taking a leading role in establishing principles and recommendations (Molin and Johansson, 2005). Dividing the role among the county councils and the municipalities creates a requirement for cooperation and coordination to provide acceptable service for the patients (De Koster, Le Duc, & Roodbergen, 2006). However, a study by Fredriksson shows that tension between the national government and local autonomy has started surfacing due to the central state overreaching and re-centralizing the Swedish healthcare (Fredriksson, 2012). One of these tensions is that the state is actively taking the role of the setting of the regulatory framework to provide national equity in terms of health services (Fredriksson, 2012). The psychiatric care in Sweden has been facing a dynamic environment in recent years (i.e. scared economic resources, increased number of patients, and demands for higher efficiency) (Beer & Nohria, 2009). With different industries–related solutions tried in hope of addressing the issues in Sweden, It is fair to say many of them failed to deliver the same results in healthcare as compared to other sectors (Beer & Nohria, 2009).

An emerging technological phenomenon that has been gradually integrated into people's lives in the shapes of speech-based assistants, smart cars, drones, and computer games is the advanced technology called AI (Von Krogh, 2018). AI is a concept that originates from the research field data science and can be described as a computer's or robot's ability to mimic human intelligence with a special emphasis on its cognitive functions (Haenlein & Kaplan, 2019). The main distinguisher from smart software is the AI's ability to autonomously and adaptively learn from data to generate either desired or new outcomes

(Haenlein & Kaplan, 2019). Due to AI's adaptive and autonomous abilities, many organizations today have adopted the technology to pursue greater economic and organizational value. The impact of AI, therefore, creates new opportunities and challenges that have reached the attention in the management research field. Since the usage of AI technology has been significantly increased in organizations to perform different tasks such as application for organizational positions, recommendations of products, financial transactions, scheduling complex logistics, diagnosing patients, and suggesting therapies (Von Krogh, 2018).

In medical literature, AI has been present since the 1970s (Shortliffe, 2012: Szolovits et al., 1988). Where a developing trend has shown that the performance of AI predictions of diagnosis and treatment has gradually achieved higher accuracy throughout the years (Davenport & Kalakota, 2019). Furthermore, in the last decade AI technology has managed to achieve high performance within oncology where cancer tumours in patients are predicted with over 90% accuracy (Jiang et al., 2017). Moreover, the adoption of AI in healthcare is still in the early days, there is a scarcity of documented organizational issues due to its implementation (Huss, 2018).

Although AI has incrementally been adopted in several areas within the healthcare sector it has not yet been able to achieve the same success within psychiatric healthcare. A reason behind that has to do with that physicians in psychiatric healthcare cannot rely on similar standards as in other medical areas such as in oncology or cardiology (Rosenfeld & Benrimoh, 2019). Where physicians often can rely on pathological analysis e.g. blood tests, as confirmation of the diagnosis. Because of that practitioners in psychiatric healthcare are heavily reliant on patient and clinician questionnaires. Which poses a unique challenge for the application of AI within that specific medical area (Rosenfeld & Benrimoh, 2019).

1.1.1 Case description

The Psychiatric affective (PA) is a department within Sahlgrenska University hospital that is specialized in the diagnosis and treatment of patients diagnosed with psychiatric disorders. At PA they recognize the potential of AI technology in healthcare but have not experienced its practical use in psychiatric healthcare. Therefore, they have requested an investigation regarding what potential benefits and challenges AI technology could imply for them in their pursuit of the goal of reducing the number of patients on long-term sick leave. When a person has been on sick leave for over 180 days, it is referred to as long-term sick leave and the reason why they want to reduce the duration is due to the harmful effect of being absent from work. It is statistically shown that the chance of a person returning to work decreases the longer time he or she is staying home. Moreover, most of the patients that get referred to the PA department are already long-term sick leave patients. Therefore, there is a sense of urgency within the department to develop a solution that results in the patients getting accurately diagnosed and receives the right treatment at the earliest moment possible (PA, 2019).

Since the PA department receives over 3000 different patients annually that to a large part have been on long-term sick leave, there is a need to improve the efficiency of their patient process. With the goal of achieving a faster way to perform accurate diagnosis and successful treatments to reduce the duration the patient needs to be on sick leave (PA, 2019).

1.2 Aim

This thesis aims to contribute with knowledge of how AI technology can improve the effectiveness of diagnosis and treatment in psychiatric healthcare. Where effectiveness is defined as the healthcare practitioner's ability to do accurate actions in their work process.

1.3 Research questions

To meet the aim of the thesis, the thesis will address the following two research questions:

1. What are the potential benefits of implementing an AI model in psychiatric treatment processes?
2. What kind of challenges would the adoption of the AI model impose?

1.4 Delimitations

Due to a limited time frame for this master's thesis, it was not feasible to both develop and implement an AI model in a psychiatric healthcare treatment process. Hence, the thesis will consider a hypothetical implementation of an AI model within the context of psychiatric healthcare. This implies that the scope of the research will be on discovering theoretical assets and complications AI usage would create in the work process.

1.5 Disposition

The remainder of this thesis is organized as followed: Chapter II presents the theoretical framework, chapter III entails the selected research approach, chapter IV describes the findings of the case study, chapter V includes the analysis and the results, chapter VI contains the discussion, chapter VII provides the conclusion and answers to the research questions of the thesis.

2 Theoretical framework

In this chapter the theoretical framework of the thesis will be presented. The theory will be portrayed in a narrative literature review approach. Where firstly the link between AI and healthcare will be described. Secondly, the fundamentals in AI theory will be presented, and lastly the challenges in the AI research field.

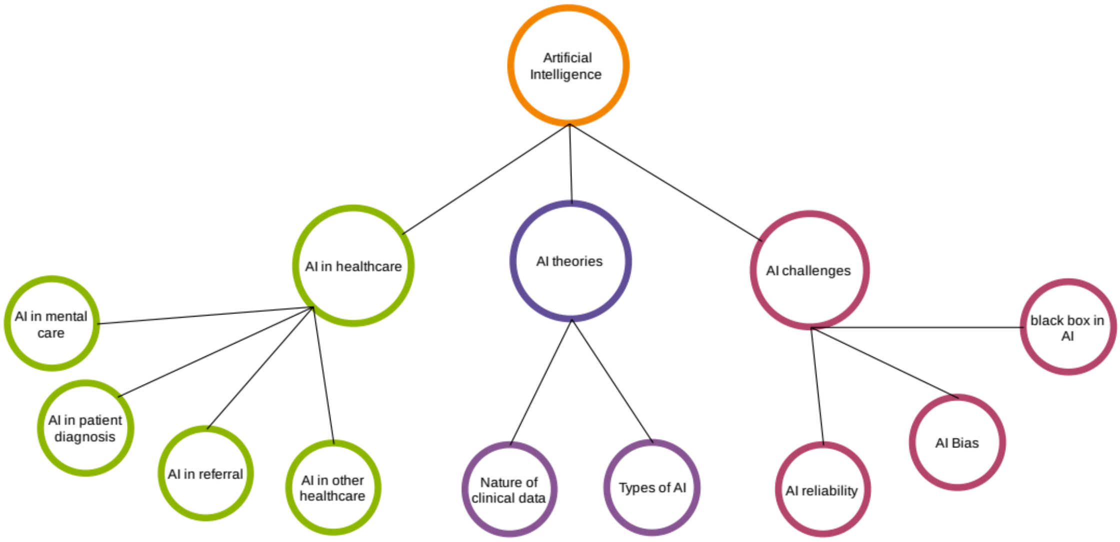

Figure 1 : Theoretical framework structure

A deep literature review has been conducted to understand topics related to artificial intelligence, specifically artificial intelligence topics related to healthcare service. From literature reviews, AI in different parts of the healthcare process will be addressed in the following section. Furthermore, AI theories and challenges will be discussed (Figure 1).

2.1 AI in Healthcare

There are several benefits to the psychiatric healthcare field with the advancements of AI. By having AI that can learn, understand, and develop reasoning, the technology can support healthcare physicians with testing, diagnosis, care treatment, and clinical decision-making (Luxton, 2019). Within the core of AI lies the ability to learn autonomously. This part of AI is what is called machine learning (ML) (Samuel, 2000). ML is especially useful in psychiatric and psychiatric healthcare since it can be used to recognize patterns in electronic health records to reveal risk indicators or highlight factors that are connected to a patient outcome (McFowland, Speakman, & Neill 2013). Therefore, ML can be used for predictive analysis and modeling to predict future patterns that could assist healthcare practitioners by reducing uncertainty in decision-making processes.
Within the core branch of ML is the technique called Artificial Neural Network (ANN). The common application of ANN today is computer vision, handwriting, and speech recognition (Haykin & Network, 2004; Jain, Mao, & Mohiuddin, 1996). ANN has been tested in psychiatric healthcare to predict the length of the hospital stay for patients with psychiatric diagnosis and response to OCD treatment (Salomoni, 2009).

Another AI method that is called an expert system has been applied in healthcare to create a Clinical decision support system (CDSS) (Finlay, 1994). The CDSS is designed to support clinical decision-making and commonly uses ML and ANN techniques to function. Since ML and ANN enable the CDSS to generate recommendations for decision without having to be pre-programmed with case-specific knowledge. The technique that enables this is called fuzzy logic which is a method of reasoning that approximates values rather than generate binary output, e,g, percentage of true or false (Finlay, 1994).

2.1.1 AI in Referral process

The increases in demand and shortage of resources are making researchers focus on the referral process. Specialty care complained that many patients coming from referral primary care are often accompanied by referrals that lack enough quality and information (Horner, Wagner, & Tufano, 2011). A study in the United States by Mehrotra et al. (2011) shows that out of ten referrals, more than six referrals lack enough quality and information (Mehrotra, Forrest, & Lin, 2011). Due to this fact, most of the referrals will either be rejected or turn in back for more information. Furthermore, delays between referrals and specialist appointments can result in lapses in communication between providers, duplication of services, and overall dissatisfaction (Liddy, Drosinis, & Keely, 2016).

Different studies have been conducted to suggest different interventions in the referral process to better manage referrals flooding into special care. Demand management, although often thought of as a means solely to limit the volume of referrals from primary to secondary care, is a term that is used in a much broader way to refer to any method that has the aim of monitoring, directing or regulating patient referrals (Blank et al., 2015). Blank et al., (2015) conducted a rigorous systematic review of literature conducted globally to study different interventions on the referral process in the hope of finding an intervention that will be applicable in the UK healthcare context. In the study, Blank et al., (2015) reviewed 286 papers in total and categorized different interventions suggested by the researchers into four groups, namely primary care education, Process Change, System Change, and Patient inventions. System change is large changes impacting all referrals made which involved the movement of staff or relocation clinics, the methods in which all referrals were triaged at the hospital, or financial arrangements for referrals (Blank et al., 2015). Out of the paper reviewed by Blank et al., 2015, six papers suggested referral management centers as gateways between primary care and specialty care. However, only one paper reported an unbiased positive effect from the interventions while three papers report negative or no effect.
Some companies have reported successful AI interventions in the referral process with a higher success rate. One of the companies that are using artificial intelligence to screen patients' medical journals to predict psychiatric disorders is Quartet Health. For instance, Quartet Health can determine if a patient has a potential of anxiety disorder based on the previous medical history of a negative test from cardiac-related disease and recommends cautionary follow-ups for a patient with a history of major illness (Parie & Sam 2018). In their Home page, Quartet Health claimed to have reduced emergency room visits and hospitalizations by a quarter (Quartet Health, 2018).

In 2018, around 410,755 visits have been recorded in psychiatric healthcare in Sweden, of which 4.8 % of patients that visited the specialty psychiatric care are an adult (aged ≥ 18)(Psykiatrin I siffror Vuxenpsykiatri Kartläggning, 2018). After the wake of the psychiatric reform act, many hospitals and regional authorities have begun appointing consultant companies to improve the link between them (general practitioner) and primary care (Wadmann et al., 2009). Among the activities the consultant company tasked, develop guidelines for referral procedures is the main responsibility (Wadmann et al., 2009). However, the hiring of the consultant companies failed to yield a significant improvement in terms of coordination between the primary care and general practitioner (Wadmann et al., 2009).

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2.1.2 AI in patient diagnosis

Psychiatric health misdiagnosis is a very common phenomenon that affects the overall patient experience in psychiatric care (Chasnoff, Wells, & King, 2015; Nasrallah, 2015; Reading, 2015). This is due to the complex and overlapping nature of the psychiatric disorder. Hirschfeld and his colleagues reported that the misdiagnosis rate for bipolar disorder could reach as high as 69% (Hirschfeld, Lewis, & Vornik, 2003). However, Shen et al. (2018) showed that the misdiagnosis rate of bipolar disorder was 76.8% in China (Shen et al., 2018). Misdiagnosis is also common in other psychiatric disorders like ADHD and depression which is sometimes misdiagnosed as bipolar or vice versa. For instance, a study by Berardi et al. (2005) found that 45% of referred patients with depression did not meet the criteria for depressive illness and 25 % of the misdiagnosed patient has been given the treatment for depression (Berardi et al., 2005). Similarly, a presumed 25–50% of children diagnosed with ADHD fail to meet the diagnostic criteria to make a diagnosis of ADHD (Michael & Rackley, 2012). The standard that is universally followed by physicians is the Diagnostic and Statistical Manual of Mental Disorders. Which serves as an authoritative guide that contains descriptions, symptoms, and other criteria for diagnosing psychiatric disorders. However, despite introducing new and improved sets of diagnostic criteria, (DSM-V) suffers from relatively low reliability in clinical settings because of its inability to consistently identify false positives and distinguishing risk from disorder (Wakefield, 2016).

Having a correct diagnosis at the early stage of patient treatment in psychiatric disorder is the essential step in the path to recovery as the treatment can be conducted in a timely fashion. The earlier the correct diagnosis and treatment, the greater the chance that the patient will recover (Shen et al., 2018). Further implications of misdiagnosis involve the cost for families that have a child assessed and treated for ADHD as well as costs within the healthcare system (Elder, 2010).

2.1.3 AI in psychiatric care

The potential of AI in the field of psychiatric healthcare to predict psychiatric disorders has been stressed by many researchers across the globe (Chandler, Foltz, & Elvevåg, 2019). IBM Research developed a machine learning speech classifier with 79% accuracy in predicting psychosis onset in those with clinically high risk (Corcoran et al., 2018). While Jaiswal et al. (2017) conducted a study to show how computer vision can detect ADHD and ASD with 96% accuracy based on video analysis of a person's behavior (Jaiswal et al., 2017). The ability of AI to analyze a set of big data and to transform it into useful patient information in a very short time is another aspect of AI that makes researchers aspirants implement AI in psychiatric healthcare. After analyzing the clinical note of the U.S. veterans from a national sample of U.S. Veterans Administration (VA), Poulin et al., (2014) successfully developed a model that predicts the risk of suicide (Poulin et al., 2014). After studying 75 veterans, the study group was classified into three classes based on matched cohorts and generated set of single keywords and multi-word phrases that can be used to categorize future veterans into the identified classes which are ''Veterans who committed suicide, veterans who used psychiatric health services and did not commit suicide, and veterans who did not use psychiatric health services and did not commit suicide ‘’(Poulin et al., 2014). Their model predicted the risk of suicide with 65% accuracy. Achieving such high accuracy with a small number of sample sizes (75) emphasizes the potential of the AI in the prediction of psychiatric disorder. Another impact AI can make in healthcare is a decision support system where the AI learns from previous clinical historical treatment plans and contracts an efficient plan for a new patient. Researchers have successfully formulated treatment planning with improved efficiency by using statistical models they developed from prior “good” cases based on best clinical judgment and knowledge and features from a current case as inputs (Wang et al., 2019).

Another way researchers have studied the potential of AI in prediction and/or diagnosis of psychiatric disorder comes from computational psychiatry where genetics and neuroimaging biomarkers are used to effectively improve understanding, prediction, and treatment of a psychiatric disorder. Current approaches for the diagnosis of psychiatric disorders largely rely on physician-patient questionnaires that are most of the time inaccurate and ineffective in providing a reliable assessment of symptoms (Fakhoury, 2019). Translating advances in neuroscience into benefits for patients with psychiatric disorders presents enormous challenges because it involves both the most complex organ, the brain, and its interaction with a similarly complex environment (Huys, Maia, & Frank, 2016).

2.1.4 AI in other heath illness

The development of the applicability of AI in healthcare is slower compared to the manufacturing industry. However, in recent years AI has achieved a great deal of success in the disease diagnosis. Physicians are expected to remember thousands of diseases they learned in medical school while keeping in a tap of the ongoing development and update in the field. This is part of the major challenge in medical imaging, where real-time errors are estimated to average between 3 % and 5 % (Lee et al., 2013). Diagnosis error accounts for nearly 29 % of total ambulatory malpractice claims (Graber, 2013). As reported by Dilsizian & Siegel, machine learning and other AI systems have the potential to be less susceptible to cognitive biases and, despite their limitations, can serve in a complementary role to human decision-makers (Dilsizian & Siegel, 2014). Currently, AI has been providing support for physicians in image processing for cardiological diagnosis. If applied properly, AI could reduce inappropriate imaging studies and help physicians adhere to practice guidelines and ever-changing appropriate use criteria (Dilsizian & Siegel, 2014). It will not long before AI starts to be applicable in another part of healthcare.

2.2 Artificial intelligence theory

In this section different AI theories will be introduced. The nature of clinical data will be addressed, followed by an introduction of different AI techniques that have been used in healthcare. Furthermore, commonly used AI training methods will as well be described in this section.

2.2.1 Nature of clinical data

Training AI to perform some activity is an imitation of early child development. Before the AI performs the intended activity, here the activity refers to categorizing, association, and outcomes of interest, the AI must be trained on healthcare data that is collected from clinical activity such as diagnosis, treatment assignment, and screening (Jiang et al., 2017). Healthcare data can take forms of demographics, medical notes, recording (in the form of image and graphics reading) from a medical device, physical examination, and result from a clinical laboratory (U.S. Food and Drug Administration, 2013). The hospital data can be classified as structured and unstructured data. Compared to unstructured data, structured data can easily be identified and extracted, however, it gives no legit information when individual data is taken out of the clinical setting (Abhyankar, Demner-Fushman, Callaghan, & McDonald, 2014).

Structured data can be generated from different sources. Major sources for structured data include but not limited to demographic data, lab results, prescription, international disease classifications code, healthcare practitioner assigned to the patient, and intervention (Scheurwegs, Luyckx, Luyten, Daelemans, & Van den Bulcke, 2015). Unstructured data, on the other hand, have free-text or semi-structured format and constitute more than two-third of clinical data (Sytrue, 2015). Sources for unstructured clinical data includes Letters, journal (e.g., summary represented by a nurse in doctor meeting), and attestations (e.g. sick-leave letter written by a doctor to Försäkringskassan) (Scheurwegs et al., 2015).

2.2.2 Types of AI

AI techniques/methods mainly classified into three namely, machine learning, deep learning, and natural language processing (NLP) (Figure 2). A major focus will be given to machine learning and different algorithms used in machine learning. Followed by a brief discussion about deep learning, natural language processing (NLP), and their usage in healthcare.

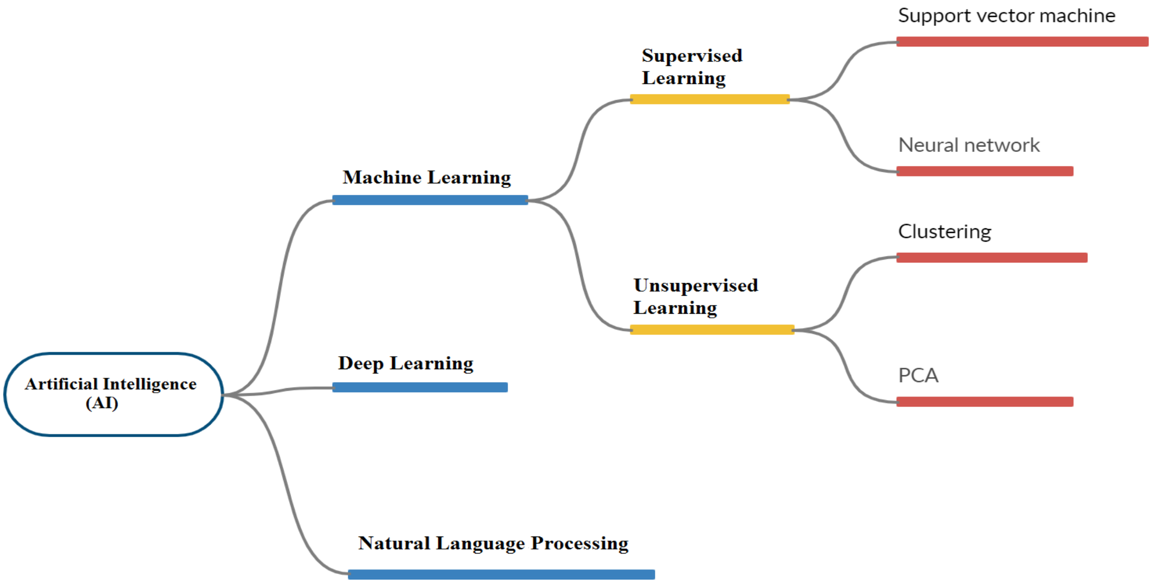

Figure 2 : Artificial intelligence

Machine learning

Machine learning trains on structured data and when these techniques are used in healthcare, it attempts to cluster patients' traits and predict the disease out with calculated probability (Darcy, Louie, & Roberts, 2016).

Machine learning can be easily explained by separating its three main processes which are used to fetch features from the data. The first part is the input, as it discloses above, the input to the machine learning in the medical arena is clinical structured data. Clinical data include patient traits and data related to the specific disease. Patient traits include demographic data, administrative data, health status, and patient-specific medical history such as diagnostic imaging, physical examination results, symptoms, medication, and so on. On the other hand, data related to a disease mostly are a finding from medical researches and include disease indicators, patient's survival times, and quantitative disease levels (Jiang et al., 2017). The second part of machine learning is the algorism, which is a program that is responsible for learning from the data. ML algorithms can be classified into two categories depending on the outcome it produces (Jiang et al., 2017).

I. Supervised learning

Supervised learning is a process where the algorithms train on input (patient traits) with outputs and develop a relationship and predict the best outputs associated with future inputs. Supervised learning is a common AI application used in healthcare to produce clinically relevant outcomes such as a forecasted clinical event, disease level, or the expected survival time (Jiang et al., 2017). The techniques that the algorithms used to develop a relationship between input and outputs include linear regression, logistic regression, naïve Bayes, decision tree, nearest neighbour, random forest, discriminant analysis, support vector machine (SVM) and neural network (Goodfellow, Bengio, & Courville, 2016). Among the techniques, two mostly used in healthcare will be discussed below.

A. Support vector machine

SVM is mainly used to find the optimal decision boundary that separates any given two groups by training and classifies the subject into either of the groups with the smallest possible misclassification error (Jiang et al., 2017). In SVM, the determination of optimal decision boundary between two groups is a convex optimization problem, therefore convex optimization tools must be used to determine the global optimum solution (Jiang et al., 2017). SVM has been a core topic in much AI-related medical research. For instance, Orrù, Pettersson-Yeo, Marquand, Sartori, & Mechelli (2012) applied SVM to identify imaging biomarkers of neurological and psychiatric disease. Sweilam, Tharwat, and Abdel Moniem (2010) studied the use of SVM in cancel related diagnosis. SVM is also used in the detection of Alzheimer’s disease (Khedher, Ramírez, Gorriz, Brahim, & Segovia, 2015).

II. Unsupervised learning

Unsupervised learning is the process where the algorithms work on the input data (pure unstructured noise) without receiving any guidance or feedback (i.e., target output and reward from the environment) and build representations of the input by extracting features. The output from unsupervised learning can be used for decision making, predicting future inputs, and structured data inputs for supervised learning (unknown resource please find the resource). Unsupervised learning is commonly used in big data analysis to increase the efficiency of supervised learning by reducing the dimension of the data or dividing it into sub-group (Jiang et al., 2017).

Unsupervised learning has two major learning methods called Clustering and Principal Component Analysis (PCA) (Farina et al., 2017).

A. Clustering

Clustering uses algorithms like k-means, hierarchical, and Gaussian mixture clustering, it groups subjects with similar traits into clusters and labels the clusters (Farina et al., 2017).

B. Principal component analysis

PCA is one oldest and most widely used analyzing method which is used to reduce the dimensionality of a large dataset without losing its statistical or other information (Jolliffe & Cadima, 2016). For example, PCA can be used in genome-wide association study (GWAS) where genes marker of the entire sets of DNA of many people are scanned and transferred onto a few principal component (PC) directions where clustering than used can to group the subject (Farina et al., 2017).

Neural network

When the relationship between the input and the output are not linear and hidden by different layer prespecified functionals, neural network algorithm can be used to estimate future output with a minimized error (Farina et al., 2017). These technologies have also been used by different researchers in recent years in an AI-medical area. Khan et al. (2001) used the neural network to categorize tumors after analyzing 6567 genes (Khan et al., 2001). Similarly, Dheeba et al. (2014) used the technology to find tumor indicators for breast cancer after analyzing texture information from mammographic images (Dheeba et al., 2014). On the other hand, a more complex neural network model was used by Hirschauer, Adeli, & Buford (2015) to diagnose Parkinson's disease-based symptoms, and neuroimages (Hirschauer et al., 2015).

Natural language processing

As much of the clinical data generated from healthcare are unstructured and have text format, it is difficult to analyze using machine learning techniques. Hence, NLP is used to analyze and extract information from unstructured data and assist clinical decision making (Manning & Schütze, 1999).

In NLP, unstructured clinical data will go into two processes. In the first process, which is called text processing, the NLP is responsible for identifying disease/medical related keywords in the clinical notes based on the historical databases (Afzal et al., 2017). Then, the identified keywords will be selected based on the role on distinguishing the normal cases from abnormal cases, then those distinguishing keywords will be used as structures data input for machine learning (Afzal et al., 2017)

In recent years, the usage of NLP has increased in clinical decision making and to that effect, many researchers have come out with impressive studies. For example, Fiszman, Chapman, Aronsky, Evans, & Haug (2000) showed that introducing NLP for reading the chest X-ray reports would assist the antibiotic assistant system to alert physicians for the possible need for anti-infective therapy (Fiszman et al., 2000). Miller et al. (2017) used NLP to automatically monitor the laboratory-based adverse effects.

Deep learning

Deep learning is the latest development in data science and an extension to classical neural network techniques in machine learning (i.e. many neural networks layers) (Jiang et al., 2017). The unprecedented increase in the volume and complexity of data have paved a way for the advanced technology as the classical neural networked failed to explore complex non-linear patterns in the data (Dilsizian & Siegel, 2014).

2.3 Artificial intelligence challenges

The competition between human and AI in terms of performance has been a question for several researchers (Brinker et al., 2019; Esteva et al., 2017; Kermany et al., 2018). AI has outperformed humans in some tasks while it is very far from doing 'all things a human does 'as predicted by AI pioneer Herbert in 1965. One of the tasks that the reliability of AI has been questioned is in clinical practices. A research paper by Shen et al. (2018) has shed some light on this topic (Shen et al., 2018). In the paper, a systematic literature review has been conducted to compare the performance of AI with human clinicians in diagnosing a patient. After reviewing nine articles, the paper concluded that performance of AI was at par with that of clinicians and exceeded that of clinicians with less experience with the help of performance indicators like diagnostic accuracy, weighted errors, false-positive rate, sensitivity, specificity, and the area under the receiver operating characteristic curve.

2.3.1 Input data format Confirmability

As different algorithms have emerged with the potential of analyzing big data, collection of data from different sources has become the norm in different industries to allow the AI to extract useful information. As a result, the collected set of big data became heterogeneous in their nature and raised the need for capturing and curating data from different sources and transformed into a uniform format. Anagnostopoulos et al. (2016) have suggested a solution to systematically deal with heterogeneous data without losing its "4V" (i.e., volume, velocity, variety, and veracity) characteristic (Anagnostopoulos et al., 2016). As a solution (shown in Fig below), several layers of middleware protocol are developed with their internal transition map of common language format for translating different data formats (Anagnostopoulos et al., 2016). The internal transition map then creates individual interoperable data sources (Anagnostopoulos et al., 2016).

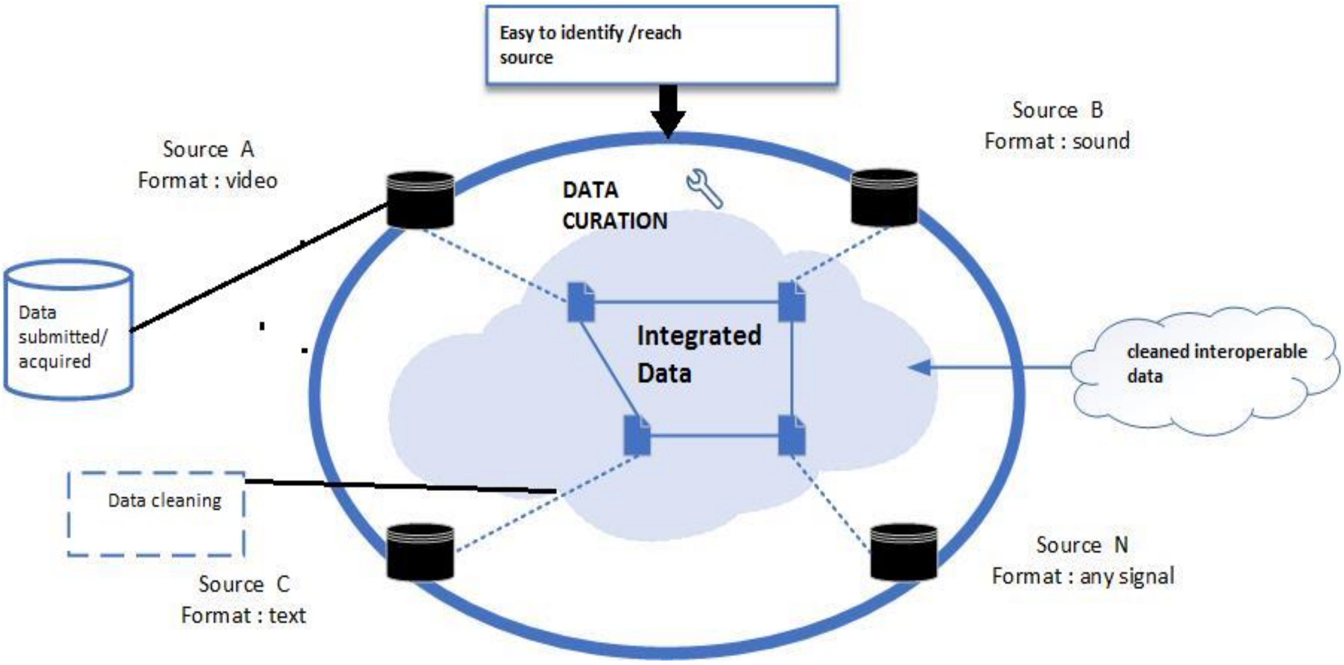

Figure 3: Internal transition map adapted from Anagnostopoulos et al., 2016

2.3.2 Bias in artificial intelligence

The technical advance in technology has led to the rapid growth of algorithm usage in service industries to potentially reduce human bias. However, different stakeholders have shown concern about the potential of unintended and undesirable biases within intelligent systems (Gu & Oelke, 2019; Koene, 2017). In this section, different literature addressing common bias in artificial intelligence will be discussed.

Bias in training data

Both qualitative and quantitative data can be biased. Qualitative data are by their nature subjective, therefore could carry human bias into the AI model. (Baer, 2019a). Even though quantitative data are objective in their nature, it can be biased in two ways. Quantitative data can be biased via the process of subjectively collecting/measuring its values (Baer, 2019a). Sometimes, the values of the quantitative data can also be a subjective element like rating (Baer, 2019a). Training data could also be biased due to conceptual flaws in the sampling approach where the sample failed to be a true representative of the populations (Baer, 2019a). For the machine to predict a future event or decide on certain stimuli, it must learn the pattern and the governing rule from past examples. If biased past decisions or patterns are presented in the training data, the machine uses them as an example and continues the bias cycle. Numerous reports of such activity by the machine have come out in recent years. For example, Mac Namee, Cunningham, Byrne, and Corrigan, (2002) reported a bias problem encountered in a machine learning approach to outcome prediction in anticoagulant drug therapy predicting clotting time for the patient. Where the ANN has predicted with 30% greater accuracy human physical but showed biased toward a frequently occurring outcome in the data and makes more false diagnoses for rarely occurring events.

Algorithmic bias

The tendency of being biased does not exist in machines, rather it is passed on by human programmers into the algorithms intentionally or unintentionally. However, developers and data scientists have a cognitive bias and they unintentionally pass it to the algorithm they develop. In the book called 'Understand, Manage, and Prevent Algorithmic Bias' the author, Tobias Baer discussed where the algorithmic bias comes from based on human psychological behaviours. According to Baer, the main sources of algorithmic bias are Confirmation Bias, Ego Depletion, and Overconfidence (Baer, 2019b). Confirmation bias is mostly detected in model design where the algorithms are asked a biased question and as a result, produced a biased answer (Baer, 2019b). Ego depletion is a natural way minimizing cognitive load as a result of psychiatric fatigue which in turn opens a door for introduction or increasing biases in the work (Baer, 2019b). Overconfidence is the effect of overlooking by data scientists' different signals of bias indicators in the model (Baer, 2019b).

Automation bias

As the frequency of autonomously made decisions increases in daily life, the decision and recommendation coming out of the artificial intelligence system will be more trusted. Number of researches have shown that humans tend to follow an automated directive or recommendation, either without verifying it with other sources or despite contraindications from other sources of information (Bond et al., 2018; Mosier & Skitka, 1999; Parasuraman, Molloy, & Singh, 1993; Skitka, Mosier, Burdick, & Rosenblatt, 2000).

2.3.3 Black box

The ability of modern artificial intelligence algorithm techniques like ANN and SVM to perform more than the traditional techniques is linked with the model's ability to work behind a 'closed-door' called a black box. In the black box, the model does not explain the predictions it makes (Adadi & Berrada, 2018). This property is particularly a challenge for the usage of artificial intelligence in healthcare where ethical principle forces healthcare providers to explain the patient to allow them to make an informed decision (Olejarczyk & Young , 2020). In terms of the doctors and the patient's interest, AI transparency is very essential in healthcare (Shortliffe & Sepulveda, 2018). This is because it is very important to check the safety of the prediction, ensure safe interpretation and avoid the bias of these predictions, especially during the development and regulation stages (Montavon, Samek, & Müller, 2018). Having an obscure model will also crush the trust of AI among healthcare practitioners and patients (McKelvey, Ahmad, Teredesai, & Eckert, 2018). Besides, in recent years, many countries are adopting regulation about the right of an explanation. For example, in 2018 the EU adopted the General Data Protection Regulation (GDPR), which contained a recital stating the right of explanation for the decision reached by AI. To face the black box challenge, developers in the past were forced to choose between developing a higher-performing model and developing explainable mode (McKelvey et al., 2018). In recent years more advanced algorithms have been developed to fix the conflict between accuracy and interpretability. However, their usability is still to be seen in the healthcare decision support system.

3 Method

In this chapter a description of the choice of research strategy and design, and research process was used to answer research questions. Besides, the choice of data collection methods and data analysis methods will be revealed and explained. Followed by a description of the quality of the research in terms of reliability, validity, and ethical considerations.

3.1 Research strategy and design

In this thesis a qualitative research strategy will be followed due to its compatibility with the explorative nature of the study's research question as well as the possibility of capturing the healthcare professional's perspective regarding the adoption of AI technology. According to Bryman and Bell (2011) research strategies can either take a qualitative, quantitative, or mixed-method approach. Where qualitative research emphasizes on subjective assessment of collected data from behavior, opinions, impressions, etc. Thus, making the qualitative research strategy an appropriate approach for the aim and research question of this thesis.

Research strategy also consists of the way it orientates with theory. Commonly, a research strategy either pursues an inductive or deductive approach. Where the inductive approach entails the collection of data and the generation of theory from it to explain the phenomenon in the data (Bryman & Bellman, 2011). This thesis will follow the inductive approach since the aim and research question of the thesis consists of unexplored areas in research. Hence, making the deductive approach less viable.

Due to the explorative nature of the research question and the aim to seek new information about artificial intelligence within a context where it is rarely used, the researchers recognized that the choice of research design for this study should follow a case study design.
The choice of research design described how the researchers will collect, analyze, and prioritize different parts of their study. The case study design is a popular approach to use within qualitative research due to the possibility of studying the case or the context in-depth where the phenomenon will be studied (Bryman & Bell, 2011). Hence, making this design an appropriate choice of design to use since artificial intelligence within the context of psychiatric healthcare is scarcely found within the current literature.

3.2 Research process

Figure 4 below illustrates how the research process in this thesis was generally outlined. Furthermore, as depicted in the figure, a description of each phase in the research process will be in this section.

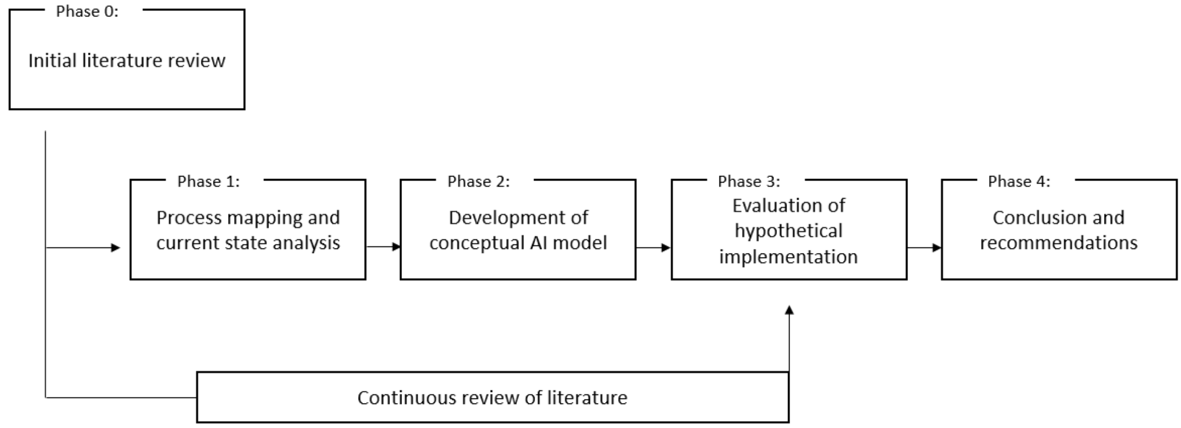

Figure 4: Research process

Phase 0: Initial literature review

Before any empirical data collection, the researchers underwent a literature review regarding the topics; healthcare, psychiatric healthcare, and artificial intelligence. This literature review would serve as an overview of the context that the researchers would engage in to study the phenomenon of AI. Furthermore, the initial literature review in combination with the researcher's previous educational background provided the fundamental foundation for the development of the research process and future interview questionnaire. Once an overall understanding of the current literature about healthcare and artificial intelligence was established, the data-gathering phase could be initiated.

Phase 1: Process mapping and current state analysis

To pursue the aim of delivering an answer regarding what the benefits and challenges with an AI implementation in the PA department would yield, the researchers decided that the thesis would be divided into three main contents. The first part would consist of a description and mapping of the current working process and will be conducted to gain a comprehensive understanding of how the PA department manages and treats their patients. Thereafter, the findings would be analyzed with the focus directed on the factors that affect the effectiveness of the work process. Where effectiveness is defined as the healthcare practitioner’s ability to do accurate actions in the work process. This further enables the patient to receive a successful treatment that results in them recovering from their disease.

Phase 2: Development of a conceptual AI model

When the current state of the PA department working process had been depicted and the most critical area of improvement related to the aim of this research had been identified, the researchers initiated the development of conceptual AI models. This phase of the research process would serve as the second main content of the thesis where the implementation would be illustrated with the use of a conceptual model. A conceptual model was used due to its ability to create a representation of a system and aid users or readers to further know, understand, or simulate a subject the model represents (Tatomir et al., 2018). Hence, being an appropriate method to use to illustrate how the hypothetical implementation of an AI method would be established.

Phase 3: Evaluation of the hypothetical implementation of AI

Phase 3 is considered by the researchers as a part of the second main content. In this phase the researchers created criteria based on the literature to assess whether the AI would be feasible or not within the current state in the case study. Further, based on the empirical material, further assessment of the benefits and challenges would be analysed and elaborated concerning the aim and research questions of the thesis.

Moreover, the authors also were mindful of the limitations of this study. Hence, variables such as development cost, time, etc. did not be taken into consideration while evaluating the AI.

Phase 4: Conclusion and recommendations
The third and last part of the thesis would serve as a summary of the results and answers to the research question. In this phase a futuristic discussion would also be included to provide recommendations for future research on this topic.

3.3 Data collection

The data that got collected and used this thesis is acquired mainly through qualitative methods. Most of the data that was used to describe the working process at the Psychiatric affective got collected through semi-structured interviews (Bryman & Bell, 2011).
For the evaluation of the conceptual model and as a foundation for answering the research questions, thorough theoretical research was conducted. Also, the researchers acquired some secondary data from the participants at the PA department. This data was further used to highlight the results of the thesis.

3.3.1 Interviews

During the case study at the PA department, 10 interviews were held with 11 different employees. Most of them working as different healthcare practitioners at the PA department and two participants working at the Social Insurance Agency, Försäkringskassan (see Table 1). The average time spent per interview session was approximately one hour. Where each interview session was prepared with a questionnaire. The questionnaires were developed to ensure that the received data from the interviews related to content that could aid to describe the PA working process. Therefore, choosing semi-structured interviews as a data collection method was appropriate for this thesis. Semi-structured interviews allowed for validity but also the opportunity to collect important contextual data that might have gotten lost in a more formal structured interview (Waller et.al., 2015). Further, the questionnaire itself had one main structure that remained the same throughout the duration of the data collection phase. That was possible because the questionnaire included open questions that were adaptable to any interview participant that was interviewed, which simplified the transcription as well. The general interview template that was used for all participants can be found in Appendix A.
Most of the interviews were held face-to-face at different Psychiatric receptions. That was advantageous because the researchers could clarify any of the questions or follow up with other questions. Furthermore, the method also allowed for collecting more data beyond the answer itself. The tone and body language of the respondent could be taken into consideration which fulfilled further value to the data that was collected.
After each interview session, the researchers had a recap meeting to ensure that a common perception about the session was established. Where the notes taken during the interviews were refined into more detailed transcriptions. This was necessary as all interviews except for one were conducted in Swedish, on the behalf of the interviewed participants. This would become a language barrier for the researchers as one of them is none Swedish speaking. Implying that some collected data might have been exposed to researcher bias during the translation which could have made the data less objective.

Table 1: List of interviewees.

Organization	Number of interviews	Role	Method
Psychiatric Affective	4	Psychiatrist	3 face-to-face, 1 phone call
Psychiatric Affective	2	Psychologist	Face-to-face
Psychiatric Affective	2	Rehab coordinator	1 face-to-face, 1 phone call
Social Insurance Agency	1	Insurance investigator	Video conference
Social Insurance Agency	1	Medical consultant, ex physician	Video conference

3.4 Formation of a theoretical framework

Bryman and Bell (2011) emphasize the importance of reviewing the existing literature in most research projects. This has to do with the fact that the literature review fulfils two main purposes. The first being acquiring specific information about the relevant research area to the research and the second is how that information will impact the research in terms of research questions, approach, and process.
In this thesis, theoretical research was conducted in two main phases. The first of the theoretical research served the purpose of formulating informational background for the researchers to further comprehend the environment in the case study. Then, as the research progressed, the theoretical research would focus more extensively on the topic of artificial intelligence. While being carried through a traditional narrative approach. The narrative approach to the literature review implies that the researchers, instead of having a deeper focus in any specific theoretical area, pursue the literature review with a wider scope (Bryman & Bell, 2011). This approach was suitable for this thesis due to the mixed areas of research areas that were included in this thesis.
The main sources that were used to search for the literature were mainly through Chalmers University of Technology's digital library services, US national library of medicine, and Google Scholar. A wide range of keywords was initially used to find relevant literature about artificial intelligence in psychiatric healthcare. As the literature progressed, the researchers could narrow down the search words in relation to knowing what hypothetical AI that would be implemented in the context of the case study.

3.5 Sampling technique

In qualitative research, there are various techniques for a sampling of data. In this thesis, the researchers found it appropriate to pursue purposive sampling since this sampling technique allows for the researchers to select participants that could be relevant for the study (Saunders, Lewis, & Thornhill, 2012). This was manageable through the support from a process leader at the PA department that facilitated the initial contact so that the researchers could receive interviews with participants that were positioned in all process steps in the PA work process.

3.6 Data analysis

A general three-step approach was utilized when performing an analysis of the data in this thesis. Firstly, by following the suggestion of Waller et al. (2016) who argues that for the benefits of keeping the analysis open in the initial phases, prevents the researchers from closing optional opportunities too early (Waller et al., 2016). This guideline was used by researchers to collect a broad view about the context in the case study.
After each interview session, the researchers performed continuous check-up meetings to ensure that the collected data was corresponding to the research questions. In this way, some minor questions in the questionnaire structure could be adjusted to better collect relevant data to the research questions. This secondary phase of analysis is what Waller et al. (2016) refer to as the second 'golden rule' towards data analysis (Waller et al., 2016). Implying the researchers attempt to immerse with the collected material to achieve a high familiarity with the material and find similar patterns of code in the transcriptions.
As the research process progressed, the research proceeded with a more iterative process of going back and forth with the collected data and the existing literature related to the research to find answers to the research questions. Furthermore, since the researchers were familiar with the material, alternative options could eventually be screened out as their relevance to the research question of the thesis diminished.

3.7 Quality of research

In this subsection, the quality of the research will be evaluated. Typically, in qualitative research, a study gets assessed through its reliability and validity (Bryman & Bell, 2011). Due to that reason, this subsection will contain a brief description of what these terms entitle and how the researchers have attempted to reach high quality in the research by fulfilling them. Furthermore, in this subsection, an elaboration concerning the ethics of the research will also be included.

3.7.1 Reliability

Reliability in qualitative research refers to how dependable the research method and subsequently the results of the research is. Furthermore, reliability can be assessed from either an internal or external perspective. Where internal reliability refers to the joint interpretation of what the researchers have observed. While external reliability refers to the replicability of the research (Bryman & Bell, 2011).

The research sought to achieve internal reliability through the choice of data analysis method described in section 3.6, where a rigorous procedure was used between the researchers after each interview session. In this way, the researchers ensured a joint agreement of the interpretation of the findings. As for the external reliability, the researchers are aware of the critique the choice of research design has on the replicability. Implicating that there is a limited possibility to achieve equal findings in another case study. However, the researchers argue that external replicability has to some degree been achieved through the applied research process that can be replicated in other Psychiatric departments and possibly other organizational settings.

3.7.2 Validity

In qualitative research, validity can be assessed similarly to how reliability is evaluated, either internally or externally. Consequently, internal validity refers to the credibility of the research which is connected to how credible the researcher's interpretations are and hence the findings of the research. Furthermore, external validity concerns the transferability of the research. Transferability refers to the degree the findings of the research are applicable in other contexts it was originally collected and is commonly coined as the term 'generalization' of the research (Bryman & Bell, 2011).

To achieve credibility the researchers interviewed at a minimum of two participants that both had the same position and role in the PA division. By following this approach any uncertainties in the first interpretation could be ascertained or corrected in the second interview with the second participant. Consequently, resulting in a higher likelihood that the findings were correctly interpreted.

As for the transferability of the findings, it has come to the attention of the researchers that different psychiatric practices in Sweden could very well work differently compared to the Psychiatric affective in Gothenburg. Hence, this implies that the transferability of the findings to other Psychiatric departments in other regions let alone other organizational contexts may be limited.

3.7.3 Ethical considerations

In qualitative research and all research in general, the authors should always consider the ethical aspects of their study. Furthermore, Bryman and Bell (2011) suggest that the subject can be assessed through four different principles that relate to the harm, consent, privacy, and deception of the participants of the study. Where the first principle concerns whether it could be harmful to participants to take part in the research. The second regards to if the participants were fully aware of the aim and the contribution they could have on the research. The third regards the privacy of the participants which is closely connected to the consent of the research and could imply avoiding publishing vulnerable information about the participant. The last principle concerning deception refers to how the researchers have approached the participants in terms of sharing who they are and what they are researching (Bryman and Bell, 2011).

The researchers in this thesis have attended to these ethical principles by following the suggested guidelines by Bryman and Bell (2011). Therefore, the researchers decided to leave out any names of the participants from the thesis report. Furthermore, not adding any sensitive statements any participant could have stated to protect the privacy of the participants and prevent them from getting exposed to any harm from participating. Moreover, the aspect of consent was addressed by the researchers by applying an open approach about what was studied at the Psychiatric Affective and why the researchers wanted to interview them. Hence, by following this approach the participant received a clear understanding of what they were contributing to which consequently also mitigated any risk of deceiving the participants.

4 Findings

This chapter will contain the empirical findings collected during the thesis. In 4.1, the PA work process will be described, including how the different healthcare practitioners work together. Furthermore, 4.2 will cover the PA department's practice associated with sick leave assessment and certificate.

4.1 The Psychiatric Affective department

The PA department is part of Sahlgrenska University hospital that specializes in the diagnosis and treatment of patients with psychiatric disorders. The PA department is divided into five different specialization categories that correspond to five main diagnoses: bipolar, neuropsychiatric, personal, affective, and fatigue disorder. Where the receptions, placed in different locations within the Western region of Sweden, are to a large extent focused on one specific disorder.

To be admitted to the PA department, the patient needs to show symptoms that correspond to any of the five categories. Further, that the patient previously has been treated in e.g. primary care without showing any signs of improvement. This decision is made by a group of practitioners that is referred to as *the referral team*. The referral team is the first process step in the PA work process and has the responsibility to assess whether the patient is eligible for treatment and what type of healthcare competence that matches the patient's needs.

Once a patient has been admitted, the patient will have multiple meetings with a practitioner, where information will be collected until a preliminary diagnosis and suggested treatment can be established. This part of the process is called the *first meeting with the patient.*

The proposed diagnosis and suggested treatment are then discussed during the next step in the process called *a team meeting*. Where healthcare practitioners with different specialties discuss the next course of action for a patient, which could be medical treatment or psychiatric therapy.

After the patient has been treated for a set amount of time and has shown clear signs of recovery, they can get in contact with a *rehab coordinator* (RC). The meeting with the RC is the rehabilitation step of the process, where a patient is prepared to be discharged from the PA process. The RC has the role to re-establish a patient's connection to the work-life by setting them up for a working life again.

The process steps highlighted in a *cursive* style sums up the PA department working process (see figure 5).

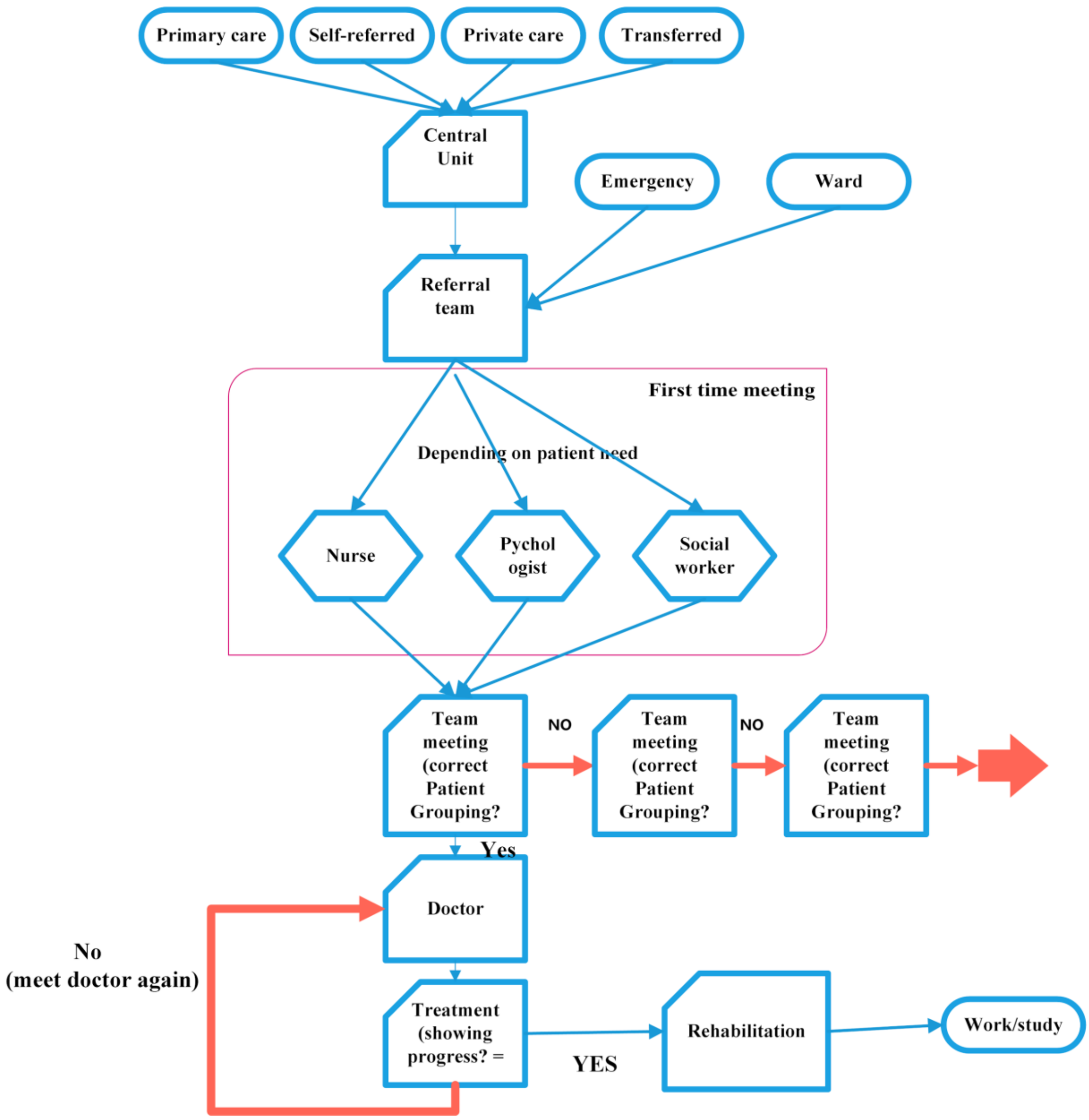

Figure 5: Psychiatric Affective work process

4.1.1 The referral team

The referral team consists of two practitioners that work in pairs. Favorably, with one member being a specialist doctor in psychiatry and the other practitioner having the corresponding specialty within psychology. Patients that are referred to the PA department can originate from primary care, private care, emergency wards, self-referral, and other hospitals.

Before a referral is received by a psychiatric reception, it is filtered through a central unit that allocates referrals to a reception that is geographically closest to a patient. However, a patient can explicitly request to be admitted to any reception in their referral.

Once a patient referral has been received at a PA reception, the referral team can assess the patient's eligibility for treatment. Multiple criteria are considered during the assessment. However, two requirements are essential. The first requirement considers the medical treatment attempts that have been pursued before the referral. This is an important piece of information since it can tell the severity of the case and further help the practitioners to be able to rule out differential diagnoses. The basic rule is that at least two attempts should have been made before a patient can be admitted. The second requirement considers drug use. The PA department has a none-tolerance policy towards drug use since the effect of narcotics hinders the practitioners to properly assess the patient. Because the drug affects the patient's neurotic functions in the brain.

When a patient is considered to be eligible for treatment, the referral team needs to decide where they should be allocated, and which healthcare practitioner shall meet the patient. To be able to make this decision, the referral team needs to know about the patient's social, working, and medical background. This information aids the practitioners to narrow down the patient's diagnosis. However, the quality of the content in the referrals commonly differs. This implies that some practitioners choose to follow procedure and delay the referral until further information can be obtained meanwhile some actively go beyond their role and retrieve the information by themselves. Furthermore, it was shown during the case study that this aspect of the work in the referral team varied from practitioner and practitioner. Where the practitioners are scheduled to work two hours per week with referrals, some practitioners choose to spend significantly more time on referral work per week.

The last part of the job in the referral team is to schedule the first-time meetings. At this point, the referral team needs to abide by legislation that regulates that patients are guaranteed an appointment that occurs before the maximum duration of 90 days. Furthermore, the average waiting for the patients differs from practitioner to practitioner but also case by case. Where factors such as the severity of the patient's condition play a big part but also the availability of healthcare practitioners at that moment.

4.1.2 First meeting with a patient

Once the referral team has decided that a patient will be admitted to the PA division, the patient will have their first meeting with a healthcare practitioner. As previously specified, the patient meets a practitioner that the referral team predicts has the matching medical specialization to successfully assess the patient. This implies that if the referral team decides that a drug-test needs to be carried out, then a nurse could perform the meeting. Furthermore, if the patient requires a psychological assessment, then a psychologist gets addressed to the patient. Moreover, if the patient needs medical assessment or is in an unstable state, e.g. suicidal, then a doctor receives the responsibility of the patient.
Additionally, a practitioner that meets the patient also becomes responsible for the patient. This means they have the responsibility to present the patient case in the upcoming *team meeting* and ensure that the patient gets in contact with the appropriate healthcare professional in the future.

Regardless of what type of healthcare practitioner who receives the responsibility of the patient, they're all provided before the meeting with the same type of information about the patient. Which consists of the patient description from primary care and the professional judgment from the practitioners in the referral team. This implies that the practitioner has limited information about the patient before the meeting.

During the meeting, the practitioner attempts to either confirm or falsify the suggested diagnosis. Where the practitioner utilizes the DSM-5 as a guideline to determine the patient's condition. However, since patients rarely can describe their condition with the same terminology used in the DSM-5, the practitioner must apply their knowledge, experience, and intuition to properly analyze and identify the reasons behind the described symptoms. Which gives grounds for how the patient is diagnosed and eventually treated.

Multiple participants in the case study claimed that the originally suggested diagnosis made by the referral team usually is correct. When this is the case then the practitioner can perform deeper analysis to identify the root-cause behind the patient symptoms. However, sometimes the practitioner has to falsify the suggested diagnosis. This implies that the practitioner needs to redo the assessment from start to look for other possible answers behind the patient’s symptoms. In cases like this there is a possibility that the patient might be instead diagnosed with a disorder that goes connected to another category. For example, if a patient originally is admitted to the PA due to the practitioner suspects the patient suffers from ADHD, then the patient would be categorized into Neuropsychiatric disorder. However, if a practitioner identifies symptoms and other indications that resemble a diagnosis that falls under another category, e.g. bipolar disorder, then the patient might have to be transferred between teams. Furthermore, once this happens there is a risk that a conflict between different teams emerges. This has to do with the fact that this situation causes uncertainty regarding which team should take responsibility for the patient. Since it is not uncommon that a patient shows signs of comorbidity which implies that a patient can show symptoms that have the characteristics that cross over multiple diagnoses. Moreover, during these circumstances the patient will sometimes be without care for an extended amount of time.

4.1.3 Team meetings

The team meetings usually occur once a week. During the meetings different practitioners discuss and seek consultation among their peers about what the next course of action for the patient should be. The team meetings are generally structured into two topics: new patient & current patients.

When new patients are brought up as a topic, there are a few standardized points that are discussed. First, they check again if the patient is drug-free. If they are not, the patient might be either rejected back to the primary care or transferred to the addiction department within Sahlgrenska University hospital. Second, they discuss which specialist that shall take responsibility for the patient next and when the patient will receive that appointment. Included in this topic could also be a matter of transferring the patient to another team.

Once new patient cases have been discussed and decisions have been made, the team puts their attention on their current patients.

With current patients, the subject surrounds how the treatment is going and whether medical or psychological treatment changes are needed. Furthermore, it could also be decided that a patient is showing a stabilizing trend which could result in lesser frequent follow-ups with that patient. If the latter is the case, then the patient might be eligible to get in contact with the rehab coordination team.

Regardless of whether the topic is about a new patient or an ongoing patient, during the meeting, the attending specialist doctor has the final word in every decision made and is medically responsible for those decisions in the team meeting.

4.1.4 Rehab coordination team

Once it is settled that the patient has shown significant improvements to their health status, they can be introduced to a rehab coordinator (RC). The RC team is the latest establishment in the PA division and has the role to aid the patients on their journey back to work. A rehab coordinator could be involved as early as the patient’s first day at the PA department but is mostly involved in a much later stage.

The RC needs specific information to be able to perform its job properly. Firstly, they need to know about the patient's health status and how stable the recovery is. With stability, the RC refers specifically to the patient's cognitive functionality. As this has a direct correlation to the patient's ability to work again. Secondly, the RC needs to know where the patient worked before being admitted to the PA department. Since, if a patient got sick in their previous working environment, they rarely could return to the same one again.

The RC team works with its patients with different expectations in mind. These expectations are related to the patients working background. For example, if a patient has been working full time before being admitted to the PA department, they can return to full time. Meanwhile if the patient has no previous working background, the same expectation on that patient is rarely made. According to the participating RC’s in this study, the commonality with patients admitted to the PA is that they have not been having full-time jobs. Hence, the common and opportunistic outcome for an RC is to be able to make the patient perform rehabilitation work. This is used as a learning process for the patient. Where the patient gets to do low-cognitive requiring labor for two hours a week. This method is used to help the patient to gain working habits which eventually is encouraged to be increased up to 10 or potentially, even more, hours a week. Once a patient has reached this level of working capacity, they become eligible to become transferred to another external organization e.g. Swedish Public Employment Service (Arbetsförmedlingen), which will support them to find a part-time job. Once this happens the patient is discharged from the PA department.

4.2 The current state of the PA sick leave process

As mentioned in the case description, the PA division mostly receives patients that already are on sick leave. Moreover, it is shown that the total number of patients that are being treated at the PA has been steadily increasing since 2013. This has led to an increased demand for healthcare practitioners from the department. Since, the treatment time for a psychiatric patient takes a significantly longer time than the average patient. Where the best case implies 1-3 months of treatment meanwhile the worst case has been documented to extend for over 3 years.

Besides assessing and treating patients, the doctors at the PA department also have the responsibility to prescribe the patient a sick leave permit. Which is a written document that explains the patient's inability to work and hence argue why the patient should receive sick leave support. However, due to the increased demand and flawed communication, approximately 50% of the sick leave permits need to be rewritten at least one time. Furthermore, in 2019 the average doctor was only in 55% of the cases able to complete a sick leave writing in a time before the patient's ongoing sick leave permit had expired. Which is a problem according to one of the managers at the PA department. Not only is it shown in the statistics that multiple doctors spend an excessive amount of time and effort on sick leave rewritings, but the patients are also consequently placed into a stressful situation, which could affect their recovery when the renewal of sick leave permit is delayed.

Medical certificates that could justify a sick leave permit are written as a means to aid the patient to have time for treatment and recovery. Furthermore, the prescribed time is also used as anticipated for the practitioners themselves to assert how long time the patient needs until recovery. The medical certificate is written today by the assigned doctor that meets the patient after the team meeting.

4.2.1 Sick leave rewriting from the psychiatrist's perspective

The healthcare practitioner at the PA department that writes the medical certificates is the doctor the patients meets after the decision during the team meeting. The certificate is written after the doctor has met and made their assessment about the patient's health status. However, the doctor uses the gathered information from the previous steps into account when making their judgment regarding the patient's ability to work.

The information the doctor needs to complete a medical certificate and either grant or deny the patient a sick leave recommendation is the following:

1. Sick leave related information about the patient
2. Previously made medical and social efforts

The first part of information refers to whether the patient is currently on sick leave and if so, how long they have been on it. Furthermore, the reason why they received sick leave in the first place, where information such as e.g. if it is work-related has a significant impact on the assessment. Moreover, the duration the patient has been on a sick leave also aids to indicate how the patient later should be assessed in terms of the social insurance agency's established time frame. The time frame describes how a patient should be assessed based on their ability to do their job in their current occupation during the three first months, jobs within the same organization up to six month, and past six month any kind of job at all.

The second requested information refers to either medical or other efforts e.g. from their employer, to improve the health status of the patient. This information is significant as it aids to describe how complex or severe the patient status is and also for how long the patient has been treated. The time the patient has been treated is very important for the doctor. Because as previously described, the sick leave certificate also serves as a forecast for how long time the doctor expects it will take to treat the patient. Hence, knowing how long the patient has already been treated followed by their current status is information that supports the doctor to narrow down a more accurate treatment plan.

The information the doctor can use before their assessment can be found in the hospital's internal journal system. It is a system that all healthcare practitioners in the PA department uploads their patient assessment and is accessible for everyone within the organization. However, the participant in the study revealed that these systems are not connected with primary care. This implies that if they originally received a poor referral from the primary care, they might lack some of the relevant information mentioned before.

The doctor is scheduled to spend approximately an hour per patient. Where it is intended that 5 minutes are spent preparing for the patient meeting. About 45 minutes for the meeting and assessment and 10 minutes for documentation and sick leave certificate writing. Which according to the interviewee is a scarce amount of time as "five minutes is not nearly enough time to fully study a new patient journal" - *Interview participant*.
Moreover, the doctor expresses that the preparation and after documentation could be more efficient if the doctor received additional support from the rehab coordinators. "As they are prominent in collecting work and sick leave related information about the patients, which is information not necessarily prioritized to collect during the first patient meetings" - *Interview participant.*

4.2.2 Sick leave writing from the Social Insurance Agency's perspective

The personnel on the receiving end of the sick leave certificate is an insurance investigator at the social insurance agency, Försäkringskassan. Their role consists of auditing and screening sick leave prescriptions following the explicit guidelines within the organization.

From the insurance investigator's perspective, they receive sick leave certificates that vary in quality in terms of the content of the certificate. Implying that in most cases, the certificate is properly filled out. However, when that is not the case, then it usually tends to happen due to insufficient information

regarding the patient's ability to work or that the certificate itself is not comprehensible. When a certificate is difficult to understand it is usually due to the sender describing the patient in ‘medical language’. This could be according to the insurance investigator:” it was particularly difficult to understand the medical certificate when for example, the patient status was described with the test results from a lab test”.
During these circumstances, the insurance investigator can receive support from a medical consultant employed at the social insurance agency. The medical consultant can aid the investigator by deciphering what is written in ‘medical language’ into a more comprehensible form for someone without the same educational background.

According to the investigator, a standardized framework has been established between the hospital and the social insurance agency. Where a determined terminology between the parts is established to enhance optimal communication and cooperation between the organizations.
In the terminology there are some ‘keywords’ and a certain structure that the certificate should follow. One keyword is that healthcare practitioners use the word ‘function-limiter’ to describe in what way the patient is unable to work. Furthermore, the structure should contain firstly, what the main ‘function-limiter’ is, e.g. anxiety. Secondly, what kind of problem is causing the limitation e.g. the diagnosis. Third, what effects it has on the patient, e.g. stress, exhaustion, low concentration, etc, and how that is affecting their ability to perform their job.
The reason why they need this detailed information is that the diagnosis and how that is limiting the patient's working ability plays a big part in terms of whether the patient is eligible to receive sick leave funding and for how long.

5 Analysis and Result

This chapter will include the analysis of the case study where improvement areas in the PA work process will be highlighted. Furthermore, in 5.2 the conceptual AI model will be presented with detailed descriptions and illustrations of how the AI would be suited for the PA work process.

5.1 Analysing the PA work process

In this section, the PA work process will be analysed in terms of its effectiveness. Where effectiveness is defined as the healthcare practitioner's ability to do accurate actions in the work process. This will be scrutinized through two points of view. First, from an organizational angle that addresses the practical aspects of the working process and organizational dynamics that occurred in the case. The second perspective will be from a technical point of view. Which digs deeper into the technical needs that the organization requires and what kind of information that is being accessed and used.

5.1.1 Identification of the problem

As described in chapter *4. Findings* and illustrated in *Figure 5.* it could be assessed that the PA work process follows a sequential work process. Implying that once the patient has been assessed or processed in one of the process steps, the patient will be transferred to the next one within the process. Furthermore, what could be understood from the interviews is that the different stages in the process are functioning as separate islands within the organization. This is what Fjeldstad et al. (2019) describe as value shops within healthcare which resemble how for example, car shops create value (Fjeldstad et al., 2019). Moreover, as with a car shop, they can create great value when they are serving cars but less if the customer has another problem. According to the participants in the study, the PA work process is effective and accurate in their diagnosis and treatment if the patient has been correctly categorized in the beginning. Implying that when mismatches or inaccurate categorization occurs, ineffective diagnosis and treatment of the patient follows as a symptom of the problem.

The categorization of the patients occurs early in the PA work process. It is the referral team that decides under what specialization and which healthcare practitioner that will initially meet a patient. During the interview, this early decision has been shown to have a great impact on the duration of a patient. If a patient is sent to the correct specialization unit, then the likelihood of a more effective treatment would occur compared to the problems that occurred if a patient were wrongfully categorized.
The problem that occurs when a patient is wrongfully categorized is that the patient eventually needs to be reallocated to another special unit. However, since these units operate as separate islands or value shops, a conflict usually emerges between them. Where the different units in some cases have a difficult time to find consensus around the patient's main diagnosis, which is deciding where the patient should be treated. This conflict between the units is what was illustrated in *Figure 5.* as the patient might have to switch from one practitioner to another and get brought in a different team meeting. Moreover, this phenomenon is what will be referred to as the horizontal loop, a term coined by the researchers of the study.

A second loop identified in the case was what the researchers would call the vertical loop. This loop occurs when the healthcare practitioner at a later stage realizes that the patient might suffer from another diagnosis than the one they are currently being treated for. These mean that the patient would have to be reallocated to another unit.

This could be caused by the limited time the treating healthcare practitioner has to complete their work. For example, a doctor on average spends 60 minutes in total with a patient where 45 of those minutes are ordinarily spent during the meeting with the patient. This implies that the doctors, in this example, receive scarce amounts of time to study the patient's background profile, which is continuously updated throughout and before the PA work process. Due to this, there is a risk that the doctor only receives a limited amount of information about the patient which could result in a lesser accurate assessment of the patient and thus lesser effective treatment actions. Furthermore, since the healthcare practitioners work with time lapses, an extended amount of time could pass while waiting for the effect of the treatment before realizing the patient needs to be reallocated to another special unit.

Regarding the sick leave process, two issues could be identified in the collaboration between the doctor writing the medical certificate and the insurance investigator who assesses it.
Firstly, a communication error is apparent between the two parts. It is an issue that has previously been addressed with a common terminology established between the two parts but that is still occurring occasionally and causing some trouble for the insurance investigators.
Secondly, from the medical perspective, they experience that they could have in some cases a difficult time to properly assess a patient's ability to work according to the Social Insurance Agency's rehabilitation framework. Because in some cases, the information needed to properly assess the patient could not be found in the medical history, as it might not have been collected during or before the patient was admitted to the PA department. Moreover, the doctors receive a limited time to complete these medical certificates due to their limited time schedules. This is an issue that is identified in secondary data which showed that multiple doctors at the PA department had a significantly low acceptance rate on their medical certificate. Furthermore, approximately 50% of the medical certificate was sent to försäkringskassan after the patient's sick leave period had expired.

5.1.2 Available data

The information used in the PA work process is medical history that describes the health status of each patient and continuously updated. The medical journal includes information that depicts a patient's medical, personal, and work background. In addition, previous attempts, medical or not, can be also included in the documentation. The information in the medical history is structured under several headlines and could, therefore, be structured data (Scheurwegs, Luyckx, Luyten, Daelemans, & Van den Bulcke, 2015). However, the amount of content under each headline in a patient journal could vary from patient to patient, due to shifting quality work from different practitioners.

What was also learned from the interviews was that the PA department journal system was not connected to the primary care journal system. This could imply the loss of relevant information if it's not documented in the initial referral. Furthermore, even though many healthcare practitioners in the PA department rigorously document their medical attempts and findings, the doctors who have the final responsibility of the course of action for a patient, rarely have time to fully study the material before meeting and assessing the patient.

5.1.3 Improvement areas

What could be assessed from analysing the case is that there is room for improvement within the PA work process. The area in the work process that could be identified to have the most impact on a patient duration was at the first process step which occurs at the referral team. It was evident that due to incorrect categorization of patient referral that patients entered the horizontal loop. Hence, by achieving greater accuracy at the referral team, it is possible to decrease the amount of time patients spend within the PA department. Which consequently would decrease the sick leave time. Additionally, another area that is identified to contribute to increased patient duration was the assessment of a patient's ability to work. Where it was discovered that the doctor's formulating the medical certificates faced difficulties of gaging the patient's functionality due to lack of information. It was further discovered that this was a problem caused by varying quality in the data gathering process in and before the PA work process. This is a symptom of a problem that could be prevented at the referral team.

5.2 The conceptual AI model

This section will contain a description of the conceptual model that illustrates how the AI technology would be hypothetically implemented in the PA work process. In the description of the model, the identified improvement areas in the case study are considered and further elaboration on how the technology would function within the context of the case will be portrayed.

The conceptual model will follow a general framework that has been popularised by multiple research and software developers and summarized by Eckroth (2018). The framework includes six logical steps explaining how an AI could be developed. The first four steps are:

1. Identify the problem
2. Prepare the data
3. Choose the algorithm
4. Train the algorithm

Besides, Eckroth addresses that the AI needs to be programmed towards what it should solve. This means that the data needs to be accessible and an appropriate algorithm that fits the job maut be selected and trained (Eckroth, 2018). The last 2 steps concerning the choice of program language and selected platform will not be included in the development of the conceptual model due to the researcher's limited knowledge about data science.
Lastly, a suggested way of how the AI could be used will also be included in this section.

The Figure below shows how the AI model involves multiple functionalities that could function in cooperation with each other or standalone. Furthermore, this section will be divided into each functionality included in the AI conceptual model.

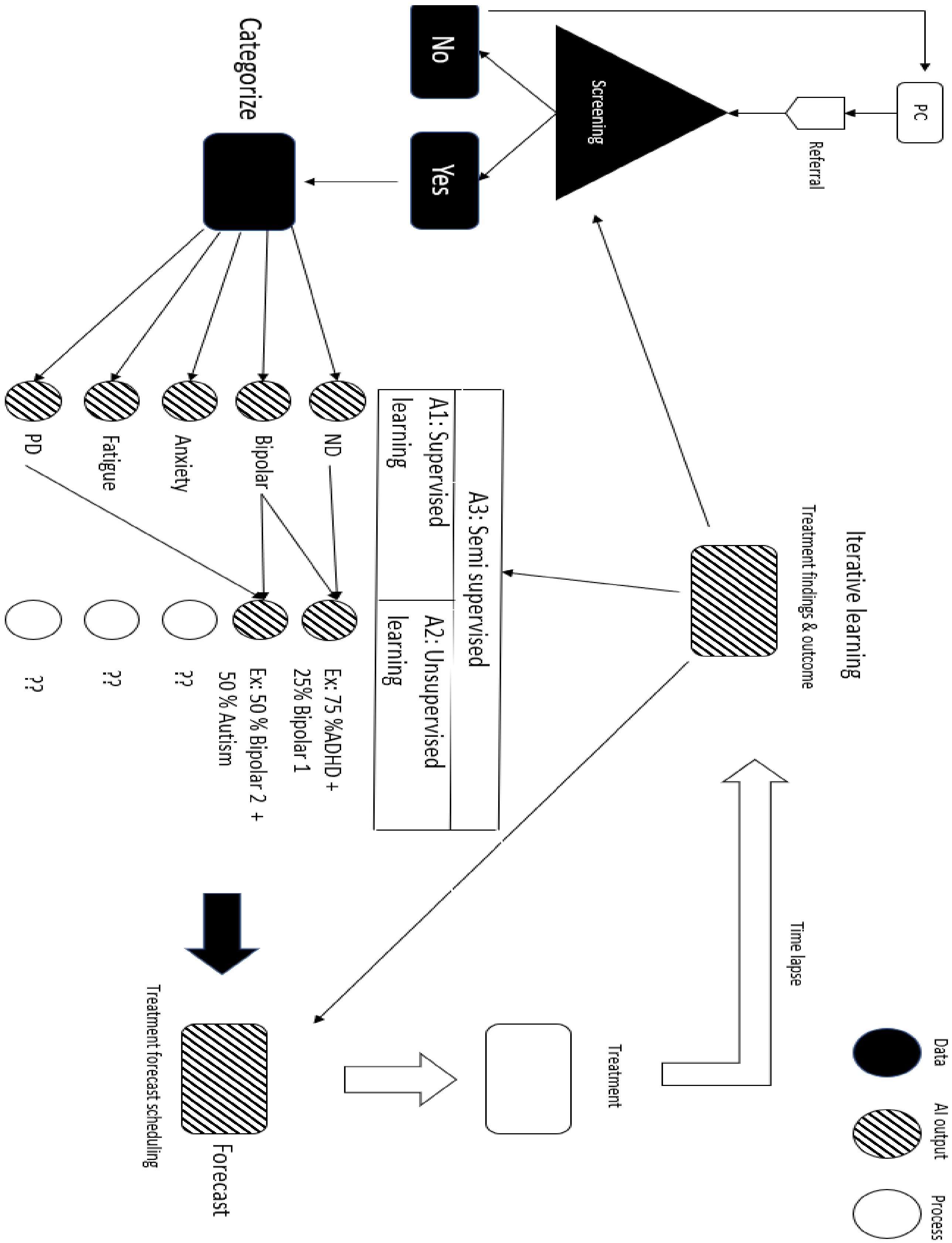

Figure 6: Conceptual AI model

5.2.1 Screening: Is the patient eligible for treatment at the Psychiatric affective?

Problem

The first part of the model involves the screening of patient referrals. The problem that gets addressed at this step is the patient's eligibility for treatment at the PA department. The desired outcome from the AI would be a recommendation that suggests that the patient is eligible for treatment at the PA department or not.

Data

The data the AI would have to access to perform its recommendation would be the referrals sent to the PA department. The referrals themselves follow a standardized format that should include descriptions about the patient health status, suspected diagnosis, and previous medical attempts. However, the content of the different parts of referrals itself could be varying. Hence, the AI should include a rule of declining referrals if it does not contain enough information to make a proper assessment. Furthermore, what could potentially be included in the rule is a similar firmness regarding information related to the patient's ability to work. These will be the information that would be beneficial for the formulation of a medical certificate later in the process.

Algorithm

To make it possible for the AI to generate the desired output, an appropriate algorithm needs to be selected for the job. First, the AI would have to be able to decipher and understand data in written text. This ability applies to all the different parts of the conceptual model since the data that is accessible and will be used are all written in text format.

The algorithm used to accomplish this would be the NLP algorithm. It can distinguish key phrases and words to eventually create an understanding out of the sentence itself (Afzal et al., 2017).

With the granted ability from NLP, the AI could then later be able to follow the rules used in the referral team to classify whether a patient is eligible or not. Hence, SVM is the algorithm that is selected to create the recommendation since the algorithm can match pieces of information into established class categories (Jiang et al., 2017). In this case, either a yes or no category.

Training

For the AI to be able to acquire the capability to facilitate recommendations that would be useful for the referral team, the AI would have to be trained.

The AI first has to learn how to make sense of texts by being able to link sentences in the text to specific values and rules. Hence, the NLP algorithm is used to learn how to read.

Once the AI has learned to read, it would be fed the values and rules that are established in the medical literature. Hence, the AI would be fed the same code the healthcare practitioners learn during their education but at a significantly rapid pace.

Furthermore, through the code the AI would eventually be able to link the taught values and meanings from the code and attach that information to the specified classes.

Both the NLP and the classification algorithm would require supervision during the training process and should favourably include personnel from e.g. the referral team for most optimized learning. However, the referral team's involvement would be indirect. Since it would be the outcome of their decisions that are made in the process that would function as an answer sheet compared to the AI's suggestions.

Usage

The intended users for the screening function would be the practitioners in the referral team. They would be able to take the AI's recommendation into consideration when assessing the referrals. Furthermore, the users would be able to access the AI's output from their computer unit and then utilize the provided suggestion as additional information during uncertain situations.

5.2.2 Categorize: Where does the patient belong?

Problem

The second part of the model performs the categorization of patients. This is the direct attempt to address the identified problem at the PA process since it is at this step of the process that the patient could potentially get admitted to the "wrong" specialist. It is causing the horizontal loops and possibly contributing to the vertical loops. The researchers suggest the AI could do either of the three different alternatives presented below.

The first alternative engages the question of figuring out where the patient belongs within the PA department. The desired outcome would be a recommendation that suggests where the patient should be sent once being admitted to the PA department. Hence, the patient will be recommended to be sent for treatment to one of the current categories within the PA department. The second alternative revolved around letting the AI generate new categories. This alternative implies a different approach to the categorization problem. Since no expected outcome can be compared to current reality. Hence, the problem formulation would instead be "which patients belong together?". This means that AI would be asked to create clusters that share common traits in the data and formulate these into different categories. The third alternative entails combined traits from alternatives 1 and 2. In this case, the AI attempts to solve the same problem as in alternative 1 but with the outcome revealed in terms of the likelihood of how much a patient fits into the current categories established in the PA department. The ability of this alternative has therefore the versatility to be used as either in alternative 1 or 2.

Data

In all alternatives, the data that AI uses would come from the same sources. The AI utilizes the internal medical journal system at the PA department that stores the medical history of every patient to generate its output in each alternative. In medical history, there should be information about a patient's medical, social, and labour background. Furthermore, the journal should include previously completed assessments and medical attempts a patient has done and what the main and bi diagnosis a patient has or is suspected to have. Moreover, like referrals, the data stored in a patient journal should be structured data due to the information being stored under standardized headlines.

Algorithm

The algorithm the AI uses in the categorization part of the model would differ depending on the desired outcome that a user would have. In the first alternative where a patient is placed into one of the current categories, a classification algorithm would be able to accomplish the requirement.
In the second alternative where there is no explicit expectation on the outcome, a clustering algorithm will be used to find commonalities between different patients and then create the new categories.
In the third alternative where the desired outcome is a combination of alternatives 1 and 2, a latent class regression algorithm would be able to accomplish the expected outcome. This type of algorithm can predict the probability of class membership on a pre-set of variables.

Training

For the AI to be able to use the data in the medical history, it requires the abilities to understand text which is acquired using NLP as described in the screening part of the model.

In the first alternative where a classification algorithm is utilized, the AI would first learn the rules and values that define each category used in the PA department. One of the examples of these is the rules and values used by the referral team when they assess a referral and decide where the patient should be located inside the department. Which includes the rules established in the DSM-5 and in the requirement to be admitted to any of the established categories in the PA department. This implies that the AI would have to be taught the rules and values under supervised learning.

The second alternative involves unsupervised learning. Since the AI would come up with clusters of patients that share commonalities. They would only be programmed the rules or values established in DSM-5 and psychiatric education before identifying the clusters without any guidance or output from the PA department.

The third alternative would involve semi-supervised learning. First, the AI receives the code that contains the values and rules as described in the first alternative. This would imply that AI would know the current categories in the PA department. The second part of the latent class regression is to let the AI calculate the probability based on the patient's profile of how much the patient fits into the current categories. This implies that the first part involving the current categories would be supervised meanwhile the second part concerning the regression would be unsupervised.

Usage

The intended user of the categorization function in the AI would be the same in all alternatives. Since the decision regarding where the patient should be located occurs already at the referral team, the researchers suggest that the practitioners in the referral team are those who should use it. Furthermore, depending on which alternative of the desired outcome, the referral team would have a different use of the AI.

The first alternative would be able to support the referral team in making faster decisions. By having the AI to provide accurate suggestions the users in the referral team could utilize the output as a means for confirmation during the decision making.

The second alternative would not directly support the referral team to be able to fit patients into the current categories in the PA department. However, the new clusters could potentially support the referral team with complex cases where it is difficult to assess what diagnosis a patient could have. Furthermore, if the AI would generate clusters with a specific pattern that differs from the current categories then they could potentially use the output to formulate a new category.

The third alternative could be used similarly to the first alternative or it can be used to identify patients with the comorbid diagnosis. In this way, the AI would be able to support the referral team in an early stage to assess if a patient might suffer from multiple diagnoses and therefore could need treatment from practitioners with cross expertise.

5.2.3 Forecasting: Treatment forecast planning

Problem

The third function in the AI model is the generation of medical treatment planning. The problem here is to figure out a patient's ability to work. This information decides how long sick leave and treatment time a patient needs until they fully recover. Hence, the desired outcome is to categorize a patient into one of the three (0-3, 3-6, or past 6 months) sick leave intervals. These three different intervals affect how the patient should be assessed in terms of sick leave.

Data

The data that is used to create the predictions is the information stored in the medical history. Furthermore, similarly described as in the previous steps in the model, the information stored in the patient journals would be retrievable under structured sections.

Algorithm

The algorithm that can achieve the desired outcome would be a classification algorithm. The classification algorithm is used to identify how the patient should be assessed in terms of sick leave.

Training

To achieve the desired outcome, the AI would have to be taught the code that entails how to assess patients into the three established categories within the sick leave rehabilitation framework. Since there is an expected outcome, the AI would be trained under supervision. The AI would utilize large amounts of data from the journal system to identify common patterns to predict the patient’s treatment time.

Usage

The intended user for this function would be the doctor who assesses the patient's ability to work and formulates the medical certificate. The output could be used as additional information during the assessment of the patient. Where the AI would support the user to accurately prescribe the patient's sick leave time based on the AI’s predicted treatment time.

6 Discussion

This chapter presents the evaluation of the conceptual model. The evaluation serves the purpose of attempting to discuss the opportunities and challenges the AI model would impose if it were hypothetically implemented in the PA department. Which will be assessed from two angles. The first point of view will engage the model's technical feasibility. Whilst the second perspective will focus on the organizational aspect where usefulness in terms of the effectiveness of the AI will be assessed.

6.1 Potential benefits and challenges

How conceptual AI is built

The AI system consists of three main parts (i.e. input, transformation, and output) (El namaki, 2019). From the conceptual model presented in section 6.2, the main inputs for the AI system at PA division are patient traits and disease-related knowledge or rules (e.g. DSM-5 symptoms). Given the data is provided in the required format, AI has proven to produce the required output (i.e. patient classification, treatment planning, etc.) with a high degree of reliability (Shen et al., 2018). The technical challenge here is to provide input data on the required format. Especially, in the screening functionality of the AI system, there will be a high risk of input data format heterogeneity. Since much of the data will be created in primary care, which is not included in the implementation scope of these AI systems. However, the solution suggested by Anagnostopoulos, Zeadally, & Exposito (2016) can be used here to transform the data into a uniform format. Disease-related knowledge or rules is also part of the input that is put to the technical evaluation. In psychiatric healthcare, some of the rules (e.g. screening rules) and diseases-related knowledge (e.g. DSM-5 severity rating) are weighted. To handle these, many researchers have suggested different approaches to developed preference modelling in AI (Dubois, Godo, & Prade, 2014).

As the rules (e.g. screening rules) and diseases-related knowledge (e.g. DSM-5 diagnosis symptoms) change over time, there is a risk that the algorithms will hang on to past rules/knowledge. However, these can be fixed with the help of Dynamic AI where the AI system will look for updates automatically. According to Sanchez-Sanchez, Izzo, & Hennes (2016), Dynamic AI can be used to do more than relying on training data but may go beyond that boundary and learn underlying dynamic principles of the models.

Transparency by design

Model AI algorithms can analyse patterns hidden in big data and recommend action. As discussed in the literature review in chapter 2, these will result in ‘’black- boxes’’ for the end-user. As Olejarczyk & Young (2020) discussed, providing transparency to machine learning systems and black boxes will be a significant technical challenge (Olejarczyk and Young, 2020). Some of the machine learning algorithms used in the AI system here will be black boxes in which verdicts are produced without any accompanying justification. (i.e. forecasting treatment planning and diagnosis prediction). These technical difficulties will hinge long term success of the AI especially in healthcare where there are high degree complicated cases with major consequences. As a result, both patients and doctors will demand explanations from the AI system (Shortliffe & Sepulveda, 2018). Besides, there can also be a legal and moral obligation to explain prediction from these AI systems (*General Data Protection Regulation*, 2016). The failure of explaining will hinder the consent needed from the patient and the doctors to approve algorithmically designed treatment plans in the short term. In the longer run, these may result in deterioration of the trustworthiness of the algorithms (McKelvey, Ahmad, Teredesai, & Eckert, 2018). In the future, algorithm developers need to address these challenges and work on how these black boxes could be opened to the level the AI models can be judged on how the AI system arrives at the conclusions by a clinician.

Mitigating bias

By considering different stages of AI models' lifecycle, the conceptual model will be evaluated for potential bias, and how the AI system potentially mitigates the bias will be discussed.

Stage one: Design stage (algorithmic bias)

Developers must avoid inserting their flawed observations inside of the black box when they create the algorithms. And they need to thoroughly evaluate their process of collecting, encoding, modelling and optimizing. To avoid bias, developers and data scientists must be aware of cognitive biases and be vigilant (Baer, 2019b).

Stage two: Development stage (input data bias)

Even If the AI is properly designed to help reduce unjustified human bias, human bias can make its way to the system via the data the AI system trains upon (Baer, 2019a). As a result, the AI system could potentially amplify unjustified human bias. The readily available patient data in PA division must be checked for existing human bias before it's used in modelling purposes. If found biased, it may be necessary to conduct a pilot project to collect completely unbiased data (Baer, 2019a). Also, human bias can be inherited from previous subjective decision making done by humans where the AI algorithm simply learns existing biases and eventually be systematically unfavorable towards some groups. This could potentially happen in the screening functionality in the AI system in PA division, where the AI learns to be biased from the referral unit. Researchers suggested opening the black box as discussed on Transparency by design section to disclosure if there are unjustified decisions. However, there is a black box problem that is not addressed yet. One method that is suggested to remove/control bias is to avoid preferential algorithms. However, without modeling preferences in the AI it is impracticable to reach any applicable decisions (Domshlak, Hüllermeier, Kaci, & Prade, 2011).

Stage three: life-long monitoring (automation bias)

The evaluation of the AI system must not be limited to one-time activity at the design and development stage. Rather it should extend to lifelong monitoring to minimize the chance biases entering the system when it is in use in the care delivery setting. Besides, the input data and knowledge/rules and the dynamic nature of the algorithms can change over time and the AI must be calibrated depending on that. The ongoing surveillance of the AI system is also important to evaluate and improve the human-centric aspect of the functionality. The AI system has an assisting role in the PA division. However, as numbers of researchers have pointed out, the presence of a decision support system will reduce the verification process needed from the user as humans tend to over-rely on the AI and delegate full responsibility to the system (Bond et al., 2018; Mosier & Skitka, 1999; Parasuraman, Molloy, & Singh, 1993; Skitka, Mosier, Burdick, & Rosenblatt, 2000). Overcoming the automation bias is also related to the opening of the 'black-box' for users, as the more engaged the users are, the easier it becomes to stay vigilant for a very long period. Insight of automation bias, the AI system hypothetically proves a better outcome in the short run, since the users are engaged, and critical of the system will keep the monitoring activity ongoing. However, as time passes and the risk of automation bias looms, the system may proceed worse than to that of the previous system.

Opportunities and challenges from a technical perspective

Considering all hypothetical evaluation facts of the AI system under PA division, the following conclusions can be made regarding the expected outcome of the AI system in a short- and long-term perspective.

Functionality one: Screening

If all the input data bias is kept away from the AI system, the AI system can be expected to produce a better outcome in screening functionality than the current referral unit (see section 2.3). The chance of injecting bias (mostly unintentional) is quite high, which will impact the effectiveness of AI systems (see Section 2.3.2). Especially, it will be difficult to gain sight of the hidden bias from the AI system at the earlier stage monitoring activity.

As the AI trains on more data to gain more knowledge and hidden data biases are monitored, it can be expected the AI produces even better outcomes in the screening functionality. Also, as time passes, it will be possible to improve the framework between the primary care and the PA divisions, so that the AI system will obtain appropriate and complete patient traits upon referring. However, in the long-run, the risk of automation bias in screening functionality is higher since the members of the referral unit are not that much keen about the screening task and believe that the task by itself is not value-adding for them.

Functionality two: Categorizations

Here, it is very difficult to say for sure whether the AI produces higher performance than the current system since there is a potential possibility of both outcomes (i.e. the AI system outperforming the current system or the current system outperforming the AI system). Theoretical speaking, the AI system (as its stand-alone system) can be expected to produce better outcomes in terms of disease diagnosis (Shen et al., 2018). However, as the AI will be integrated into the current psychiatric care system in the division and used as a decision support system, the interaction between will play a huge role in the performance of the AI. Due to the existence of the 'black-box' and the lack of explanation accompanying the recommendation, the recommendation AI system produces from all alternatives (i.e, Alternative 1, Alternative 2, and Alternative 3) could be overlooked by the clinicians.

In the long run, all three alternatives have technical ability to produce better output as more trust is built between the system and clinicians, and the issue of the 'black-box' is surpassed (the clinicians will stop seeking an explanation for every recommendation, the system proved itself). The risk of automation bias can still exist in this functionality as well, however, it will not be as bad as screening functionality. This is because the clinical (doctors) will not abandon their task and rather, they will positively consider and reflect upon the recommendation of the AI system. This is to mean that, as the doctors actively interact with the AI system, it will not be difficult for them to keep being vigilant and monitor the AI system.

Functionality three: Medical treatment planning

The potential of the AI system to predict future events is undoubtedly better than humans (Shen et al., 2018). However, the accuracy of the predicting depends significantly on the quality of data. Though, it is safe to say that AI will get better through time in predicting future events, considering the current system performance of the medical treatment schedule, the AI system could be expected to produce better outcomes.

In the long run, as the AI trains on more data, and as the trust in AI systems improves, it can be expected even better outcomes from this functionality. However, the risk of automation bias is as high as in the screening functionality.

6.2 Would the AI model improve effectiveness?

New technological innovations are usually promoted with attractive abilities that could elevate an organization to the next level. However, prior to implementation, it is beneficial to assess whether an organization is susceptible enough to receive its full benefits. Thus, It is helpful to determine if the AI model would improve the effectiveness of the healthcare practitioners' ability to do accurate actions in the work process.
Davis (1989) formulated a framework called the technology acceptance model (TAM). As it is illustrated in Figure 7., TAM is used for assessing an organization's acceptance to new technology. The researchers will take inspiration from the model to assess a hypothetical implementation of the conceptual model within the described context gathered during the case study.

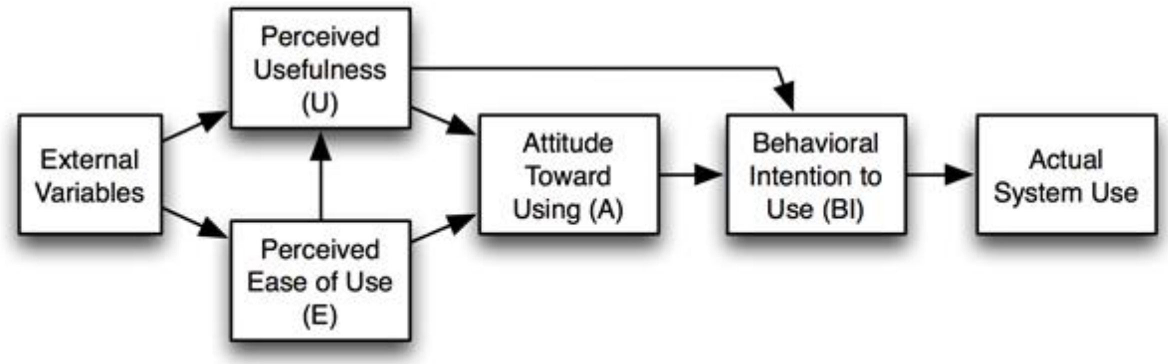

Figure 7. Technology acceptance model (TAM)

As Figure 7. depicts, two factors together influence the attitude towards using technology. Namely, the perceived ease of use and usefulness of the technology. Hence, the researchers will follow a similar structure by discussing the opportunities and challenges the conceptual model could bring to the organization from these two factors and, how that might influence the outcome of a hypothetical AI implementation.

Ease of use
In the case study, it is observed that the healthcare practitioners did not utilize advanced technology, nor did they necessarily required it to perform their jobs. This was also observed during the team meeting, where the concentration and flow got interrupted multiple times by poor usage of information technology. Furthermore, the researchers noticed that it was only due to the circumstances caused by the global pandemic that some participants in the study start using video-conference technology as a tool for communication. This was a new way of working that many participants perceived as an efficient tool for communication in many aspects.
Moreover, when the participants were asked about their general perception about AI as a warm-up question before the interviews, the responses were rather mixed-up. However, most participants were quite positive towards potential efforts that could improve their practice in helping the patients. This shows signs that the healthcare practitioners at the PA department might be amenable for new technological innovations as long as it serves their common purpose.
With this in mind, would the AI describe in the conceptual model be easy for the healthcare practitioners at the PA department to use? The short answer is that it would entirely depend on how the AI would be used.

The intention behind the conceptual AI model was to engage the same problems that the healthcare practitioner faces in their jobs in the PA work process. The problems the AI should undertake were narrowed down to the screening of referrals, categorizing patients, and planning of medical treatment, as these steps had the most impact on the patient duration in the PA work process. Furthermore, to generate output that would facilitate the decision-makers in the different parts of the PA process with additional information to improve the odds of them making a better decision in each process step. The researchers designed the use of the model like how people are expected to use a weather forecast application. Where the user would be served with additional information that could be taken into consideration when deciding on bringing an umbrella or not for an example. Thus, the application is not deciding for the users, they just get provided with information that could influence it. So, when the application informs the user it's not going to rain but it's cloudy outside, the user has to make their judgment based on the information, experience, and knowledge. This is the intended use of the conceptual AI. Where it would provide the users with additional information that could be useful to make a correct assessment of a situation. However, there is a scenario where the AI could potentially cause more uncertainty than there must be. This would occur once the healthcare practitioner comes up with one conclusion and the AI suggests another one.

It is the practice at the PA department that healthcare practitioners put their heads together when patient cases are uncertain to ensure the patient gets diagnosed correctly and receives the right treatment. This is what formally occurs during the team meeting, where different practitioners can review different views about a patient case and where everyone participating has the opportunity of becoming wiser after new knowledge has been shared between them.
This shape of two-way communication would not be as easy to accomplish with an AI. Since the AI would be programmed to provide e.g. suggestions based on the rules and values established in the medical knowledge field. However, with the limitation of not being able to include a reasonable explanation behind the suggestion. This implies that depending on how much the users chooses to rely on the suggestion made by the AI, an opposing view from the AI could, therefore, cause more uncertainty. Since the user is unable to further question the reasoning behind the suggestion. Furthermore, if the users perceive the output to be very reliable, the practitioners will likely stop assessing the patients themselves which could potentially lead unintended consequences further down the road in terms of accountability. Since who would have to take the responsibility of the AI would get it wrong?

By reviewing AI in the medical literature, it could be found that researchers have been able to predict diagnoses in different medical fields with a precision rate of up to 85-90%. Which would in the context of the case study imply that approximately 1 of out 10 patients would be inaccurately categorized. It is a ratio that most practitioners at the PA department likely wouldn't perceive as a significant improvement compared to today's standard.
This leaves the healthcare practitioners with limited use of the AI. Since they can't completely rely on the output which means that the AI itself can't autonomously contribute to the organization. This leaves the expression that the potential usefulness of the AI might be limited as well.

Perceived usefulness

In the literature, AI is described to possess the capability, if developed correctly, to reach a level of performance that could potentially match or even surpass the healthcare practitioner's ability to screen, categorize, or schedule patients. That is a capability that would sound promising in any context let alone psychiatric healthcare. However, the question is how long it would take until the AI would reach that level. The simple answer is that it depends on the amount of data that is available for AI training.
AI needs a vast amount of data with a certain degree of diversity. This means that, depending on how

much data that is accessible at the PA department, the AI training could take everything from weeks, months, or even years before the AI has reached a level of accuracy that is acceptable for usage within the PA department. Could healthcare practitioners at the PA department wait that long? That would probably depend on how the AI would be introduced to the organization.
There is one scenario where the AI gets introduced to its potential users before it has reached its "potential". Similarly, to how a software program can be tested in an alpha or beta version. It is an approach that has the benefits that the users would familiarize themselves with a limited version of the software while the creators will be able to collect user feedback from their explicit rapports and the implicit user data. However, the downside with this approach is that the AI could eventually be perceived as the "the shepherd boy who cried wolf"**.** Since in an alpha version, the AI world probably has it wrong most of the time. This could turn into that it would not be perceived as reliable despite the AI improving itself over time. Then there is the other scenario where the AI has been trained behind the curtains for an extended time and is introduced to the organization once it has surpassed a certain accuracy threshold established by selected managers and physicians, for example. In this case, the introduction might be too abrupt since the users would not be able to completely rely on the output of the AI since the users had too little experience with the technology.

The latter scenario is what the researchers had in mind during the development of the conceptual model. To cope with the drastic change AI technology could imply for the organization, the researchers created different alternatives of output the AI could contribute. The alternatives were incorporated into the categorization of patients. Where every alternative engaged the same problem however with a different way of solving it. Where one of the alternatives was intentionally designed to be more familiar with the current practice at the PA department than the others.

The first alternative addresses the categorization problem and is intended to produce an outcome that has a matching fit to how the PA department works today. In the short term, this would be the alternative the researchers speculate has the most potential of being accepted by the users of the organization. Since the algorithm provides an output that would fit into the current categories established in the PA department in the present. However, in the long term this approach might not lead to substantial improvements in terms of effectiveness. Since through the current practice followed today, incorrect categorization is unfortunately made. The reason behind that could be explained by pointing towards the human factor. However, organizations usually tend to follow a system that allows for that kind of variance. This leads to the criticism against the DSM-5 where an opposing view from many researchers in the field argues that the curriculum and rules are flawed. Where for example, a factor such as cultural origin is not taken into consideration in the evaluation of a patient. It is a factor that could potentially affect the patient's psychiatric health. This implies that the alternative can reach a level of performance as good as the current practitioners or slightly above due elimination of human errors.

The second alternative engages the categorization problem by trying to create new categories. The intention behind this alternative is to potentially identify and develop new ways of categorizing patients. By generating clusters of patients that share commonalities in medical history. It is an output that has the potential of significantly improving the categorization if it's successful. Although, this approach wouldn't yield any benefits in the short term for the users in the PA department. This could, therefore, affect how the AI would be perceived to be useful in the organization and thus less likely to be accepted as a technology.

The third alternative approach to the categorization is like the first alternative yet adds an element to the output. This added element is the calculated likelihood the patient fits into one of the current categories in the PA department. This output has the potential to be either used as the first alternative or the second alternative suggests. Since the output could either support the users to easier fit the patients into current categories or approach a specific case with an additional focus lens. This could occur when, for example, the AI would indicate that a patient has a high probability of matching with two or more diagnosis categories or that he/she has a low probability of matching with any diagnosis category at all. Both scenarios would draw equal amounts of attention since in both cases it would not be clear where the patient should be categorized. Thus, giving the incentive to the practitioners to further assess special patient cases.

This was also the intention behind the alternative, to be a more versatile combination of the two alternatives above. Although, the output yielded in percentage could complicate the decision for the user. Since for example, 90- 95% could both be interpreted, during many circumstances, as high probabilities of an event happening. Yet very few would be willing to take that chance if it were the likelihood of their airplane landing. Hence, depending on how much the users in the PA work process perceives the consequences of an incorrect assessment has on the patient, that would influence how much they could rely on the AI's output.

Attitude towards using the AI

It could be assessed from the perspectives above that the AI could be easy to use if it is used as intended. The AI could increase the effectiveness by facilitating valuable additional information to the decision-makers in the PA work process. However, the information itself could also potentially create more uncertainty.

In terms of usefulness, the AI would have to first surpass a certain accuracy threshold before the output of the AI would be considered reliable by its users. Which is a feature related to the amount of available data that is accessible for AI training. Therefore, not until the AI has reached an acceptable performance level would its output be considered reliable by its users.

This leads us to a futuristic perspective. What would happen once trust has been established? Would the process become more effective? Would the users be able to accomplish more with fewer resources? Positive results would probably be able to be identified if new measurements were taken after the AI implementation. However, this is also a scenario that could lead to a deteriorating effect on the PA work process. Since when the users can trust the AI, it would be the path of least resistance for the user to let the AI perform the screening and scheduling of patients entirely by itself and possibly even the categorization. This is a risk since the AI is taught the rules and values established in the current system which is unfortunately flawed. Hence, mistakes or incorrect decisions would in the future inevitably occur if the users stopped monitoring the AI. This implicates that the key for AI to become an asset that improves the effectiveness of the PA work process is that it would be trusted. However, the generated output should never be considered to be 100% accurate.

7 Conclusion

This chapter outlines the concluding parts of the thesis. First, the theoretical implications and the answers to the research questions will be presented. Secondly, the researcher will provide a few selected practical implications for the participants in the study and suggestions for future research.

7.1 Research findings

As Rotter et al. (2017) described the worldwide concern regarding increased medical costs and the need for improved effectiveness in healthcare. And many stakeholders have in recent years turned to industrial-related tools and techniques such as AI to solve these problems (Baker, 2001). It is a technology that has shown a developing trend by gradually improving its performance in the last decades (Davenport & Kakalota, 2019). However, the adoption of AI has yet matured in psychiatric care. This is due the fact that the psychiatrist cannot rely on the same standards as the physician can do in other medical fields (Rosenfield & Benrimoh, 2019). Hence, this thesis aimed to contribute with knowledge on how AI technology can improve the effectiveness of diagnosis and treatment in psychiatric healthcare. As well as identify the challenges that coincide with the adoption of AI. Hence, the researcher's theoretical contributions from the study will be presented below.

Research question 1:
What are the potential benefits of implementing an AI model in psychiatric treatment processes?

The conceptually developed AI model presented in Section 5.2 has the potential to deliver capabilities that could improve the basis for the practitioners in the PA work process to be able to make effective medical decisions. Furthermore, the next step that needs to be realized in the AI model is to make the required data available and ready to serve as the input for the AI.
This implies in the short term, the PA department could gain benefits from using the AI model’s screening and planning features. Since both features possess the capabilities that show great compatibility with the current practice in the PA department.
In the long term, the features have promising potential in achieving high accuracy in its generated output. Since as time passes the AI would continuously improve itself to a point where its performance would potentially be able to surpass the human ability to complete the same task.
Furthermore, although the categorizing feature in the AI model is theoretically feasible there is only a small chance that the feature itself would be able to accomplish increased effectiveness. Due to how the PA work process is structured today, the categorization feature potential would be considerably restrained.

Research question 2:
What kind of challenges would the implementation of the AI model impose?

The first challenge would be encountered during the development phase of the AI. Once the required inputs were going to be prepared and ready for intake, the data would also have to be screened for bias before the AI could use it. This is a necessary step to distinguish what factors should be weighted in and which one should be excluded (i.e discriminating biases) in the decision-making process.

The second challenge is apparent during the initial phase once the AI model has been implemented. The

users would at first face the challenge with the black box phenomenon, which is a technical limitation that implies the AI would not be able to justify its recommendations. This would make practitioners hesitant to utilize the AI's output. Furthermore, it limits the AI's usefulness and potential to improve the effectiveness of the PA work process.
Although, by monitoring the AI's performance over time, the users would be able to overcome the limitation since it would be possible to observe the accuracy rate the AI achieves. Hence, increasing the trustworthiness of the AI.

A third challenge that could emerge in conjunction with increased confidence in the AI is the risk of automation bias. This is prevalent in situations where the tasks could be perceived monotonous, such as in the screening and planning part of the work process. While it is beneficial for the effectiveness to allow the AI to be autonomous, the performance of the AI could eventually deteriorate if it is not continuously monitored.

Finally, while the categorization feature of the model has theoretically the greatest potential to improve the effectiveness in the PA work process, the feature itself would consequently be heavily resisted due to the limitation of the black box. Since the categorization task involves a high amount of complexity and risks.
Hence, in conclusion, what truly hinders the AI from truly blossoming and delivering benefits to the organization might just be the incorporated and deeply integrated practices in psychiatric healthcare. Where the general perception surrounding the concept of AI usage is to replace simple work tasks. Potential users should rather broaden their view about what opportunities AI could bring to an organization. Since the potential benefits that could be realized are not entirely limited by the technology itself. Rather it is that organizations today need to be able to evolve and develop along with new technology to gain the benefits that AI can provide for organizations and to the society.

7.2 Recommendations

The thesis was initiated with a request of investigating how AI could benefit the PA department to reduce long term sick leave. In this section the discoveries that were made during the case study that was out of the scope to be included in the thesis but that could benefit the department in their pursuit of reducing long term sick leave will be presented.

- Enhance requirements on the referral information

It came to the researcher's attention that occasionally the referrals were lacking in information and specifically sick leave-oriented ones. This complicates it for the practitioners to perform the task and makes the sick leave assessment more difficult later.

- Collecting sick leave-oriented information in the PA work process

By emphasizing also collecting sick leave-oriented information during the first meeting would simplify the medical certificate assessment later.

- Incorporating the rehab coordinators earlier in the process

Multiple participants were under an agreement that involving rehab coordinators in an earlier phase would facilitate improved chances of collecting and formulating correct sick leave-oriented information that would be needed to do correct sick leave assessments.

- Observe the development in the AI research field

While the AI black box may be an overwhelming obstacle for psychiatric healthcare today. Future research predicts that the black box might be opened soon. See more about the opening of the black box in *7.3 future research.*

7.3 Future research

The main objectives of this paper were to study the potential and the challenge of using artificial intelligence in specialty psychiatric care supporting different activities to improve the effectiveness. Through the evaluation of the conceptual model in chapter 7, it found out that the main challenges of using AI in the short and long term in PA division were the existence of the black box problem hindering the AI models' ability to produce an explainable outcome. Since the AI model will be introduced as a decision-supporting, transparency is very essential to improve the trust of end-users in the AI. As such, a highly recommended study that could be looked at in the future would be how the black box problem can be opened. The opening of the black box can be achieved by developing an AI model that helps the end-users to understand the reason behind every recommendation and/or by helping the end-users understand how the black box behaves or respond to the inputs. Also, it is highly recommended to look at how AI can be implemented in psychiatric care in the future considering the opening of a black box.

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A. Appendix 1

General Semi-structured interview questionnaire
1. Questions about INPUT 2. OUTPUT related questions 3. PROCESS related questions about HOW the person practically does it. 4. Additional questions for DISCUSSION
OUTPUT

1. What is it that you do in the e.g. “first meeting”, “referral team”, etc.?
  a. What is the expected outcome of this process?
    i. Diagnose?
    ii. Treatment?
    iii. Health/patient journal?
  b. How long does each session take?
    i. How many sessions per patient?
    ii. How long is the waiting between sessions?
      1. When does the team meeting occur?

INPUT
1. What kind of information do you receive before this process step? 2. What patient cases do you usually get?   a. Is there any difference?
PROCESS

1) How do you process the information, so the expected outcome happens?
  a) *Theoretically? (DSM-5?)*
  b) Practically? (Criteria and rules?)
2) What happens when the process does not produce the expected outcome?
  a) Why does that happen?
  b) Why is that a challenge?

DISCUSSION, (Open questions)

1. How familiar are you about AI in general?
2. When a patient has been on a sick leave for an extended amount of time, they tend to have increased difficulty in returning to work?
  a. Is this true? What do you think about this?
3. How difficult do you think it is to set the right diagnosis at the “first attempt”?
  a. How important is it to identify the correct diagnosis to provide effective treatment?

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