Developing a recommender system artifact for patient tailored therapy in the COPE project

Personalizing Self-Guided Internet-Based Congitive Behavioral Therapy

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Abstract

Mental health disorders affect people from all over the world of all ages. Depression is of the most common mental health problems and is commonly experienced by women during and after breast cancer treatment. Cognitive Behavioral Therapy (CBT) is a therapy form that has been proven effective in treating symptoms of depression. While CBT has traditionally been given face-to-face with a therapist, Internet-based CBT (iCBT) has shown higher efficiency, without the cost of efficacy. Self-guided iCBT provides an inexpensive alternative of treatment as it does not require a therapist involved, leading to better scaling. It has not shown the same effectiveness and user adherence.

This project is part of a larger research project called COPE aiming at providing self-guided iCBT to breast cancer patients in a patient tailored and more efficacious manner. This thesis examines the possibility of integrating the advantages of a therapist guided iCBT into a self-guided iCBT application.

An artifact was designed and developed through the method of design science, in an effort to make self-guided iCBT personalized. The artifact is a recommender system that uses content and patient data to recommend the most suited therapy content, as well as a simulation tool for insight and evaluation.

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1 Introduction

This master thesis project is part of a larger project, COPE. Within COPE, there are four sub-projects assigned to four master students. The COPE project aims at developing a truly adaptive internet-based therapy application for breast cancer patients suffering from mental health related side effects after having gone through breast cancer treatment. These side effects include depression, stress, anxiety, and other forms of lighter mental disorders (Deshields et al. 2006). The COPE application will be implemented in an environment that facilitates innovative research on internet-based therapy.

The proposed COPE application facilitates for therapy that is personalized to each patient, based on various user data such as patient health data related to cancer treatment, psychometric data from multiple screenings throughout the therapy, each patient characteristics, goals, needs and various usage data collected from the patient's interaction with the application. The application contains modules of exercises and learning material with features from both Cognitive Based Therapy (CBT) and Mindfulness Therapy. In order to facilitate for personalized therapy, the COPE application uses a patient data model combined with decision rules and tailored patient guidance, as well as new data fed back to the system as the patient progresses through the application.

The COPE application is innovative in the sense that it combines internet-based therapy in a personalized way with adaptive algorithms that decide best-suited exercises and learning material based on CBT and mindfulness. In addition to facilitating for personalized internet-based therapy, another goal of the COPE application is to serve as a platform for research in multiple fields related to adaptive net-based therapy. It will provide for research on personalized internet-based therapy from both medical and psychological perspectives, as well as from technological and ethical perspectives. Also, structured patient data from the application can be integrated into the Cancer Registry of Norway (Brystkreftregisteret, a national quality registry) and vice versa. Research can be conducted on these new and innovative ways of delivering truly adaptive therapy and how to evaluate the progress of the patients undergoing the therapy.

1.1 Motivation

Mental health disorders cover multiple disorder types, each with a variety of symptoms. These disorders affect people of all ages, all over the world. The most common ones are depression and anxiety. The World Health Organization (WHO) has estimated that globally over 300 million people suffer from depression alone, and the number is increasing (World Health Organization 2017).

Depression is a common mental health problem that affects how you feel, think, and behave. It is a mood disorder that causes a persistent feeling of sadness and loss of interest. It affects one in six people during life, and more women than men will experience the illness. With close to 800 000 suicides per year as a result of serious depression, it is also a major contributor to the total amount of suicides (World Health Organization 2019*b*). Depression requires long-term treatment, and most people with depression feel better after getting medication and/or psychotherapy (The National Institute of Mental Health 2018).

There are varying degrees of depressive disorders. The symptoms of depression range from mild to severe, where we find minor depression (mD) on the mild end, and major depressive disorder (MDD) on the severe end. According to a study by Fils et al. (2010), the difference between the two includes the level of psychiatric stress and psychosocial functioning. People with minor depression can have their symptoms escalating over time if they do not receive treatment, which can lead to major depression (Weissman et al. 2010).

Depression can be a heavy burden for the individuals affected by depression, as well as for their families. The society is also affected, especially economically, through health care spending. Economically, the society can benefit from reducing the numbers of patient suffering from depression, as shown from a study from Canada (Tanner et al. 2019). The study concluded that every patient suffering from depression added, on average 8.244 CAD in extra cost per year, resulting in 12 billion CAD in excess spending for the Canadian health-care system annually. Consequently, it is essential to have accessible treatment, such as the COPE application, early on to prevent minor depression from worsening.

The number of patients suffering from mental disorders in Norway is steadily growing, as shown by statistics from the Norwegian Patient Register (Indergård et al. 2019). Also, it is an increase in incidences of mental illnesses and disorders among young people in Norway and other Western European countries (Kalseth et al. 2015). Due to a shortage of mental health workers and a lack of accessibility to therapy, there exists a substantial "treatment gap" worldwide. This gap is particularly present in low- to middle-income countries and shows a clear presence in developed countries. This shows a clear need to streamline the treatment (Kakuma et al. 2011).

Breast cancer is the most common type of cancer worldwide the (Ferlay et al. 2019). According to World Health Organization (2019*a*) 2.1 million women are diagnosed with breast cancer every year, and an estimate of 627,000 women died in 2018 as a result of breast cancer. There has been an increase in research focusing on the survivors' health-related quality of life (HRQoL) as a result of an increase in cancer patients and improving the survival rate (Coleman et al. 2011). The treatments that are given to breast cancer patients may cause a range of menopausal symptoms of great discomforts, such as hot flushes. Alongside the physical symptoms, mental distress problems are also common for women dealing with this condition. Among women with breast cancer, almost 30% are premenopausal, which is concerning for younger women when undergoing the treatment. Research shows, however, that cognitive behavioral therapy is having a positive impact on these symptoms which breast cancer patients are experiencing, either in a group setting or guided self-help, according to a study by Ayers et al. (2012). Findings from Atema et al. (2019) suggest that the internet-based approach to CBT is feasible and promising for reducing these treatment-induced menopausal symptoms.

Mental health disorders, such as depression and the corresponding symptoms, can be treated or reduced in different ways. The treatment can be given in the form of psychotherapy or medication, which has various outcomes and effects on the patient. Among psychotherapeutic treatments, we find Cognitive Behavioral Therapy (CBT), which since the development of the practice from the 1960s, has become one of the most commonly used therapies. Cognitive behavioral therapy is a type of psychotherapy that focuses on how to alter dysfunctional thoughts, emotions, and behaviors for the better by learning coping skills and about one's mind (Hofmann et al. 2012).

Internet-based cognitive behavioral therapy (iCBT) is a CBT program adapted for mobile and computer use and has the benefit of treating more patients in a given time span using CBT. Guided iCBT involves a therapist in the treatment and shows to be an effective treatment for the majority of patients in routine care (Nordgreen et al. 2018). The treatment's effectiveness, together with Folker et al. (2018) reporting that guided iCBT can help to consult three times as many patients show a promising future for the treatment form so far. Both guided and self-guided iCBT are scaling better than traditional CBT when it comes to delivering the treatment to as many patients as possible in need.

Another type of internet-delivered CBT is self-guided iCBT. With internet-based CBT, alongside the greatly increasing access of the internet worldwide, self-guided iCBT applications have blossomed on the market. Self-guided iCBT is a form of iCBT where no therapist is part of the therapy process. While these applications break down barriers that are typical for face-to-face therapy, such as cost and availability, the rate of users dropping out before the therapy was completed is significantly higher, according to a study done by Webb et al. (2017). The dropout rate for self-guided iCBT was 74% which is significantly higher than both guided iCBT and traditional face-to-face CBT, with 28% and 17%, respectively.

There are many variables that can be the cause for a patient to drop out of treatment before its completion. In a meta-study done by Melville et al.

(2010) investigating causes for patients dropping out from internet-based treatment programs for psychological disorders, three main categories of variables are included: socio-demographics, psychological, and treatment-related. Age and gender had a significant impact on whether a patient dropped out, as well as the severity of the patient's symptoms, where patients with less severe symptoms were more likely to drop out. Another meta-study done by Torous et al. (2020), with 18 independent studies included looked at dropout rates of smartphone apps for depressive symptoms. The meta-study shows that the applications (n=7) which involved human feedback had significantly lower dropout rates (11.74%) compared to the self-guided applications (33.96%). Applications with built-in mood monitoring did also show significant results, with 18.42% dropout rates compared to applications with no mood monitoring, with 37.88%. This study, however, found no relationship between dropout rates and age, nor gender.

In order to decrease the dropout rate while improving the mental health of the users as good as evidence shows guided iCBT does, self-guided therapy applications would need to include or simulate some of the beneficial human supported features provided in guided iCBT. The big difference between the two types of iCBT is the availability of a therapist, usually no more than 15 minutes each week to go through the exercises done by the patient, maybe giving some feedback, and then recommending what to do next. By replacing the therapist with the recommendation of suitable learning material and exercises by an algorithm, the self-guided iCBT application may increase user adherence, as well as effect compared to other self-guided applications (Webb et al. 2017).

We have done extensive search in the research database Medline and Google Scholar for applications providing adaptive net-based therapy without having found any. After having searched through the literature for whether similar applications exist, none have been found. We are, however, aware of the use of applications with such features advancing adaptivity in some subfields of ICT in education.

Adaptive tutoring systems and learning environments have shown promising results in recent studies. A study on students' academic competence in mathematics in higher education using an adaptive learning environment shows a significant increase (Foshee et al. 2016). The use of an adaptive tutoring system, customizing the user interface and content based on the users' preferences and proficiency level, resulted in significant improvement in the students' critical thinking, reading, and writing skills (Yang et al. 2013). By recommending the most suited learning material and exercises to the patients, as well as in the user-preferred modality, the user might be more willing to continue the therapy, especially if it allows the user to postpone or omit therapy modules they do not need.

A study done by Pugatch et al. (2018) had the objective of conducting a systematic review on Information Architectures of web-based interventions for improving health outcomes. It refers to a publication investigated information architecture exclusively with tunneling structure. It was found that information architecture with a tunneling structure improved site engagement and behavior knowledge but decreased the user's perceived efficiency. The systematic review finds that there is no clear relationship between information architecture and health outcomes due to limited empirical evidence. So far, guided iCBT has shown to have a better effect and less dropout. It is, therefore, important to create applications for improving health outcomes without tunneled structure to allow studies to be conducted on this matter.

An artifact is created in this research project that can be used to demonstrate how a recommender algorithm may be used in COPE. It is in its initial form meant as a tool for discussion with therapists about its functionalities and further development.

1.2 Research questions

RQ 1 How can we implement an algorithm for recommending iCBT content?

RQ 2 How can we implement an algorithm for recommending iCBT content tailored towards the needs of each individual patient?

RQ 3 What data from a patient model can be used for making iCBT adaptive using a recommender system?

RQ 4 How can we implement an artifact that can be used to demonstrate and inspect a recommender algorithm, that also can serve as a platform for discussing the design of an app capable of providing for personalized iCBT?

1.3 Research method: Design Science

We chose Design Science as the research method for this master thesis project (Hevner et al. 2004). The aim of the research work was to contribute to the development of an application for a real problem that has not been done before, by creating an artifact. As Design Science is described below, it seemed to be the most fitting research method for this thesis. The artifact created is a recommender system for recommending exercises and learning material for breast cancer survivors suffering from symptoms of depression, as well as a simulation tool for testing the algorithm.

Design science is one of two research paradigms that characterize the Information Systems field: behavioral science and design science. Behavioral science is concerned with trying to understand, explain and predict why people and organizations behave as they do. Design science, on the other hand, seeks to effectively and efficiently solve both human and organizational problems by creating innovative artifacts (Hevner et al. 2004). While both paradigms have the objective to better the information systems discipline, design science does this by presenting a concise framework with clear guidelines to follow. This helps the research to be understood, executed and evaluated. A contribution to the knowledge base in the field can be achieved after the process of building, testing and presenting this designed artifact. Also, design science has proven to be effective as a research method within software engineering (Wieringa 2014).

A later extension to the methodology for conducting design science research for information systems was proposed by Peffers et al. (2007). The process model contains six steps for producing and presenting the research. The six proposed steps are as follows:

1. Problem identification and motivation
2. Definition of the objectives for a solution
3. Design and development
4. Demonstration
5. Evaluation
6. Communication

Problem identification and motivation is the first step following Peffers' model. The motivation behind the development and research on internet-based cognitive behavioral therapy is described in section 1.1, as well as its relevance. This is done in accordance with the first guideline proposed by Hevner et al. (2004) stating that "the objective of design science research in information system is to develop technology-based solutions to important and relevant business problems". The following sections, 1.3.1 and 1.3.2, describe the problem identification and the objectives to achieve for successfully creating a solution to the problem. The design and development process is described in section 3, and the implementation in section 4. Demonstration and evaluation of the artifact can be found in section 5.

1.3.1 Problem identification

At the start of the COPE research project, a meeting was held between researchers, supervisors and master students participating in the project. The subject of the meeting was the possibility of creating an adaptive iCBT application for treatment of women with symptoms of depression after breast cancer that would also include a platform for research to be conducted on the data gathered from the application. Various sub-projects of the COPE project was discussed and at a later stage assigned or chosen by each student.

On multiple occasions, meetings took place at the Centre For The Science Of Learning & Technology (SLATE) in Bergen, Norway. Among the discussed modules of the COPE application was a recommender system module for the application which would allow the iCBT application to deliver therapy based on the patients' needs.

1.3.2 Objectives for a solution

After the problem had been identified in section 1.3.1, objectives for the artifact had to be formed to solve the problem. Defining these objectives should be based on knowledge about the state of the problem and on a currently existing solution if there are any. Google Scholar and Medline was used to pursue this knowledge, searching for literature supporting patient tailored self-guided iCBT applications, without results. The COPE research project is unique in the way that as of today there are to iCBT or other net-based therapy applications that deliver individualized therapy adapted to the needs and preferences of their users.

The main objectives for a solution include:

1. creating a recommender system that allows for a simulation of activities, including using dependencies
2. integration of patient data, e.g., psychometric screening data, goals and preferences presented through an interactive
3. graphical simulation environment

These objectives will manifest themselves in the iterations and are presented in section 3.1.

1.4 Thesis Structure

This section presents the outline of the thesis where the main topics of each chapter are briefly described.

Chapter 1 presents the motivation for this thesis, problem identification, and lastly, the objectives for the solution.

Chapter 2 provides a theoretical background for the relevant subjects of the thesis. First, the COPE project is introduced, with all its sub-projects. Then, CBT and its adaption to modern technology are described. The different types of ICT systems that allow for adaptive therapy are presented to give an understanding of the choices taken with regards to the technologies used in the final artifact. Finally, challenges and related work is discussed.

Chapter 3 presents the method used to implement the artifact, as well as each iteration of the process. Further on, the design of the artifact is presented in detail.

Chapter 4 presents the language and the framework used to implement the artifact, and furthermore, how the system was realized using Horn-like rules to conceptualize the system. Finally, a detailed description of how the system is structured and how activity recommendations are given.

Chapter 5 describes how the work has been demonstrated and evaluated, both during the development phase and through a final evaluation. Discussion of the research findings in relation to the research question is also presented.

Chapter 6 concludes the thesis and discusses and presents ideas for further work.

2 Background

In this chapter, an introduction is given to the relevant subjects in this thesis. The first section is about the COPE project and its sub-projects. The sections following are about cognitive behavioral therapy (CBT), internet-based CBT (iCBT) and the sub-categories iCBT is divided into: guided iCBT and self-guided iCBT. We will look at these two sub-categories for both positive and negative effects that both the COPE project and this thesis project can build on. Further into the background section we will look at and discuss information and technology systems used for making applications adaptive with personalized recommendations to each individual user. Recommender systems and intelligent tutoring systems are included as the artifact created for this thesis is closely related to and uses principles and techniques from these systems.

2.1 COPE

The COPE project is a research project aiming at developing adaptive net-based interventions for woman suffering from various mental disorders, in particular stress, after having gone successfully through breast cancer treatment. The project is a collaboration between Western Norway University of Applied Sciences (HVL), The Centre for the Science of Learning & Technology (SLATE), a research center at the University of Bergen (UiB), and the Cancer Registry of Norway (Kreftregisteret).

Among the objectives of the project is to develop net-based interventions based on cognitive behavioral therapy and mindfulness, to address the stress-related problems these women are suffering from. Various types of patient data will be collected through the application, which will be used to support for adaptive therapy to each of the individual patient's needs. As an example, if the application collects data that indicates that the patient suffers from poor sleep quality, the application will present the patient with learning material and exercises tailored and adapted to the needs and preferences of the patient.

Figure 2.1 show the initial architecture of the COPE application. At the start of the project there were initiated four master thesis projects, each advancing aspects of the various modules presented in the COPE architecture.

This project covers parts of the Adaptive Algorithm module. As stated in chapter 1, the goal of the project is to implement and artifact that can . For the full COPE application the Adaptive Algorithm module will be responsible for presenting the patients with therapy tailored to their needs, and adapting the therapy as new data is gathered. It will rely on information about the patient represented in the Patient Model and content of CBT and Mindfulness represented in the Content Module. The therapy will be presented to the users through the COPE application interface. The users actions will be monitored by the Monitor Module which updates the Patient Module continuously.

The clinical goal of the COPE application is to provide successful adaptive net-based therapy for women suffering for stress-related problem after breast cancer treatment.

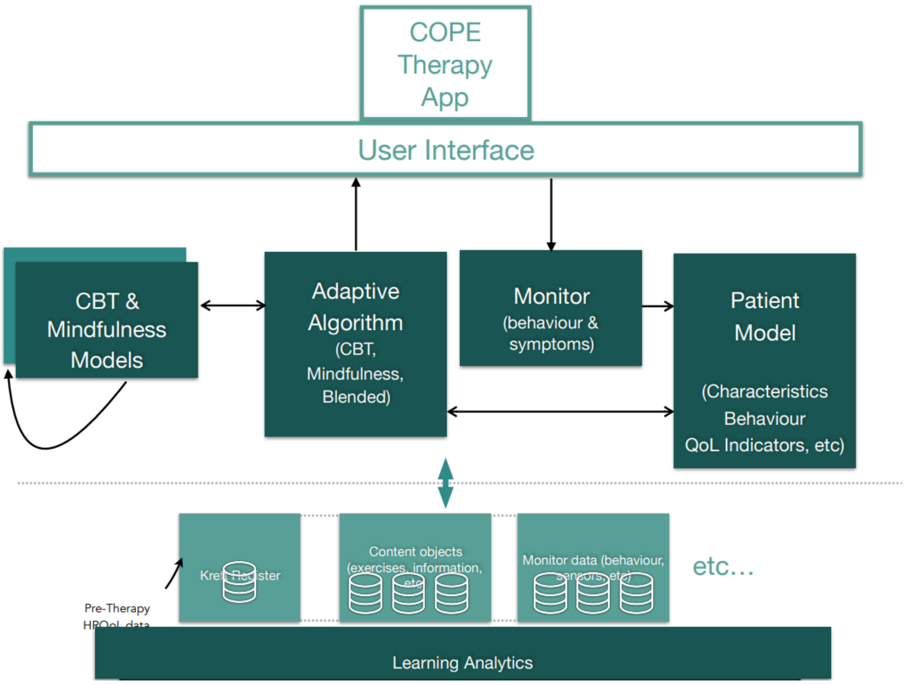

Figure 2.1: Overview of the different parts of the COPE application

2.2 Cognitive Behavioral Therapy

Cognitive Behavioral Therapy (CBT) is a psychotherapeutic treatment for mental illnesses (Field et al. 2015). The treatment is given through sessions face-to-face with a therapist, psychologist or psychiatrist. Additionally, the patients are given exercises and homework to do between these sessions. CBT focuses on changing negative cognitive behaviors and distortions, such as thoughts and attitudes, by developing coping strategies for these problems. The therapy is designed to treat depression but has subsequently been further developed to treat other mental health conditions, such as anxiety and stress.

Before starting a patient on a CBT program, modern CBT programs require the patient to fill out a clinically validated diagnostic questionnaire which will capture the current mental state of the patient. Some common questionnaires used in CBT are MADRS (Svanborg & Åsberg 1994) for depression, GAD-7 (Spitzer et al. 2006) for anxiety, QOLI (Frisch et al. 1992) for measuring the quality of life for a population with depression and anxiety and the Standard Stress Scale for measuring stress (Gross & Seebaß 2014). The questionnaires are typically done before, during and after the entire treatment program, to get a baseline and outcome measures (Månsson et al. 2017).

2.2.1 Internet-based Cognitive Behavioral Therapy

Internet-based cognitive behavioral therapy (iCBT) is a promising treatment form derived from CBT where the user usually interacts with a computer or smartphone during the duration of the therapy. In CBT programs, the user gets learning materials and exercises to perform, which is subdivided into modules. The modules' content is typically derived from a particular topic within CBT that improves the patient's coping techniques or ability to cope with a specific symptom. Modules may be divided into sub-parts based on coping techniques and particular aspects from CBT, such as behavioral activation, cognitive reconstruction and problem solving or based on symptoms. The content delivered to the user can be in the form of video, audio, text and interactive elements (Farrer et al. 2011). The modules in COPE may be structured in a similar manner to those in StressProffen. StressProffen is a guided iCBT application for managing stress (Børøsund et al. 2019). The modules in StressProffen are structured as shown below:

Module 1: What is stress

Module 2: Stress, QoL, and planning

Module 3: Thoughts, feelings, and self-care

Module 4: Mindfulness, rational thought replacement

Module 5: Stress and coping

Module 6: Social support, humor, and meditation

Module 7: Anger management and conflict style awareness

Module 8: Assertiveness and communication

Module 9: Health behaviors and setting goals

Module 10: Review and summary

CBT has shown sound effects on the outcome for the patients (Hofmann et al. 2012). A meta-study done by Xiao et al. (2017), shows significant improvement in the mental health for patients suffering from depression after breast cancer surgery by CBT treatment. However, the number of patients a therapist can consult per day is significantly lower than of a therapist consulting patients using guided internet-based cognitive behavioral therapy (iCBT). A therapist can consult 3-4 patients a day with traditional face-to-face CBT, whereas providing therapy through guided iCBT, 10-12 patients could get treatment, given at eMeistring in Bergen, Norway (Folker et al. 2018). This is an important finding and argument for iCBT as the number of people suffering from mental disorders is increasing worldwide (World Health Organization 2017).

Among internet-based therapy applications, we distinguish between different therapies that both have their advantages and disadvantages: guided iCBT and self-guided iCBT.

2.2.1.1 Guided iCBT

Guided iCBT is a form of therapy where a patient interacts with a form of an internet application, e.g. a web application through a browser, a standalone computer program or a mobile application. A therapist is involved in the course of treatment, and the role of the therapist is to guide, monitor and assess the patient's progression through the modules. The guidance is done via a short phone call, email or messages through the system with, by or from the therapist. The conversations between therapist and patient usually summarize to 10-15 minutes per week (Andersson et al. 2014).

With the iCBT therapy assisted by a therapist, the treatment can be more tailored towards each patient's individual needs, like in traditional face-to-face therapy. The therapist can assign specific CBT modules with tasks and content that will have a better effect on some patients, depending on the patients' underlying problems and goals. This can partly prevent the "one size fits all" tunnel vision problem most iCBT programs have with the assignment of treatment modules for the patients where all patients are presented with some order of the CBT modules, indepentent of what their symptoms, problem and doagnosis are (Kelders et al. 2012). A study by Johansson et al. (2012) found that standardized, non-tailored depression therapy was less effective compared to tailored treatment. Therapy that is tailored to specific symptoms the patients are experiencing shows great results. Another study by Atema et al. (2019) showed significant effects of iCBT therapy tailored towards patiants with more specific menopausal symptoms.

Several studies have investigated the impact of guided iCBT. In a meta-study from 2014, the effect of such therapy was investigated in use for the treatment of psychiatric and somatic disorders, including depression. The meta-study found that overall iCBT was equally effective to face-to-face CBT and was a cost-effective alternative to traditional face-to-face CBT (Andersson et al. 2014).

While guided iCBT has shown great effect and user adherence (Webb et al. 2017), it has its drawback. The biggest drawback of the guided iCBT is due to its cost compared to self-guided iCBT. According to a study by Holst et al. (2018), on average the total cost for a patient using guided iCBT was approximately 4000 SEK. The same study found that the cost of traditional face-to-face CBT was no more than 400 SEK more than guided iCBT. Thus, the different types of CBT treatments have a relatively similar cost, with no significant difference in effect. Even though more patients can be treated with the use of a therapist with guided iCBT per day, it remains to be a problem of scalability, as opposed to self-guided iCBT.

2.2.1.2 Self-guided iCBT

Self-guided Internet therapy is a promising alternative to the previously mentioned treatment method. Unlike guided iCBT, the users of these iCBT-applications do not interact with a therapist in any part of the course of treatment, only with the application itself. The application contains the information and exercises needed for users to undergo the treatment on their own. The amount of effort the users of the application are willing to put down is entirely up to themselves. Self-guided iCBT is an inexpensive alternative that general practitioners can refer patients to who cannot or will not pay for an appointment by a therapist. Cost is one of several barriers to access therapy, as well as the limited availability of therapists and fear of stigma (Mohr et al. 2006).

More and more research with a focus on self-guided iCBT is being done as these applications are made more available due to the evolving smartphone technologies. Several studies have been done to evaluate the effect of therapy.

A meta-analysis was published in 2017 comparing results from 13 studies on the effect of self-guided iCBT for people over 18 years (Karyotaki et al. 2017). This meta-analysis found that self-guided iCBT is effective in treating depression. Despite being effective and considered as evidence-based treatment, it has also been found that this form of treatment has several limitations. One of the more critical negative aspects is a significant dropout rate, as shown in a meta-study that investigated more than 40 iCBT studies. The study found that as many as 74% of self-guided iCBT users dropped out of the therapy before it was completed (Webb et al. 2017).

Despite the high dropout rate, one could argue that self-guided iCBT is still a good alternative for treating and preventing symptoms of depression as it reaches a greater amount of users. Two of the most used self-guided iCBT application for depressive symptoms, MoodGYM and Beating The Blues, costs 24 EUR for a 12 months subscription and 67 EUR for eight weekly one hour sessions, respectively (MoodGym 2020, Beating The Blues 2020). Compared to the numbers from Holst et al. (2018), where guided iCBT and traditional face-to-face CBT were given over a 12 week period cost 4044 SEK and 4434 SEK, respectively, self-guided iCBT costs significantly less.

As shown through the research findings reported above, the main problem of self-guided iCBT is the applications lack of possibility to provide for personalized guidance. In order for a self-guided iCBT application address this shortcoming, like traditional CBT and guided iCBT offers, some sort of system needs to be implemented to simulate a therapist's capabilities to provide for patient tailored guidance, to a certain extent.

2.3 ICT for adaptive therapy

Making therapy adapted to each patient's needs require systems that make use of various data, such as therapy and patient data. How the data is used to infer suitable treatment for the patient varies between the different systems. The two main categories of systems that may offer the functionality to make an adaptive self-guided iCBT application are *Recommender Systems* and *Intelligent Tutoring System.*

2.3.1 Recommender System

A recommender system is a system that can use techniques, algorithms and data to provide a suggested item for a user (Ricci et al. 2011). Recommender systems can be utilized to recommend items such as movies based on a user's movie history and ratings or that of similar users, or a good match for online dating, by using data from a the user's profile, such as personal preferences. These systems are particularly useful for users that lack experience and knowledge about the items to evaluate and choose the most suited item. It may also be quite time consuming to evaluate every item's properties, seeing as there may be an overwhelming amount of items to choose from.

There is a wide range of approaches and strategies to choose from when creating a recommender system. Which data the systems use and how the data is processed differs from system to system. Hybrid solutions, using two or more recommendation strategies where advantages from the respective strategies synergize to make better recommendations, is not uncommon (Çano & Morisio 2017).

2.3.1.1 Collaborative filtering

One of the most used approaches in recommender systems is collaborative filtering. The system recommends items based on the assumption that users who have had similar taste in the past will have similar taste in the future. Collaborative filtering uses data from profiles of different users. Identifying which users are similar to the user of the system can be done by scanning through the history of the users' item ratings, as well as other users' rating histories and then comparing the ratings. If the users' ratings of the items are similar, the users are considered to have similar tastes. Identifying the users' similarities can be done by a k-nearest neighbor (kNN) algorithm (Peterson 2009).

One of the advantages of using collaborative filtering is that it does not rely on knowledge of the items that are being recommended, but accurately recommend items based on user data alone. There are some problems with using collaborative filtering. One problem is referred to as the cold-start problem, which occurs when the system lacks data of a user to base the initial recommendation on. This is typically when the user is new to the system (Ricci et al. 2011).

2.3.1.2 Content-based filtering

Another approach where the initial lack of data is a problem is the content-based approach (Lops et al. 2011). A content-based system recommends items that are similar to items the user has rated in the past. The similarity between the items is based on the features of the items, and those features that match the user's profile, such as interests and preferences, as shown in 2.2. The data in the user profile is generated when the user interacts with the system. For instance, if a user tends to watch action movies and rate them positively, other movies tagged as 'action movie' will likely be of interest and therefore recommended.

Content-based filtering has several advantages. Unlike collaborative filtering, this approach is user-independent. Recommendations are solely based on ratings given by the current user and the user's profile, and not on the ratings of others. On the other hand, this requires enough ratings collected from the user in order to provide a good recommendation. As for new items added to the system, the only data needed to recommend these are their respective attributes. This means that the system does not require the item to be rated by any users before being recommended. Content-based systems are also transparent, meaning explanations for why an item is recommended can easily be given to the user, in the form of a list of item attributes that the system used. The types and the number of attributes an item has are naturally limited. Consequently, in order for the system to give a recommendation that captures the user's interest, and distinguishes fitting items from those the user dislikes, knowledge about the domain and content is needed. Systems based on content filtering may also experience the concept of over-specialization. When basing recommendations on the features of rated items, the system will continue to output items that are quite similar, which is not always what the user wants, limiting the expansion of the user's interest. This is called the serendipity problem. For example, if a user only has liked a book by the same author, the items recommendation will most likely be books by the same author, unless the system has implemented a form of randomness in the algorithm (Lops et al. 2011).

2.3.1.3 Knowledge-based recommender system

Knowledge-based recommender systems are described by Burke (2000) as systems that use knowledge about the user and the products. It is used to generate recommendations with a knowledge-based approach, deciding what product meets the user's requirements. Knowledge-based recommender system differs from the other approaches as they use different techniques to generate recommendations. Content-based and collaborative filtering is most suited when recommending items that are frequently bought, such as books and movies. On the other hand, if items are rated infrequently, the system will rely on deep domain knowledge. The data used comes from a user profile and a knowledge base. A knowledge base is one of the main components of knowledge-based systems, along with an inference engine.

There are multiple types of knowledge bases, depending on the application of the system. A knowledge base can vary from being a plain database to containing formalized knowledge, or a domain ontology (Bouraga et al. 2014). Which type of knowledge base to choose comes down to what recommendation strategy the system is using. In order for a recommender system to provide personalized recommendations, a user profile is needed. These profiles can contain data such as basic user personalia, age and sex, preferences for a type of item categorization, needs and results from questionnaires. Other types of data, such as trends and progression may also be stored, e.g. based on questionnaire responses in a given time frame. An advantage of using such a system is that it does not require a large data set to work well. Consequently, the shortcomings of other systems, such as the cold-start problem and the issue regarding new items, is not occurring in knowledge-based systems. The only downside of these systems is the complex task of creating a knowledge base. It requires having solid knowledge within the domain and how to represent it.

There are two common types of approaches within knowledge-based recommender systems: case-based and constraint-based.

2.3.1.4 Case-base recommender systems

Case-based systems recommend items by trying to find items that are similar to what the user has queried. The similarity matching uses each item's well-defined item features, such as size, color or genre. The system will treat the query as a case and look up similar cases that have been solved in the past, and that are stored in the knowledge base (or case base). A case consists of two parts: the specification and the solution. The specification describes the problem of the case. This is used to match with the specification part of the case currently at hand. The second part is the solution, which describes how to solve the problem. The solution is tweaked to fit the problem's specifications (Smyth 2007).

2.3.1.5 Constraint-base recommender system

The second type of knowledge-based recommender system is constraint-based recommender system, which is also referred to as rule-based recommender system (Ameen 2019). It is similar to case-based in the sense that it uses the user requirements and can give an explanation of the recommendation produced. However, how the recommendations are inferred differs between the two. Where case-based systems use similarity matching, constraint-based systems use predefined constraints, or rules, from the knowledge base to decide on how to match user requirements to the features of the items. If an item's features satisfy the constraints, or rules, and match the requirements, it will be recommended.

The rules take the form of an "**if** ... **then** ..." clause. The construct consists of two parts, the *antecedent* and the *consequent*. The antecedent, or the if-part, is a conditional expression that is checked for whether it is fulfilled and returns true or false. It needs to be fulfilled in order for the consequent to execute. A condition consists of one or more boolean expressions, i.e. true or false, in conjunction, or disjunction (Amatriain et al. 2011). The consequent part of the if-then clause specifies what actions that will be taken once the conditional expression is fulfilled. A collection will be contained in the system of rules that it will run through to check which ones are satisfied, and then being executed.

The constraint-based recommender system has a knowledge base that commonly contains two distinct sets of variables *(V_C, V_{PROD})* and three sets of constraints *(C_R, C_F, C_{PROD})*. In order for the constraints to be satisfied, the variables need to be instantiated (Felfernig et al. 2006). The following variables and constraints are explained in the context of a recommender system for mental health exercise and learning material.

> *User Properties (V_C)* describes the possible requirements of a user. An example of a customer property is *preferred modality*, referring to the user's preference of learning material content modality, e.g. audio, video or text.
>
> *Content Properties (V_{PROD})* describes the product properties. *Tag* is an example of a property, which could be a list of tags describing for which mental health problems the item may help with.
>
> *Constraints (C_R)* defines which instantiations of customer properties that are allowed. As an example, a user diagnosed as suicidal can probably not be allowed to use a self-guided mental health application.
>
> *Filter conditions (C_F)* defines the relationship between the properties of a user and of the content, i.e. which exercise or learning material that will be selected. In an iCBT application, an example could be that if the learning material has a *Mindfulness*-tag in its properties, the user cannot score higher than a certain threshold on a certain psychometric item. If the user scores above this threshold, the learning material will be filtered away.
>
> *Product constraints (C_{PROD})* defines which product properties, or the set of products, that are restricted from being instantiated, and are represented by a conjunction of variables (V_{PROD}).

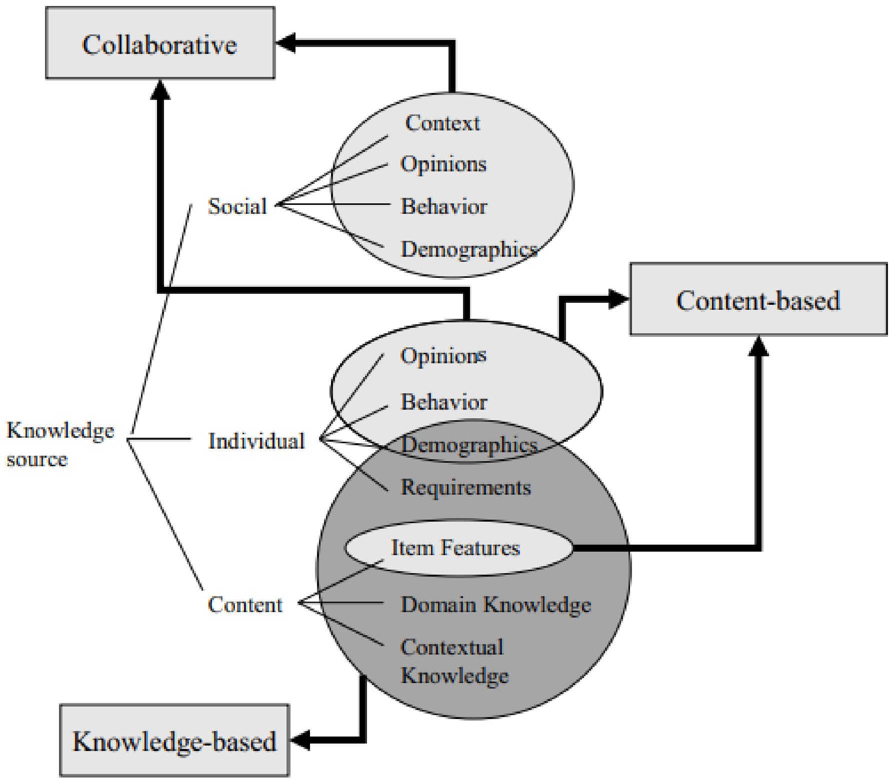

Figure 2.2: Knowledge sources and recommendation types (Burke & Ramezani 2011)

2.3.2 Intelligent Tutoring Systems

An Intelligent Tutoring System (ITS) guides the user through the process of interactive learning, with the goal of resembling the effect of having a personal tutor. The system uses a learner model to give the most suited exercises and learning material at all times, based on data on the user's knowledge, competency and progression. It may also personalize the learning based on the student characteristics, preferences and current status, such as emotion, mood and learning style (D'Mello et al. 2010, Yannibelli et al. 2006). This is referred to as a Student Model in the basic architecture presented in figure 2.3 by Morales-Rodríguez et al. (2012). An ITS also uses a domain model to represent the subject the user is currently working on, shown as a Knowledge Domain in the figure. In addition to the domain model, it uses a pedagogical model for a suitable tutoring strategy, e.g. whether or not, and to what degree the system should intervene with hints (Nkambou et al. 2010). As shown in the figure, when the student interacts with the system through the User Interface, data about the student is being sent to and updating the student model. Consequently, the updated student model is a more accurate representation of the student, which will make the next instructions tailored more accurately.

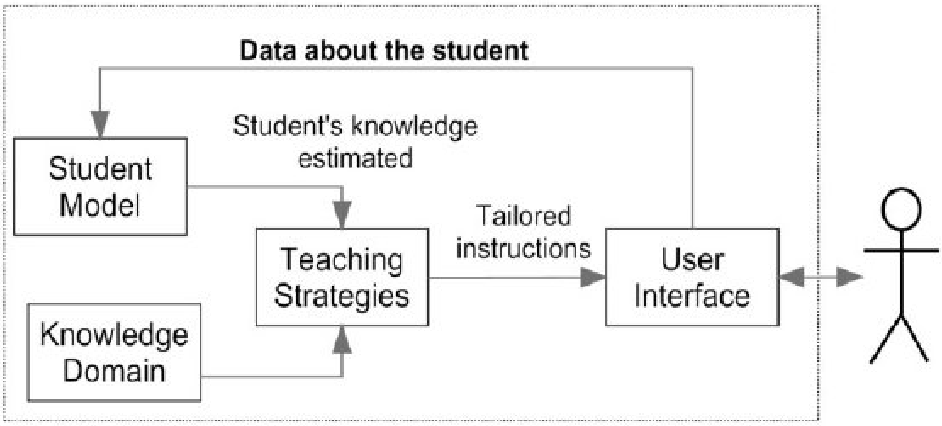

Figure 2.3: Basic architecture of an ITS (Morales-Rodríguez et al. 2012)

Intelligent tutoring systems are already assisting students in many different domains, in all parts of the educational system. Students attending primary and secondary education are usually interacting with an intelligent tutoring system either using the school's or the students' own computers. Studies have proven that using these tutoring systems, students show greater learning gains than the other student that are not utilizing them (Koedinger et al. 1997, Corbett 2001). As mobile units, such as smartphones and tablets, have become ubiquitous in today's society, a natural next step would be to develop intelligent tutoring system applications to these units (Cook et al. 2011). The next learning session could be available at all times, easily accessible, both within and outside of school hours.

While the final product of what COPE aims to become has similarities to an Intelligent Tutoring System, there are certain aspects of such a system that might be omitted initially. Giving immediate feedback, such as hints, to the patient while doing exercises, as part of a teaching strategy, are among the functionalities that will not be included for now. Among the important functionalities an ITS offer, which is a goal for COPE, is to present the most suited content for the patient in a way that enhances the patient's learning. This can be achieved either through preferred content presentation or through cases and examples in the exercises and learning material matching the patient's specific demographic, age or health history.

2.4 Challenges

One of the challenges of this thesis has been to develop an artifact that is somewhat dependent on the works of the other project members. Each of the student's thesis project should preferably have the finished artifacts of the others when working on their own, which are naturally not possible. For instance, if the ontology of the patient model added or removed an important property and the recommender system was dependent on using an updated patient model, crucial changes have to be made. Meetings have been held more or less on a regular basis throughout the time since the beginning of the project. The topics on these meetings have been, among other things, to exchange information of the respective work being done and changes being made that may affect the work of others.

A matter to take into consideration is to what degree the thesis projects should be dependent on each other. On the one hand, in a project where every part is relying on fitting perfectly together, a substantial increase of time and effort has to be made for the different artifacts to adapt to every change made in the other projects, or the projects would have to rely on pre-defined APIs. Although a lot of changes have to be made, the result of the project might have a higher chance of successfully working with every student's artifact together interconnected and working as one, as initially intended. On the other hand, without the students being codependent and working on their respective tasks more freely without being interrupted by change every now and then, the individual project results might end up in a better state, on their own. As meetings have been regularly held, each participant has good insights into the others' projects. With this insight and knowledge, the students with inter-project dependencies were able to continue with their work by creating either a mock or somewhat equivalent artifact of what was needed, and where the equivalence is expressed at conceptual levels. For instance, both the domain model and patient model used in the recommender system is fairly similar to what has been shared and discussed during meetings. However, as the work of others is subject to change, parts of the artifact might be outdated. As long as these subprojects fit on a conceptual level, there might not be any vital problems.

2.5 Related Work

As briefly pointed out in section 1.3.1, there has not been done research on adaptive iCBT therapy for depression, let alone for depressive symptoms after breast cancer. There exist quite a few iCBT applications for depression and other mental health disorders, both guided and self-guided. These applications are either commercial or used for research projects. As shown in a systematic review of web-based health interventions by Kelders et al. (2012), out of the 83 interventions included, 90% (n=75) structured the content in a tunneling linear manner. Interestingly, all interventions with a focus on mental health, as opposed to lifestyle interventions, the used tunneling approach.

2.5.1 Insomnia after breast cancer

A study by Zachariae et al. (2018) tested the efficacy of self-guided iCBT with a focus on insomnia (iCBT-I). Among cancer survivors insomnia is up to three times more common than in the rest of the population (Howell et al. 2014). As iCBT specifically for insomnia has shown great results for people without a history of cancer, the study tested the efficacy with breast cancer survivors. A total of 255 women were divided into either getting iCBT treatment or into a waiting list control group. The treatment was delivered over a six weeks period, each week with a new module of iCBT-I content, which takes 45 to 60 minutes to complete. Based on daily diaries that the participants needed to fill out, the participants would receive automatically tailored recommendations for restriction of sleep. In the same way as COPE, the content would be presented through text, video, interactive activities and graphics. Sleep-related outcomes, i.e. insomnia severity and sleep quality, were compared to baseline at post-intervention and follow-up, 9 and 15 weeks after, respectively. Almost 60% of the women completed all the six modules, and more modules completed were associated with better improvements for insomnia severity, sleep quality and efficiency. This low-cost treatment application showed significantly beneficial outcomes, with an effect lasting after treatment and showed great improvement. The effect size was greater than compared to both face-to-face CBT-I and iCBT-I for the general population. This shows that iCBT, with a focus on specific health related problems and symptoms, can be efficacious.

2.5.2 Intelligent Tutoring System with Learning Styles

Morales-Rodríguez et al. (2012) proposes an architecture for an intelligent tutoring system that aims to improve the education of the students. The education will be adapted to each student, with individualized instructions, which is the most effective way, shown in an analysis by Bloom (1984). An ITS includes a student model, a knowledge module and a tutoring module, as displayed in figure 2.3. Among the tasks of the tutoring module is the teaching strategy for choosing the content and provides assistance for the students. The proposed architecture presented in the paper includes a process of choosing the content suited for the student's learning style. A student preferred learning style is determined after gathering data from a questionnaire presented to the students initially. The learning styles are part of the VARK model, which includes the sensory modalities *Visual*, *Aural*, *Read/Write* and *Kinesthetic* (Fleming & Mills 1992). After the student has reported which modality that is most and least preferred for each question presented in the questionnaire, the most suited one is obtained. A similar implementation can be beneficial for the COPE project, to ensure a personalized learning experience.

2.5.3 MoodGym

MoodGYM is an internet-based CBT program focused on depression and anxiety. The program is a self-guided tool for individuals to prevent and cope with symptoms of these mental health issues. It is developed by the Australian National University and made available to the end-users for free (Farrer et al. 2011, Twomey & O' Reilly 2016). It has reached over a million users worldwide and translated into multiple languages. Over the years MoodGym was translated into German, Chinese, Norwegian, Dutch and Finnish. However, it is currently only available in English and German as the versions including the other languages have not bee updated, as of June 2020 (MoodGym 2020).

MoodGYM has some similarities to what the COPE project has as its goal of becoming, but it does not tailor the therapy to each individual. The content of MoodGym is structured in the normal "tunnel view" manner, meaning each user has to go through the same five modules in their complete order. The modules include learning material, exercises and quizzes. The user may skip some of the exercises, which is discouraged, but there are quizzes one has to complete in order to proceed in the modules. MoodGYM also includes a section called Workbook which contains all the exercises and quizzes that have been encountered throughout the program. This lets the user continue using the application, even after having completed the modules. It may also be available on beforehand if a user does not want to go through all of the content of the application first (Twomey & O' Reilly 2016). COPE will have a similar functionality once it has reached its final form, allowing the users to more or less freely redo the content that has already been completed.

As reported in a meta-study by Twomey & O' Reilly (2016) of the effectiveness of MoodGYM, the results show a small effect size for treating symptoms of depression after a comparison between 11 studies. It shows the effect to be non-significant when adjusting for publication bias and removing the lowest quality studies. Although the application is available for anyone, which has resulted in an enormous user base, the user adherence is very low.

A study with over 38000 participants found that less than 7% of the users stayed to continue with the third of five session of the program. The study concluded that the application is an intervention on a population-level, and while it will likely not be beneficial for most, it will be for some.

2.5.4 Section summary

Both guided and self-guided iCBT has its strengths and weaknesses. Guided iCBT, where a therapist is involved, has shown to have the same effect as traditional face-to-face CBT, although with not quite the low dropout rate. Getting therapy delivered through an application at home, makes the therapy more accessible, whether it is due to physical limitations or psychological barriers.

Guided iCBT has a higher cost than the other type of iCBT, namely the self-guided iCBT. This is due to the involved therapist. Both the cost and the involved therapist might be a barrier to some people, which are not found in self-guided applications. Self-guided iCBT applications have the ability to reach a greater amount of users, lower cost, but have not shown quite the same effect in the literature and significantly lower user adherence.

The COPE project's objective is to combine different advantages from both traditional CBT and guided iCBT, with the scalability benefits from self-guided iCBT. To our knowledge, this has not been done before, and for sure not with the focus on treating depressive symptoms after breast cancer. Different principles and techniques have been briefly described as these are possible solutions for similar systems. The architecture of the project's solution is similar to the basic architecture of an Intelligent Tutoring System, as shown in figure 2.3. It contains similar modules, such as domain knowledge and student model, specifically a patient model in this case. Both knowledge about the content and the patient will be used by the system that recommends the most suited next step through the therapy. Data will also be gathered from the patient's interaction with the system, feeding back into the patient model. Making use of ideas and technologies from recommender systems can be useful in this project as some systems recommend items for the user based on a user model. In COPE, the user model is referred to as a patient model. It contains data about the patient, such as age, but also which symptoms they experiences and its degree.

A recommender system contains interesting functionalities and different techniques to recommend items (modules and exercises in COPE) for the patients to work with. Some techniques primarily focus on the user's demographic data, e.g. age and location, to match them to other users of the same demographic, in order to estimate the users' interest in the item. Another type of system that may be useful is knowledge-based, where it uses the knowledge of an item to match with a user's preferences, e.g. whether the patient is not comfortable with exercises with an extensive amount of text (Khusro et al. 2016). Weighing up the pros and cons of each type of recommender system, a knowledge-based recommender system seems to provide functionalities and techniques suited for this case. It makes use of knowledge about the therapy content, as well as from knowledge about the users, such as preferences. A patient's psychometric score is also among the used data. Using principles from content-based systems might also work, once overcome the initial cold-start problem of content-based recommender system.

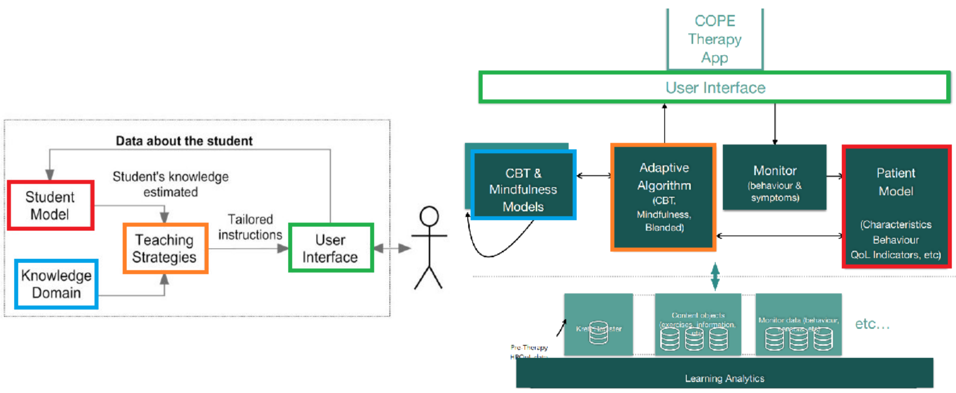

Figure 2.4: Comparison between the basic ITS architecture from 2.3 and the COPE architecture from 2.1.

3 Method and Design

This chapter presents the artifact. First, the iteration of the design and development process is described. Then, the central components of the system, such as patient and therapy content models and the recommender system, are explained. Finally, a graphical user interface for testing the recommender system is presented.

As mentioned in section 1.3.2, the practical work of the master thesis was divided into three main objectives which are described in the following section. The main objectives are:

1. creating a recommender system that allows for a simulation of activities, including using dependencies
2. integration of patient data, e.g., psychometric screening data, goals and preferences presented through an interactive
3. graphical simulation environment

.

3.1 The design process

Throughout the entire time frame of developing this artifact, meetings were held. Most participants of the COPE projects have been present at these meetings; master students of Software Engineering, supervisors with experience in iCBT, the director of the Centre for The Science of Learning and Technology (SLATE), as well as a psychologist. These have been held at Western Norway University of Applied Sciences or at SLATE, Bergen, or via video conferencing services during the COVID-19 outbreak. Meetings with only master students and supervisors were held every second week, whereas the meetings with the other attendees as previously mentioned, approximately once a month. At these meetings each student's sub-project artifact were presented, where the artifact features and recent changes were discussed. After the COVID-19 outbreak it was harder to keep the regularity in the project meetings.

There are five iterations that had a natural division in this development process. These iterations had specific requirements and goals which would either be presented, discussed or evaluated at the meetings. The artifact implementation from the last iteration would be presented and evaluated. Most iterations had sub-goals that needed to be fulfilled, typically in the form of a feature or rule that needed to be implemented. The main objectives of each iteration will be presented below:

1. Problem identification and initial ideas for solution
2. Hard content prerequisites and psychometrics
3. Extended patient data inclusion
4. Visual representation
5. Frequent reports of patient status

Iteration one: In the initial iteration, plenty of discussions and exchange of ideas helped to make a somewhat clear picture of the end result, conceptually. As a result of not knowing how integrated each student's sub-project would be into each other's, some challenges occurred. In this phase, questions regarding which language the system would be written in and whether a pre-existing system should be used had to be answered. It was decided that each student should focus on their assigned artifact without considering any detailed requirements for integration. Instead, we were to think about future integrations at a conceptual level.

For this master thesis project, the initial idea was to create a simple rule-based system with a few hard-coded rules. The first objective was to start by having the artifact recommending content based on the last reported psychometric screening and display it in the console.

Iteration two: A structure needed to be implemented that would let the system base recommendation on whether a patient was eligible for the content. To achieve this, the following functionalities were implemented:

- A patient has to complete a certain learning material before doing an exercise.
- Patient psychometric score in a certain screening item has to be below a certain threshold in order for the patient to be allowed access to specific content. Values for the thresholds and which type of content being prerequisite is at this stage arbitrary, and only used to represent the functionality.
- Exercises and learning material have been tagged with predefined tags. The total set of tags includes mostly symptoms of depression equivalent to those found in the psychometric screening, Montgomery and Åsberg Depression Rating Scale (MADRS), which is currently being used. The tag set also includes a tag that tells if the content belongs to CBT or Mindfulness.

Iteration three: In iteration three, the focus was on integrating the patient model in the system. Among the most important improvements to the recommender system were:

- Recommendations are not only being based on which exercises the patient has done already and how the patient scores on a screening, but also on which goals the patient has.
- Content modality of a patient's preference is implemented, allowing the patient to receive recommendations of learning material or exercises in the format of video, audio or text.
- Multiple adjustments have also been made to the recommender, such as added extra weight (or score) to an activity, if a therapist sees it to be of great importance.
- A change in the prioritization structure was also implemented. From sorting an array of content based on different parameters, and then choosing the one on the top of the list, the prioritization was after the third iteration based on an associated score.
- In previous iterations, the learning material was strongly connected to an exercise, whereas in this iteration the two of them were separated

with both extending a common model named Activity.

Iteration four: In the fourth iteration, a rather simple graphical user interface was implemented. This made it easier to manually test the system and to get an understanding of how it works through a simulation. The following functionality were implemented:

- Check which activity is eligible for the patient, and which is being recommended
- Display the scores of each parameter making up the total activity score for either eligible or completed activities.
- A visual representation of the patient, i.e. various details, such as psychometrics and personalia.
- The ability to generate a random screening at any point throughout the simulation.
- Also, visual feedback were added to display whether a patient is suicidal, scores over a certain threshold, or is ineligible for doing a certain activity due to too severe symptoms.

Iteration five: In the fifth and final iteration, additional functionality was implemented. This was based on feedback from a Human-Computer Interaction (HCI) and an analytics expert, collected through evaluation of the artifact. It was suggested to include a simulated functionality in the graphical user interface, simulating a daily "this is how I feel like today" from the patient. After implementation, a patient is able to report the daily status of how the patient feels. For example, whether the patient has gotten more sleep or is feeling more stressed than usual. The ability for the tester of the system to add daily reports have been added to the GUI, which affects how the system recommends activities.

3.2 Artifact description

The artifact is a recommender system that uses knowledge from the CBT content and the current representation of the patient in the form of an abstracted patient model. It gives recommendations on which activity that is most suited for the patient at any given time based on a combination of data from these two components. The relevant concepts to the artifact will be described below to give an understanding of what is being used to recommend CBT content to the patient.

3.2.1 Activities

An activity is an object that can be either a presentation of some learning material or an exercise. It is a superclass that holds properties that both the two subclasses inherit. A simplified representation of what an activity looks like is shown in figure 3.1. The reason behind this abstraction is that it allows for an easier handling of the two subtypes in the implementation. An activity, and subsequently learning material and exercises, hold properties such as an activity title, prerequisite activities, tags, completion status and scores/weights. A detailed class diagram in figure 3.2 shows the properties that *Activity* holds, and subsequently the subclasses *LearningMaterial* and *Exercise*, which inherits the properties from its parent class *Activity*. These models are themselves abstractions of the work another master student in the COPE project.

The Learning Material object holds, naturally, the material that a patient is supposed to learn. The learning material is either content from cognitive behavioral therapy or mindfulness. Some learning material may have prerequisite activities that have to be done before gaining access to it. With the goal of making the content suited for each patient, the material will be available in different modalities to accommodate patient preferences, e.g. text, audio and video.

The second subclass of which activity is being extended is Exercise. Like the learning material, it includes content from either CBT or mindfulness. An exercise can contain just exercise text which tells the patient to do exercises for themselves, without necessarily giving an answer back to the system. An example of this is to do a breathing exercise, with or without the help of visual aid. An exercise may also be in the typical question and answer format. The question can also be answered with a free-text answer, a single radio button answer or through a multiple checkbox answer.

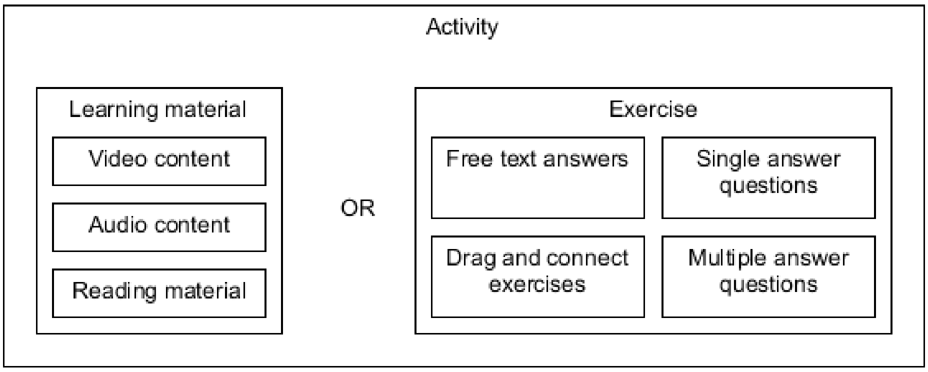

Figure 3.1: A model of Activity, parent class of Learning Material and Exercise.

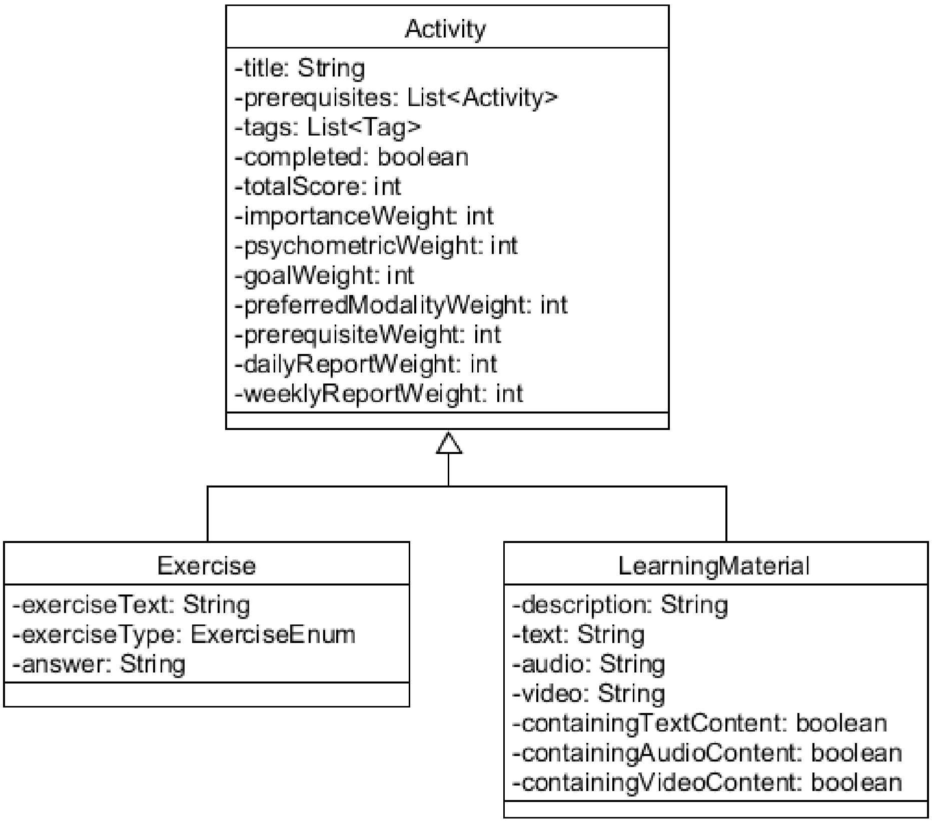

Figure 3.2: A class diagram of Activity, and its subclasses Learning Material and Exercise.

3.2.2 Modules

A module is a container for exercises and learning material. The modules contain activities that typically have a common theme, such as a specific symptom. It can also be an introductory module the patients have to go through before starting the therapy. Activities can also be subdivided into sub-modules, based on activities that might form a chain of prerequisites. For instance, an exercise might require some learning material or another exercise to be done beforehand, within a sub-topic of the module's content, as shown in figure 3.3. An activity can require the patient to complete an activity from another sub-module, displayed by the two prerequisite arrows going into the second sub-module in figure 3.4.

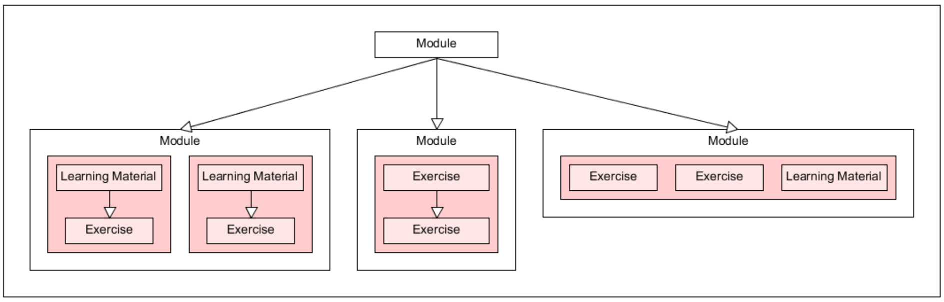

Figure 3.3: A simplified model of module structure COPE, displaying sub-modules, and the activities within.

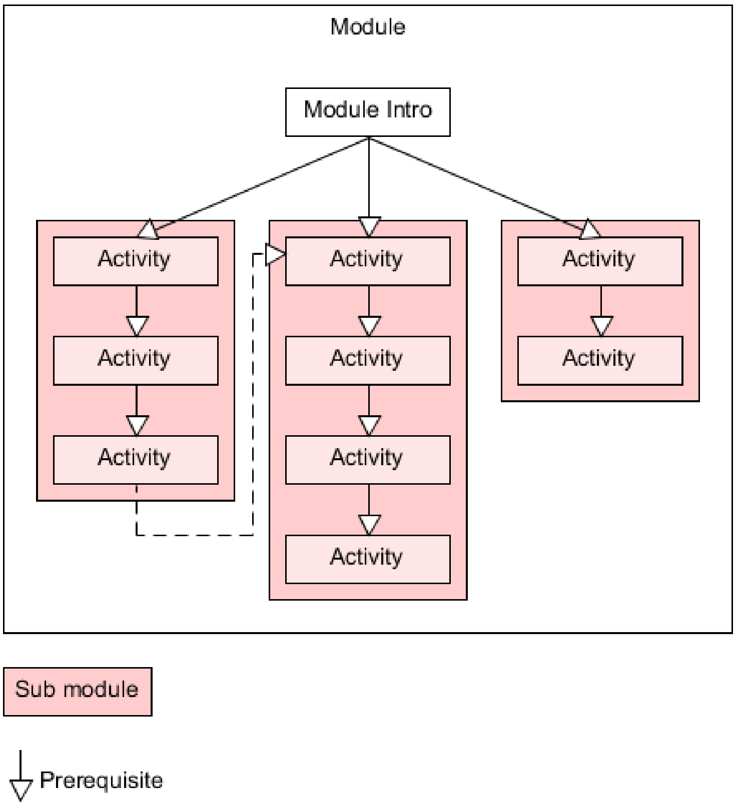

Figure 3.4: A model of a module, a conceptual container for activities.

In a similar manner to activities, a module can also hold a list of prerequisites. These prerequisites are other modules the patient has to complete in order to continue the path through the therapy application, as shown in figure 3.5. It is, however, no requirement of finishing a module in a single session. Nor is it required to finish the module in order for the patient to be able to do another module, as long as it is not a prerequisite module, as seen in most CBT applications following a tunnel structure (Kelders et al. 2012). In other words, the patient is able to jump back and forth between activities from different modules as he/she or the recommender system finds it suitable within the scope of the set prerequisites. Figure 3.6 exemplifies two out of many different paths a patient can run through the activities, with the index numbers displaying the order. The module structure in figure 3.5 shows which modules that have to be completed before continuing the next module, represented by the arrows. The reader has to be aware of that this is just a simplified representation of the prerequisite functionality and not how tightly coupled the actual COPE modules are once the application is populated with proper CBT and mindfulness content. Modules are also storing a list of tags associated with the content it holds, e.g. *Sleep* and *CBT*. A detailed representation in the form of a class diagram of a module is shown in figure 3.7

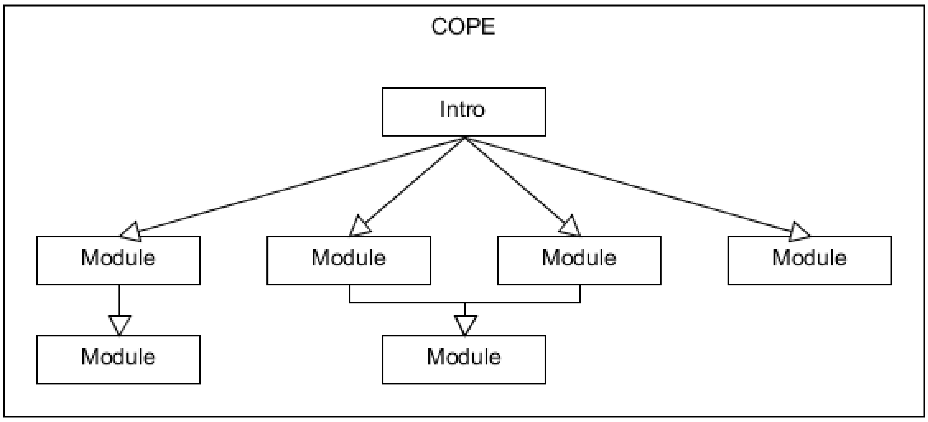

Figure 3.5: A simplified model of the module structure of COPE, displaying the flow using module prerequisites.

For the COPE application to be able to provide for therapy that is personalized to the needs of each individual user, the modules and the activities within the modules, can not follow the tunnel structure from A to Z with

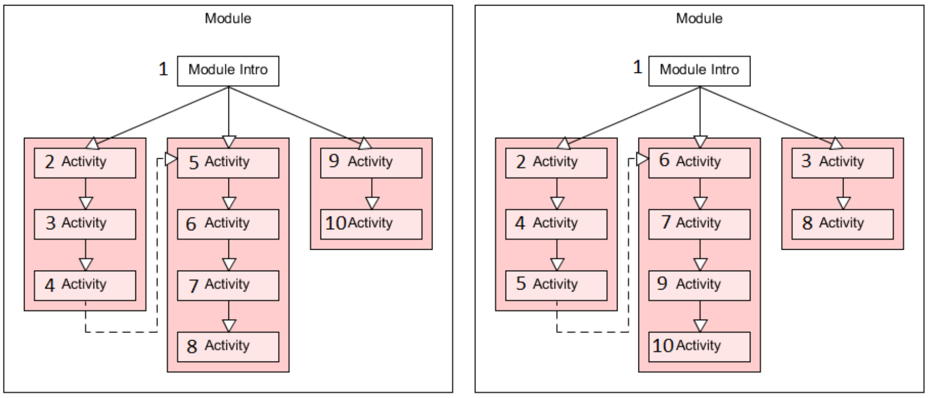

Figure 3.6: Two examples of the order one can run through the activities.

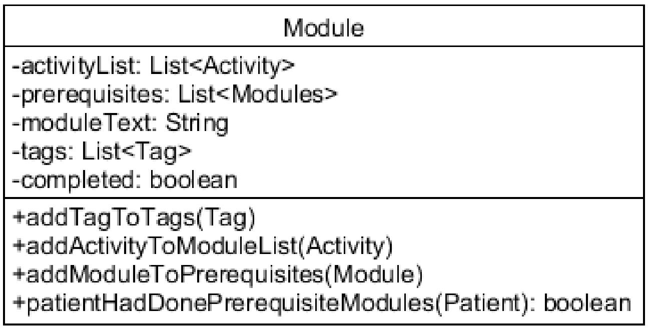

Figure 3.7: A class diagram of a Module.

the tight order set by prerequisites from one element to the next. For instance, one does not have to complete the entire *sleep* module before one is allowed to do content in the *stress* module. Figure 3.8 shows an instance of how the COPE content can be structured, where E represents an exercise and LM represents learning material. However, the introductory module for the COPE application is a requirement to do before granted access to the other, which is among the reasons why module prerequisite functionalities have been implemented. COPE will then have the possibility of offering the therapy in different modes with a varying degree of strictness, e.g. tunnel/strict mode, semi-free mode and free mode. There may be useful data to be gathered from running the therapy in different modes within the same environment. This will be among the many interesting future research themes for the COPE project to investigate through the future COPE research platform.

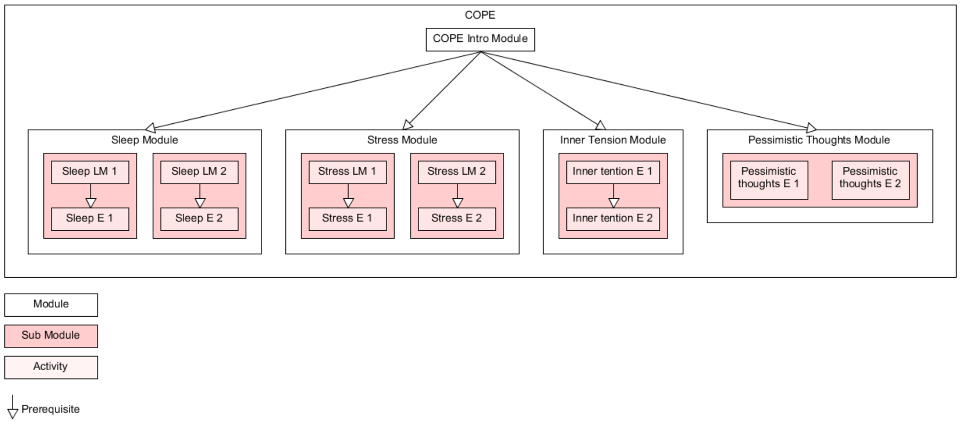

Figure 3.8: A model of module and activity structure of COPE - an exemplified instance.

3.2.3 Patient Model

In order for COPE to be able to provide for personalized therapy, the Patient Model (fig 2.1) has to be based on a well structured data model that represent various important characteristics of the patient. This is done in detail within another master thesis project. Representing a patient in the form of data is a vital part of personalized therapy. Identifying which data may be found useful for the recommender system and for research projects afterward has been a central topic in multiple master meetings. Creating an ontology model to represent a patient is not an easy task, as it is not to be found in the literature. For the artifact developed in this thesis, an early simplified version of the Patient Model being developed in the other master thesis project has been used. Due to this alteration, presumably, there will be patient data that could be found useful in recommending therapy content, not present in the model. For instance, some patient data from an Electronic Health Record (EHR) or the cancer registry, like a patient's past and current diagnosis, is not included in the patient model.

Among the data found in the patient model is general personal information, such as the patient's first name, last name and age. This personal information is currently only being used for displaying the patient to visually differentiate between multiple patients during the simulated runs. The age of the patient certainly could affect the outcome of the system, either through what content is being recommended or how the content is presented. However, due to limited time, this has not been implemented in the system so far. A class diagram of a Patient is displayed in figure 3.9.

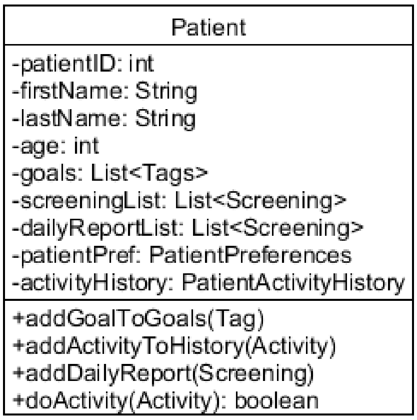

Figure 3.9: A class diagram of a Patient.

Other data in the patient model, which have a greater impact on the recommendation, are patient goals, a list of psychometric screenings, the patient's content modality preference and activity history.

A patient's modality preference is also included in the patient model. Once the COPE application has been started for the first time, the patient will enter to what degree the different content modalities the patient prefers. Content can either be presented in text, via audio or video. How much of the content that will be available in text, audio and video, is not clear at this point. In addition to addressing the preferences of users, this functionality is also implemented so that various types of impairments, such as hearing or visual impairment, do not hinder the patient from doing the therapy.

In order for the system to recommend content based on the state of a patient's mental health, the patient has to go through psychometric screenings. At least for the time being, the self-rating version of Montgomery and Åsberg depression rating scale, MADRS-S, is the one used for rating the patient's depression symptoms (Cunningham et al. 2011). The rating scale includes the following items:

1 Reported Sadness

2 Inner Tension

3 Reduced Sleep

4 Reduced Appetite

5 Concentration Difficulties

6 Lassitude

7 Inability To Feel

8 Pessimistic Thoughts

9 Suicidal Thoughts

Apparent sadness is omitted from this scale. In addition to these symptoms, a patient's perceived stress is added to this screening. This is temporarily just implemented as a single question with the scale from 0 to 6, like the symptoms from MADRS-S. At a later stage of the COPE application artifact, a proper stress rating scale should replace this, like the 10-item Perceived Stress Scale, to capture a patient's perceived stress (Lee 2012). After the evaluation of iteration 5, *Fatigue*, *Musculoskeletal Pain*, *Feeling Blue* and *Feeling Anxious* was added as suggested by the psychologist. The scores from such screenings are stored in a list in a patient model object.

The patient's daily reports of the current status is stored in another list within the object based on the patient model. The daily report is a lightweight screening, asking how the patient is doing that day. A quick question can be prompted on whether the patient feels more stressed or had a good night's sleep for a change. The patient can choose to answer, using the same scale as MADRS, 0 to 6, and the answer will be part of the inference of recommended activities. The daily report functionality is included as the longer and perhaps more tedious screenings are not requested to be answered every day. Consequently, the screenings will not represent the patient's mental status every day the patient is interacting with the COPE application.

The patient's goals is a list of goals represented by tags. A patient's goal is what symptoms or problems the patient wants to work on. How this is currently designed is that a goal's tag is just another one from the list of predefined tags which is shared between modules and activities as well. The tags are defined based on the symptoms from MADRS-S psychometric screening, such as *inner tension* and *pessimistic thoughts*. A goal can be a long time goal the patient wants to work towards reaching. It can also be simply a goal for the therapy session, as the patient's goal may vary from one day to another.

An activity list is also stored in the patient model. This list represents the activities the patient has completed, learning material and exercises. This data is useful for recommending the next content for the patient, to see what type of content has already been done, and which prerequisites have been fulfilled. It is also important data for the research on how to improve the personalization of COPE in particular, and more adaptivity/personalization of iCBT in general.

3.2.4 Recommender system

The recommender system implemented in this artifact can be considered a hybrid system. It uses central techniques from both knowledge-based and content-based recommender systems. The system has a deep knowledge of the items it can recommend. The patient will be required to do an initial screening to determine the mental state of the patient in the COPE application. Once this is done, the cold-start problem is averted. A patient model is also heavily used in the system. Not only is it used to recommend suited therapy based on the patient's screenings, but also based on the patient's preferences and recently done activities that are similar.

All activities are processed in a filtering mechanism early in recommendation procedure. This process involves a set of conditions the activities have to meet in order for them to continue further through the filtering process. Among the conditions that need to be fulfilled is the check for whether a patient is eligible for the activity or not. A patient can be eligible for an activity if the patient has completed all the necessary activities required in order to continue to the next in line. Some activities may be discarded due to the state of the patient's mental health does meet the requirements.

Once the activities have gone through the filtering phase, the total score of each remaining activity is calculated. The total score is a sum of the different weighted properties of an activity. There are different ways of weighting the properties, depending on how the recommender system is implemented. A content-based system may base the weighting on similarities between features and attributes of the items (Debnath et al. 2008). Another solution is to summarize the weights calculated from different recommendation techniques (Bostandjiev et al. 2012). Among the weighted properties in the artifact are the patient goal weight and preferred modality weight. Each weight will be explained in detail in chapter 4. The activity with the highest score is chosen as the most suited activity for the patient, and is consequently being recommended. An overview of the recommendation process is shown in figure 4.1.

3.2.5 Graphical user interface for testing

All recommended activities, patient data, activity data and variables used in the recommendation process are displayed as a text-based output in the console of the integrated development environment (IDE) used to program the system. This gives a limited overview of what is going on, as well as limiting the user interaction with the system, e.g. requesting the next recommended activity. By creating a graphical user interface (GUI) to interact with the system, both the developer and anyone else who wants to inspect or evaluate the system, get a greater overview and understanding of how the system works. This part of the artifact will help adjusting and fine-tuning the recommender algorithm. It will also allow for discussions and understanding for psychologists and psychiatrists which will help the further development of the COPE application and research platform.

As displayed in figure 3.10, the GUI is divided into six sections.

- Eligible Activities:
  Displays a list of all the activities a patient is eligible for, with their respective total scores of which they are sorted by.

- Completed Activities:
  Displays a list of all the activities a patient has completed, sorted by the sequence of which the activities were completed.

- Activity Score:
  Displays the different weights or scores associated with the selected activity. The user can select an activity from either the list of eligible or completed activities. These are the weights that make up the total activity score. The calculation of this score will be explained later in section 4.

- Psychometrics:
  Displays the patient's latest psychometric screening is presented in a list. Each item from the screening shows the respective answer, the rating scale and its associated severity percent, together with the item name.

- Daily Report:
  This section contains input fields for *Sleep* and *Stress*, where a rating can be entered of how a patient feels that day, of the respective screening items.

- Weekly Stress Reports:
  A display of the last seven days of reports, which is used to calculate a weekly score of how a patient is doing, e.g. in stress.

- Patient Data:
  General patient data is displayed, such as name and age, together with the patient's goals (tags) and content modality preferences (text, audio, video).

When interacting with the GUI, the user has the ability to run through the system using the buttons at the bottom of the GUI. The **Next** button will request the system to recommend an activity, complete it and add it to the completed activity list. The **Do all** button simply runs through the simulation, asking for the next activity to do until the list of eligible activities is empty. **Reset** will reset the system, making it so that the patient has not done any activities yet, as well as creating a new randomly generated psychometric screening **Add report** will take the entered values from the input fields and add a daily report to the list of weekly stress reports found in column 6. Finally, the **Add new screening** button will add a new randomly generated psychometric screening to the patient, which will work as the last screening the patient has done. This can be done at any point during the testing process, as the recommender system is currently basing the recommendation on the last screening, together with the other patient and content data.

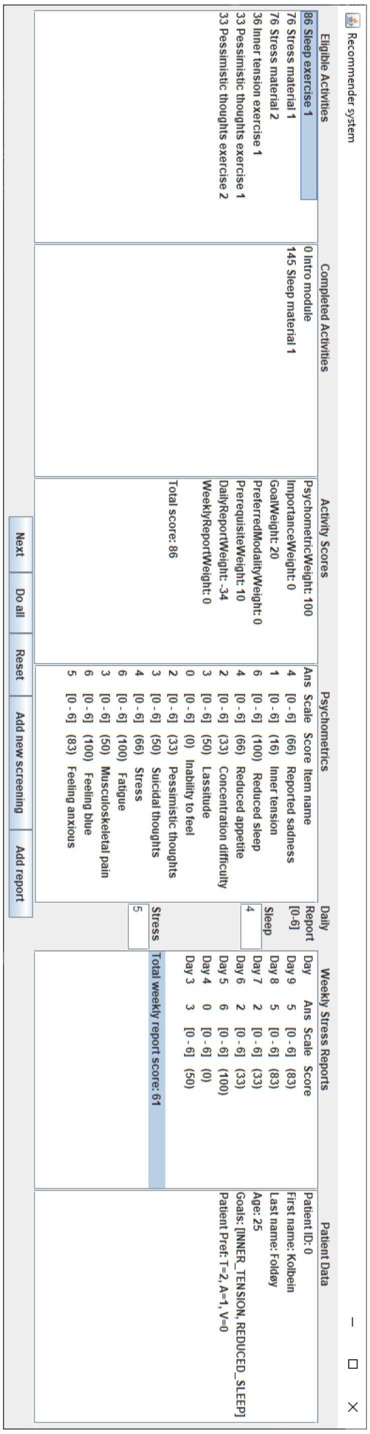

Figure 3.10: A graphical user interface for getting an overview over and interacting with the recommender system.

The GUI will also give visual feedback whenever various conditions have been met that will limit the size of the activity pool. As shown in the right side (top) GUI in figure 3.11, the *pessimistic thoughts* item of the psychometric screening is highlighted in yellow color. This is due to a rule that has been fulfilled, which says that the value of pessimistic thoughts item is above a certain threshold. As a result, pessimistic thoughts activities with the *Mindfulness* tag associated with it, will render the patient ineligible to do mindfulness related activities.

Another example of visual feedback is when a certain rule has been fulfilled regarding a patient's suicidal status. As mentioned in section 2.1, a patient is considered to be suicidal when scoring four or above on *suicidal thoughts* in the MADRS screening. Once a patient's last screening contains data that indicates the patient might be suicidal, a condition is met, resulting in the inability to continue the therapy in COPE. Every activity will be removed from the list of eligible activities and the *Suicidal thoughts* screening item is highlighted in red, as shown in the left GUI in figure 3.11. The patient is then encouraged to seek professional help.

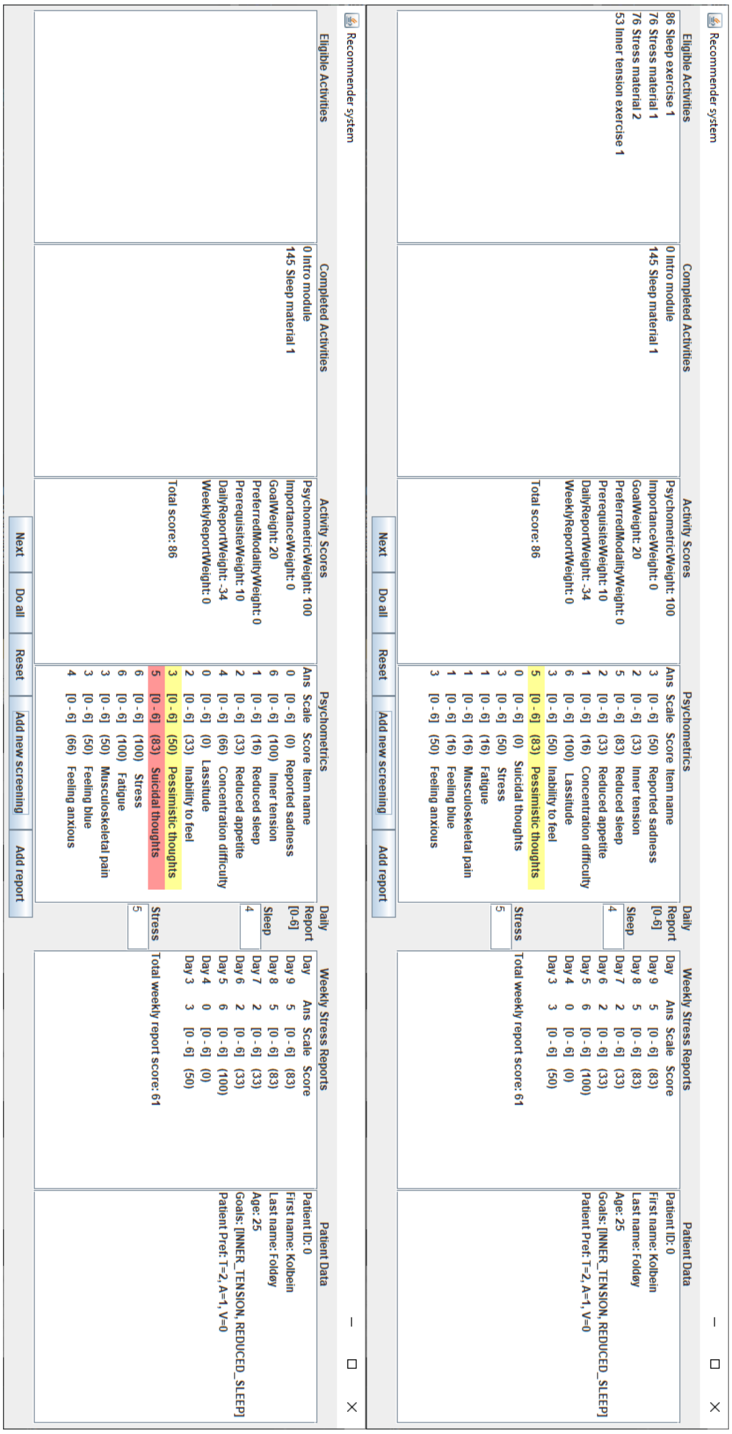

Figure 3.11: Visual feedback in the graphical user interface. The patient is suicidal and unable to continue, in left GUI. Pessimistic thoughts above the limit, removing associated activities, in right GUI.

4 Implementation

The design and central components of the artifact have been explained in the previous chapter. In this chapter, a more in-depth explanation of how the artifact is implemented will be presented. This includes the language and framework used, the process of deriving the recommender system from conceptual rules, and presenting the structure of the system.

4.1 Language and framework

Throughout the implementation phase of the artifact, Java was the programming language primarily used to write the code. Parts of the implementation was done in Javascript in an attempt to make the artifact compliant with the other master students' artifacts. Due to the decision to focus on building the artifact work as a standalone program independent of the work of the others, this was rewritten in Java. The choice of writing the code in Java was based on a couple of reasons. Firstly, Java was the most used language of the programming courses at HVL, resulting as the language of which I am most comfortable with. Secondly, if this artifact is to be further developed through another master thesis project, Java will most likely to be a language most students are comfortable with. Also, Java is object-oriented, meaning it is about creating objects that can hold data and methods. This results in the code having a clear structure that can be modified and extended with ease. For an artifact, such as this recommender system, being able to easily troubleshoot makes the development process smoother.

For the graphical user interface for testing the recommender system manually, a toolkit for Java called Swing was used (Oracle 2020). It is a lightweight widget toolkit for creating GUIs with interactive functionalities to Java applications, with components such as buttons, panels and list views.

4.2 Conceptualizing with rules

When starting the design process of the recommender module, two main options were present. We could either implement a recommender system using machine learning or a system based on a set of manually written rules. Creating machine learning applications require quite a lot of experience in the field and the system ends up giving recommendations that are not easily explainable, known as a black box (Guidotti et al. 2019). Also, a recommender system based on machine learning would require a set of data to start working with. Currently, the COPE project has no such data available. This made a recommender system based on rules a clear first option. Also, a system based on rules that explicitly does what is intended by the programmer, and which can be extended with rules, makes the building process considerably more manageable. However, further extensions will require a more solid system design.

At the beginning of the design process, rules were written to help conceptualize what was needed to create the system. These rules were written in a Horn-like manner, with conditions of boolean expression in conjunctive or disjunctive form. Once the clause's condition is satisfied, an action is performed, shown on the right hand of the right arrow. This is exemplified below:

$$\begin{aligned} &(\ suicidalThoughtsScoreGreaterOrEqualFour\ ) \\ &\qquad \Rightarrow recommendGettingProfessionalHelp \end{aligned} \tag{1}$$

In addition to rules with actions, definitions of a condition were also defined with boolean expressions in conjunctive or disjunction form. These are useful for displaying the meaning behind the conditions in some of the rules. The "meta condition" is a set of multiple other conditions that are compacted into a single condition, as shown below:

$$\begin{aligned} exerciseCompleted(e) = (\ &exerciseContainsLearningMaterial \\ &\wedge learningMaterialCompleted \\ &\wedge exerciseAnswered\ ) \end{aligned} \tag{2}$$

The *exerciseCompleted* condition is then used in another condition definition where a module is checked whether it is finished:

$$moduleCompleted(m) = (\ \forall e \in moduleExercises(m),\ exerciseCompleted(e)\ ) \tag{3}$$

After a multitude of rules had been created, from what defines a specific condition to rules where that condition is used, a clearer picture would emerge. Furthermore, a decision had to be made regarding whether a premade rule engine could be used, or if it was more suitable, to create a system from scratch to manage these rules. Using a premade rule engine can come with some advantages. Some of the available rule engines use a pattern matching algorithm called Rete, which is efficient for systems of many rules (Forgy 1989). One of the systems using Rete is JBoss' Drools (Bali 2009). On the other hand, rule engines, like Easyrules, uses a simpler implementation that is just iterating over the set of rules (Hassine 2019). Using rule engines like the ones mentioned can make it easier to maintain and reuse parts of the system. Scalability is also an important factor to consider when creating these systems, which the Rete algorithm gives.

However, there are more factors to take into consideration when deciding how to implement a recommender system. Based on the relatively small size of this project, making use of a rule engine might lead to an abundance of complexity beyond what is needed, consider how few rules that would need to be implemented. After having looked through the literature for rule engines, few have been thoroughly presented in any research. The ones that have been properly presented through published papers, such as CLIPS-OWL by Meditskos & Bassiliades (2011), are systems that use ontology models written in Web Ontology Language (OWL) (Grau et al. 2008). Writing the patient ontology and the rules in OWL was not prioritized as it would require too much dependency on having the patient ontology developed and finished by one of the other master thesis projects going in parallel. Although using a rule engine comes with its advantages, the decision was made to create a system without the use of a rule engine, like the ones mentioned, despite the drawbacks it comes with. This is a topic to look into when looking at the further development of the system, including the integration of the results from the current.

4.3 System structure

The system is structured in a way that upholds the principle of separation of concerns, where functionalities are contained in the different models' utility classes, for *Patient*, *Activity* and *Screening*. The most central class of the system is called *RuleEngine*, where most of the functionality is contained, regarding prioritizing activities that can be recommended, as well as the rules themselves. The name is not quite befitting the class as it is not a rule engine in the common sense that the rule engine does not take a set of execution rules and data objects as input. This system only takes the data objects as input and has the set of execution rules defined inside the class as functions. It will be called *Recommender* from here on.

As an example of what the rules and conditions described in section 4.2 look like, the check for whether a patient is suicidal is as follows:

```java
/**
 * Check if patient is suicidal. 4/6 or higher score.
 * @param p patient
 * @return true if severity score >= 66.
 */
public boolean cPatientIsSuicidal(Patient p) {
    boolean suicidal = false;
    int suicidalSeverity =
        ScreeningUtils.getPsychometricSeverityPercentByTag(p,
        Tag.SUICIDAL_THOUGHTS);
    if (suicidalSeverity >= 66) {
        suicidal = true;
        ...
    }
    return suicidal;
}
```

The functions are using another function from the *ScreeningUtils* class to get the patient's latest screening, followed by calculating the severity of the patient's score in a specific screening item. In this example, *Suicidal Thoughts* was given as a parameter, which returns the score severity in percent. If it is greater or equals 66, the function will return true. This can again be used as a sub condition for another condition, as shown below:

```java
/**
 * Check if not completed activity a and done prerequisite
 * activities to a, + check for mindfulness and suicidal
 * @param p patient
 * @param a activity
 * @return boolean for whether patient is eligible for
 *   activity
 */
public boolean cPatientIsEligibleForActivity(Patient p,
    Activity a) {
    return !cPatientHasCompletedActivity(p, a) &&
        cPatientHasCompletedPrerequisiteActivities(p, a) &&
        cEligibleForMindfulness(p, a) &&
        !cPatientIsSuicidal(p);
```

The data objects that the recommender receives are of the Patient class and a list of modules and activities, as described in the artifact description in section 3.2. The objects are implemented as plain old java objects (POJO). The patient object and all the therapy content, the activity and module objects, are constructed and instantiated upon program startup and fed into the system. The decision to not create an external database for the patient and therapy models was due to incompatibility between the other master students' work and time limitations.

Once the system has started, the module and activity data is only fed into the recommender once. The data which the module and activity object contains is never changed once the system is ongoing. The patient model, however, is updated regularly. Every time the patient has done an exercise or learning material, the patient activity history which is contained in the patient model is updated. This is done whenever the patient has done the activity that the system recommends or whichever activity the patient pleases among the unlocked activities. Not only does the patient activity history tell the system which activity has been completed, but also in which order they were completed. This information is used in the calculation of the total activity score, explained in 4.3.1

What is not certain at this point in time is how often the patient will be required to do a psychometric screening. This can be set and changed later. The more accurate representation the system has of the patient's mental health, the better the recommendation will be. However, the patient might easily be tired of doing psychometric testing too often, e.g. after every time the application is started, resulting in poor adherence. As a countermeasure, a short optional screening of the patient's daily condition is implemented. Subsequently, the recommender will be fed and use this data upon recommending activities, as presented in figure 4.1.

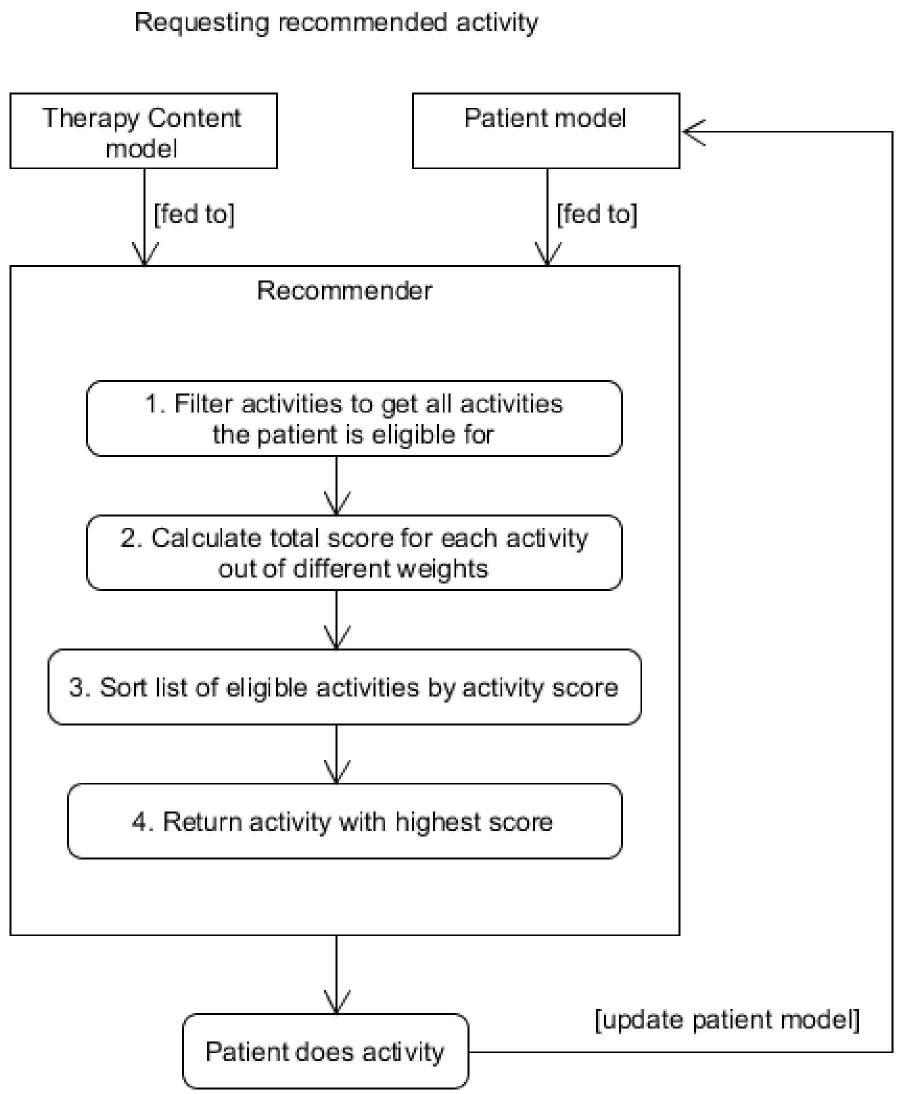

Figure 4.1: A simplified representation of how the recommender works, and which data models are used and updated.

4.3.1 Activity score calculation

Once the activities have gone through the process where activities ineligible for the patient have been discarded, a total activity score is calculated. After five iterations, there are six differently weighted variables contributing to the calculation of the total score. After the total score of every remaining activity have been calculated, the one with the highest total score is considered to be the most suited activity for the patient at the time.

- **psychometricWeight** is a weight that corresponds to the severity percentage of a patient's answer from a psychometric screening. In MADRS, the range of allowed answers is across a zero to six continuum for every item. Accordingly, the weight goes from 0 to 100 in increments of approximately 16 (1/6). For example, if a patient rates *Pessimistic thoughts* as *5/6*, it amounts to a psychometric score of 83.
- **goalWeight** will be 20 if the activity is tagged to help achieve the patient's goal, or 0 if it does not. The system checks if one of the tags associated with the activity equals to one of the tags found in the patient's list of goals.
- **importanceWeight** is implemented as an option for a therapist to add additional weight to specific activities. This is meant for activities the therapist deems as particularly important. The weight may be set to whatever the therapist sees fit, but is currently set to 10.
- **preferredModalityWeight** will increase the likelihood that an activity with content modality which the patient prefers will be recommended. The first time the COPE application is started, the patient is asked to rate which modality is preferred. Zero means to avoid, one means indifferent, and two means preferred. If an activity only contains modalities rated as zero, it gets weighted as -20. If the activity contains the preferred activity, the weight is set to 20 and 0 if not.
- **prerequisiteWeight** is implemented for the purpose of reinforcing a sense of cohesion in the sequence of activities being recommended. This weighting can prevent a patient from being recommended back and forth between the different modules for every recommendation if the scores are similar. The score is added to activities that have the most recently completed activity as a prerequisite. This could also have been done based on the activities tags, or a premade set of companion activities. A score of 10 is added to these activities.

- **dailyReportWeight** is a weight that will counteract the system from basing the recommendation on the rather infrequent psychometric screenings. Instead, it will take into consideration how the patient is doing each day. It is weighted as the daily score severity *((answer / 6) * 100)* subtracted by the psychometric screening severity. If the patient feels the same as rated in the screening, weight is 0. If the patient reports that symptoms are worse than usual, the weight is a positive number, and negative if the patient feels better. In the extreme cases, the weight is either 100 or -100, *((0/6)*100 - (6/6)*100).*

- **weeklyReportWeight** uses the last seven days of daily reports to calculate a score that works as a trend for how the patient is doing. For instance, if the patient is reporting an increasingly worsening level of stress, compared to what was scored in the latest big screening, it is more likely for the patient to receive stress related activities. The more recent a daily report is, the higher the report is weighted.

$$\frac{\sum_{i=1}^{7} i * dailyReportAns_i}{1.68} \tag{4}$$

  The most recent report's answer is multiplied with 7, the day before that is multiplied with 6, decrementally down to 1. The sum of the seven products is divided by 1.68 to adjust the score to fit the range of *dailyReportWeight*, i.e. [-100, 100]. The calculation of the weekly report score is an example of how more recent reports are weighted higher, and would need to be altered in later iterations to more accurately represent the patient's need for certain activities.

Once the different weights have been calculated and set, a summation of the weights results in the total score of each activity. The activity, from the list of eligible activities with the highest total score, is selected as the most suited for the patient.

5 Demonstration and Evaluation

The fourth and fifth steps in the proposed process model for conducting design science research by Peffers et al. (2007), is *Demonstration* and *Evaluation*. A demonstration of the artifact shows the results of the development. During the evaluation, a comparison is made between the objectives of the artifact solution and the demonstrated results. Both steps have been carried out during the development phase for each iteration and for the final evaluation of the artifact.

5.1 Evaluation during development

Throughout the development process, the artifact has gone through multiple iterations. Each iteration followed the steps proposed by Peffers et al. (2007). During the first iteration, a problem and motivation were identified as a result of multiple meetings to discuss and establish the end goal of the COPE project. The first, as well as all the subsequent iterations, included the step of defining an objective of a solution and a design and development phase. At the end of the iteration, the artifact was demonstrated and evaluated. Most of the iterations' demonstration and evaluation steps took place in meetings where most participants of the COPE projects attended.

For each iteration, the artifact was demonstrated by presenting the objectives of the iteration, followed by presenting the changes and additions to the artifact. This was done by sharing the screen via a projector or an online conference call. Program code, rules or diagrams were displayed and thoroughly explained, which would allow for questions, discussion and feedback from the participants of the meetings.

Due to the nature of the artifact development, it was evaluated in a qualitative manner through a Zoom meeting. After the demonstration of the artifact, an evaluation was done by the two experts on the COPE project. One of the experts is a psychologist, researcher and full professor who is an expert on the content that is being delivered. The second expert is the project owner, a full professor, researcher and expert in HCI and analytics.

After the first iteration, a rather simple system had been implemented as a considerable amount of time was spent to conceptualize the system writing rules and conditions during this phase. It lacked core functionalities which would be implemented later. At this point, it could recommend content based on a psychometric screening with few items of which had randomly generated ratings assigned. As it was still early in the development process, there were few points to be given feedback on and evaluate. However, the psychologist wanted to see screening items from well-known screenings, such as MADRS. The expert found the screening useful, but pointed out that it would not capture the state of the patient accurately enough to suggest activities on a daily basis. The screenings can be cumbersome to complete regularly, and which problem the patient wants the work towards may change from day to day. This was taking into consideration in a later iteration. The functionality of requiring certain activities to be completed before starting others was also suggested.

Based on the evaluation and feedback from the experts of the last iteration, the system was further developed to include the functionality of having prerequisites for learning material and exercises. Additionally, the content was being tagged to easily distinguish which symptoms the activities have working towards bettering. However, the system was still in an early version, with essential features missing. Including relevant patient data into the recommendation was needed, as requested by the experts.

During the third iteration, the system had seen a great improvement in focusing on integrating a simplified patient model in the system. As discussed during previous meetings, preferred content modality and which problems or symptoms the patient has a goal of working towards, needed to be factored in. The experts were also pleased with the scoring system of the activities, which was prioritizing and sorting the eligible activities.

As the system grew bigger, it got more challenging to visualize how the system works. As a result, the graphical user controller interface was implemented after the fourth iteration, which the HCI expert found helpful (see figure 3.10). After having displayed the system through the graphical user controller interface in a meeting, daily report functionality was suggested, as explained in section 3.1.

An evaluation meeting was later held with the psychologist and the HCI and analytics expert regarding the latest implementation of daily patient reports (through a Zoom meeting due to COVID-19). A thorough explanation of the GUI was given as only the HCI expert had seen it before. After the walk-through, a few minor GUI flaws were pointed out, e.g. screening item data were not labeled, resulting in confusion regarding what the different numbers represented. Both experts were otherwise pleased with the GUI. The psychologist was excited about the newly implemented functionality of daily reports, and pleased with the consistency in the scales used. To complete the testing environment, a few more daily report options could be added, either for each screening items or for problems related to the different symptoms. As a result of the meeting, an additional feature of using reports of a whole week was requested by the psychologist, which might improve the recommender system. For each added feature, the GUI had to be updated.

5.2 Final evaluation

In the final evaluation, the artifact was demonstrated in a similar way to the previous iterations. The artifact was demonstrated using the graphical user interface for displaying the artifact's functionalities and outcomes. It was presented to an expert with a focus in psychology. After the demonstration, the artifact was evaluated by the expert through a semi-structured interview.

Semi-structured interviews are frequently used in the field of software engineering as a technique to collect data. These interviews allow for the collection of data that cannot be collected by quantitative measures, such as qualitative data. When researching a problem of qualitative nature, qualitative evaluation is the appropriate method (Hove & Anda 2005). A semi-structured interview with an expert was used to collect valuable data bout the artifact as its objectives are of a qualitative nature. This allowed a combination of specific and open-ended questions for the expert to answer, bringing forth both expected and unexpected types of information.

The expert has some knowledge about the system beforehand, but for the sake of a precise understanding of the system, each fundamental functionality is explained in detail in the demonstration. The expert was encouraged to ask questions at any time during the demonstration to make sure the system is well understood. The meeting took place in an online conference call (Zoom due to COVID-19) with both audio and video being recorded, and by accessing the artifact through the graphical user controller interface shown in figure 3.11.

The structure of the interview is as follows:

1. The attendees of the meeting are requested to consent for the evaluation meeting to be recorded.

2. The expert in psychology is asked to state her experience with CBT and internet-based CBT.

3. The artifact is briefly explained - of what the recommender system / algorithm is basing the recommendation on and what it recommends. Further, it is explained that it works as a simulation at first, and that it can be used to validate the algorithm behind the scene.

4. A demonstration of the artifact. Each fundamental feature and construct is explained with the help of the graphical user interface.

5. The expert is encouraged to test the artifact via the interviewer, and asked to give opinions or questions she may have as the artifact is being tested.

6. The expert is asked both specific and open-ended questions to give useful information. The information is used to evaluate the artifact and answer the research question through qualitative data.

After the expert was asked to state her experience with CBT and iCBT, she answered that she had done quite a few research projects in the field. She has supervised research fellows testing the effects of CBT, as well as written about it. It is stated that she is not a clinical psychologist, but does have a degree in cognitive sport psychology, working with healthy people.

After the artifact was both briefly explained and demonstrated, the expert was asked the following evaluation questions:

5.2.1 Semi-structured interview

Q1: Do you think the graphical user interface, as presented, was useful for understanding the system, its calculations and its flow?

> **A1:** Yes, I do. If you were not present to explain to me in detail how it works, it would be a little bit harder to understand what the different things mean, for instance, what each weight represents. It works very well once the different things are explained. It would be nice to have info buttons, for instance, on each activity score.

Q2: Do you think that an artifact like this is suitable for demonstrating and evaluating?

> **A2:** Yes, I think so. It does currently require someone like you between the system and the one who is looking at the system. Once I've gotten an explanation, it is all fine. As far as the evaluation goes, it would be really good to have a group of people like me to interact with the system, manually do screenings and get a feel for how it works, compare the recommendation to what we would give. Further, I would like to test on 50 people, and then get back to this system for readjustments. A lot of interesting things to do, but there are some things that remain to be implemented before that.

Q3: Do you think the activity score is a viable way of recommending activities?

> **A3:** I think so. However, it is a little bit abstract still. I like the idea a lot, but if I were to manually enter screenings and study the recommendations and activity score, I would get a better feel for

what exactly the activity scores should be weighted. I really like the fact that it is using weights/score, that there are so many different ones and that they are made visible to us.

Q4: Could the recommended activity be looked upon as similar to what a therapist would recommend based on the patient data?

A4: Well, yes, but it would depend more on what exactly the different activities contain. A system that suggests activities based on the psychometrics and activity scores is very good, but again, I would need to get a better feel for what the content of the activities does. I am very interested in testing this once the activities have gotten more content. Then we could compare the results of a therapist to the system. It would also be nice to compare the activities and effects of this system, another system with strict ordering of activities and a therapist's recommendations.

Q5: Do you have suggestions for other daily reported data that could be useful to include, both for the value of the data itself, as well as for the trend of the parameter over a time period?

A5: Musculoskeletal pain and fatigue would be interesting to have more data on. It depends on who the target group is, e.g. for cancer patients, it would be great to gather data regarding fatigue. Stress and sleep, as you already have implemented, are interesting as they are two sides to the story but the extremities in a way. It would be nice to see how these two compare to each other over time, and if there was any delay for one of them, one could analyze the causality between the two.

Q6: Are there other features you would like to see included in a system like this?

A6: The possibility of clicking the different fields and features to get more information about how the algorithm works and scores are calculated. This would decouple yourself from the system, allowing anybody to understand it more easily, and it would easily avoid any "black box effect" one could experience.

Q7: Are there any activity scores missing or that should be removed?

A7: No, not off the top of my head. You have covered very much.

Q8: What are your thoughts on a future recommender system like this, with the capabilities to recommend suitable next activities, etc. for a patient, can be useful in internet-based CBT and/or other internet-based therapies?

A8: I think this is the future, very forward-looking. After a while when we have gotten more real data on how these systems work, about the recommendations and effects, it will result in more personalized therapy.

Q9: Any suggestions for improvements or change of the system?

A9: The ability to manually changing the weighted score could be an interesting improvement to the system. We could then play around with it, adjust the weights and study the outcome based on the data we enter. Also, combining this system with a visual analytics system that was developed last year could be very interesting. To get a clear overview of how it works on a large cohort.

5.3 Evaluation summary

In this chapter we have described the evaluation phase of the developed artifact which was done in a less formal way throughout the first iterations of the development process. Feedback from these evaluations led to new features and/or changes in the design of the artifact. As the artifact got more mature with respect to design and features, we had it undergo three more formal qualitative evaluations which both resulted in further improvements. Then, finally, we did the final evaluation as a semi-structured interview through Zoom with the psychology expert.

The developed artifact can through its graphical user controller interface be seen upon as an artifact for:

- Testing how a simplified content model together with a simplified patient model can provide the needed data for the recommender algorithm
- Testing and validating the recommender algorithm through a graphical simulation interface
- Discussions between CBT therapists and developers/researchers of the adaptive iCBT application COPE, on how to validate and further develop the CBT content, the patient model and the algorithm to provide for adaptive personalized iCBT

The results from the final evaluation shows that the artifact has the potential to provide valuable help addressing these tasks. Although the psychologist did comment on it initially being somewhat hard to understand the use of the interface, it did not take long for her to understand how to operate it, what could be gained from running the simulation, and even more important: she immediately came up with her own ideas for other interesting topics that could be investigated through such an artifact, as well as giving ideas for further improvements in both the design and functionalities for the artifact.

5.4 Discussion

In this section we discuss the results achieved from this master thesis research work and providing for research contributions in the form of additions to the knowledge base.

5.4.1 Contributions to the knowledge base and answers to the research questions

To a large extent, the contributions to the various knowledge-bases overlaps with the answers to the research questions.

RQ 1: How can we implement an algorithm for recommending iCBT content?

Through this master thesis project, the algorithm for recommending iCBT content was created using a rule-based approach in an iterative development process. After having researched various types of systems, the rule-based recommender system seemed to be fitting for this task. The rule-based recommender system was an approach that was manageable to use, at least on a smaller scale. However, the system would require some restructuring as it grows larger. It was implemented without the use of third party programs, and it was build from bottom up adding more and more rules to the program. The input of the system were filter, organized and evaluated based on the data fed to the system. This included data about the iCBT content itself and data from the patients.

RQ 2: How can we implement an algorithm for recommending iCBT content tailored towards the needs of each individual patient?

To make the algorithm recommend iCBT content that is tailored for each patient, it requires data of both the content and the patient. A simplified model of a patient was used as a representation. A central part of making the system recommend content for each individual patient, was the use of screening data in combination with goals of the patient, e.g. wanting to work with stress related content. A weighting system was implemented to score each activity based on multiple parameters which would prioritize activities suited for the patient. Daily and weekly reports, screenings, content modality, prerequisites, activity history and order was among the data used to score the activities.

RQ 3: What data from a patient model can be used for making iCBT adaptive using a recommender system?

The recommender system can be made adaptive using patient data like content modality preferences and patient activity history. By storing which iCBT content the patient has completed and which is available, the system can recommend content that the patient would want, based on patient goals and content that can be delivered in a specific modality, e.g. audio. By making use of the patient's psychometric screening results, the algorithm can prioritize what iCBT content that might be most suited for the patient. This might vary from day to day to a certain degree, which is why daily and weekly patient reports were implemented. The use of infrequently answered and tedious psychometric screening cannot be used alone to decide what to do next.

RQ 4: How can we implement an artifact that can be used to demonstrate and inspect a recommender algorithm, that also can serve as a platform for discussing the design of an app capable of providing for personalized iCBT?

Through multiple iterations, each with evaluation with the help from design science, has an artifact been created with the purpose of demonstrating and inspecting the algorithm. The artifact was finally used to evaluate the algorithm through a semi-structured interview with a psychology expert. The expert expressed excitement, especially since the artifact can be used as a medium for discussing how to further develop and implement an application with desired functionality like in COPE. The artifact presents relevant data and the possibility to run through the simulation with different parameters, such as screening data, patient goals and reports.

6 Conclusion and Further Work

6.1 Conclusion

Through the use of design science an artifact was designed and implemented to facilitate patient tailored therapy. A rule-based recommender system was implemented using data from both the iCBT content and a patient model. In addition to the recommender system, a graphical user controller interface was implemented which would allow for inspection and evaluation of the artifact. Also, it would allow for important discussions regarding adaptive iCBT in general and further development of the COPE project.

6.2 Further Work

There are multiple crucial features that are needed in order for the recommender system to be used in a practical setting. As suggested by the psychologist evaluating parts of the system, more specific patient data should be included in the recommendation process, such as their history of cancer treatment and symptoms. Other features the psychologist would like to see that was not implemented due to time limitation is the possibility to recommend activities that have already been completed. Anxiety and musculoskeletal pain could also be added, as the screening items used should be altered.

In the current state of the recommender system, it is not possible for other systems to use it. In order for a mobile application to use the recommender, functionalities for interacting with a database and web services should be implemented. Once the other sub-projects of the COPE project is completed, it would allow for a more manageable integration between the artifacts.

The system could be further improved by implementing a pre-existing inference engine with rules written independently in a specific format. This would make it more manageable to further develop the system with additional rules, as the complexity of the system increases with the number of rules, otherwise. A pre-existing rule engine could also improve the recommendation by adding rules for specific cases without altering the code.

Another possibility is to introduce more modes to the system, with varying degrees of restriction to which activities are eligible at a given time. It would allow for research to be conducted in a homogeneous environment on different ways of delivering therapy. Examples of modes could be to let the patients freely choose activities they see fit, restrict the activities to those the recommender system recommends, or deliver the therapy in a tunneling structure. The latter would allow for comparisons to be made between similar self-guided iCBT applications using tunneling.

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