Christoffer Stundal Pram

Web-based dashboard for physiotherapy recommendations

Master's thesis in Computer Science
Supervisor: Kerstin Bach
December 2022

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Abstract

Case-based reasoning is a process for solving new problems with knowledge retrieved from previous similar experiences. It combines artificial intelligence and cognitive psychology to recreate the human's thought process. This process is very useful for treating patients with non-specific musculoskeletal disorders. Applying case-based reasoning to clinical decision support systems will support clinicians' decision-making by proposing improved treatment recommendations in primary care. Nevertheless, it is still unclear how to properly visualize a case-based reasoning tool to improve decision support for clinicians during a first consultation. A clinician dashboard is developed here to visualize the necessary information needed for solving patient cases and provide helpful treatment recommendations. It lets clinicians filter by attribute value which similar cases shall form the basis for the treatment. The final design proposition looks clear and comprehensible, but it needs more infographics to represent important case attributes with sufficient context at-a-glance.

Sammendrag

Saksbasert resonnement er en prosess for å løse nye problemer med kunnskap hentet fra tidligere lignende erfaringer. Det kombinerer kunstig intelligens og kognitiv psykologi for å gjenskape menneskets tankegang. Denne prosessen er svært nyttig for å behandle pasienter med uspesifikke muskel- og skjelettskader. Å anvende saksbasert resonnement til kliniske beslutningsstøttesystemer vil hjelpe klinikeres beslutningstaking ved å foreslå forbedrede behandlingsanbefalinger i primærhelsetjenesten. Likevel er det fortsatt uklart hvordan man skal visualisere et saksbasert resonnementsverktøy for å forbedre beslutningsstøtte for klinikere under en førstekonsultasjon. Et klinikerdashbord er utviklet her for å visualisere den nødvendige informasjonen som trengs for å løse pasientsaker og tilby nyttige behandlingsanbefalinger. Prototypen utforsker systemets evne til å gi beslutningsstøtte og hvordan man finner de riktige datarepresentasjonene. Det lar klinikere filtrere på attributtverdi hvilke lignende saker som skal danne grunnlaget for behandlingsanbefalingene. Det siste designforslaget ser oversiktlig og forståelig ut, men det er behov for mer infografikk som representerer viktige saksattributter med tilstrekkelig kontekst på et øyeblikk.

Preface

This report is the final product of my master thesis, called Web-based dashboard for physiotherapy recommendations, in the course TDT4900 - Computer Science, Master's Thesis at the Norwegian University of Science and Technology autumn 2022. The research has been conducted as part of the SupportPrim project, for which I am grateful.

I want to give my sincere gratitude to my supervisor for her guidance throughout my research. It really means a lot! I want to thank the researchers from the musculoskeletal disorder research group at the Department of Public Health and Nursing (ISM) for the cooperation and also for providing the medical data for this research. I also appreciate the counseling I received from the Faculty of Information Technology and Electrical Engineering at the Norwegian University of Science and Technology.

And finally, to my dear family and closest friends, thank you for all the support. You are the best!

Christoffer Stundal Pram
December 21, 2022

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Chapter 1

Introduction

Which treatments to be practiced for a particular disease in primary care today is decided based on the clinicians' education and experience. If there is no sufficient solution at hand, they have to go back and look up the problem in books or search the internet to find solutions. That is a situation in which decision support in primary care is crucial. By utilizing machine learning to find, select and evaluate information, the aim is to build a suitable system for primary care that can collect and learn from past treatments to help in making more effective and better-informed decisions based on limited information.

SupportPrim[1] is a research project aimed at musculoskeletal disorder (MSD) and physical therapy in primary care. The goal is to create a clinical decision support system (CDSS) for clinicians that improve the quality of musculoskeletal pain treatment recommendations by applying artificial intelligence (AI). The patient data used in this research is obtained from the SupportPrim project.

Case-based reasoning (CBR) is a problem-solving method that uses solutions from past experiences to solve new problems. The purpose of this master's thesis is to design and develop a front-end web application that utilizes CBR to support decision-making for clinicians in primary care (physiotherapists, general practitioners, etc.). The prototype will focus on proper visualizations in order to provide a great user experience. The development process of the web application will be incremental in close cooperation with medical researchers. They will be able to identify and adapt the design choices according to their requirements and experience. Valuable feedback will be gained from their evaluations on how well the system is adapted to clinicians.

[1] `https://www.ntnu.no/supportprim`

This thesis begins to explore how data from the CBR system can be visualized for clinicians. Then, the technical possibilities and limitations of the visualizations are investigated. The overall goal is to implement a clinician dashboard that makes use of the CBR system and proposes relevant treatment recommendations to patients with MSDs.

1.1 Motivation

During a first consultation in primary care, clinicians have limited time to treat their patients. This is where CBR is useful to improve the efficiency of the treatment. In this research, CBR is applied to a clinician dashboard to support the clinicians' decision-making. The clinician will be able to look up patient cases at-a-glance and get insight into the problem situation. The dashboard retrieves the most similar cases from the CBR system, which are calculated based on a similarity measure, and propose their treatment plans as recommendations for the current case. The clinicians can then select the similar cases that are relevant to the patient in question, and focus on using these cases' treatment recommendations.

It will be interesting to find out how to adapt such a system to clinicians. The clinician dashboard requires a design that visualizes the information clearly and comprehensibly to provide high usability. It also needs smooth and intuitive interactions for handling the treatment recommendations. The prototype developed here will explore how to visualize the CBR data and find efficient ways to provide decision support to clinicians.

1.2 Research Goals and Research Questions

The master's thesis has three goals. The first goal looks into the state of the art of healthcare systems in primary care. The second goal deals with how to build a web application to fit the clinicians' functional requirements. The final research goal is to make an intuitive web application that is easy to use and learn.

1.2.1 Research Goal 1

The first research goal is to find the state of the art of dashboard looking CDSSs in primary care. A literature review will be conducted to explore the existing dashboard applications in healthcare and investigate why they are powerful and efficient tools. The literature can provide some useful experiences and be of inspiration for the development of the clinician dashboard prototype.

RQ 1.1 What is the state of the art of dashboard-based decision support systems used by clinicians in primary care?

1.2.2 Research Goal 2

The second goal of this research is to create a visualization tool for clinicians that presents treatment recommendations to their patients and supports co-decision-making. This tool is going to be a prototype that requests patient cases from a CBR system and presents similar cases conveniently. Finding an effective visualization to handle the data will be of high priority.

Research Questions

RQ 2.1 How can clinicians interact smoothly with the CBR system?

RQ 2.2 What kind of information is required from the CBR system for the clinicians to perform better treatment decisions?

RQ 2.3 How can the results from the CBR system be visualized to be used most effectively by the clinicians?

1.2.3 Research Goal 3

The third goal of this research is to adapt the web application to the clinician's needs. The challenge will be to identify the necessary and useful information that makes the decision-making process more efficient. The similarity measure needs to be performed transparently to the clinicians, and its results must be presented in a comprehensible manner. The design requires a high focus on usability to provide a smooth workflow for the clinicians. The information must be presented clearly and concisely, and the user interactions have to be distinguishable.

Research Questions

RQ 3.1 What features do a dashboard need to streamline the clinicians' working routine?

RQ 3.2 What is a suitable dashboard design to support these features?

1.3 Research Methods

The research starts by conducting a literature review of existing CDSSs that uses a dashboard solution. The findings will help to shape the design choices of the clinician dashboard later. The iterative development process of the clinician dashboard happens afterwards. The user requirements will be defined by the medical researchers, and a mock-up is created accordingly to acquire initial feedback. The feedback is then evaluated and forms the basis for the first prototype. The next step is the implementation.

A second round of evaluation and planning will be performed before the implementation of the following iteration. The development process ends with an evaluation of the second prototype. Finally, the results from the evaluation are discussed to answer the research questions.

1.4 Thesis Structure

This thesis is divided into 3 parts. The introduction and background form the foundation, followed by the related work, methodology and implementation which describes the core of this thesis. The third part discusses the findings and concludes the research.

The introduction explains what the research is about and why it is important. It presents the research questions and the research goals, and how they can be achieved. The background describes what CBR is, and the related work will find the state of the art of the research area. How the CBR system operates is explained in the methodology section, and it includes a presentation of the data set and the architecture of the clinician dashboard. The development chapter demonstrates the iterative process of implementing the clinician dashboard. It discusses how the design choices were adapted and improved. A discussion of the final implementation is conducted in the following chapter and answers the research questions. The final chapter is the conclusion which concludes the whole research.

Chapter 2

Background

The background will provide context to the main topics that influenced the development of the clinician dashboard presented in this thesis. The clinician dashboard is a CDSS that aims to assist physiotherapists with decision-making when treating patients in primary care, but it is also applicable to clinicians in general. Physiotherapists treat patients based on their work experience from previous cases. The clinician dashboard utilizes this experience-based process, called case-based reasoning, to offer more accurate solutions from a larger set of patient cases. The following sections will provide insight into CDSSs and CBR, and discuss user interface design for dashboards.

2.1 Clinical Decision Support Systems

A clinical decision support system is a digitized tool to manage health information and helps to improve the workflow and quality of healthcare services. Clinicians are presented with targeted health knowledge and patient information to make better clinical assessments when treating patients. Modern CDSSs are primarily used at point-of-care and have come a long way since their introduction in the 1980s, as mentioned by Sutton et al. [2020]. They make improved suggestions of recommended diagnosis and provide more enhanced decision-making.

CDSSs are classified into two main types, knowledge-based and non-knowledge-based. A knowledge-based CDSS uses predetermined rules that follow medical knowledge to evaluate the data source and produce results. A non-knowledge-based CDSS utilizes AI or machine learning to assess on the health data. Nijeweme-d'Hollosy et al.

[2018] show promising results in this using machine learning.

Adapting CDSSs as web applications is useful for supporting multiple different devices (desktops, tablets, smartphones, wearables, and monitoring instruments). Integration of electronic health records can offer benefits to how data is stored, but there are still challenges regarding ethical and legal issues that need to be resolved. The next chapter looks into related work to provide a state-of-the-art overview of CDSSs in healthcare.

The clinician dashboard presented in this thesis is a non-knowledge-based CDSS that uses CBR to assess pain problems and provide treatment suggestions.

2.2 Case-Based Reasoning

Case-based reasoning is a type of machine learning for problem-solving and learning. The process uses a data-driven approach to propose solutions to new problems by reusing past experiences. Such a problem situation is called an experience or a case, and it contains the problem description and the corresponding solution. Accumulated experiences from previous cases are stored in a knowledge base, also known as a casebase. If a new case is considered an interesting experience, it will be accepted as a useful lesson in the knowledge base. Using CBR in healthcare is very useful where knowledge is driven by experience, says Bichindaritz and Marling [2010].

CBR is inspired by human reasoning. Humans use their accumulated knowledge to learn and solve problems in their daily life. Likewise, CBR is designed to utilize knowledge from past experiences to solve new cases. Kolodner [1993] gave the first comprehensive text on the subject where he presented the state of the art at the time and guidelines on how to build CBR systems. Watson [1998] demonstrates how to apply CBR to information systems and develop intelligent applications, and Sandal et al. [2021] show how CBR can be utilized as a patient-centered tool.

The CBR process can be explained using the classical model of the CBR cycle, written by Aamodt and Plaza [1994] as an early overview of the topic. The CBR cycle follows four steps: retrieve, reuse, revise and retain, and is reproduced in figure 2.1.

A new case is defined by the problem description that arises. In this instance, the patient will consult with the clinician when a medical problem occurs. A case representation is made from the problem description and is used to compare it against similar cases in the knowledge base, [see Bergmann, 2002, chapter 3].

The first step of CBR is to *retrieve* the most similar cases from the casebase. A similarity assessment is performed on the case representation to find relevant solutions,

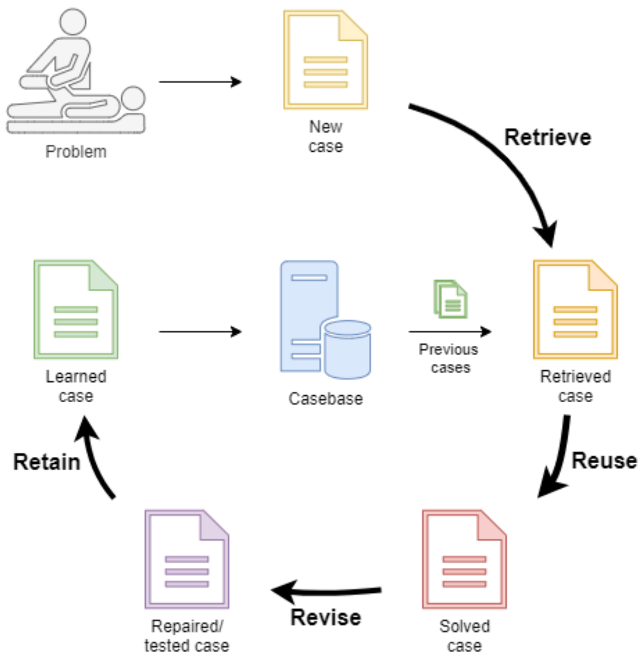

Figure 2.1: The CBR cycle adapted from Aamodt and Plaza [1994].

[see Bergmann, 2002, chapter 4]. The patient's problem will be compared to all the other cases in the casebase, and the CBR system will retrieve the most similar ones. The clinician can select the most applicable treatment from one of the earlier cases and *reuse* it as a baseline for the current case.

The case is then *revised*, meaning the solution is tested out and evaluated accordingly. Adjustments are made to the solution if necessary. In healthcare, the clinician will monitor the patient undergoing the treatment and record its effectiveness over a period of time. The treatment may be customized for each patient's needs.

After the problem is solved, the experience is *retained* for future problem-solving. This is the last step of the CBR cycle and handles the learning process of the knowledge base. If the experience from the case is deemed useful, regardless of whether the outcome is successful or not, the case is updated and stored in the casebase as a learned case. The reason for failure can be equally important to prevent the same missteps again. The lesson becomes available in the casebase and is ready to be used for future problems.

The following discusses the tool that was used to build the CBR system for this thesis.

2.2.1 myCBR

myCBR[1] is an open-source tool and a software development kit (SDK) to develop CBR systems. The project is a cooperation between the Competence Centre CBR at DFKI in Germany and the School of Computing and Technology at UWL in the United Kingdom. The myCBR workbench is used to model and manage the casebase and the similarity-based retrieval functionality. The CBR model is implemented into the system with the use of the myCBR SDK. There are also a number of other well-known CBR tools available, such as Colibri Studio[2], CAKE[3], and Clood CBR[4].

The CBR system uses a casebase that contains all the patient cases and manages them during the CBR process. A case represents the data set of all attributes related to the problem situation. The data set used in the thesis is presented in section 4.3. The case representation defines the basis for the similarity measure. It is a subset of the patient case consisting only of the attributes used for CBR. The data attributes are

[1] `http://mycbr-project.org/`

[2] `https://gaia.fdi.ucm.es/research/colibri/colibristudio/index.php`

[3] `https://www.uni-trier.de/en/universitaet/fachbereiche-faecher/fachbereich-iv/faecher/informatikwissenschaften/professuren/wirtschaftsinformatik-2/research/cake-platform`

[4] `https://github.com/RGU-Computing/clood`

weighted according to how valuable they are, where a higher weight corresponds to higher importance in the similarity measure.

During the case-based retrieval, every case in the casebase is compared to the new case. For each attribute in the case representation, a local similarity measure is performed between values of the new case and each case stored in the casebase separately. The local similarity measure of each attribute pair results in a local similarity score based on its weight in the case representation. To compare the current case to another in the casebase, a global similarity measure is performed. All the local similarity scores are summarized, and the average will provide a global similarity of the two cases. For the clinician dashboard, only the ten stored cases with the highest global similarity scores are retrieved. The clinician is then able to select which ones to reuse for solving the new patient case.

To interact with the myCBR system and execute case-based retrieval, it needs an interface for communications. The myCBR REST API is a customized interface to support interactions with the CBR system and is developed with Spring IO[5]. The usage of the myCBR REST API is demonstrated in Bach et al. [2019b].

Further explanation of how the CBR system is implemented into the clinician dashboard is discussed in section 4.2.

2.2.2 Application Domain - SupportPrim

This research is part of the SupportPrim project[6] which aims to apply AI to improve the primary healthcare management of common musculoskeletal pain disorders. The clinician dashboard presented in the thesis uses a casebase with pre-collected data. The snapshot of the patient cases, stripped of sensitive information, is acquired by the ISM as part of the SupportPrim project.

The data foundation of SupportPrim was carried over from an earlier research project, called Fysioprim. The Fysioprim project[7] finished in 2020 and researched physiotherapy in primary care. The research was a collaboration between UiO, NTNU, Trondheim municipality, and five partners from different physics institutes in Norway. The goal was to establish methods and tools for systematic and standardized data recording relevant to clinical practice. The collection of data characterized patients and analyzed them to achieve more useful statistics. This was meant to help clinicians choose the right treatment for patients' illnesses. The arena of study is presented in

[5] `https://spring.io/`
[6] `https://www.ntnu.no/supportprim`
[7] `https://www.med.uio.no/helsam/forskning/grupper/fysioprim`

Lillehagen et al. [2013]. Infopad[8] was developed to conduct medical questionnaires and collect data, which laid the foundation for the casebases.

Another project that SupportPrim is inspired by is SelfBACK[9], which operated until the middle of 2021. SelfBACK was a study about self-management of low back pain by Mork and Bach [2018]. The patients were advised for self-management via a mobile application, such as physical activity and strength and flexibility exercises. Through the app, they could communicate with the clinician and get feedback on their progression. They used co-decision-making to make adjustments to the treatment plan. SelfBACK had the initial idea of using a clinician dashboard and was primarily used for monitoring self-management.

2.3 User Interface

2.3.1 Cognitive Fit

Cognitive fit theory, developed by Vessey [1991], explains the importance of finding the correct presentation of information for a specific task to increase problem-solving performance. The efficiency depends on creating a good fit for the mental representation when a problem representation is applied to a problem-solving task. The theory takes into account when graphs or tables are best suited for decision-making. Graphical representations perform better for emphasizing spatial information while tabular representations perform better for emphasizing symbolic information.

2.3.2 Dashboard Design

A powerful dashboard manages to visualize data effectively and efficiently. Dashboards are very useful when you need to display a lot of information at-a-glance. Therefore, the data must be presented clearly and precisely to provide quick insight of the current state. A reliable overview is to be able to offer good analysis to identify trends and patterns efficiently. To support high usability and learnability, a practical user interface is necessary.

Few [2006] reviews best practices in dashboard design and gives great understanding of the concepts to build such applications. Specific visualization principles and features are proposed by Yigitbasioglu and Velcu [2012]. They encourage flexibility, that is giving users more control and freedom to customize the views of each component in

[8] `https://www.infopad.no/`
[9] `http://www.selfback.eu/`

the dashboard. A dashboard consists of multiple components that present different parts of the information. Tufte [1985] discusses how to properly visualize quantitative information and he explores many different graphics, charts and tables during his research.

In this thesis we present a CDSS to enhance the workflow for clinicians in primary care. The tool utilizes CBR to support decision-making and requires therefore a suitable design to visualize the results clearly. There are some challenges regarding usability and safety of EMR and EHR systems, as mentioned by Zahabi et al. [2015]. The review proposes design guidelines on how handle these issues when developing user interfaces for health systems.

2.3.3 Google's Material Design

In 2014, Google invented a new design system, called Material Design[10], to improve the quality of their Android apps across different platforms. It quickly became so popular that the design principles were adapted to every digital platform over the years. The concept originates from the *card* component from Google Now and is based on a paper's capability. By digitizing a sheet of paper, you can expand and reshape without destroying it permanently. Material Design combines skeuomorphism and flat design to create reusable components that imitate how objects behave in the real world. The guidelines facilitate a basis for simpler and cleaner looks to the application's components and contributes to a more responsive and intuitive feel to user interactions. Lightning, shadows, colors, responsive animations and transitions contribute in giving the components an immersive effect. It helps to highlight meaningful information and makes user interactions clearer.

There exist other design languages as well, such as Microsoft's Fluent Design System[11] and Apple's Human Interface Guidelines[12].

[10] https://material.io/
[11] https://www.microsoft.com/design/fluent/
[12] https://developer.apple.com/design/

Chapter 3

Related Work

This chapter discusses the state of the art of dashboard looking CDSSs in primary and secondary care. Research question 1.1 is addressed here. A literature review is conducted with Google Scholar[1] to find relevant scientific papers.

The goal of this chapter is to get an overview of the research area and look into the related work. The structured literature search is performed systematically, and the relevant research is analyzed according to Kofod-Petersen [2018]. The findings are organized into appropriate groups based on the given criteria. The following sections will present the related works and explain why they are of relevance to this research.

3.1 Methods

The structured literature review was conducted using Google Scholar and limited to publications published after 2014 to focus on the more recent studies. Five search terms were made through trial and error according to what gave the most satisfying and relevant results. The number of papers reviewed in each step of the search process is shown in table 3.1. The number of hits by keywords indicates how many results were found by Google Scholar for each search term. The relevant titles within the field of study were sorted from the first 500 search results. Then the abstract of the remaining papers was examined, and those suitable for this research were included in this thesis.

[1] `https://scholar.google.com/`

Table 3.1: Structured literature review with search terms and their findings.

Search term	# of hits by key-words	# of hits by title	# of hits by abstract	# of hits in-cluded in paper
“case-based reasoning” dashboard in healthcare	168	21	5	2
“user experience” of a clinical “decision support” dashboard	565	33	7	7
“user interface” of an analytic “web application” in healthcare	2720	21	9	4
“web application” for “health data” aggregation	692	10	3	1
“web design” of a clinical “decision support” dashboard	86	5	2	2
Total	4231	90	26	16

3.2 Results

The findings from the structured literature review are divided into three main categories: the capability of the software, the intended care type and the targeted audience. Table 3.2 presents an overview of how the related work is categorized. All the approaches included here present systems that encompass clinical dashboards. The dashboard is therefore excluded as a part of the capability category in this table since all related work use dashboards as the core of the presented work.

For each publication listed in the table, they are assessed whether the presented software systems support complex decision-making processes and are marked accordingly in the table. The category involves papers proposing a DSS that manages comprehensive health information and produces outcomes to facilitate the course of action. Furthermore, the literature is differentiated into whether the proposed system is aimed at primary care or secondary care and divided between for whom the system is designed for, whether it is for clinicians, patients or them both.

Five fitting groups are created to structure the literature review. The first grouping contains papers presenting healthcare systems targeting *clinicians in secondary care*

Table 3.2: Categorization of the included papers.

Paper title	Capability	Care type		Audience	
	Decision-making	Primary care	Secondary care	Clinicians	Patients
Chu et al. [2018]			x	x	
Ho [2017]			x	x	
Jurcău and Stoicu-Tivadar [2016]			x	x	
Kopanitsa et al. [2015]			x	x	
Umer et al. [2018]	x		x	x	
Hernandez et al. [2017]	x		x	x	
Luz et al. [2018]	x		x	x	
Jones et al. [2016]	x		x	x	
Hartzler et al. [2015]	x		x	x	
Faiola et al. [2015]	x		x	x	
Brown et al. [2016]	x	x		x	
Duke et al. [2014]	x	x		x	
Bach et al. [2019a]	x	x		x	x
Cruz-Ramos et al. [2018]		x		x	x
Wolpin et al. [2015]			x	x	x
Teves [2015]		x		x	
Nguyen et al. [2015]		x	x	x	x

and is therefore the least relevant group to this thesis. The second group is similar to the first one, but the proposed systems also support decision-making processes. Papers presenting DSSs used by *clinicians in primary care* are gathered in the third grouping. Healthcare systems addressing both *clinicians and patients* are included in the fourth grouping, but the papers in this category target different care types and do not necessarily include decision support. Finally, the fifth grouping involves papers with a more directed focus on the *user interface and the visual presentation* of the dashboards in healthcare.

3.3 Clinical Dashboard Approaches in Secondary Care

The first grouping viewed in table 3.2 consists of four papers and presents the state-of-the-art dashboard solutions that target clinicians in secondary care. In the following, the papers are briefly described regarding their purpose, methods and findings.

A survival metadata analysis responsive tool (SMART) was developed for clinical researchers by Chu et al. [2018] to conduct an interactive, web-based analysis of patients' survival rates and risks. It provides an automated modeling tool and an interactive user interface to automatically preview the data set, metadata configurations, descriptive statistics, incidence density of the event and draw the survival curve based on the Cox proportional hazards (Coxph) model to determine overall survival rate and disease-free survival rate. Clinical researchers enter their raw data into a metadata generator and convert it to a standardized CSV-file for further use. The metadata is then imported into SMART and filtered according to the clinicians' needs. SMART presents the descriptive statistics in tables and the survival analysis in adjustable charts adapted to the analytical target.

The correlation between handwritten notes and EHRs was studied by Ho [2017] to improve the efficiency of documentation workflow. The thesis identifies challenges in managing heterogeneous patient data. A clinician's time spend is affected by the usability of the user interface and the interoperability of medical records between hospitals. Observations and interviews with clinicians were conducted and analyzed to propose a hybrid design solution that combines the efficiency and consistency of EHRs with the cognitive advantages of handwritten paper notes. The result is a digital app that is used together with existing EHR to extract and edit patient data. A patient information sheet can be printed out as a useful note-taking tool, called a "transitional artifact", to assist the physicians' memory workload.

Jurcău and Stoicu-Tivadar [2016] conducted a user experience analysis of a web application for managing EHRs. The analysis is performed with the use of automated evaluations and usability tests. The automated evaluations of the web application apply mathematical methods to calculate aesthetic measures of the interface and provide feedback about user activity. The usability testing is a user scenario about a fictitious consultation with a patient. It was executed by several clinicians and their inputs were monitored. The findings of this study showed improvements of the user experience. Making headers more compact will decrease excessive space and allow more inputs to be displayed and dividing the form into two columns will contribute to symmetry and reduce the need for unnecessary scrolling. Supporting customization of the input order will help the clinicians to adapt better and gain more control of their workflow.

An information model for building user interfaces for archetype based medical data was researched by Kopanitsa et al. [2015]. The information model was developed according to the ISO 13606 archetype model and the user interface was evaluated following the Guideline for Good Evaluation Practice in Health Informatics (GEP-HI) by Nykänen et al. [2011]. Medical content related attributes, data type related attributes, user-related attributes and device-related attributes were determined as important elements to be included in the model. A visual medical concept (VMC), developed based on the ISO 13606 archetype model, was implemented into an existing EHR system as a presentation layer separated from the archetype model to fetch the correct medical data from different archetypes into the user interface. The data is presented in a web application and provides three different views: a traditional table view, a dynamic graph view and a smartphone view. The findings from the evaluations revealed more flexibility and control of the data presentations and an increased efficiency for both clinicians and patients working with the EHR system.

3.4 Clinical Decision-Making Approaches in Secondary Care

The second grouping consists of six papers and presents the state-of-the-art CDSSs that target clinicians in secondary care, as viewed in table 3.2. This group differs from the first one because the systems explained below make use of decision-making.

A study by Umer et al. [2018] was conducted on diagnostics and treatment planning of traumatic brain injury (TBI). This paper examines a decision support system to treat TBI in hospitals. The DSS visualizes complex TBI data and utilizes a disease state index machine learning algorithm to assess a patient's state and predict possible outcomes. The system comes with three modules: a patient overview, a disease-state prediction and imaging. The clinician is assisted with the information presented by the three modules to perform more efficient decision-making when treating a patient. The system was tested in two hospitals, one in the United Kingdom and one in Finland during the research which gave positive clinical feedback. A validation study of the usability was performed and the results stated that less experienced clinicians benefited the most from the use of such a decision support system.

Hernandez et al. [2017] researched infection management at point-of-care (POC). This paper presents a decision support system to manage infections at POC to counter antimicrobial resistance. The DSS utilizes CBR to improve the visualization of clinical data and to provide more accurate and effective antibiotic therapies like those prescribed by expert clinicians. The design of the web application was a dashboard divided in 3 parts: the current patient case with retrieved similar cases, a graphical view of the historically recorded data and a collection of the selected cases provided by a CBR system. The usability of the system was determined to be good, but with some difficulties, by a system usability scale (SUS) survey with a score of 68.5, which is considered to be slightly above average. The clinicians participating in the research suggested further changes to improve the system. The first suggestion was better guidance requirements for junior clinicians to improve the learnability of the system. The second suggestion was to adapt the workflow to be less time consuming while prescribing antibiotic therapies. A final proposition from the medical staff was to extend the integration of the prescription workflow by including more parameters.

A web application for infection management, called Rapid analysis of diagnostic and antimicrobial patterns in R (RadaR), for antimicrobial stewardship teams was developed and tested by Luz et al. [2018]. It provides access to patient information, rapid analysis of diagnostic and antimicrobial patterns and outcome measures in an interactive dashboard when treating patients troubled with infections. The findings are acquired by filtering large data sets of individual patient data. Analytical graphs and statistical summaries are visualized using bar charts, combined histogram and density plots, a bubble plot and a Kaplan-Meier curve. The filtered data sets are also available to download as a CSV-file for further analysis.

Jones et al. [2016] proposed applying business analytics (BA) to decision support systems in radiology departments. The study investigated if the use of a BA software tool could improve decision-making and resource management. A prototype consisting of two dashboards was developed as web applications and utilized BA to display key performance indicators (KPI) for monitoring and predicting radiology throughput performance. The KPI dashboard displayed the clinical data defined in the requirements for the KPI data model. The predictive analysis dashboard visualized predictions of the radiology data. A qualitative evaluation proved that the BA software tool could assist in managing and forecasting radiology throughput performance and therefore have the potential to increase efficiency and performance of clinical decision-making.

A study by Hartzler et al. [2015] introduces patient-reported outcomes (PROs) in healthcare to improve clinical decision-making and user experience of visual dashboards. It uses human-centered design (HCD) methods to improve the presentations of patient-reported pain and disability outcomes following spine surgery in three steps: stakeholder interviews, group-based iterative design, and iterative design with individual users. Stakeholder interviews gave context to the use of PRO dashboards. User requirements were determined based on use case scenarios during group-based iterative design and then used to develop and evaluate prototypes in communication with the stakeholders. Iterative design with individual users established design specifications for the implementation of the PRO dashboard through adaptations and usability testing. This approach to develop a PRO dashboard helped customize the user interface and enhance the quality of care and patient outcomes according to the healthcare providers' needs. It included at-a-glance overviews of trends and quarterly snapshots, PRO data analysis with data filters and user-defined views to share and reuse. Using healthcare providers as stakeholders when developing and customizing healthcare dashboards according to their user requirements improved functionality, visual design and usability of the dashboards.

Faiola et al. [2015] present an information visualization dashboard for intensive care units (ICUs), called Medical Information Visualization Assistant, version two (MIVA 2.0), combining data from bedside monitoring devices and EMRs to reduce cognitive load during clinical decision-making. It was designed with a human-centered approach to optimize diagnosis speed and accuracy by supporting rapid analysis of real-time clinical data-trends. Both qualitative and quantitative methods were conducted using performance and usability testing, post-test questionnaires and open-ended interviews to compare MIVA 2.0 with ICU paper medical charts. It was shown by the findings that EMR dashboards reduced the cognitive overload of information and improved clinical workflow and clinical decision support efficiency for the participants.

3.5 Clinical Decision-Making Approaches in Primary Care

This grouping is similar to the second, but it targets primary care instead of secondary care. Two papers were found relevant to state-of-the-art CDSSs in primary care targeting clinicians, as shown in table 3.2. Brief summaries of them are presented here.

Brown et al. [2016] presents recommended guidelines for the development of user-centered design of electronic audit and feedback (e-A&F) systems. e-A&F systems are used as a quality improvement technique to measure and evaluate a clinician's or a healthcare team's clinical performance in primary care. It is different from a CDSS in that it provides strategies and encourages changes to the clinical practice according to evidence-based guidelines. Despite being different, the presented system used decision support to build their recommended actions component. A web-based dashboard tool called PINGR (the Performance Improvement plaN GeneratoR) was developed as an e-A&F system for primary care based on findings from previous research. It was designed for use cases of hypertension and asthma and aimed to help primary care clinicians in the United Kingdom. The usability of the system was tested with a combination of heuristic evaluation and cognitive walkthrough methods by eight evaluators to identify usability issues of the system. The test results were then analyzed and converted into recommended design guidelines for the user-centered design of e-A&F systems. The guidelines provided an interface consisting of four key components: summaries of clinical performance, patient lists, patient-level data and recommended actions. The interface design recommendations for e-A&F systems were later refined by Brown et al. [2018].

Duke et al. [2014] present an update on further development of Regenstrief Institute's customized EMR system, called the Medical Gopher. Through agile development utilizing user-centered design and close cooperation between developers and providers, the system has been designed to improve patient care focusing on usability, safety, and advancement of biomedical informatics research. Gopher is a seminal computerized order entry system providing order entry, clinical documentation, result viewing, decision support, and clinical workflow. The patient overview consists of data regarding the patients, recent orders, a to-do list, and recommendation for prevention. The order entry is inspired by e-commerce and takes advantage of using an orders cart to manage orders. The clinical documentation benefits from a natural language processing which displays user suggestions such as potential orders for consultations, medications, and lab tests. The system provides a chart search feature which the clinician can use to fetch and review clinical data (reports, labs, medications, diagnoses, and notes). Evaluation of the new implementations remains to be done.

3.6 Clinical Dashboard Approaches for Both Clinicians and Patients

Three papers were examined to present state-of-the-art CDSS that targets both clinicians and patients, viewed in table 3.2. The first two papers involve primary care and the last one involves secondary care. All three are explained in this section.

The research on selfBACK by Bach et al. [2019a] provided motivation for this thesis.

It presents the first CDSS on non-specific low back pain and utilizes co-decision making between clinicians and patients in primary care. However, co-decision making has been used before within other medical areas by Segal and Shahar [2009], Eiring et al. [2017] and Collins et al. [2016]. The selfBACK system is divided into two application cycles: a mobile platform accessible to the patient as a self-management tool and a web application of a clinician dashboard used for co-decision making along with a clinician. The paper includes functional specifications for the clinician dashboard, drafted wireframes of the interface and intended user scenarios. Time constraint and user privacy was identified as important factors when designing a clinician dashboard for co-decision making. Since a consultation between clinicians and patients are usually limited to a short time (e.g., 30 minutes), it is important to facilitate the clinician dashboard to provide more efficient consultations.

Cruz-Ramos et al. [2018] shows a medical decision support system, called DiabSoft, which addresses the prevention, monitoring and treatment of diabetes, but can also be adapted for other similar chronic-degenerative diseases. It displays the patient profile, monitoring, consultations, habits, recommendations, and previously seen clinicians. The monitoring of patient health parameters is used to collect data on vital signs, daily habits, and symptoms to propose medical recommendations based on collaborative filtering and shared knowledge for patients and healthcare professionals. Observations from the literature review of existing tools for managing diabetes showed that they were fairly limited, and they did not cover all the phases of diabetes. DiabSoft has been developed to address these issues, and therefore has significantly improved the quality of life for people with diabetes. In the future the authors want to expand DiabSoft to include wearables to monitor patients and automatically collect their health data. They do also plan to develop a medical opinions repository based on health- and medical-related information obtained from social networks and evaluate their generated recommendations to identify user behavior patterns.

The latest version of the Electronic Self-Report Assessment for Cancer (ESRAC) web application was designed and developed by Wolpin et al. [2015] as part of a larger clinical trial. ESRAC is a symptom and quality-of-life information (SQLI) support system for management and monitoring of patients' cancer treatment. This iteration had a patient-centered design approach for the new features on how to gather and present health information and support patient-control of the data. Two research methods were used. New design preferences were established and analyzed during focus groups. Individual usability testing was performed quantitatively and qualitatively with low- and high-fidelity mock-ups to identify usability issues. An eye tracker was used to record the user's eye movement during the testing. The new interface features were developed based on user-centered design principles instead of the opinions of the providers, researchers, or vendors. Features regarding the graphical display and management of symptoms, navigation paths and information sharing were refined in the process.

3.7 Design Choices for Clinical Dashboards

Two papers were found regarding design choices targeting user interfaces of dashboards in healthcare. The content of these papers is of interest to this thesis due to their design approaches of clinical dashboards. These papers are categorized similarly to the other papers in table 3.2 because of consistency, even though their topics are angled a bit differently. The first paper by Teves [2015] performs a user-centered approach on clinical dashboards to differentiate the use of tables, graphs, and infographics when treating patients with diabetes. The second paper by Nguyen et al. [2015] improves a search feature for health information portals to present more relevant data. Its dashboard design seemed to be more relevant during the structured literature search, but it has been deemed less relevant compared to the other papers included in this thesis. The search features from this paper are not that interesting to this research either.

Teves [2015] did a study on how to design effective clinical dashboards adapted to treatment of patients with diabetes by using user-centered design. The study extends the use of cognitive fit theory by Vessey [1991] to include infographics and applies it to distinguish the perception and effectiveness of tables, graphs and infographics. The different types of visualization are evaluated for their suitability to present symbolic or spatial information tasks and their presentations of daily or monthly data views. Symbolic information is data values in a data set without context, while spatial information is data trends registered over time or in a confined space. The effectiveness of the visualization types were examined based on accuracy, performance and preference. The results showed that the best displays for symbolic tasks were tables and infographics regardless of information type, and the best displays for spatial tasks and monthly information were graphs. The research confirmed previous studies showing that there is an inconsistency between users' performance and their preferences.

The paper by Nguyen et al. [2015] discusses how health information portals (HIPs) are used to provide reliable and relevant health information, and how this information can be improved by studying usage data to address search issues by users. Two tools were proposed: a content-issue reporting tool and a usage-driven topic search feature. The content-issue reporting tool consists of three parts: an issue-focused menu, a smart listing panel and an action panel. The issue-focused menu contains different usage services and puts the issues into groups for task-specific usage reporting. The smart listing panel provides reports of possible failed searches which occur when user-based searches mismatch with the system's indexed terms. The action panel shows analysis and recommended actions on how to handle the failed search issues. The other tool, the usage-driven topic search, provides alternative searching options to the user when their searches fail. The tool is divided into two columns, the most popular content, and the top searches by users. The first column presents the most popular topics in the system and the second column shows the most popular topics searched by users. These features are intended to provide relevant search alternatives to avoid failed searches in HIPs when user-based and system-based search topics will not correlate. The streamlined user interface was used to help reducing the complexity of presenting heterogeneous usage data.

3.8 Summary

The majority of the applications described in this chapter have been deployed in secondary care and have targeted clinicians. The papers by Hernandez et al. [2017], Luz et al. [2018], and Hartzler et al. [2015] are particularly interesting to this thesis in how they designed their dashboards to enhance workflow and reduce time consumed when clinicians treat their patients. Bach et al. [2019a] and Cruz-Ramos et al. [2018] are also of significance because they allow patients to report their own health data to the clinical system. Suggested treatment plans are given in co-decision with the clinician and are accessible to the patient in the application.

The effect of how to present data in dashboards was highlighted by Jurcău and Stoicu-Tivadar [2016] and Teves [2015]. It is challenging to display heterogeneous clinical data in a dashboard properly. The aim is to fit large amounts of data in a single view while allowing clear readability, reducing cognitive load and lessening the use of scrolling to make the dashboards more efficient.

Overall, there have been a lot of attempts in creating effective dashboards in healthcare, but few have been adapted to physiotherapy. This thesis will learn from the related work that was found and use it to provide more effective dashboards for treating unspecified back, neck, and shoulder pain. The next chapter will describe the methods used to achieve the results for this research. The strategies carried out during the research process will be presented there together with a conceptual framework and a holistic architecture of the system.

In hindsight, the search terms used in the structured literature review were a bit too complicated. Simpler keywords such as “clinical decision support system”, “clinical dashboard” and “case-based reasoning” could provide promising results without you narrowing down the search. On the other hand, the literature found from this search has shown that software tools in healthcare have various purposes. They can be useful to monitor diseases, manage and analyze clinical patient data, reduce medication errors and improve decision-making and treatments.

Chapter 4

Methodology

This chapter describes how the research is conducted. Developing a unified view for physiotherapists is challenging because the underlying clinical data is heterogeneous, and the contextual setting in which co-decision making is used can vary. The chapter starts off describing a typical physiotherapy consultation scenario, and how the system is applied in that situation. Furthermore, it continues describing the CBR process for a patient scenario and presents the case representation used by the CBR system to match patient profiles. Then follows an overview of the architecture and the workflow of the system. Finally, the chapter concludes by elaborating on the process of creating mock-ups and prototypes and defining the requirements of a clinician dashboard that facilitates co-decision making in a primary care setting.

4.1 Conceptual Framework

4.1.1 Use-Case Scenario during a Physiotherapy Consultation

In this section we present a possible scenario of a consultation between a patient and a physiotherapist using the clinician dashboard. It can also be adapted to other clinician types (chiropractors, general practitioners, secondary care). The scenario will focus on the first-time consultation, but the clinician dashboard can be used for follow-up visits as well. We assume that the patient's data has already been entered into the system before the consultation begins. Therefore, the patient needs to fill out a web-based questionnaire from home beforehand, so the data becomes available in the clinician dashboard.

A consultation between a clinician and a patient can address the following questions:

- How does the patient currently perceive their physical functionality?
- What level of pain is the patient experiencing?
- Is the patient motivated to take action to improve their situation?
- How is the treatment affecting the patient's condition?

The clinician dashboard supports two interactions: the clinician's preparation for the consultation and the co-decision-making with the patient about their treatment. During the preparation time, the clinician can look into the patient's case and stay up to date with the progress. When the clinician and the patient are discussing the treatment plan, the clinician dashboard provides enough information to efficiently aid the co-decision-making. The CBR system does only focus on the recommendation part. The learning process has not been implemented yet, but it will handle how valued experiences are built into the CBR system. The process of how the CBR system manages a patient's case is viewed in figure 4.1.

4.1.2 Preparation for the Clinician

The clinician opens up the clinician dashboard and looks up the patient case to prepare for the upcoming consultation. During the preparation time, the physiotherapist can have a brief look into the latest data on the patient and prepare for the initial phase of the discussion.

The patient case is retrieved from the CBR system. Upon retrieval, the patient data can be investigated immediately in the clinician dashboard, ready to be discussed. It contains information about the patient, a problem description, suggested treatment recommendations, and the latest scores from questionnaires. The first view of the clinician dashboard that the clinician sees is an overview of the patient case. More details about the patient case are divided into separate views that the clinician can look into; the profile, the problem description and the treatment plan. A final view shows the results from the similarity measure that supports the decision-making. It presents the treatment recommendations retrieved from other similar cases. The retrieval of similar cases happens transparently to the user.

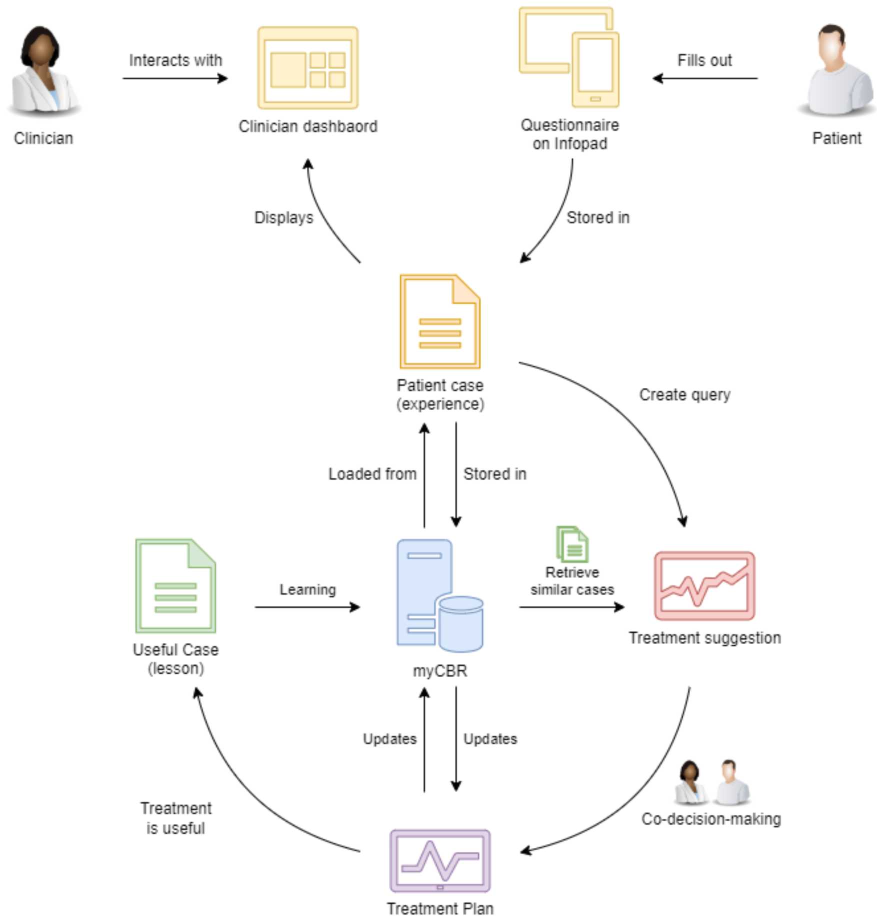

Figure 4.1: The process of case-based reasoning on a patient case.

4.1.3 Co-decision-making

Once the patient arrives, the clinician and the patient start the co-decision-making by looking at the visualized data in the patient case. The clinician interviews the patient about the health problems and listens to the patient's thoughts on the matter. Then, the clinician takes a look at the suggested treatment recommendations, which are generated based on similar cases from the CBR system, and presents them to the patient. The clinician can also investigate similar cases to be acquainted with different treatment trajectories.

It is important to talk about how the condition will change with time by monitoring the data trends of the patient. The clinician and the patient discuss the treatment recommendations together and agree on a treatment plan. The co-decision-making will help the patient to take an active part in the planned treatment and therefore become more motivated to carry it out. The clinician will teach any necessary exercises to ease the pain. Videos, leaflets, and web pages can also be used as supplementary material to teach certain exercises.

4.2 Case-Based Reasoning

This section discusses how CBR is used to provide decision support in the clinician dashboard. It will first explain the source for collecting the patient cases and how to implement them into the casebase. Then follows a description of how myCBR is used to support the decision-making of non-specific neck, shoulder, and back pain. The case representation and the similarity measure are presented, and it is described how patient cases are retrieved in the web application.

The casebase contains patient cases. A patient case contains only fragments of the whole patient record. The mobile app Infopad[1] is intended to be used as a source for collecting new patient case entries. Infopad is a tool for conducting surveys in medical projects. It allows for defining individual questionnaires and stores the data securely. Whenever a new case is created, the clinician will add the patient to Infopad. The patient will log into Infopad to fill out an introductory questionnaire before the first consultation. The results are stored in the respective patient case in the casebase.

At the beginning of the consultation, the clinician opens a patient case in the clinician dashboard by searching for the case ID. A query with the case ID is sent to the myCBR REST API to retrieve the correct patient case from the casebase. The response from the

[1] `https://www.infopad.no/`

myCBR server is a JSON object of the patient case that contains all the attributes that are essential for treating the patient. The patient case is now loaded into the clinician dashboard and is ready to be inspected.

A patient case consists of two parts, the attributes that are filled in by the patient and the clinician before the first consultation and the attributes derived from the treatment plan. The attributes related to the treatment plan include different treatments (active, passive and other types), advice and involved parties. The treatments and advice values can be registered with a frequency of *much*, *some*, or *none*. The involved parties are registered as *yes* or *no* depending on whether they are in contact with the patient or not.

The case representation is a subset of the patient case that is used for the similarity measure in the CBR system [see Bergmann, 2002, chap 3]. The phenotypes from the paper by Meisingset et al. [2020] are used to define the case representation. The similarity measure in the myCBR uses the global similarity model from Jaiswal et al. [2019] and the local similarity model is created by using the method described by Verma et al. [2018]. The case representation contains values about the patient that is used for the similarity assessment between the patient cases, such as age, gender, BMI, type of work, and scores from different diagnostic questionnaires. All the attributes that constitute the case representation of a patient case are explained in table 4.1.

Table 4.1: The case representation of a patient. This is a subset of the patient case data set used in the similarity measure.

Description	Attributes	Weight	Value Range
Case ID	id	0	0 - 100000
Patient ID	patientId	0	1 - ∞
Reusable outcome	outcome_01	0	0, 1 (no, yes)
Age	age	1	0 - 150
Gender	gender	1	female, male
BMI	bmi	1	0.0 - 100.0
Smoking	smoking	1	no, yes
Education	education	2	primary school, high school, up to 4 years higher education, more than 4 years higher education, other
Main complaint for seeking GP	body_main	4	neck, shoulder, back, hip, knee, multisite
Daily activity level	activity	4	not reduced, slightly reduced, quite reduced, very reduced
Walk aid	walk_aid	4	no, yes

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Table 4.1 – continued from previous page

Description	Attributes	Weight	Value Range
Work situation	employ	1	working or other, disability pension or work assessment, sick leave
Work characteristic	work_type	2	mostly seated, much walking, much walking and lifting, heavy work using the body
Work ability	work_ability	4	0 - 10
Comorbidity count	comorbidity_count	1	0 comorbidity, 1 comorbidity, 2 to 3 comorbidities, 4 or more comorbidities
EQ5D - Mobility	eq5d_walk	1	no problem, slight problem, moderate problem, severe problem, unable
EQ5D - Self-care	eq5d_care	1	no problem, slight problem, moderate problem, severe problem, unable
EQ5D - Anxiety	eq5d_depr	2	not, slightly, moderately, severely, extremely
15D - Sleep	qol15d_q5_sleep	4	sleep normally, slight problem, moderate problems, great problems, severe problems
15D - Vitality	qol15d_q14_vital	1	healthy and energetic, slightly weary, moderately weary, very weary, extremely weary
Örebro-1: Pain duration	pain_duration	4	less than 1 month (1-3), 1 to 3 months (4-6), 3 to 6 months (7), 6 to 12 months (8-9), more than 12 months (10)
Örebro-2: Pain last week	pain_last_week	1	0 - 10
Örebro-7: Long-lasting ailments	oreb_q7	4	0 - 10
Örebro-10: Stop activity	oreb_q10	1	0 - 10
Number of pain sites	painsite_number	2	0 - 10
Temporality pain	pain_continuous	1	no, yes
Mental distress	hscl_score	8	0.0 - 4.0
Keele STarT MSK	mskt_risk	4	low, medium, high
MSK-HQ-7: Social activities and hobbies	mskhq_q7	1	not at all, slightly, moderately, severely, extremely
MSK-HQ-15: Physical activity level	mskhq_pa	2	none, 1 day, 2 days, 3 days, 4 days, 5 days, 6 days, 7 days

Continued on next page

Table 4.1 – continued from previous page

Description	Attributes	Weight	Value Range
Pain self-efficacy and fear avoidance	pseq_score	2	0 - 12
Tampa 1-item: Fear avoidance	fear	1	0 - 10

End of Table

When the clinician looks at the treatment recommendations, the clinician dashboard will retrieve them from similar cases transparently. It sends a query to CBR system that requests the ten most similar cases. The CBR engine executes the similarity measure, where the patient case is compared to all the other patient cases in the casebase, and returns the result back to the clinician dashboard. The calculation is based on the weight of each attribute in the case representation. The global similarity measure is calculated using the formula for global similarity score with the amalgamation function for a weighted sum, as shown in equation 4.1 [see Bergmann, 2002, chap 4].

$$sim(Q,C) = \frac{1}{\sum w_i} \sum_{i=1}^{n} w_i \cdot sim_i(q,c) \tag{4.1}$$

$sim(Q,C)$ is the global similarity function between a query Q and a case C, and it is the weighted sum of all local similarity scores. The result is a score value between 0 and 1. The local similarity measure, $sim_i(q,c)$, of attribute i compares the attribute value q from the query and the respective attribute value c from the case. w_i is the weight of each attribute's local similarity measure used in the amalgamation function.

The weight of each attribute relates to the attribute's prioritization in the similarity measure, where a higher weight score equals a higher priority. The more important attributes are weighted higher, such as mental distress with the highest weight score of 8.0. Other favored attributes are the main complaint for seeking a general practitioner, daily activity level, the Keele STarTBack score, long-lasting ailments, pain duration, sleep, use of walking aid, and work ability with a weight of 4.0. The weights were determined based on the experience from Meisingset et al. [2020] and are presented in the case representation in table 4.1.

The response from the CBR system is a JSON object containing a structured list of all the similar cases. They are listed in descending order by the most similar to the less similar in the clinician dashboard, and the clinician can select which to include in the main view. The treatment plans from the selected cases will be proposed as a treatment recommendations for the current case.

This is how the clinician dashboard provides decision support with high quality choices to help clinicians do a more effective treatment. It presents proposed treatment recommendations together with a tabular view of the most similar cases. The table gives more accurate insight to the key attributes and comparisons between them. The clinician and the patient use this information to perform co-decision making and decide on a definite treatment plan to deal with the patient's problem. The patient case will now contain both the patient data and the treatment decision, and it will be updated in the casebase.

The patient case closes at the end of treatment and is stored in the casebase. The outcome of the treatment, attribute *outcome_01*, decides if the patient case will be available for CBR in future smimilarity measures. If the treatment is successful or provides sufficiently high utility, then its results are a useful lesson. The outcome of the patient case is therefore set to 1. The patient case is then regarded as a reusable experience and will be included in future similarity assessments by the myCBR to improve the decision-making support even more. Otherwise, if the treatment is ineffective, the outcome will be set to 0 and the patient case will be excluded from future similarities.

4.3 Data set

The data set used in this thesis is similar to the data set used in Jaiswal [2018] and has been acquired by the ISM as part of the SupportPrim Project[2]. It contains 449 patient cases with non-specific MSDs that are already implemented into the casebase in the CBR system. The data have been de-identified, meaning that they do not include any sensitive or identifying information about the patients. The stored patient information has a general description of the patient, a description about their problem with scores from questionnaires to measure their physiological and psychological condition, and a treatment plan.

The data set contains all the attributes that are relevant to the patient case. The attributes included in the case representation were shown in the previous section, table 4.1. The remaining attributes that are of interest to the clinician, can be seen in table 4.2. These attributes are visualized in the clinician dashboard to provide more context about the patient case, such as highlighting the patient specific function scale (PSFS) and the pain values in diagrams. The final prototype's primary focus is handling and visualizing

[2] https://www.ntnu.no/supportprim

the treatment recommendations, so only the attributes in the case representation are considered. Hence, the additional attributes are disregarded from the patient cases.

Table 4.2: The remaining attributes in a patient case not included in the case representation.

Description	Attributes	Value Range
Case ID	caseID	n/a
Global perceived effect	gpe_3	very much improved, much improved, minimally improved, no change, minimally worse, much worse, very much worse
PSFS	psfs1_1	0 - 9
PSFS (3 months)	psfs1_3	0 - 9
PSFS activity	psfs1_act_1	n/a
MSK-Tool Score	mskt_score_1	0 - 12
Sum score Örebro - 10 item	oreb_score_1	0 - 100
Örebro-1: Duration of current complaint	oreb_q1_1	0 to 1 week, 1 to 2 weeks, 3 to 4 weeks, 4 to 5 weeks, 6 to 8 weeks, 9 to 11 weeks, 3 to 6 months, 6 to 9 months, 9 to 12 months, more than 12 months
Örebro-2: Pain	oreb_q2_1	0.0 - 10.0
Örebro-3: Work	oreb_q3_1	0.0 - 10.0
Örebro-4: Sleep	oreb_q4_1	0.0 - 10.0
Örebro-5: Tense/stressed	oreb_q5_1	0.0 - 10.0
Örebro-6: Depression	oreb_q6_1	0.0 - 10.0
Örebro-8: Work in three months?	oreb_q8_1	0, 1, 2, 3, 4, 5, 7, 8, 9, 10
Örebro-9: Stop activity due to pain	oreb_q9_1	0, 1, 2, 3, 4, 5, 7, 8, 9, 10
Temporality pain (3 months)	pain_continuous_3	no, yes
Varying intensity of pain	pain_vary_1	it is stable, no, yes
Varying intensity of pain (3 months)	pain_vary_3	it is stable, no, yes
Pain variation description	pain_variation_1	it varies from day to day, it varies within the day, other
Pain variation description (3 months)	pain_variation_3	it varies from day to day, it varies within the day, other
Pain frequency	pain_freq_1	every day, one or more times a week, one or more times a month
Pain frequency (3 months)	pain_freq_3	every day, one or more times a week, one or more times a month
Use of analgesics	medic_1	no, yes

End of Table

The following will go into detail explaining the nine attributes with the highest weight in the data set and give an understanding of why they have such a big impact on the similarity measure. The data distribution is displayed to provide an overview of the value range and the distribution for each of the selected attributes.

Mental distress (*hscl_score*) is measured by the Hopkins Symptom Checklist - 10 (HSCL-10) and indicates symptoms of anxiety and depression. HSCL-10 is a shorter version of the more comprehensive Hopkins Symptom Checklist - 25 (HSCL-25), but the results are sufficient according to Strand et al. [2003]. The questionnaire gives an average score between 1.0 and 4.0, and a score higher than 1.85 is estimated to be the definition of whether a patient is mentally distressed.

Most of the patients in the casebase have a score lower than 2.0, which means that most of the patients do not have any symptoms of anxiety and depression, as seen in figure 4.2. The patients scored from 1.0 to 3.2 on the questionnaire, except for two single outliers. 75 % of the patients have scores below 2.0 and therefore the distribution is grouped towards the left side of the diagram. Half of the patients have scores between 1.2 and 2.0 as you can see grouped inside the blue box. The distribution of the HSCL-10 scores is asymmetrical with a median of 1.5 and skews to the right.

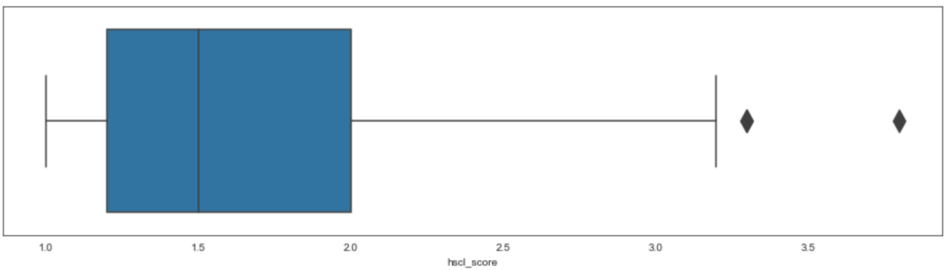

Figure 4.2: Box plot of the mental distress distribution. The median is 1.5 and half of the patients' scores between 1.2 and 2.0.

The main cause for seeking a general practitioner (*body_main*) describes in which area of the body the patient is feeling pain. The patient cases are mostly evenly distributed between the categories, as shown in figure 4.3. The attribute for the main complaint will therefore help a lot in differentiating the patient cases when they are compared. Patients with back pain should generally not be treated the same way as those with neck or shoulder pain. About 20 % of the patients have problems in multiple areas of the body, *multisite*. The main problem area with the most occurrences in the casebase is both shoulder and back with over 100 registered cases in each category. The figure shows that knee problems are the least common main complaint.

The daily activity level (*activity*) is a measure of how the pain affects the patient's

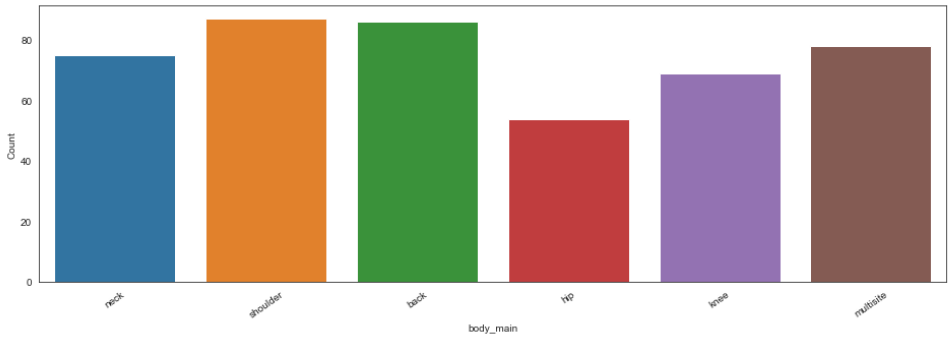

Figure 4.3: Bar Graph of the main complaint for seeking general practitioner distribution.

activity during the day. The attribute distribution of all the registered patient cases can be seen in figure 4.4. Three fourths of the patients in the casebase have a value of slightly or quite reduced daily activity level, whereas the majority of the cases in the casebase have a slightly reduced. The rest of the cases are divided evenly into the categories of not reduced or very reduced.

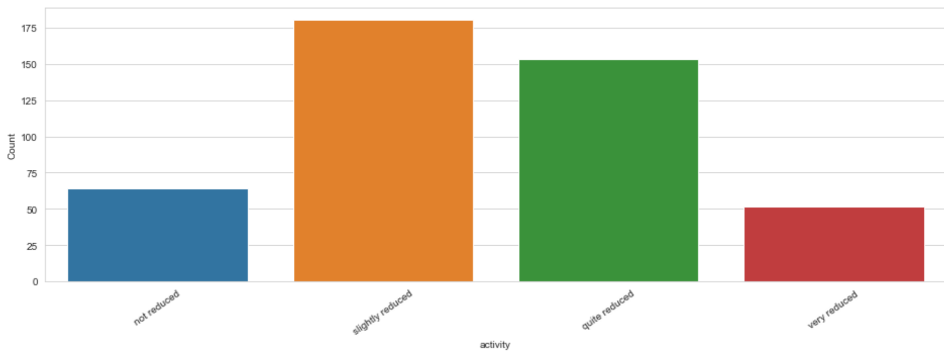

Figure 4.4: Bar Graph of the daily activity level distribution.

Patients are asked a yes or no question if they need walk aid (*walk_aid*) in their everyday life. As you can see from figure 4.5, none of the treated patients required walk aid. Therefore, the distribution of the data set is very skewed towards the answer *no*. Hence, the walk aid data attribute does not help very well in differentiating similar patient cases. But it is important to point out how crucial this information is when the treatment plan is being designed.

Work ability (*work_ability*) describes how well the patient can perform their work. The attribute scales within the range from 0 to 10, where 0 means that the patient is

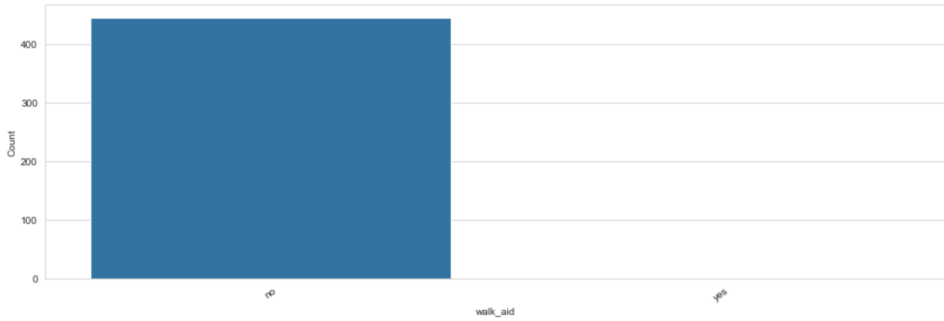

Figure 4.5: Bar graph of the walk aid distribution.

not able to perform any work at all and 10 indicates that the patient is in their best capability to perform work. The data set has recorded values across the entire value range of the work ability attribute, as shown in figure 4.6. 75 % of the patients have a work ability score higher than 5, and this indicates that most of the patients can at least do some work or better. The median is to the right of the box with an estimated value of 7. Therefore, the data distribution is asymmetric around the median and it skews to the left. The left quarter of the patients are very limited to work with work ability scores lower than 5. 25 % of the patients are within the right quarter and say they can work without any problems.

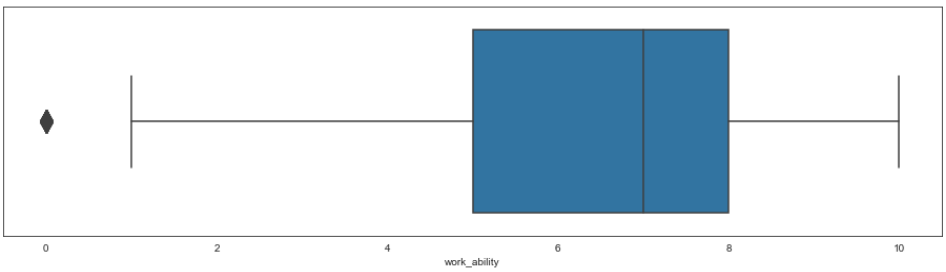

Figure 4.6: Box plot of the work ability distribution. The median is 6 and half of the patients' scores between 4 and 8.

How well the patients sleep (*qol5d_q5_sleep*) is measured as part of the 15D instrument of health-related quality of life (HRQoL). 15D is a questionnaire of 15 questions (15-dimensional) to assess the patient's health status. It generates a single index number score between 0 and 1 which presents a health profile of the patient.

The sleep distribution of the patients in the casebase is presented in figure 4.7. Close to 25 % of the patients sleep normally, a bit less than half has minor troubles falling asleep, and the rest (about 35 %) have difficulty sleeping to some extent. The distribution will be able to help differentiating the similar patient cases.

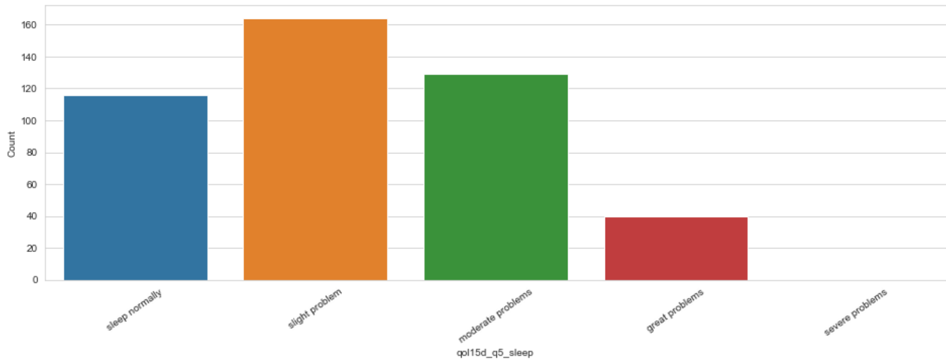

Figure 4.7: Bar graph of the 15D - sleep distribution.

The data on pain duration (*pain_duration*) and long-lasting ailments (*oreb_q7*) are obtained from the Örebro Musculoskeletal Pain Screening Questionnaire. Örebro is a tool developed by Linton and Halldén [1998] to detect "yellow flags" that predicts psychosocial risk factors for developing long-term disability and failure to return back to work, such as pain duration and long-lasting ailments. The form is most used for patients with acute low back pain, but it can also be used for patients with sub-acute or long-lasting ailments, neck patients, shoulder patients and patients with generalized musculoskeletal pain. The questionnaire contains 21 questions that score between 0 and 10, and the total score is summarized at the end with a maximum of 210. A score above 105 means that the patient has an increased risk of developing possible long-lasting ailments and a reduced chance of going back to normal as before the pain in question occurred. A shorter version of the Örebro Musculoskeletal Pain Screening Questionnaire[3] is used to collect the Ôrebro data in the data set.

The values of the pain duration in the data set are distributed unevenly as displayed in figure 4.8. The pain duration is a measure of how long a patient has had the current pain problem before seeking professional help. The score on pain duration from the Örebro questionnaire is originally a value range from 1 to 10, corresponding to a range from 0 days to over 1 year, but the data has been modified into smaller groups. The value ranges 1–3, 4–6, 7, 8–9 and 10 represents *less than 1 month*, *1 to 3 months*, *3 to 6 months*, *6 to 12 months*, and *more than 12 months* respectively. About 20 % of

[3]`https://www.cesphn.org.au/documents/filtered-document-list/204-oerebro-musculoskeletal-pain-screening-questionnaire/file`

the patients have experienced short-term ailments of less than three months, around 30 % have been in pain for three to twelve months, and close to half of the patients have been in pain for more than a year. The attribute differentiates very well between patients with pain duration of up to one year, but it differentiates less between those who have had ailments for longer than that.

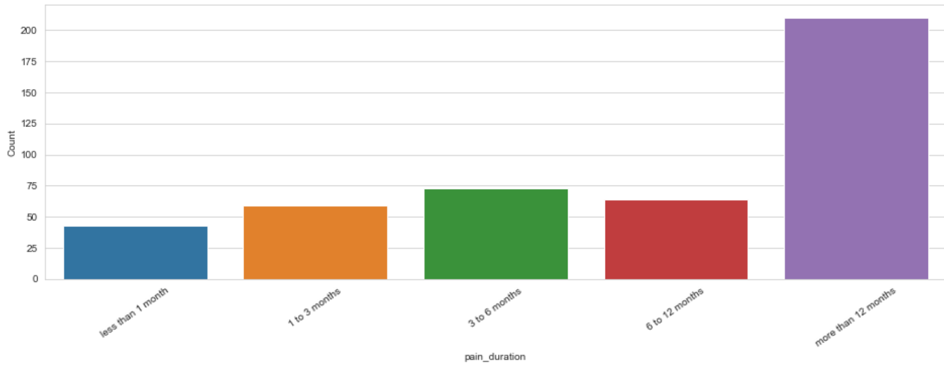

Figure 4.8: Bar graph of the Örebro-1: pain duration distribution.

The long-lasting ailments attribute measures the patient's view on how large the risk is that their current pain may become persistent. It has a value range from no risk (0) to very large risk (10). The attribute distribution is viewed in figure 4.9 where you can see that the data are grouped around the upper end of the value range, between 5 to 10. 75 % of the patients have scored higher than 5, which means they believe there is a medium to high risk that their current pain may become persistent. The median is 6 and corresponds to a medium to high risk. Half of the patients' score between 5 and 8, which is close to the median. 25 % of the patients believe there is a very large risk that their pain will be persistent. The last 25 % of the patients think there is medium to very little risk for their pain problem to become persistent. The data distribution of long-lasting ailments is asymmetric and left-skewed. There is an outlier with a score of 0, meaning no risk, that could give very different results from the similarity measure compared to the majority of the patient cases.

The Keele STarT MSK tool, developed within the Keele Aches and Pains Study (KAPS)[4], is a screening tool to help clinicians estimate the risk of a poor outcome for patients with common musculoskeletal pain (mskt_risk), meaning the risk of the pain becoming a chronicity. At the first consultation, the patient receives the questionnaire of 10 items asking about function and disability, pain and coping, comorbidity, and the

[4] `https://www.keele.ac.uk/startmsk/`

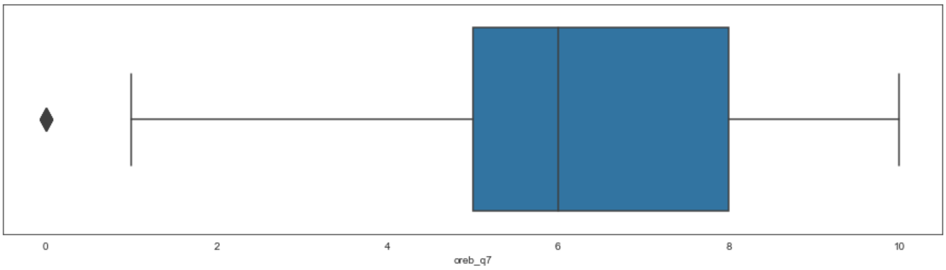

Figure 4.9: Box plot of the Örebro-7: long-lasting ailments distribution. The median is 7 and half of the patients' scores between 5 and 8.

impact of pain. A total score is calculated by the clinician and assigns the patient into one of the three risk categories: low, medium, or high. The result is used to support clinical decision-making by predicting the most efficient treatment. The data distribution of the risk assessment is presented in figure 4.10. It shows a skewed distribution with a very low frequency of high-risk scores. A little bit more than 10 % of the patients are at a high risk for a poor outcome. Half of the patients were estimated to have a medium risk, and a third to have a low risk.

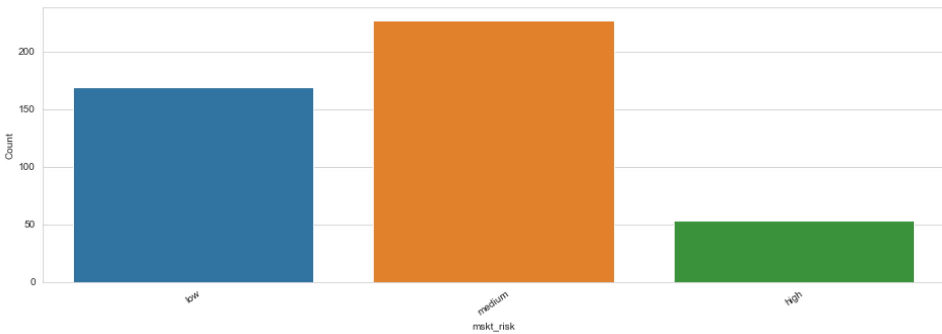

Figure 4.10: Bar graph of the Keele STarT MSK distribution.

4.4 Architecture

The architecture of the web application uses a client-server model, as shown in figure 4.11. The system is divided into two parts, a front-end and a back-end. The front-end is the clinician dashboard presented in this thesis and is accessible to the users as a web application. The back-end is a server built with myCBR to provide clinical decision support. It manages patient cases in the casebase and supports similarity measures to predict treatment recommendations.

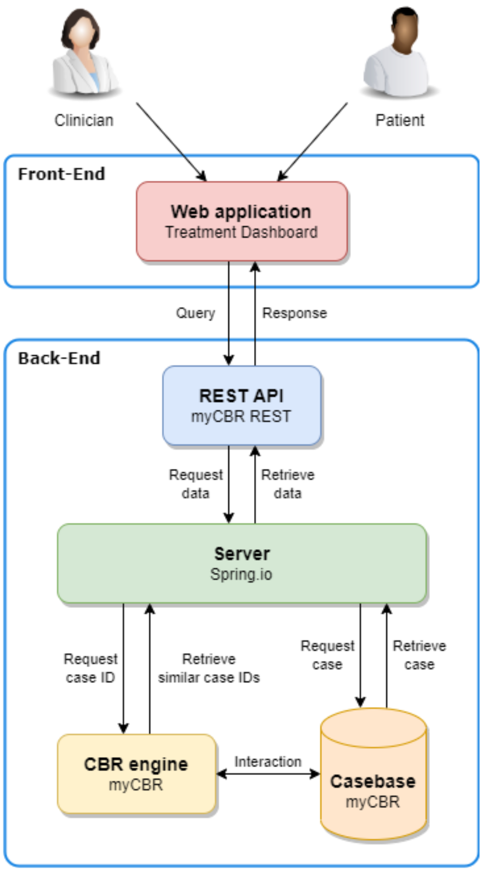

Figure 4.11: System architecture.

The front-end is a decision-making support tool developed for treating patients with unspecified neck, shoulder, or back pain. This part is the clinician dashboard and the focus of this thesis. The tool helps to improve the decision-making between clinicians and the patients when they decide on a treatment plan. The clinician can investigate patient cases and create treatment plans based on similar experiences from previous cases. The clinician dashboard is used to request clinical data from the server. It needs to send queries to the server's REST API to get access to the patient cases. The server responds to the REST API call by returning the requested data back to the web application. The data is now ready to be presented in the clinician dashboard.

The back-end is a RESTful server developed with SpringIO that utilizes myCBR to manage the clinical data. The myCBR tool consists of a casebase and a CBR engine that interacts with each other. The casebase is a database that contains all the patient cases, while the CBR engine handles the similarity measure of a patient cases and the retrieval of its similar cases. The myCBR server is accessible through the myCBR REST API. The REST API is demonstrated by Bach et al. [2019b]. The server transforms the REST calls into methods usable for interactions with the casebase and the CBR engine, and then provides a response back to the client.

The myCBR REST API provides an interface with a set of methods the clinician can use to operate the CBR system. The clinician can look up and examine a patient case in the clinician dashboard. The clinician dashboard will then send a query to the REST API to request the patient case with the case ID from the server. The server finds the patient case in the casebase and returns it back to the front-end. The case is now available in the clinician dashboard for the clinician to examine.

To create a treatment plan for a patient with an unspecific pain, the clinician will have to do CBR on the patient case. The clinician dashboard will send a query to myCBR REST API, requesting to do a similarity measure on the current case. The server tells the myCBR engine to investigate all the experiences (patient cases) in the casebase and perform a similarity measure on all of them. A list of the ten most similar cases is returned to the clinician dashboard and presented in the user-interface. The similar cases are listed from the most relevant to the least relevant when retrieved, and they are displayed in the same order in the web application. A treatment plan is proposed based on the results. A possible security problem may be that other patients' data are exposed when presented in the list of similar cases. All data shared from other patient cases will therefore be quantified information and thus anonymous. It does not reveal the identity of the patients.

The clinician dashboard is designed as a single-page application with six distinctive views. Four of these are presentations of the patient case, and the last two displays the similarity measure and the similar cases. The four views about the patient case are an overview page, a patient profile view, a problem description view, and a treatment plan view. The view of the similarity measure displays the similar cases and the treatment recommendations. The last view is a modal presentation of a similar case. The relation between the pages are shown in figure 4.12. The clinician will be presented with an empty page on startup. From there, the clinician can look up a patient case and get access to them in the patient views. The results from the CBR can be found in the similar cases view.

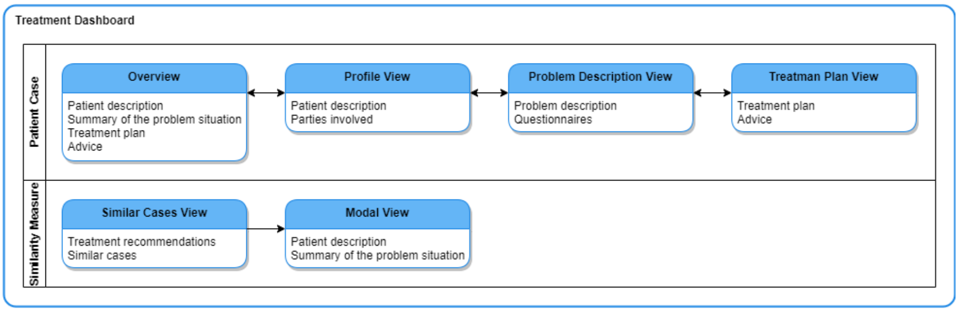

Figure 4.12: Workflow of the web application.

The *overview* is the first view the clinician sees when a patient case is opened in the clinician dashboard. It displays an overview of all the information most relevant to the patient case. The view summarizes the problem situation, highlights the most important attributes, and presents the treatment plan and the given advice. More detailed information regarding the patient case is divided into the other patient views. A short description of them is given below.

The *profile view* gives a general description about the patient and presents any involved parties. The *problem description view* shows the complete presentation about the patient's problem situation, including all the results from screening tools used by physiotherapists. The *treatment plan view* displays the decided treatment plan and the given advice.

The *similar cases view* presents the results from the similarity measure. The treatment recommendations are proposed based on the lessons from similar patient cases retrieved from the myCBR system. The ten most similar cases from the similarity measure are listed here. The treatment recommendations are picked from a selection of the similar cases and visualized as a list. They can also be selected based on equal attribute value to the current case. Key attributes of the similar cases are displayed in a tabular representation for ease of reading and comparison with high accuracy. Each of the similar cases can be examined further in the *modal view* for more details. A short summary of the selected case is displayed there.

The web application presented in this thesis is a prototype and not a fully deployed system. Its purpose is to investigate the clinicians' needs, and therefore the system's capability to provide decision-support is prioritized. For a deployed system, more security measures need to be in place beforehand. Such as encryption, authorization and restrict clinicians to only having access to a single patient case at a time.

4.5 Agile Development Process

The development of the clinician dashboard was an iterative process conducted in three steps: The first iteration conceptualized a mock-up of the front-end, and the latter two dealt with designing and implementing the prototype. The final design choices were achieved after several rounds of feedback and adaptations. The following describes each iterative step of the development process.

4.5.1 Mockup

The first iteration of the web application was simple drawings on a piece of paper based on dialogues with the medical researchers. Ideas were made into basic requirements and a design was drafted. The draft was recreated as a static website in HTML, CSS and JavaScript with the use of the framework Bootstrap. The website was presented to the medical researchers for further discussion to gain feedback. The clinician dashboard, the components and the information displayed, were evaluated and new changes were proposed. The adaptations were included in the next step, the implementation of the prototype.

4.5.2 Prototype

The second iteration is about the implementation of the first prototype. Its development was heavily influenced by the medical researchers' feedback regarding the digital mockup made with the CSS fram Bootstrap[5]. More dynamic interactions and functionalities were needed. Therefore, the static website was transformed into a dynamic web application. The new requirements were visualized with the use of the JavaScript (JS) library ReactJS[6] and customized CSS to achieve a unique visualization.

The third and final iteration continued the development of the prototype with ReactJS. The evaluation of the first prototype led to some adjustments to the design choices. New features were introduced, the presentation of treatment plans. The database got updated to support the new alterations of the data. The finalized version is presented in section 5.4.

[5] https://getbootstrap.com/
[6] https://reactjs.org/

Chapter 5

Development

The clinician dashboard is created following an iterative development process. This chapter describes all the steps taken from the first meeting with the medical researchers to the final implementation of the dashboard. The remaining research questions, RQ 2.1 to 3.2, are addressed here. Throughout the development, the use of the CBR data has changed, and the dashboard design has been redone several times. The following gives a summary of the process, while the rest of the chapter gives an in-depth description of the whole development of the clinician dashboard.

The first few weeks were spent on the initial planning. Meetings with the medical researchers and my supervisor introduced me to the task ahead and the user requirements for the system were defined. The discussions founded the design ideas of the dashboard and were drawn as paper mock-ups. Later, the paper mock-ups were turned into a digital version as a static website.

The website was presented to the medical researchers in the second round of meetings. It was evaluated and the adaptations set the basis for the upcoming prototype. The dashboard was then reworked into a dynamic web application to fit the new features. The medical researchers conducted an evaluation of the first prototype and provided feedback. Afterwards, the feedback was then evaluated with my supervisor and further customizations were established for the next iteration.

The next and final iteration of the development process was the implementation of the second prototype. The design choices were changed once again, and more essential features were added, especially the implementation of the treatment recommendations. The CBR system was updated to support the new features from the back-end.

5.1 User Requirements

The thesis started with an introduction about the topic by my supervisor. The task was to create a web-based prototype of a clinician dashboard to support decision-making for clinicians in primary care with the use of CBR. Several user meetings were held with the medical researchers and my supervisor during the initial phase of the thesis in the first phase of the research.

The data set was introduced. The medical researchers expressed their preferences on how they wanted the data set to be visualized. The user interface was discussed and the user requirements were defined. Ideas were founded and drawn into paper mock-ups. This part of the thesis was about exploring the data and being creative with design and functionality.

The medical researchers then provided insight into how a physiotherapy consultation takes place. The paper mock-ups were transformed into a digital mock-up, created as a static website. The mock-ups are described in the next section. As part of the agile process, the data set changed multiple times while the mock-up was being designed. New variables were added. The most important ones were chosen to be highlighted more in the mock-up. Lastly, the variable names were edited to be more consistent with the casebase.

5.2 Mock-up

The user requirements from the earlier user meetings formed the basis of the digital mock-up. The clinician dashboard's early phase was about creating a static website with HTML and the CSS framework Bootstrap. A randomly picked patient case was used as a template in the mock-up. Afterwards, the mock-up was evaluated, and adaptations were discussed before the development process moved on to creating a functional prototype. This section presents the initial ideas of the CDSS and displays my perception of the user requirements and the data set.

5.2.1 Design and Creation

The clinician dashboard is designed with two views, a patient view and a treatment view. The patient view displays all the attributes of the looked-up patient, as shown in figure 5.1. The patient data is organized according to the groupings in data set that was provided by the medical researchers. The data are divided into patient specific (information filled in by the patient before the first consultation), common (questions answered jointly with the clinician), and questionnaires from multiple screening tools. The attribute groupings are displayed as lists inside separate containers. The containers have the ability to be collapsed so less important attributes can be hidden if desired.

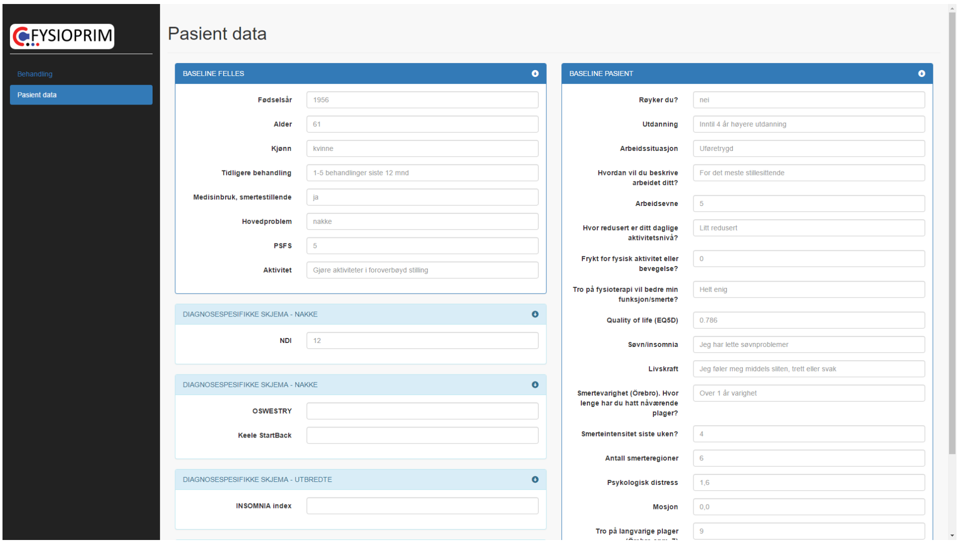

Figure 5.1: Mock-up of the patient view.

The treatment view, shown in figure 5.2, visualizes similar cases of the inspected patient fetched from the CBR system. The view is divided vertically in two, the similar cases are listed on the left side of the dashboard and graphs presenting PSFS and pain intensity are placed on the right. The list contains the ten most similar cases related to the inspected case and is sorted by the most similar case. The similarities are distinguished by a color pattern resembling traffic lights and with a similarity score.

The graphs display the PSFS and the pain intensity of all the similar cases during the treatment periods. The graphs in the mock-up are linear because the accessible data are limited to only include data values from the beginning of the treatment and three months later. The clinician can choose which charts to be visible and select which similar patients to be included.

Each patient case in the list of similar cases can be expanded and further investigated, as shown in figure 5.3. Uninteresting cases can also be removed from the list by clicking the cross in the top right corner. The most interesting attributes presented for each case are determined by the medical researchers in the provided data set and highlighted for each patient.

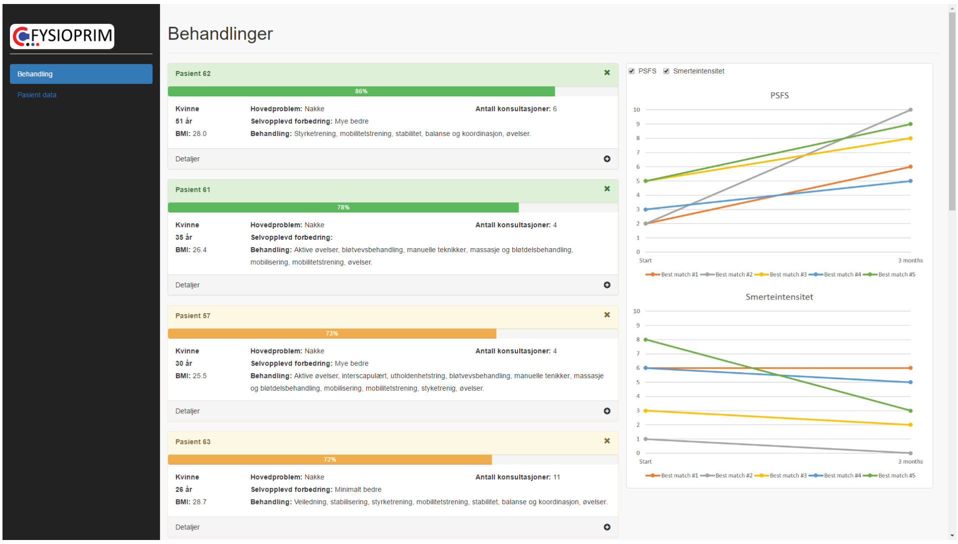

Figure 5.2: Mock-up of the treatment view with listed similar patient cases and charts for both PSFS and pain intensity.

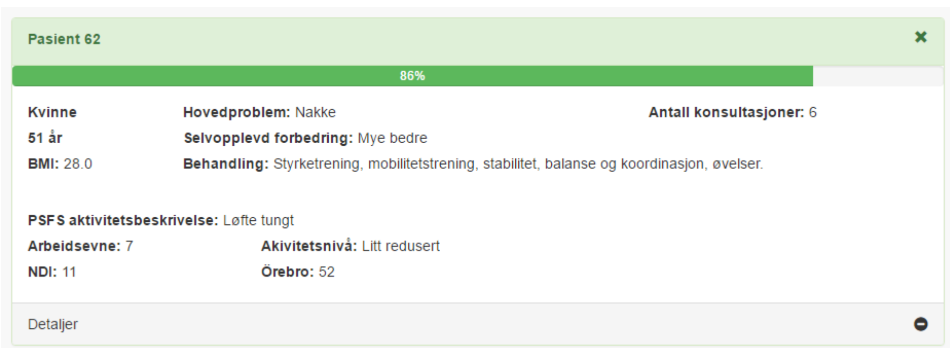

Figure 5.3: Mock-up of when a similar patient case is expanded for more details.

A third view of the clinical data is also designed on behalf of the medical researchers' request. They wanted to see what information was available when a patient case was compared to other similar cases and retrieved from the casebase. The data set was given to me as a CSV-file. A simple Python script was made to convert the file into HTML tables that could be used in the mock-up. The patient case and its similar cases are presented in a big table with all the available attributes in the data set, as viewed in figure 5.4. The table is structured according to the groupings in the data set.

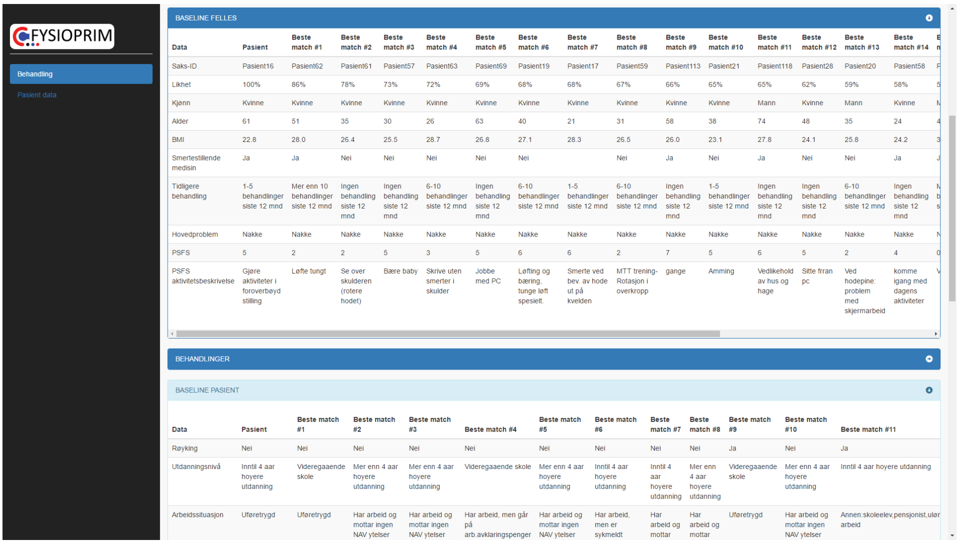

Figure 5.4: Mock-up of the available data when similar patient cases are requested from the CBR system.

5.2.2 Feedback and Evaluation

The final iteration of the digital mock-up was presented to the medical researchers a few weeks later. The mock-up demonstrated the ideas and the preferences given earlier, and it was a step in the right direction of what they asked for. They had already chosen what data was more important and needed to be highlighted for each view, so the most interesting thing about this iteration was how the data were displayed and getting a perception of the design. We discussed the dashboard and evaluated it during the meeting.

The design was well received, but some new changes were proposed. They wanted more functionality regarding the retrieval of similar cases and the comparison between them. The clinical data needed to be fetched from the CBR casebase given by the medical researchers and my supervisor. The data presentation needed more adjustments too. When comparing similar cases in the treatment view, each patient attribute had to be grouped better to notice the differences more efficiently. The patient data presented in the patient view were adapted according to changes in the data set.

The new suggestions provided the basis for the next iteration, the prototype. The static website needed to be transformed into a dynamic web application following a client-server model. The system lets the CBR system do the CBR and manage the patient case queries. Then, the web application would present the fetched patient data and case similarities according to the retrieved data set instead of using mock-up data. The creation of the first prototype is described in the next section.

5.3 Prototype

The development of the prototype started from scratch, but with the gained knowledge from the digital mock-up in mind. The previous static website needed to be replaced with a more dynamic approach to implement the new features. This section explains the development process of the prototype and how the new functionality was explored to fit clinicians in primary care. This iteration of the dashboard was evaluated before the development of the final implementation started.

5.3.1 Analysis and New Design

A similar design structure to the mock-up is retained in the prototype. The main improvement in this iteration is the usage of real data values from patients in the casebase. The first prototype in this thesis is developed as a clinician dashboard web application. The front-end enables interactions with the back-end, with the use of the REST API, to fetch patient data and perform CBR.

The size of the dashboard area stays the same. The menu is still placed on the left side of the application to provide easy navigation between the web pages; the front page, the patient view and the treatment view. The last item in the menu navigates to a view that gives insight into the whole casebase. It displays what data that can be retrieved from the casebase and how the values will look in the web application. It is primarily added to explore the possibilities of using the clinical data.

The patient view is divided vertically into two parts, as seen in figure 5.5. The patient data is displayed on the left side and categorized according to the updated data set. Graphs are included on the right side of the patient view and shows data trends of PSFS, pain intensity and fear of movement.

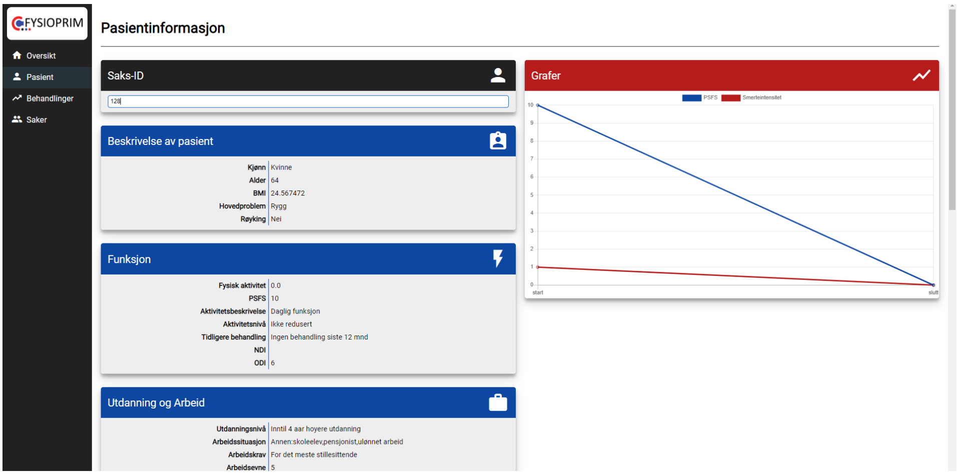

Figure 5.5: The patient view in the prototype.

The design of the treatment view is reworked a bit, as viewed in figure 5.6. The list of similar cases on the left side of the dashboard is made slimmer to provide better comparisons between patients. Since the treatment view is also split in two vertically, there is limited space for the elements inside the list. Patient attributes are therefore grouped in pairs in each column. The graphs on the right side are left unchanged, but they are now created based on the retrieved patient data from the casebase. The key attributes displayed for each similar patient case are changed into BMI, PSFS, pain intensity, kinesiophobia, main problem area and number of pain sites. They have been acknowledged to be more important than initially thought.

5.3.2 Implementation

The web application is developed with the front-end JS library ReactJS, created by Facebook together with a community of individual developers and companies. ReactJS is chosen because it excels when developing a single-page application. It is fast, flexible, scalable, simple to use, and popular. The user interface is built from many building blocks, called React components, and is put together to create the clinician dashboard. The components are structured in separate files and connected with dependencies. They are divided by the content of each web page in the application and by their feature. Webpack is a module bundler and generates a dependency graph of the whole project.

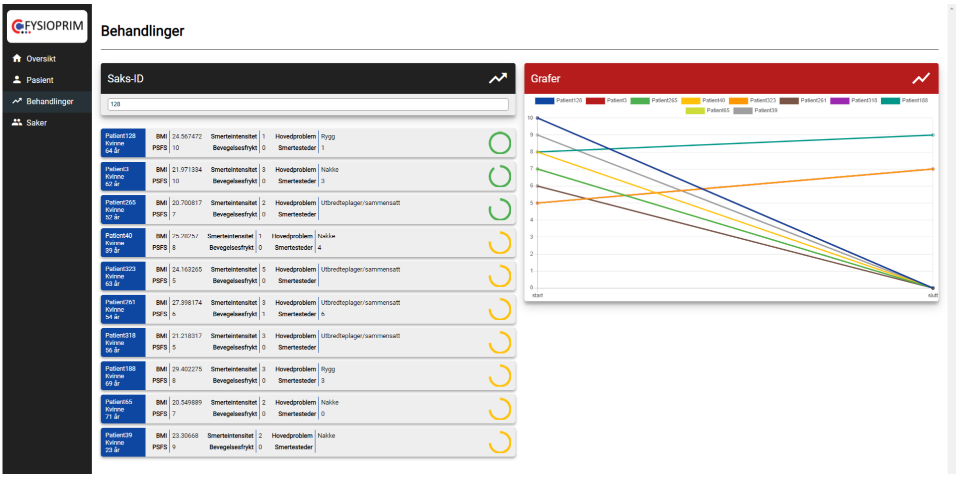

Figure 5.6: The treatment view in the prototype.

It bundles all the custom files with dependencies and transforms them into static assets such as .html, .css and .js. Support for older web browsers is resolved with BabelJS converting the latest version of ECMAScript into a backward compatible version of JavaScript.

Clinical information systems can be very complex due to all the different attributes recorded about each patient. The data can also be heterogeneous which makes it very challenging to work with. The data set retrieved from the CBR system contains attributes with many different values, as described in section 4.3. When using React, the patient case data are stored as states in the front-end. The states are data objects that can be altered by the React components in the web application.

As the clinician dashboard takes form, the JavaScript library React Redux[1] is used to manage the complexity of all the application's states and centralizes them in a single store. The clinician dashboard communicates with the CBR system by sending queries to the REST-API in the back-end. The Redux store does not handle asynchronous logic by default, so the package Redux Thunk is used to create a middleware to enable Asynchronous JavaScript and XML (AJAX) queries to get access to the Redux store and change states accordingly. The server responses from the CBR system are retrieved as .json files and stored as JS objects in the store. The data flow of the web application with the use of Redux is shown in figure 5.7.

The user interface of the clinician dashboard is inspired by the guidelines provided

[1] `https://redux.js.org/`

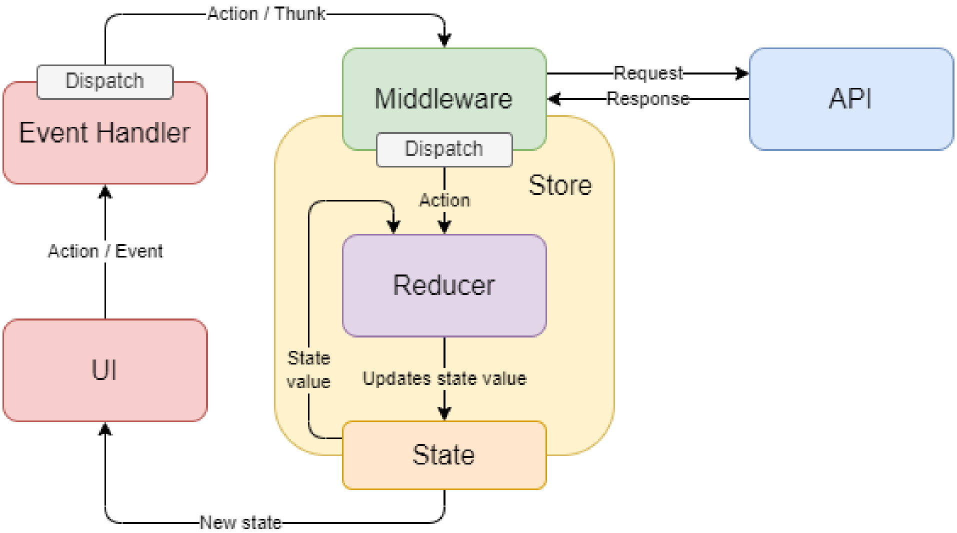

Figure 5.7: The data flow of the web application using Redux. This is an adapted figure from the Redux website.[2]

by Material Design. Material Design is visual design principles developed by Google that are based on the laws of nature. The intention is to support building high-quality applications for Android, iOS, Flutter, and the web with good design. The components provided by Material Design are not used directly in the web application, but the design concepts help shaping the custom-made components.

The patient case attributes are grouped into components inspired by cards, which is the most iconic component from Material Design. The card components structure the data and presents it clearly, concisely and comprehensibly inside the viewport. They are elevated from the background with shadow effects to make them more detectable.

The color usage of the UI elements in the clinician dashboard is taken from the Fysioprim logo. The color shades follow the color palettes provided by Material Design. The benefit of choosing this color system are to better highlight text and icons that are in front of such colored surfaces. Roboto is selected as the text type in the web application because of its high readability, and it is the default system font for Android. Material icons are added to UI elements to help them express their meaning in a visual way. Icons helps to optimize menu elements and make navigation between the web pages more intuitive, and to supplement headings with more meaningful context that describes the content.

[2]https://redux.js.org/tutorials/essentials/part-5-async-logic

5.3.3 Feedback and Evaluation

The first iteration of the clinician dashboard prototype was reviewed by the medical researchers. The reviews provided qualitative feedback and indicated that the development was going in the right direction. The new design style was perceived simple and clear and the newly added dynamic features in the user interface looked promising. The review results were discussed that led to new proposals for adjustments regarding the next iteration.

The web pages needs small refinements to prevent excessive scrolling in the dashboard. The displayed information feels overwhelming for a single view, so adjustments are necessary to prioritize the more important attributes. The treatment page is insufficient in visualizing the differences between patients. The list of similar cases has limited horizontal space. So to include all six patient attributes, they were grouped in pairs in three columns to fit inside the list element. The visualization becomes cluttered and it makes the comparisons between attribute values unnecessary difficult. To distinguish the similar cases better, the list will require adjustments to its presentation.

Further, we decide to implement a new feature from the back-end server. The CBR system can provide a proposed treatment plan fitting the problem description in the patient case. It is highly desired that this will be implemented in the next version of the web application. The next iteration, written in the following section, will address this and all the other alterations.

5.4 Final Implementation

This iteration began after processing the evaluation of the first prototype. The following discusses the new adaptations and the development process of the final prototype. The new features were discussed with the medical researchers to provide valuable feedback for the upcoming work.

5.4.1 Analysis and New Requirements

Adopting concepts from Material Design works really well, but the previous dashboard is still in need of a rework to make the dashboard more intuitive and efficient to use. The first prototype is created with customized styling that follows the guidelines by Material Design. The latest version of the clinician dashboard uses the Material UI library[3] which includes fully functional React components and default styling based on Google's design guidelines. The benefits of using this UI tool is a faster and more effective development process with consistent design guidelines. The components are simple to use, and they support powerful functionality and customization options that gives a unique touch. The clinician dashboard's different features are built using several combinations of these components.

The views in the first prototype has too many empty spaces that can be utilized better. This will also fix the issue with excessive scrolling. More useful information can utilize the unused space to be presented at-a-glance. Using a proper structure for the data will make the views more clear, and not be overwhelming to the user. The CBR system and the casebase are updated to support the new features of the clinician dashboard. One specific functionality that is desired to be included in this iteration, is enabling the CBR system to recommend treatment plans based on the similarity measure.

5.4.2 Implementation

The development of the next iteration of the clinician dashboard continues to use the ReactJS and the React Redux libraries. ReactJS makes it easy to divide the code into smaller reusable components to use them as building blocks in the web application. The state of the application is stored in a centralized store and managed with Redux Toolkit (RTK)[4], the standard way to write Redux logic.

The reducers handle state changes as immutable objects to make the code more predictable during tests and it makes it more readable and easier to debug. Mutating the state directly may cause unwanted side effects as the application expands. Redux RTK on the other hand enables mutable syntax in the reducers to alter the state in the store. That is because the RTK uses the Immer package to convert mutable objects into immutable objects. The toolkit does also reduce unnecessary boilerplate code when writing action handlers.

The Redux Toolkit Query (RTKQ) addon is used to create an API layer for the web application. It is a powerful tool that simplifies data fetching from the myCBR server and handles the caching. The RTK Query provides a store that manages the data retrieved from the myCBR server and caches a temporary state of the data in the front-end. The cached query is active if the data is in use by the clinician dashboard. When a patient case is looked up by the clinician, the RTKQ API will fetch the requested data from the

[3] `https://mui.com/`
[4] `https://redux-toolkit.js.org/`

myCBR server and cache it in the front-end. The cache is stored if the clinician has the patient case open in the clinician dashboard. When the patient case is closed, the RTKQ API will unsubscribe from the cached query and free up memory in the web application. This way, the RTK will prevent memory leakage in the system.

The development of the second prototype starts with creating simple logic for fetching and storing a patient case in the application with Redux. The dashboard template by Material UI is used as a starting point that the application can expand from. The layout stays like the previous iteration by keeping the navigation bar on the left side. Teal is chosen as the primary color together and, together with the use of contrasts, it highlights the different parts of the application. Material icons and the Roboto text type are still used for their distinctive design. They provide good readability and are clear and concise.

The navigation menu connects all the pages that the single-page application consists of. React router[5] is used to handle the routing. An app bar is added to the top of the view to present the title of the clinician dashboard, the status of the application and the input field used to look up the patient case. The top bar and the navigation menu are intended to be always visible. Therefore, the layout is designed small to take up as little space as possible inside the viewport and give more space to the main view.

The input field, where you look up a patient case, is moved from the home view to the app bar so it is accessible from anywhere inside the application. The patient cases are still fetched from the CBR system in the back-end with a query, but the data set is changed to support the new features. The CBR system uses an updated casebase containing data attributes that focus on the treatment recommendations. The groupings of the data have been adjusted as well.

The information is now displayed in a grid pattern, instead of splitting the view in two vertically. Cards are still used to distinguish data between different groups. Key attributes are highlighted even more by placing them inside their own card in the grid system. If a single attribute value is a number, it is displayed alongside a bar that visualizes the range and the median of the attribute to provide a proper reference to its value.

This iteration of the development focuses more on handling the treatment recommendations. The data set has been reduced consequently because of that. Some attributes that are not used in the similarity measure are excluded from the data set, such as the PSFS and measurements on pain intensity and pain variation. These attributes record progression of the patient during treatment, and their data trends were

[5] https://reactrouter.com/en/main

visualized in charts in the previous iteration. The current data set does not contain any values that are recorded regularly during the period of the treatment. Therefore, the latest version of the clinician dashboard does not visualize any data in charts. Tables are a better representation to visualize quantitative data, that stay unchanged during treatment, more accurately.

The routing structure of the web application has been preserved, but two additional pages are added. The overview page, shown in figure 5.8, is representing a summary of the patient case instead of just containing an input field for patient look up like in the first prototype. The overview page displays the problem description, the treatment plan, the given advice and the key attributes that are most useful to the clinician. The complete content of the patient case is divided into three separate pages according to their topic; the profile, the problem description, and the treatment recommendations.

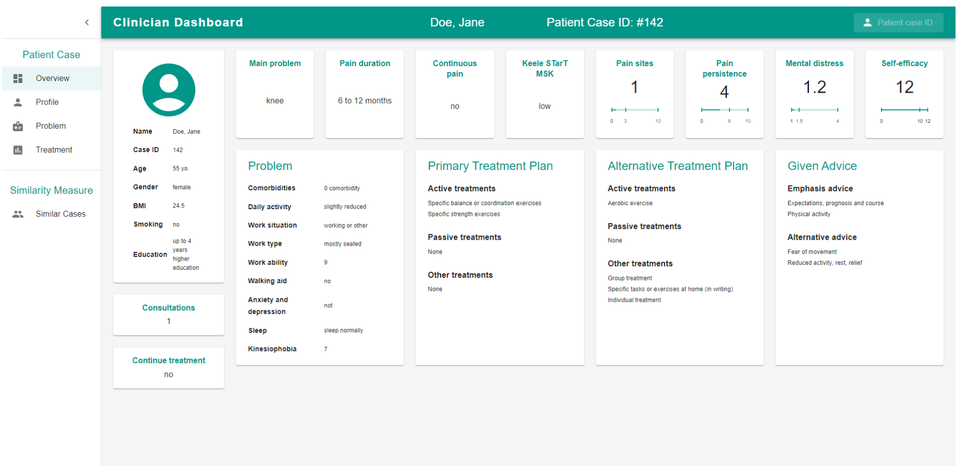

Figure 5.8: The overview of the patient case.

The profile page, presented in figure 5.9, contains general information about the patient and those who are involved in the case. The problem description page, viewed in figure 5.10, consists of the data that describes the patient situation, an extended problem description of the pain and results from specific questionnaires. There is still enough room in this view to fit the excluded attributes from the previous data set.

The treatment view repeats the presentation of the treatment plan and the given advice from the overview. This view represents the outcome of the patient case that is stored in the casebase, which can be used as a lesson for future similarity measures. The view is shown in figure 5.11. They are categorized into primary and alternative

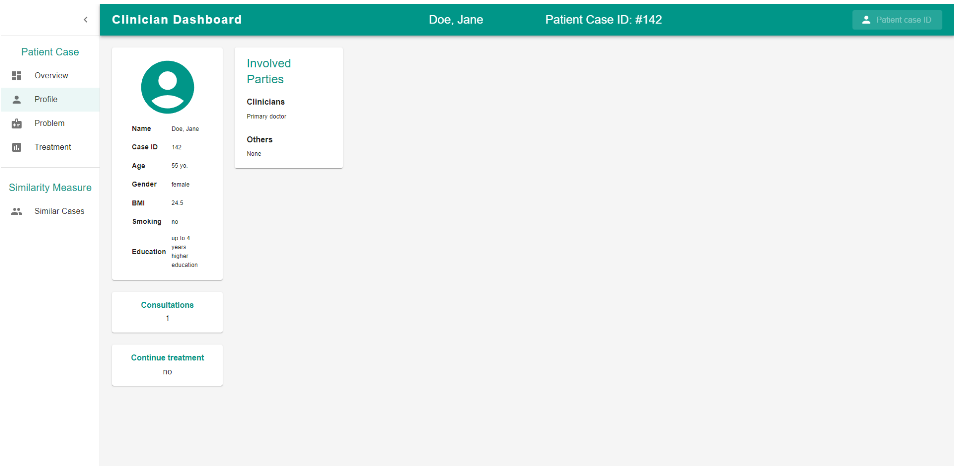

Figure 5.9: The profile of the patient case.

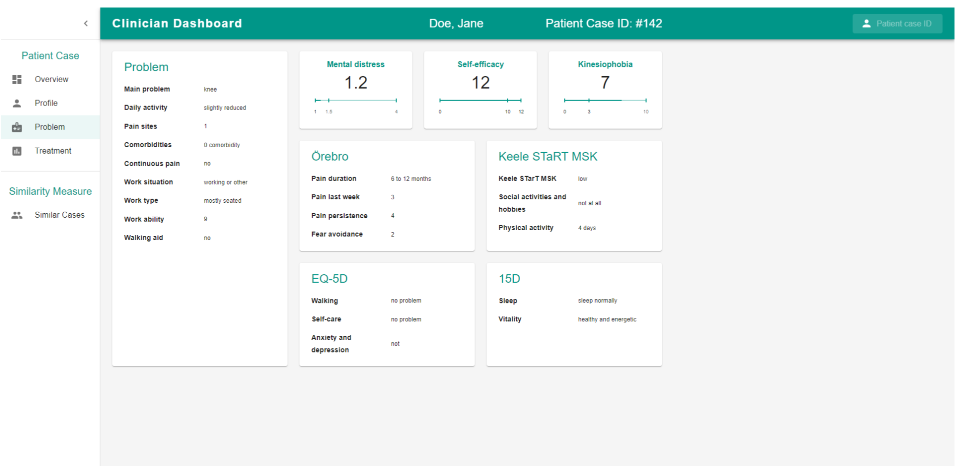

Figure 5.10: The problem description of the patient case.

recommendations. Recommendations in the primary category indicates the treatments and advice that were performed most frequently, likewise, the alternative category show those that were performed less frequently.

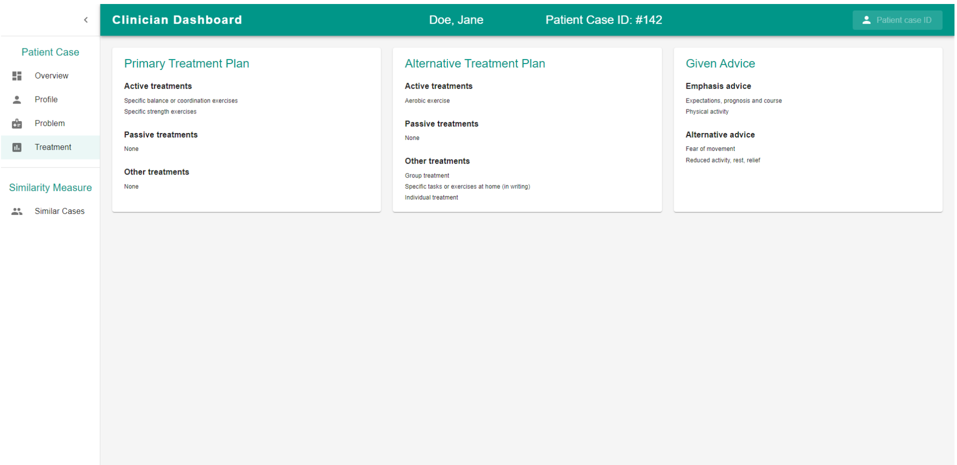

Figure 5.11: The treatment plan of the patient case.

The similarity measure is shown in a separate view, and it is displayed in figure 5.12. This view simulates how the CBR data will look like for the clinician and the patient during the first consultation. The pre-filled problem description will be calculated in the similarity measure and the result is presented in this view. By using the proposed treatment recommendations based on past experiences from similar cases, a treatment plan for the current patient can be created in co-decision.

The view still displays the list of the ten most similar cases, but the user can now select which cases from the list they want to include in the view. When a similar case is selected from the list, its treatment plan is used as suggested treatment for the current patient case. If the treatment or advice attribute has the given value of *much*, it is regarded as a emphasis treatment recommendation. Otherwise, if the treatment or advice attribute has the given value of *some*, it is regarded as an alternative treatment recommendation. The clinician dashboard will prioritize showing emphasis treatments and advice over alternatives.

The list items contain only the case ID and the similarity score of similar cases to keep the list slim, but readable. Next to the similarity score is a button that can be clicked to gain access to more details about that similar case. When clicked, it will present the clinician with a modal view that summarizes the selected case with a general

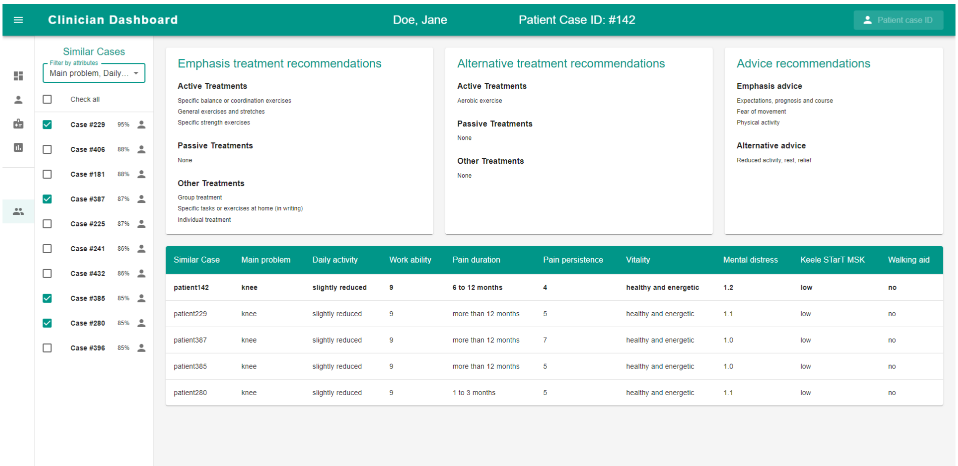

Figure 5.12: The similar cases view presenting the patient cases calculated from the similarity measure. The list of similar cases is filtered by main problem, daily activity, and work ability.

info, problem description and scores from questionnaires, as shown in figure 5.13.

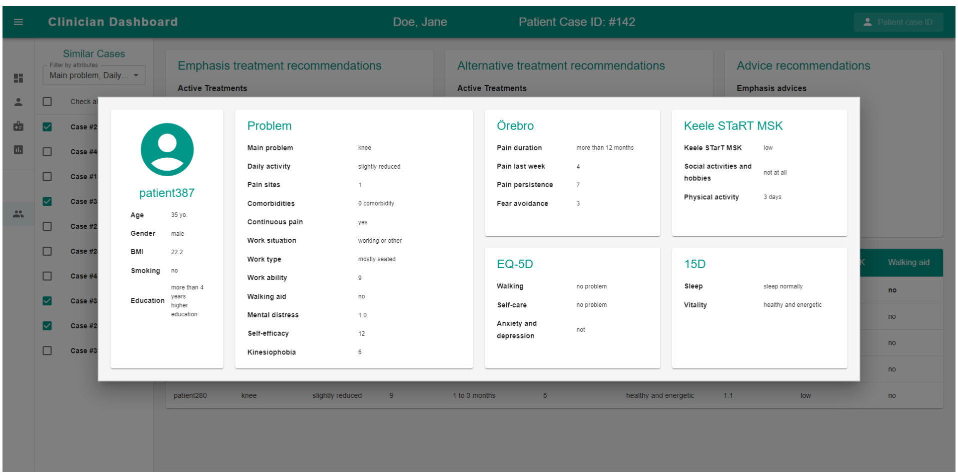

Figure 5.13: A modal view that presents details about a similar case.

The main view of the similar cases page presents the data subtracted from the similar cases. It visualizes treatment and advice recommendations as lists and a tabular representation of the most important attribute values. The table is useful to enable accurate comparisons between the patient cases. The view will update to only include data from the selected similar cases in the list. The similar cases can also be filtered based on attributes that have similar values to the current patient case. The current patient case is emphasized by placing it as the first entry in the table. The column attributes represent the most significant attributes that affect the similarity measure.

5.4.3 Feedback and Evaluation

A new round of discussions has been conducted with the medical researchers to get some valuable feedback on the latest iteration. The clinician dashboard's new design and features seem promising and inspiring. The medical researchers are currently working on a fully functional clinician dashboard as part of the SupportPrim project[6]. They find it interesting that my design proposal ended up being fairly like their current system in terms of how the information is structured neatly in a grid system. They say that this dashboard design proposal reassures them that they are on the correct path in terms of visualizing their own application.

The biggest criticism about the clinician dashboard is the wall of text in the overview. The information is not very concise. The dashboard needs more infographics that can explain the attribute values more intuitively at-a-glance than what plain text does. A combination of the two is preferably the best solution. The listing of the treatments and the advice, on the other hand, gets good feedback for presenting them explicitly. Using the median as a reference to the numeric values can be very useful to the researchers, but it needs to be investigated further whether it is useful for a clinician to make use of this knowledge.

The handling of the similar cases from the similarity measure receives positive reactions. Letting the clinician be able to select which similar cases they want to include in the view is a beneficial feature to have. To filter the selection by specific attribute values is a powerful functionality that the medical researchers have thought of themselves but is not yet a part of the currently operating CDSS. They also said that it is desirable to enable sorting of the data in the table based on other attribute values than those used in the similarity measure, such as the PSFS. They think this functionality may be of interest to the clinicians, since each case is treated differently.

The received feedback is very valuable for further improvement of my clinician dashboard. It is also positive that some of my features spark interest among the medical researchers and that my design proposal can be of motivation to improve their current CDSS. The next chapter will continue a constructive discussion about the clinician dashboard and emphasize on its advantages and disadvantages.

[6] `https://www.ntnu.no/supportprim`

Chapter 6

Discussion

In this chapter, the latest version of the clinician dashboard is used to answer the research questions. It will elaborate on the findings and describe how well the approach is implemented to provide treatment recommendations from a CBR system to a clinician. The dashboard's advantages and disadvantages are investigated and explained based on the medical researcher's evaluation. The following will discuss the research questions one by one.

6.1 Clinician Dashboards in Primary Care

The first research goal has been achieved by conducting a structured literature search and exploring relevant research. The research question regarding this goal is *What is the state of the art of dashboard-based decision support systems used by clinicians in primary care?* The findings propose useful features from other healthcare sectors that may prove to be applicable to physiotherapy. What they have in common is providing effective methods for presenting clinical data and making dashboards more efficient and user-friendly. Since decision support systems can be very useful to new and inexperienced users, it is important to prioritize how easy they are to learn.

Several of the papers use a user-centered approach to design their systems. They involve the users during the development process and focus on the users' intentions when they suggest new solutions. User tests are executed to get proper assessments and to find suitable adaptations where it is crucial. Another important thing is to create a distinctive design that is recognizable to the user. That will make the whole experience more familiar.

The dashboards in healthcare have some common characteristics in terms of their designs. When supported features display different pieces of information, they are divided into separate views. The navigation between the pages of the application is handled with a menu that is usually placed on the left side of the dashboard. This leaves plenty of room left to visualize the clinical information in the main view.

The dashboard organizes the information into groups using a grid system to make the visualization of the dashboard more consistent. This also makes it easier to provide the correct space and location to display any type of data representation, whether it is texts, lists, tables, charts, or infographics. The idea is to take advantage of any free space and reduce unnecessary scrolling.

A view can get cluttered very quickly when a lot of information are present in a single view. It is therefore important to structure the information properly with careful attention to reduce cognitive load. This means that the representation of information requires high usability. The information must be presented with high clarity, so it is easy to perceive at-a-glance, and with high comprehensibility, so that it is not possible to misunderstand its meaning.

To highlight important single attributes in a dashboard, infographics shall be used extensively to increase their detectability. Lists are better for showing multiple attributes of the same feature. Forms shall be used for representing input fields when either new data are added to the system or existing data are being edited.

When it comes to reading and comparing a large amount of data, the two most used data visualizations are tabular and graphical representations. They can be used interchangeably, but they have their own advantages and disadvantages. Tables are best used when the data representation must be distinguished accurately. Charts, on the other hand, are better for presenting data trends, such as when data are recorded over time. Choosing the correct data visualization will have a big impact on the user experience.

Supporting customized views will provide in better user experience by giving the user more control. They shall be able to choose how they want the information to be displayed. There are large amounts of data to be presented in a clinician dashboard. Therefore, it is necessary to provide some sort of filtering mechanism to make all that information read well, and let the user select what data to display.

6.2 Visualizing CBR Data

The clinician dashboard presented in this thesis will help answering the next research goal, how to let clinicians use data from the CBR system efficiently. First, the CBR data must be loaded from the server effortlessly, and then it must be visualized clearly and comprehensibly in the dashboard. The aim is to provide clinicians with sufficient data to for better decision-making performance. The feedback mentioned here are from the evaluation by the medical researchers.

How can clinicians interact smoothly with the CBR system? This is the first research question regarding this goal. A user-friendly dashboard needs to provide intuitive interactions that return immediate responses back for every user action. Such a response is to indicate the clinicians clearly where in the application they are by emphasizing the selected page in the navigation menu. It is necessary to clarify to the user what is going on in the web application, and therefore make it easier to operate.

Patient cases can be opened quickly in the dashboard by entering the case ID in a search field. The search field is recognizable with a person icon and a suitable label. The dashboard will update the view and present the patient case when the retrieval is successful. Any data retrieval from the CBR server happens transparently. This is useful so the clinician can focus on the consultation.

In the similar cases view, the clinician can select which similar cases to include in the main view. The list representation of the similar cases has checkboxes that shows which cases that are included. They can also be selected with a filtering feature based on the attribute value. The clinician can use the multiple select component located directly above the list containing similar cases to do this. When the component is clicked, it shows a list of preferred attributes that can be included in the filtering function.

These interactions were perceived as very intuitive during the evaluation, since they did not lead to any confusion. Therefore, they seem very promising to deal with the CBR data.

The next research question about visualizing CBR data is as follows. *What kind of information is required from the CBR system for the clinicians to perform better treatment decisions?* For the clinician dashboard to provide better and more efficient decision-making, it is important that the system offers the necessary information. The overview is intended to give the clinician a quick insight into the patient's case. It visualizes a summary of the problem situation, the treatment plan, the given advice and the most important attributes are also highlighted to make the perception better.

But the similar cases view is the most important view for supporting decision-making.

It visualizes all the similar cases and retrieves treatment recommendations from their treatment plans. These treatment attributes, which are experiences from similar cases, are therefore a necessity for performing decision support. The similar cases are sorted by similarity score. However, each patient case that treats a non-specific musculoskeletal disorder is different, and therefore some attributes may be more important to look at in one case than in another. The clinician can use the filtering function for this, but not all attribute values are good for distinguishing the similar cases efficiently.

Therefore, it is important to find out which attributes can distinguish similar cases more effectively. The attributes with the highest weights in the case representation have their distribution shown in section 4.3. You can see from the figures that most of these attributes are suitable for distinguishing the patient cases, except walk aid and pain duration because their distribution has little variability.

The clinician dashboard can point to what information is useful for decision making, but it has no definitive result. To find a more accurate answer, user tests must be carried out with physiotherapists.

The last research question regarding how to use the data from the CBR system is next. *How can the results from the CBR system be visualized to be used most effectively by the clinicians?* A physiotherapy consultation lasts approximately 15 minutes. There is a limited time to look through the problem description and decide on a treatment plan. For that reason, the clinician dashboard will need to present the necessary information at-a-glance. The overview is made for this, so it is very important that it has a perceptible design.

The single attributes presented in the overview have been chosen to be highlighted because of how well they describe the problem situation. The numeric values are presented with a reference to the attribute's value range and median. Displaying the median received positive feedback, but it needs to be investigated further to see if that information is useful for a clinician.

The attributes associated with the profile and the problem description are conveniently presented in lists. The same visualization has been chosen to show the treatment plan and given advice. Lists are easy to read and resembles a cooking recipe that people are familiar with. The treatment and advice attributes are stored with a value of *much*, *some* or *none* that corresponds to the frequency of the activity. The representation of them is therefore structured in a way to give them more context. The treatment plan is divided in two separate parts, a primary treatment plan consisting of the attributes with a value of *much* and an alternative treatment plan with the attribute values of *some*. The given advice groups the values as emphasis and alternative advice.

This was perceived as overwhelming during the evaluation, because most of the information is visualized as text. The information is comprehensible, but attributes presented as text lacks context. This means that it must be read in its entirety to be understood. It was pointed out that more of the information should be visualized as infographics. Infographics are a very powerful visualization to allow information to be perceived more quickly, but they are time-consuming to make them great. In particular, the emphasized characteristics are better explained as infographics to improve their visibility and provide them with more context.

The representation of the treatment and advice recommendations are visualized like the treatment plan and the given advice in the overview. The difference is how they operate. Letting the clinician have control over which similar cases to include in making the treatment recommendations is a smart design choice. The demonstration of how the recommendations changed depending on the chosen criteria was very well received. The filtering function is a powerful functionality that makes it easier to adapt the treatment recommendations to the current patient case.

The tabular representation of the similar cases provides accurate insight of important attributes and enable comparisons between them easily. This was expected according to the literature review. The table is also useful for finding out appropriate attributes to filter the recommendations with.

A feature that the medical researchers wanted is a way to show additional information about an attribute by hovering the mouse over it. Sometimes an attribute value can seem diffuse to a clinician, so it can be useful to get a better explanation of what the attribute represents. The clinician dashboard does not support this feature, but it is something that should be included to provide better learnability.

The evaluation of the clinician dashboard is fairly positive, especially the similar cases view. Although the presentation of the treatment recommendations displays a lot of text, the presentation is clear and concise. One thing that remains to be seen is whether the attribute description makes sense to the clinician, but this needs to be investigated.

6.3 Dashboard Design

The last research goal deals with how to adapt the visualization of a dashboard to be effective for clinicians in primary care. The first research questions to acknowledge this is as follows. *What features do a dashboard need to streamline the clinicians' working routine?* First, the application needs proper navigation. The clinician should not have any problem finding the correct information. The first view the clinician encounters is the overview, but can access more detailed views if desirable. The overview contains the most essential data to understand the problem situation of a patient case, so that the clinician searches for as little information as possible during a consultation. Which data is most needed in the overview needs to be investigated further.

For the clinician dashboard to provide better and more efficient decision-making, it is important that the system offers relevant treatment recommendations. Therefore, the most useful feature of the clinician dashboard is how it presents treatment recommendations provided by the CBR system to provide decision-making support.

The most powerful function in the clinician dashboard is to enable filtering of similar cases based on a given attribute value. All selected similar cases will then have the same attribute value as the current patient case for that particular attribute. The clinician can select which similar cases' treatment plan is to be reused as treatment recommendations for the case in question. It is possible to filter the patient cases based on multiple attributes as well.

This is a very effective and useful utility, and the selection happens immediately. It is a highly desired feature by the medical researchers and they believe this will be useful for future visualization tools of CBR systems. There are some attributes, not included in the similarity measure, that are of practical use to clinicians and may be good for distinguishing the similar cases. The medical researchers showed interest in making it possible to sort similar cases based on PSFS, and should be explored.

What is a suitable dashboard design to support these features? This is the final research question of this thesis. A user-friendly dashboard requires clear and concise views to make the data presentation comprehensible immediately. Its design should remain consistent across all views to keep a familiar look. The clinician dashboard accomplishes that by structuring the data visualizations inside a grid system.

Material UI is a component library that follows the strict guidelines by Material Design to provide consistency and to design a high-quality digital experience. The UI tool is chosen because it fits well with the design requirements of a dashboard. The paper component is used to divide the different data into distinct groups and provide clear and spacious representations. The clinician dashboard uses a single color palette and shadings to emphasize the app bar, the navigation menu, headers and user inputs. The design choices turned out great. By following the design guidelines by Material Design, the dashboard received a clean and simple dashboard design.

Chapter 7

Conclusion

This thesis examines how to visualize treatment recommendations provided with case-based reasoning that streamlines the clinician's decision-making during a first consultation in primary care. A literature review was conducted to explore the state of the art of existing clinical decision support systems to identify useful design choices. Then, a clinician dashboard is developed by following Material Design guidelines to produce a modern design with high usability.

The web application presented here is a design proposal that explores how to visualize a clinician dashboard for treating patients with musculoskeletal disorder with the use of case-based reasoning. It presents patient cases at-a-glance, and it highlights the most useful information regarding the problem situation clearly and concisely. The system proposes a practical solution for displaying treatment recommendations derived from similar cases. The clinician can select which similar cases to use, based on preferred attribute values, to generate the treatment recommendations.

Going forward, the clinician dashboard should be properly tested in practices. A feasibility study can investigate the system's capability to provide decision-support when treating patients with musculoskeletal disorder and find out how valuable the data representations are. A randomized controlled trial can find out how efficiently the system handles different problem situations and see if it provides acceptable treatment recommendations.

The clinician dashboard can become a powerful and efficient tool for clinicians in primary care with the correct use of visualizing data. Following guidelines from design languages, such as Material Design, will help immensely in developing effective dashboards that ensures good solutions for the user.

It will be interesting to find out which infographics will provide the best comprehensible and concise information about the problem situation to a clinician. An infographic representing an attribute can provide more context to a data value than plain text, but it requires more space in the view. Therefore, it is necessary to find a balance between how much information a clinician needs presented simultaneously in the dashboard to provide sufficient context about the situation versus how detailed certain value needs to be visualized to be perceptible at-a-glance.

It will also be of interest to give the clinician the opportunity to filter similar cases based on local or global similarity scores as needed. Then, when the clinician predicts that it is necessary to focus on a specific attribute of a particular patient case, the list of similar cases can be sorted according to the attribute's local similarity score.

Bibliography

Aamodt, A. and Plaza, E. (1994). Case-based reasoning: Foundational issues, methodological variations, and system approaches. *AI communications*, 7(1):39–59.

Bach, K., Marling, C., Mork, P. J., Aamodt, A., Mair, F. S., and Nicholl, B. I. (2019a). Design of a clinician dashboard to facilitate co-decision making in the management of non-specific low back pain. *Journal of Intelligent Information Systems*, 52(2):269–284.

Bach, K., Mathisen, B. M., and Jaiswal, A. (2019b). Demonstrating the mycbr rest api. In *ICCBR 2019 Workshop Proceedings*, ICCBR-WS 2019, pages 144–155. CEUR Workshop Proceedings.

Bergmann, R. (2002). *Experience Management*. Springer-Verlag Berlin Heidelberg.

Bichindaritz, I. and Marling, C. (2010). *Case-Based Reasoning in the Health Sciences: Foundations and Research Directions*, pages 127–157. Springer Berlin Heidelberg.

Brown, B., Balatsoukas, P., Williams, R., Sperrin, M., and Buchan, I. (2016). Interface design recommendations for computerised clinical audit and feedback: hybrid usability evidence from a research-led system. *International journal of medical informatics*, 94:191–206.

Brown, B., Balatsoukas, P., Williams, R., Sperrin, M., and Buchan, I. (2018). Multi-method laboratory user evaluation of an actionable clinical performance information system: Implications for usability and patient safety. *Journal of biomedical informatics*, 77:62–80.

Chu, Y.-C., Kuo, W.-T., Cheng, Y.-R., Lee, C.-Y., Shiau, C.-Y., Tarng, D.-C., and Lai, F. (2018). A survival metadata analysis responsive tool (smart) for web-based analysis of patient survival and risk. *Scientific reports*, 8(1):1–9.

Collins, I. M., Bickerstaffe, A., Ranaweera, T., Maddumarachchi, S., Keogh, L., Emery, J., Mann, G. B., Butow, P., Weideman, P., Steel, E., et al. (2016). iprevent®: a tailored, web-based, decision support tool for breast cancer risk assessment and management. *Breast cancer research and treatment*, 156(1):171–182.

Cruz-Ramos, N. A., Alor-Hernández, G., Sánchez-Cervantes, J. L., Paredes-Valverde, M. A., and del Pilar Salas-Zárate, M. (2018). Diabsoft: a system for diabetes prevention, monitoring, and treatment. In *Exploring Intelligent Decision Support Systems*, pages 135–154. Springer.

Duke, J. D., Morea, J., Mamlin, B., Martin, D. K., Simonaitis, L., Takesue, B. Y., Dixon, B. E., and Dexter, P. R. (2014). Regenstrief institute's medical gopher: A next-generation homegrown electronic medical record system. *International journal of medical informatics*, 83(3):170–179.

Eiring, Ø., Nytrøen, K., Kienlin, S., Khodambashi, S., and Nylenna, M. (2017). The development and feasibility of a personal health-optimization system for people with bipolar disorder. *BMC medical informatics and decision making*, 17(1):1–11.

Faiola, A., Srinivas, P., and Duke, J. (2015). Supporting clinical cognition: a human-centered approach to a novel icu information visualization dashboard. In *AMIA Annual Symposium Proceedings*, volume 2015, pages 560–569. American Medical Informatics Association.

Few, S. (2006). *Information dashboard design: The effective visual communication of data*. O'Reilly Media, Inc.

Hartzler, A. L., Chaudhuri, S., Fey, B. C., Flum, D. R., and Lavallee, D. (2015). Integrating patient-reported outcomes into spine surgical care through visual dashboards: lessons learned from human-centered design. *eGEMs*, 3(2).

Hernandez, B., Herrero, P., Rawson, T. M., Moore, L. S., Charani, E., Holmes, A. H., and Georgiou, P. (2017). Data-driven web-based intelligent decision support system for infection management at point-of-care: Case-based reasoning benefits and limitations. In *Proceedings of the 10th International Joint Conference on Biomedical Engineering Systems and Technologies - HEALTHINF, (BIOSTEC 2017)*, pages 119–127. INSTICC, SciTePress.

Ho, K.-T. (2017). *Taking Note: A Design Solution for Physician Documentation to Balance the Benefits of Handwritten Notes and Electronic Health Records*. PhD thesis.

Jaiswal, A. (2018). Personalized treatment recommendation for non-speciffc musculoskeletal disorders in primary care using case-based reasoning. In *Workshop Proceedings of ICCBR*, pages 214–218.

Jaiswal, A., Bach, K., Meisingset, I., and Vasseljen, O. (2019). Case representation and similarity modeling for non-specific musculoskeletal disorders-a case-based reasoning approach. In *The Thirty-Second International Flairs Conference*.

Jones, S., Cournane, S., Sheehy, N., and Hederman, L. (2016). A business analytics software tool for monitoring and predicting radiology throughput performance. *Journal of digital imaging*, 29(6):645–653.

Jurcău, D.-A. and Stoicu-Tivadar, V. (2016). Evaluating the user experience of a web application for managing electronic health records. In *International Workshop Soft Computing Applications*, pages 276–289. Springer.

Kofod-Petersen, A. (2018). How to do a structured literature review in computer science. *Ver. 0.2. October*, 1.

Kolodner, J. (1993). *Case-based reasoning*. Morgan Kaufmann.

Kopanitsa, G., Veseli, H., and Yampolsky, V. (2015). Development, implementation and evaluation of an information model for archetype based user responsive medical data visualization. *Journal of Biomedical Informatics*, 55:196–205.

Lillehagen, I., Vøllestad, N., Heggen, K., and Engebretsen, E. (2013). Protocol for a qualitative study of knowledge translation in a participatory research project. *BMJ Open*, 3(8).

Linton, S. J. and Halldén, K. (1998). Can we screen for problematic back pain? a screening questionnaire for predicting outcome in acute and subacute back pain. *The Clinical journal of pain*, 14(3):209–215.

Luz, C. F., Berends, M. S., Dik, J.-W. H., Lokate, M., Pulcini, C., Glasner, C., and Sinha, B. (2018). Development of an interactive open source software application (radar) for infection management/antimicrobial stewardship. *bioRxiv*.

Meisingset, I., Vasseljen, O., Vøllestad, N. K., Robinson, H. S., Woodhouse, A., Engebretsen, K. B., Glette, M., Øverås, C. K., Nordstoga, A. L., Evensen, K. A., et al. (2020). Novel approach towards musculoskeletal phenotypes. *European Journal of Pain*, 24(5):921–932.

Mork, P. J. and Bach, K. (2018). A decision support system to enhance self-management of low back pain: protocol for the selfback project. *JMIR research protocols*, 7(7):e9379.

Nguyen, B. V., Burstein, F., and Fisher, J. (2015). Improving service of online health information provision: a case of usage-driven design for health information portals. *Information Systems Frontiers*, 17(3):493–511.

Nijeweme-d'Hollosy, W. O., van Velsen, L., Poel, M., Groothuis-Oudshoorn, C. G., Soer, R., and Hermens, H. (2018). Evaluation of three machine learning models for self-referral decision support on low back pain in primary care. *International journal of medical informatics*, 110:31–41.

Nykänen, P., Brender, J., Talmon, J., de Keizer, N., Rigby, M., Beuscart-Zephir, M.-C., and Ammenwerth, E. (2011). Guideline for good evaluation practice in health informatics (gep-hi). *International journal of medical informatics*, 80(12):815–827.

Sandal, L. F., Bach, K., Øverås, C. K., Svendsen, M. J., Dalager, T., Stejnicher Drongstrup Jensen, J., Kongsvold, A., Nordstoga, A. L., Bardal, E. M., Ashikhmin, I., Wood, K., Rasmussen, C. D. N., Stochkendahl, M. J., Nicholl, B. I., Wiratunga, N., Cooper, K., Hartvigsen, J., Kjær, P., Sjøgaard, G., Nilsen, T. I. L., Mair, F. S., Søgaard, K., and Mork, P. J. (2021). Effectiveness of App-Delivered, Tailored Self-management Support for Adults With Lower Back Pain–Related Disability: A selfBACK Randomized Clinical Trial. *JAMA Internal Medicine*, 181(10):1288–1296.

Segal, I. and Shahar, Y. (2009). A distributed system for support and explanation of shared decision-making in the prenatal testing domain. *Journal of Biomedical Informatics*, 42(2):272–286.

Strand, B. H., Dalgard, O. S., Tambs, K., and Rognerud, M. (2003). Measuring the mental health status of the norwegian population: a comparison of the instruments scl-25, scl-10, scl-5 and mhi-5 (sf-36). *Nordic journal of psychiatry*, 57(2):113–118.

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., and Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. *NPJ digital medicine*, 3(1):1–10.

Teves, J. P. (2015). *Data visualization that" fits": Designing effective dashboards for healthcare providers, patients, and family caregivers to patients with diabetes*. PhD thesis, Wichita State University.

Tufte, E. R. (1985). The visual display of quantitative information. *The Journal for Healthcare Quality (JHQ)*, 7(3):15.

Umer, A., Mattila, J., Liedes, H., Koikkalainen, J., Lötjönen, J., Katila, A., Frantzen, J., Newcombe, V., Tenovuo, O., Menon, D., et al. (2018). A decision support system for diagnostics and treatment planning in traumatic brain injury. *IEEE journal of biomedical and health informatics*, 23(3):1261–1268.

Verma, D., Bach, K., and Mork, P. J. (2018). Modelling similarity for comparing physical activity profiles-a data-driven approach. In *International Conference on Case-Based Reasoning*, pages 415–430. Springer.

Vessey, I. (1991). Cognitive fit: A theory-based analysis of the graphs versus tables literature. *Decision sciences*, 22(2):219–240.

Watson, I. (1998). *Applying case-based reasoning: techniques for enterprise systems*. Morgan Kaufmann Publishers Inc.

Wolpin, S. E., Halpenny, B., Whitman, G., McReynolds, J., Stewart, M., Lober, W. B., and Berry, D. L. (2015). Development and usability testing of a web-based cancer symptom and quality-of-life support intervention. *Health informatics journal*, 21(1):10–23.

Yigitbasioglu, O. M. and Velcu, O. (2012). A review of dashboards in performance management: Implications for design and research. *International Journal of Accounting Information Systems*, 13(1):41–59.

Zahabi, M., Kaber, D. B., and Swangnetr, M. (2015). Usability and safety in electronic medical records interface design: a review of recent literature and guideline formulation. *Human factors*, 57(5):805–834.

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