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Decision support in patient-centered health care

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Abstract

This thesis aims to create exercise plans for patients with low back pain and is a part of the research project SELFBACK . Case-based reasoning is used to create the exercise plans, which is the process of solving new problems by reusing solutions of similar previous problems. The main focus of the thesis is to explore how the reused solutions can be adapted to fit the needs of the patient better. Different adaptation methods are explored, and two methods are applied within the SELFBACK setting. In the experiments, the solutions created by the adaptation methods are evaluated against solutions where no adaptation is performed. The results of the experiments show promising results, indicating that adaptation further improves the creation of exercise plans.

Sammendrag

Denne oppgaven tar sikte på å lage treningsplaner for pasienter med korsryggsmerter, og er en del av forskningsprosjektet SELFBACK . Case-based reasoning, som er prosessen med å løse nye problemer ved å gjenbruke løsninger av lignende tidligere problemer, er brukt for å lage treningsplanene. Hovedfokuset til oppgaven er å undersøke hvordan de gjenbrukte løsningene kan bedre tilpasses til pasientens behov. Ulike metoder for tilpasning utforskes, og to metoder blir testet som en del av SELFBACK prosjektet. I forsøkene blir løsningene som er laget med tilpasning vurdert mot løsninger der det ikke gjøres noen tilpasning. Resultatene fra forsøkene er lovende, noe som indikerer at automatisk tilpasning av treningsplanene resulterer i bedre treningsplaner for pasientene.

Preface

This thesis is a result of the work conducted in IT3903 - *Informatics Postgraduate Thesis: Artifical Intelligence* at Norwegian University of Science and Technology (NTNU). The work was done in the period August 2016 - June 2017.

I would like to thank my supervisor Kerstin Bach for all the useful guidance, encouragement, and for always being available. Additionally I would like to thank Paul Jarle Mork for all his insight on the medical field, and Agnar Aamodt for keeping his door open for any questions I may have. Lastly I would also like to thank all my friends who have helped and encouraged me.

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Abbreviations

ACL	=	Anterior Cruciate Ligament
CBR	=	Case-Based Reasoning
GA	=	Genetic Algorithm
LOOCV	=	Leave-One-Out Cross Validation
LBP	=	Low Back Pain
NN	=	Neural Net
RBR	=	Rule-Based Reasoning
SDK	=	Software Development Kit
SLR	=	Systematic Literature Review

Chapter 1

Introduction

This chapter introduces the background and motivation for this thesis. It also presents the research method used working on this thesis, as well as the research questions created to reach the goals set for the work conducted. The chapter ends with a presentation of the report structure.

1.1 Background and Motivation

Up to 80% of the adult population in Norway will experience low back pain (LBP) during their lifetime, and a study showed that 50% of them had experienced pain during the last 12 months (Lærum et al., 2007). About 85% of these will experience non-specific LBP, i.e., pain without a known pathomechanism (Brox, 2009). Back pain is the largest single cause of sickness leave in Norway, and it costs about 2% of the gross domestic product. Even though the amount of research in the area has increased, as well as the access to treatment and less physically demanding work, the costs have significantly increased over the last 30 years (Lærum et al., 2007). General physical activity along with specific strength and stretching exercises constitute the core components in the prevention and management of non-specific LBP. The exercise plans are individualized but share a number of common traits. The main motivation for this thesis is to help create these exercise plans to provide better care for patients that suffer from non-specific LBP thus help reduce the cost of treatment. This thesis will explore if it is possible to improve the creation of exercise plans as a part of the SELFBACK project. Case-based reasoning (CBR) is the main methodology in SELFBACK , and has been used in the domain of health science for a long time. Its method of using past experiences to solve a new problem lies very close to how clinical medicine is performed by specialists today, and it is also a field where you often have the advantage of already having a collection of past cases to use when you review a new problem (Bichindaritz and Marling, 2006). Over the past ten years, it has become a specialized area within the domain of CBR research and applications because the use of CBR in health sciences has proven to be popular. CBR systems that are used commercially in the field of medicine exists, but it has not become as successful here, in terms of succesfully deployed applications, as in many other domains (Bichindaritz, 2008), (Choudhury and Begum, 2016). In addition, adaptation is a part of the CBR-cycle that has not been researched as thoroughly as other parts, like for example the retrieval step. It is a research area that was not given a lot of attention at the beginning of research on CBR, and while methods for adaptation exists, they are still domain dependent, and new adaptation techniques usually have to be applied to new applications (Schmidt et al., 2001).

1.2 Main Goal and Research Questions

The practical problem for this thesis is to treat patients with non-specific LBP with the creation of individual exercise plans, as a part of the SELFBACK project. More specifically, it will look at different adaptation techniques and whether the application of these can create better solutions than without adaptation. The thesis will also deal with the cold-start problem which is the common problem in recommendation systems of initially not having collected enough cases for recommendations to a new user (Lam et al., 2008). A main goal and research questions are formed to address the mentioned issues.

The main goal of this thesis is to check how adaptation can be applied in SELFBACK to improve the creation of personalized exercise plans, and if an addition of an adaptation phase to the SELFBACK project will help to improve the quality of created exercise plans further.

To be able to answer the main goal, four research questions are formed. These are sub-goals that will help to answer the main goal:

RQ1 What are the possible adaptation techniques to apply?

RQ2 What solutions do other medical applications apply?

RQ3 How to apply different adaptations techniques to the given domain?

RQ4 How well do the applied adaptation techniques perform compared to no-adaptation?

1.3 Research Method

To answer the research questions, two different research methods are used. The first method is a systematic literature review (SLR) based on Kofod-Petersen (2015) and Kitchenham and Charters (2007). This method is applied to establish the state-of-the-art of medical CBR systems and adaptation techniques in the field of CBR. The results of this review are used together with other relevant theory presented in chapter 2, to form the background theory for the rest of the thesis. The literature review answers the first two research questions.

The second method is to develop a proof of concept prototype that applies the relevant adaptation techniques to a CBR system in the domain of LBP. Experiments will compare how well the applied adaptation technique will perform to a no-adaptation solution. This method answers the last two research questions. The third question is addressed in the method chapter, while the results from the experiments help answer the fourth question.

1.4 Thesis Structure

The thesis is structured in the following chapters:

Chapter 1 - Introduction Chapter 1 presents the background and motivation for the thesis, and introduces research goals and methods.

Chapter 2 - Theory Chapter 2 consist of the systematic literature review conducted at the beginning of the thesis, and presents other relevant theory.

Chapter 3 - Methods Chapter 3 describes the representation of the cases, and the case base. It also presents the applied adaptation methods.

Chapter 4 - Experiments Chapter 4 describes how the experiments are conducted, and presents the results.

Chapter 5 - Discussion Chapter 5 evaluates the results from the experiments.

Chapter 6 - Conclusion Chapter 6 concludes the paper and presents thoughts on future work.

Chapter 2

Theory

This chapter will introduce the background theory for the thesis. The first part presents CBR, the myCBR tool, and the SELFBACK project. The second part is a systematic literature review performed to find possible adaptation techniques, and their pros and cons. The review also aims to find out what other medical application exists and what type of solution they create.

2.1 Case-Based Reasoning

CBR is used as the main method in the SELFBACK project. It is often viewed as a sub-field of machine learning, which uses knowledge from previously experienced situations to solve new problems. In CBR a case consists of a problem and a solution. Previously solved cases are used to help find solutions for new cases. The CBR-method consists of four steps, known as the CBR-cycle.

2.1.1 CBR-Cycle

The CBR-process can be captured as a cycle consisting of four steps. The CBR-cycle's (Figure 2.1) four steps are retrieve, reuse, revise, and retain, also known as the 4Rs. The cycle starts with a new case, and uses the retrieve step to retrieve the most similar cases.

In the reuse step, the solutions of the old problems are reused to solve new cases. In revise the solution is evaluated and possibly repaired, and in retain the new solution is stored so it can be used in later problem-solving. The learning aspect in CBR lies within the retain step, where new cases are stored to reuse for a later problem, and thus adding to the understanding of the problem (Aamodt and Plaza, 1994). The CBR-cycle's four steps can be broken down into separate tasks for each step. In the reuse step you can choose between the two tasks; copy solution and adapt solution. It is within this step the focus for this thesis lies.

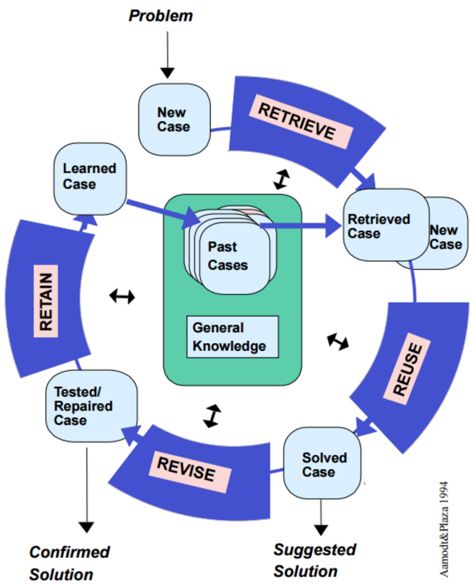


Figure 2.1: CBR Cycle from Aamodt and Plaza (1994)

2.2 SELFBACK

The SELFBACK project aims at creating a self-management tool for patients with non-specific LBP, which will support them to self-manage their pain by obtaining personalized advice and continuous follow-up. After an initial screening of the patient using questionnaires, the patient gets access to a wearable device (e.g., a wristband) and a smart phone app that is the interface for the decision support system. The wearable is used to track activities and obtain objective measurements. The smart phone app displays feedback, shows progress in achieving the patient's goals, and obtains regular follow-up on pain, function, and self-efficacy development. This information includes whether the pain level decreases, the functionality increases, and how the coping with pain improves. Figure 2.2 gives an overview of the architecture. A more thorough description of the CBR approach in SELFBACK is given in "Case Representation and Similarity Assessment in the selfBACK Decision Support System" (Bach et al., 2016).

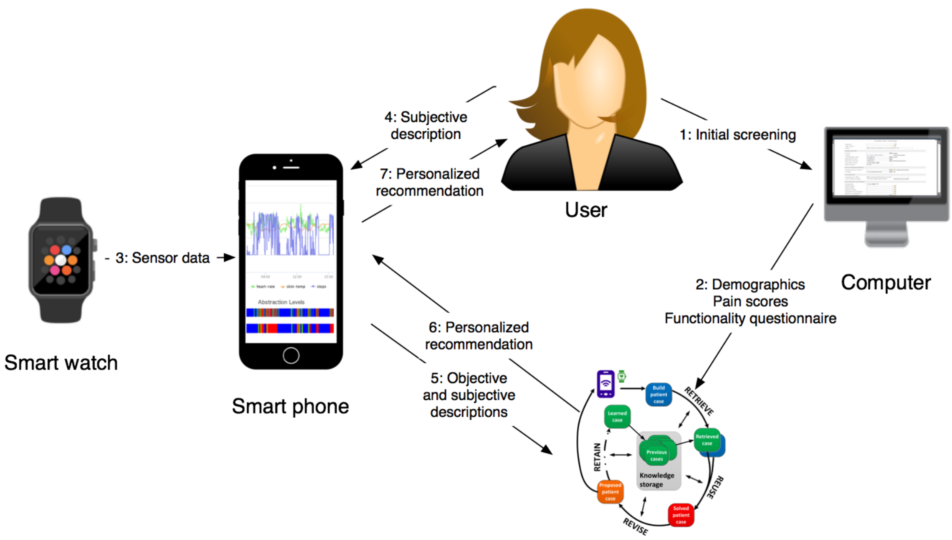


Figure 2.2: Overall SELFBACK architecture (Bach et al., 2016)

2.3 myCBR

myCBR[1] is an open-source CBR tool developed by the Competence Centre CBR at the German Research Centre for Artificial Intelligence (DFKI), Germany, and the School of Computing and Technology at University of West London (UWL), UK. myCBR consists of two parts: a software development kit (SDK) and a workbench. The myCBR Workbench is used to structure the knowledge of a CBR project, by building models of the domain and similarity functions for the attributes in the model. The use of the myCBR

[1] http://www.mycbr-project.net/

workbench to prototype enables the possibility to do fast prototyping of the model representation and similarity measures, and to test if the retrieval works as desired based on these measures. The SDK is used to integrate the CBR project with Java, for further developing of the retrieval.

2.4 Systematic Literature Review

This section contains the results of the SLR. It reviews research studies and presents the findings, to create a theoretical background. An SLR is a systematic approach to review literature in a fair manner. It increases the probability of finding all relevant literature, and it helps make sure you avoid doing duplicate work. The method also tries to assure that personal bias is avoided, thus making this chapter of scientific value. The method is in widespread use in the field of medicine, but in later years it has also been successfully applied to the field of Computer Science (Kitchenham and Charters, 2007).

2.4.1 Systematic Literature Review Method

The method used to conduct the SLR is influenced by Kitchenham and Charters (2007), but have been adapted to fit the domain of this thesis. In addition, some ideas were taken from Kofod-Petersen (2015). The process was performed in these steps:

1. Define research questions
2. Search for relevant studies
3. Selection of studies
4. Quality assessment
5. Data collection
6. Data synthesis and analysis
7. Dissemination

Search Questions

Search questions were defined for the SLR, to help outline the scope of the review, and to help answer RQ1 and RQ2 for the thesis. It is necessary to create search questions for the SLR because it exists a vast amount of research, and because of time constraints the study has to be limited by a set of parameters. During this review the following five research questions were created:

SQ1 What type of solutions are provided by CBR used in health sciences?

SQ2 What adaptation techniques are used in CBR?

SQ3 How do the solutions found in SQ1 and SQ2 respectively compare to each other?

SQ4 What is the strength of the evidence in support of the different solutions?

SQ5 What implications will these findings have when creating the new CBR system?

Search for relevant studies

Several digital libraries were used to find the relevant sources likely to contain studies relevant for the review. The list of digital libraries from Kofod-Petersen (2015) was used as the basis, and four of them was chosen. The final list of digital libraries used are shown in Table 2.1

Source	URL
IEEE Xplore	http://ieeexplore.ieee.org/
Web of Science	http://www.webofknowledge.com/
ScienceDirect	http://www.sciencedirect.com/
SpringerLink	http://link.springer.com/

Table 2.1: Digital libraries used in SLR

To be able to retrieve relevant studies, different groups of search terms were made, and organized into groups were all terms in a group were either semantically related or synonyms. The first group contains words related to CBR, the second to health, and the third to adaptation. All keywords are listed in Table 2.2. A study was assumed relevant if it contained at least one of the terms in the first group, and at least one term from either group 2 or group 3. 33 different search strings were created when combining the search terms with these constraints. These search strings gave a library of 4 618 774 studies, and the distribution of articles is shown in Table 2.3. This amount is too many articles to revise in this review. Thus some trust was put into the filtering of the articles on the respective digital libraries. To further shorten down the amount of articles, only the top 25 articles were kept for each search string. This led us to a set of 2845 articles, and the distribution of these is shown in Table 2.4

	Group 1	**Group 2**	**Group 3**
Term 1	Case-based Reasoning	Health	Adaptation
Term 2	CBR	Medicine	Adjustment
Term 3	Expert system		Modification

Table 2.2: Search terms used in SLR

Library	**Hits**
IEEE Xplore	11 690
Web of Science	14 448
ScienceDirect	3 558 289
SpringerLink	1 034 347

Table 2.3: Hits per source on search strings

Library	**Hits**
IEEE Xplore	618
Web of Science	586
ScienceDirect	821
SpringerLink	825

Table 2.4: Search results filtered by top 25

Selection of studies

The goal of the study selection was to find the most relevant studies out of the 2845 found in the last step. To decide if a study should be included or not, the articles were filtered by the following inclusion criteria:

IC1 The article is written from a computer science view

IC2 The main concern of the study is CBR systems used in health and/or adaptation of cases

IC3 The study focuses on adaptation of cases or recommendations in health

IC4 The study presents empirical results

IC5 The study describes a solution to their problem

The articles were filtered through the following steps:

1. Title inclusion criteria screening
2. Abstract inclusion criteria screening
3. Full-text inclusion criteria screening
4. Full-text quality screening

Title and abstract inclusion criteria screening During the first screening IC1, IC2, and IC3 were the main inclusion criteria that were addressed. The title was looked at first, and if it was any doubt the abstract was skim-read. After this, 72 articles were kept which could be of interest. In the remaining articles the abstract was read even more carefully to reduce the amount of articles further. This reduced the set to 34 articles to be revised in a full text screening.

Full text inclusion criteria screening A full-text version of the 34 remaining articles were downloaded and reviewed full text. In this screening criteria IC4 and IC5 were in focus, to make sure the article was of scientific value. After this reduction, 22 articles made it to the next step for quality assessment.

Quality assessment

To be able to end up with the final article set, the full text of the articles were evaluated through a set of 10 quality criteria. Each study was given a grade on each criterion dependent on how well the criterion was met. If the criterion is met it was given a score of 1, if it is partly met it was given a score of 0.5, and if it is not met at all it was given the score 0. All studies had to fulfill QC1 and at least partly QC2 to be included, and it also had to have a score of more than 6 to be included. In total 14 articles ended up passing the quality assessment. The following are the ten quality criteria that were used to score the articles:

QC1 There is a clear statement of the aim of the research

QC2 The study is put into context of other studies and research

QC3 Are system or algorithmic design decisions justified?

QC4 Is the test data set reproducible?

QC5 Is the study algorithm reproducible?

QC6 Is the experimental procedure thoroughly explained and reproducible?

QC7 Is it clearly stated in the study which other algorithms the study's algorithm(s) have been compared with?

QC8 Are the performance metrics used in the study explained and justified?

QC9 Are the test results thoroughly analyzed?

QC10 Does the test evidence support the findings presented?

Data collection, Synthesis, and Analysis

Data from the studies that passed the quality assessment were collected to be used in the analysis when answering the research questions for the SLR. The most important part of information was what type of adaptation techniques are used, and what type of solution the medical systems provided for the patient. Additionally, the research about why CBR should be used in the health domain was an important part of information. The different solution types presented for adaptation and health were grouped according to similar traits.

Dissemination

The findings from this review will be presented in the next section, and it is used as background for writing the rest of the thesis, and in the paper ”Evolutionary Inspired Adaptation of Exercise Plans for Increasing Solution Variety” accepted for the main track of ICCBR 2017[2]. The paper is included in Appendix A.

2.4.2 Results

Table 2.5 shows the different papers that were included after the full-text inclusion criteria screening, with a unique study id, authors, and title. Following is a summary of the findings from the articles that passed the quality assessment.

Health systems

CBR is used in several health systems today, in different areas such as clinical diagnosis and treatment in psychiatry and epidemiology (Petrovic et al., 2016). It has become a recognized and well-established method for the health sciences, and because the domain of health sciences is offering a variety of complex tasks which are hard to solve with other methods and approaches, nowadays this drives the CBR research forward. Because CBR is a reasoning process that works similar to the reasoning of a doctor or clinician by using previous experiences to solve the same or similar cases, it has become medically accepted and is also getting increased attention from the medical domain (Begum et al., 2011). There are several advantages of using CBR in the medical domain, one is that with the use of CBR it is possible to find solutions to problems even though the complete understanding of the domain is not captured, or if the domain is very complex. The reuse of past solutions saves time since it is not necessary to solve every problem from scratch, and it allows learning from mistakes. The fact that cases hold a lot of information makes it usable for a number of different problem-solving purposes, compared to rules that can only be used for the purpose they were designed for (Petrovic et al., 2016). Systems from the papers that target the healthcare domain with the use of CBR are presented below to help answer SQ1 and RQ2.

[2] http://research.idi.ntnu.no/cbr/iccbr2017/

Study ID	Authors	Title
S1	S. M. N. A. Senanayke, O. A. Malik, P. M. Iskandar, D. Zaheer (Senanayke et al., 2012)	A hybrid intelligent system for recovery and performance evaluation after anterior cruciate ligament injury
S2	Wenyi Qian, Xin Peng, Bihuan Chen, John Mylopoulos, Huanhuan Wang, and Wenyun Zhao (Qian et al., 2014)	Rationalism with a Dose of Empiricism: Case-Based Reasoning for Requirements-Driven Self-Adaptation
S3	Huan Li, Dawei Hu, Tianyong Hao, Liu Wenyin, Xiaoping Chen (Li et al., 2009)	Adaptation Rule Learning for Case-Based Reasoning
S4	Chun-Guang Chang, Jian-Jiang Cui, Ding-Wei Wang, Kun-Yuan Hu (Chang et al., 2004)	Research on case adaptation techniques in Case-Based Reasoning
S5	Shahina Begum, Mobyen Uddin Ahmed, Peter Funk, Ning Xiong, and Mia Folke (Begum et al., 2011)	Case-Based Reasoning Systems in the Health Sciences: A Survey of Recent Trends and Developments
S6	Wahidah Husain, Lee Jing Wei, Sooi Li Cheng, Nasriah Zakaria (Husain et al., 2011)	Application of Data Mining Techniques in a Personalized Diet Recommendation System for Cancer Patients
S7	Pau Herrero, Peter Pes, Monika Reddy, Nick Oliver, Pantelis Georgiou, Christofer Toumazou (Herrero et al., 2015)	Advanced Insulin Bolus Advisor Based on Run-To-Run Control and Case-Based Reasoning
S8	Sanja Petrovic, Gulmira Khussainova, Rupa Jagannathan (Petrovic et al., 2016)	Knowledge-light adaptation approaches in case-based reasoning for radiotherapy treatment planning
S9	Rainer Schmidt, Stefania Montanib, Riccardo Bellazzib, Luigi Portinalec, Lothar Gierla (Schmidt et al., 2001)	Cased-Based Reasoning for medical knowledge-based systems
S10	Claudio A. Policastro, André C.P.L.F. Carvalho, Alexandre C.B. Delbem (Policastro et al., 2008)	A hybrid case adaptation approach for case-based reasoning
S11	Dina A. Sharaf-Eldeen, Ibrahim F. Moawad, Khalid El Bahnasy, and M.E. Khalifa (Sharaf-Eldeen et al., 2012)	Learning and Applying Range Adaptation Rules in Case-Based Reasoning Systems
S12	Isabelle Bichindaritz (Bichindaritz, 2008)	Case-Based Reasoning in the Health Sciences: Why It Matters for the Health Sciences and for CBR
S13	Alicia Grech and Julie Main (Grech and Main, 2004)	Case-Base Injection Schemes to Case Adaptation Using Genetic Algorithms
S14	Kathleen Hanney and Mark T. Keane (Hanney and Keane, 1996)	Learning Adaptation Rules From a Case-Base

Table 2.5: The final studies included in the SLR

CASEY CASEY is presented in study S9 and is one of the earliest medical decision support systems that applies CBR. The solution CASEY provides is a heart failure diagnosis. It first retrieves similar cases, then looks at the differences between the current case and the similar case. If the differences are not too important, it transfers the diagnosis of the similar case to the current one, and if they are too different, it attempts to explain and modify the diagnosis. It falls back on a rule-based domain theory if this does not work, or if no similar case can be retrieved.

FLORENCE FLORENCE is a system that gives a solution to the three basic planning tasks; diagnosis, prognosis, and prescription, and the system is presented in study S9. The diagnosis part of the solution is meant to answer what health status the current patient has. It applies rules, and then the health status is determined by the score of the indicator weights. CBR is used to give a solution for the prognosis, and it compares the current patient to earlier patients to get an idea of how the health status progression for the current patient will be. This takes into consideration both the health situation and further possible treatments for the patient. Lastly, the prescription part gives an answer to how the health status can be improved by suggesting different treatments with their effects, and how these treatments worked on similar patients. This part uses a combination of a rule-based approach and CBR.

Recovery and Performance Evaluation After Anterior Cruciate Ligament Injury The system described in study S1 deals with anterior cruciate ligament (ACL) injury, and it combines fuzzy logic with CBR (Senanayke et al., 2012). The system is not intended to interact directly with the user, but with experts such as sports trainers, coaches, and clinicians for multiple purposes in the context of the ACL injury such as monitoring progress and predicting performance. It uses body mounted wireless sensors to retrieve the input data for the case, while the solution part consists of recovery classification, treatment at different stages, as well as performance evaluation and prognosis. All the information is stored in the knowledge base with a profile of the patient and information about the recovery sessions.

Personalized Diet Recommendation System for Cancer Patients Cancer is one of the top fatal diseases in the world, and as a part of patients treatment, they get diets to make the side-effects of the treatment easier to withstand, as well as making sure they get sufficient nutrition to boost the recovery cycle. Study S6 presents a system that generates these diet recommendations. This system makes use of the data mining techniques of CBR and combines it with Rule-based Reasoning (RBR) and a Genetic Algorithm (GA). The CBR part of the system retrieves a set of diet plans from the case base, while the RBR is used on this set to do further filtering of irrelevant cases. Then the GA is used for the adaptation phase to make sure each diet menu is customized according to the patient's personal health condition. The solution part of this system consists of a menu recommendation that suggests dishes for the patient, as well as a list of specific nutritional values to be taken daily.

Radiotherapy treatment planning Study S8 deals with radiotherapy treatment, to destroy tumor cells with radiation. Radiotherapy treatment planning tries to make sure the radiation dose is sufficient to destroy the cells without ruining healthy organs in the tumour-surrounding area. In real life, the process of creating a solution to this problem can take everything from 2-3 hours to a few days, which makes it time-consuming. It also includes a group of experts in the area that you are dependent on. The case base consists of cases made out of brain cancer patient descriptions as well as the plan used for the treatment. The treatment (solution) consist of the number of beams applied to the planning treatment volume (tumor) and the angles of those beams. The system creates a new solution for the patient based on earlier patient cases and their treatment plans.

Advanced Insulin Bolus Advisor Based on Run-To-Run Control and Case-Based Reasoning People who have diabetes need to inject insulin to keep their blood sugar at a normal level. The system presented in study S7 is an advanced insulin bolus advisor to help with this and is made available to the patient through a smartphone. It aims to enhance the performance of a standard bolus calculator by providing more adaptability and flexibility. It combines CBR with run-to-run that uses continuous glucose monitoring data to create a solution.

Adaptation techniques

The adaptation part of the CBR is one of most challenging issues in CBR and the health sciences, and has traditionally been carried out manually by experts of the domain. However, the problem has been of more interest in the later years of CBR, and several systems explore different approaches to automatic and semiautomatic adaptation strategies (Begum et al., 2011). It has also been argued that the adding of adaptation is what makes the CBR system intelligent, and that without it, it can be seen as a simple pattern matcher (Grech and Main, 2004). The challenge with the adaptation phase is that it is hard to find a general strategy to case adaptation, and therefore the adaptation techniques generated are domain specific. Adaptation is not only a challenge in the medical domain, but it is usually more complex here because cases often consist of a large number of features (Schmidt et al., 2001). The reason for doing adaptation is because usually you can not reuse solutions of cases directly when you have a new case (Chang et al., 2004). The adaptation techniques from the studies in Table 2.5 are presented next:

No-Adaptation Adaptation is not always necessary, and it is seen as a big challenge when creating a CBR system. Due to this, some authors skip the adaptation phase, referred to as no-adaptation, null-adaptation, or retrieval-only. It can be justified by the fact that it is too complicated or even impossible to acquire adaptation knowledge in the given domain. Systems that are no-adaptation may just reuse the solution of the case that is closest to the problem case, or present the information of the most similar cases to the user. Some also point out important differences between the current case and similar cases. The system may present the most important information to an expert of the system, while the experts then manually create the new solution for the current patient. This approach has been successfully used in systems in the field of image interpretation and organ function courses (Schmidt et al., 2001).

Another way to avoid the adaptation problem is to combine CBR retrieval with other reasoning methodologies (Marling et al., 2005). The interest in these multi-modal approaches that involve CBR is increasing in different areas, including the medical domain. They can be combined in the same application, one reasoning process can be used to support the other, or the system can switch between the different reasoning processes. RBR, as well as reasoning from extended probabilistic and multi-relational models, may be combined with CBR. A straight-forward combination is that rules and cases cooperate such that rules deal with reasonably standard or typical problems, while CBR faces exceptions, but they can be integrated in other ways (Schmidt et al., 2001). Another example is to use rules or other generalized models as explanatory support to the case process (Kofod-Petersen et al., 2008).

Generalized cases Generalized cases is an adaptation technique that could be used when dealing with an extreme specificity of each case. It generalizes from one single case into abstracted prototypes or classes. The main idea for this approach is not adaptation, but rather other areas such as to help structure the case base. It can help to decrease the storage amount by erasing redundant cases and thus speed up the retrieval. In addition, it can be used to at least partially solve the adaptation process, by learning general knowledge about the case base. The technique also makes it easier to see the differences between the cases. Generalizing as an adaptation task only works for diagnostic tasks. Diagnoses are represented as abstracted typical cases, where additional specific features of former single cases are neglected. The abstracted cases could be sorted in a hierarchy, which would make the adaptation a top-down search to find the most specific case that fits the current problem (Schmidt et al., 2001).

Adaptation rules Adaptation rules is an adaptation technique were all parts of a solution that does not fit are replaced based on a set of rules. It reorganizes the solutions and changes part of it, but the overall structure of the solution is kept. Adaptation rules can be simple addition and subtraction rules, or more complex rules on how the solution should be changed. An example where this is done is in the Advanced Insulin Bolus Advisor, where they look at the solution and then change the parts of it that are not deemed satisfactory.

Derivational adaptation Derivational adaptation takes advantage of the process used to create a solution. After retrieving the closest case it does not reuse the solution. Instead, it creates a solution for the new problem by reusing the same process that was used to create the solution for the past case.

Compositional adaptation Compositional adaptation creates a new solution by combining the solution of several past cases. In this approach, the user problem is divided into different subsets. The different cases to be used for the solution are in turn retrieved based on the different subsets that are created. The parts of the retrieved solutions are combined into one new solution based on what subset they fit.

Adaptation rule learning In this approach to the adaptation problem, the main point is that the adaptation rules should be updated according to the information in the case base. The goal of this is to make sure the rules are never outdated with new discoveries in the given field. In Li et al. (2009) they have made a system that uses this approach. The rules are created by analyzing the case base and generating rules based on this. After the rules are created they are refined, and rules that appear more than once are merged into one rule with a high confidence value. Rules that have the same antecedent but different consequents are clustered into one cluster and ranked according to their frequency. When new cases with suitable solutions are generated, new adaptation rules are made. These are added to the existing rule set, with the same process as when generating rules, increasing the confident value if it is a duplicate, and arranging it into a cluster if it exists another rule with the same antecedent but different consequents.

Genetic algorithms GAs are adaptive heuristic search algorithms that are based on the natural process of evolution, known as survival of the fittest. Systems that use GA are modeled loosely on the principles of evolution via natural selection through variation-inducing operators such as mutation and crossover. To have success, you have to have a meaningful fitness evaluation and an effective GA representation. One reason to use this method is that it is capable of discovering good solutions in search spaces that are large, complex or poorly understood, where the domain knowledge is limited, or the expert knowledge is difficult to encode in rules or other models. The use of GA may not find the optimal solution, but it usually comes up with a partially optimal solution (Husain et al., 2011).

Neural nets Neural nets (NN) are computational models of the way the brain works, with interconnected input neurons, layered hidden neurons, and output neurons. Connections between the different neurons are assigned weights which are activated and updated during the training of the network, and the trained weights are used for creating solutions. NNs have been successfully used in machine learning in a variety of problem domains and is also used in the solution for the Radiotherapy treatment planning mentioned under health systems that use CBR (Petrovic et al., 2016).

Naive Bayes classifier When attributes are assumed to be independent of each other, and the range of input attributes are highly varied, Naive Bayes classifier is often used. It uses all attribute differences as one input, and their overall effect on the outcome is observed. The method is successfully used in practice, and it has also been applied to CBR systems. The Radiotherapy treatment planning uses this to try to detect attributes that play a more considerable role in creating the solution (Petrovic et al., 2016).

2.4.3 Quality Assessment

In section 2.4.1 a collection of quality assessment criteria were defined that were used to score the studies kept after the screening. Out of the studies that were scored, a total of 14 articles scored above the threshold of six as explained in section 2.4.1, and were therefore kept. Their scores are shown in Table 2.6. All of the studies met QC1 - *There is a clear statement of the aim of the research.* This criterion was secured by the screening process. Every study also at least partly met QC2 - *The study is put into the context of other studies and research*, QC5 - *Is the study algorithm reproducible?*, QC9 - *Are the test results thoroughly analyzed?* and QC10 - *Does the test evidence support the findings presented?*. The criteria that got the lowest average score was QC7 - *Is it clearly stated in the study which other algorithms the study's algorithm(s) have been compared with?*.

2.4.4 Analysis

In this section, the search questions set for the SLR will be answered according to the findings presented.

Study ID	QC1	QC2	QC3	QC4	QC5	QC6	QC7	QC8	QC9	QC10	Total
S1	1	0.5	0.5	0	0.5	1	0	1	1	1	6.5
S2	1	1	0.5	0.5	1	1	0.5	1	1	1	8.5
S3	1	1	1	1	1	1	1	0.5	0.5	1	9
S4	1	1	0	1	1	1	1	0	0.5	0.5	7
S5	1	1	1	1	1	1	0	0	1	1	8
S6	1	1	1	0	1	1	0	0.5	0.5	1	7
S7	1	0.5	1	1	1	1	0	1	1	1	8.5
S8	1	1	1	1	1	1	1	1	1	1	10
S9	1	1	0.5	1	0.5	0.5	1	0.5	1	1	8
S10	1	1	1	1	1	1	1	1	0.5	1	9,5
S11	1	0.5	1	1	1	0.5	1	1	0.5	1	8,5
S12	1	1	0.5	1	1	0	1	0.5	1	1	8
S13	1	1	1	0.5	1	1	0.5	1	1	1	9
S14	1	1	1	0	1	1	0	1	0.5	1	7.5
Total	14	12.5	11	10	13	12	8	10	11	13.5	Avg = 8.2

Table 2.6: The scores for the included papers

SQ1 What type of solutions are provided by CBR used in health sciences?

SQ2 What adaptation techniques are used in CBR?

SQ3 How do the solutions found in RQ1 and RQ2 respectively compare to each other?

SQ4 What is the strength of the evidence in support of the different solutions?

SQ5 What implications will these findings have when creating the new CBR system?

SQ1: What type of solutions are provided by CBR used in health sciences? Six different systems that use CBR in health sciences were looked closer at in this review. These systems either interacts directly with the patient or with experts of the domain. The six systems deal with different solution types, which will be described below. Some of the systems present several solutions, e.g., both a treatment plan as well as prognosis.

Interacting directly with patient Systems that interact directly with the patient are not dependent on an expert of the domain to be used. The patient interacts with the systems through an interface that should be easy to use, and they work as a personal guide for a given problem.

Supplement for expert Most of the medical systems explored works as a supplement for an expert. These systems handle the presentation of a solution in different ways. As for the diet recommendation system for the cancer patients, the system does provide a solution to the problem, but it is given to an expert to review the given solution. While the case is reviewed, the system asks questions to why the adaptations are done, and creates rules according to this, thus creating better adaptation rules. With this solution, the expert intervention will appear more rarely with time, as the case base is expanded. In other systems, the solution is just displayed to the expert, which can, in turn, change the solution as he likes without any guidelines. This type of system does not have any learning on how to create a better plan but evolves by adding the expert adapted solution into the system, thus increasing the case base quality.

Classification One type of solution the medical systems present is classification. Here the system already has a collection of predefined groups with different characteristics. The solution for the system is to classify the patient into one of these predefined groups based on the patient's features.

Treatment plan Treatment plans is another type of solution. There are different types of treatment plans; some encourages the patient to do activities, while others set up plans for how and what types of medicine that should be taken over a time span. The solution should be personalized for the patient based on his traits.

Diagnosis In the diagnosis solution, the system tries to identify what type of illness a patient has. It can also find out if a patient does not have any diagnosis, hence is healthy.

Prognosis Prognosis tries to predict the evolution of a patient's illness. It does this by comparing the patient to similar patients progression, and by this suggesting a prognosis for the new patient.

SQ2: What adaptation techniques are used in CBR? In this review, nine different adaptation techniques were identified. The adaptation techniques have two different approaches to the adaptation problem, one is dependent on the information from an expert, while the other uses the information already in the case base. The different adaptation techniques work best on different types of cases. Some provide better solutions on large and complex cases, while others have a better effect on domains were the information and adaptation is more straight-forward.

Expert knowledge adaptation Expert knowledge adaptation is one of the two approaches to the adaptation problem. This approach to the adaptation problem is dependent on input from an expert of the domain. It uses the information from the medical expert to create the adaptation knowledge that is added to the system.

Knowledge-light adaptation It can be hard to get specific knowledge from a medical expert, especially in complex domains where it is difficult to say anything in general about each case. Additionally, you may not be in contact with a medical expert to develop the necessary adaptation knowledge. Knowledge-light adaptation is researched because it is independent of the experts in the field. This approach creates adaptation knowledge from analyzing the cases that are already stored in the database. To be successful with this approach, you have to have a sufficient number of cases to analyze.

No-adaptation No-adaptation is the most used technique, where it skips the adaptation phase. This approach makes the system independent of an expert while creating the system, but it will depend on an expert to supervise while in use. This technique works for both complex, and not so complex cases.

Generalized cases This solution creates generalized cases that are abstracted from the cases in the case base. It is a good solution if you have cases with many attributes and large complexity. To be able to create the generalized cases, you will need input from an expert of the domain.

Adaptation rules Adaptation rules consist of a set of rules that changes the solution. It can be either deletion, addition, or changing the attributes of the solution. The rules should be created together with an expert. It may be hard to formulate rules for the expert, especially on complex domains, and this technique is therefore more applicable on cases that have little complexity.

Derivational adaptation Derivational adaptation reuses the process of how to create a solution to create a new solution. This solution is dependent on expert input to show how the new cases are created.

Compositional adaptation Compositional Adaptation combines different cases. It is dependent on expert knowledge on how to combine the different cases. Compositional Adaptation can be used on more complex cases, as well as cases that are simpler.

Adaptation rule learning This adaptation technique is knowledge-light and is therefore not dependent on an expert on the domain. It works well on simple cases, and it can also find information about systems that is hard for an expert to see.

Genetic algorithms GAs is a complex adaptation technique that works best on more complex domains. The reason for this is that it is not very good at giving the optimal solution, which should be possible on simple cases. Nevertheless, it does work well for complex domains, or where rules are hard to define since they usually give a partially optimal solution. GAs are dependent on an expert to help with deciding fitness of solutions.

Neural nets NNs are a complex solution that imitates the way the brain works. The solution is dependent on expert knowledge for the supervised data set to train the network. NNs work well on complex domains where it is hard to find rules for the adaptation.

Naive Bayes classifier Naive Bayes classifier is a solution that works well with cases where the attributes are assumed to be independent of each other. This approach does not need an expert, as it analyzes the difference of attributes, and sees how they affect the solution

SQ3: How do the solutions found in SQ1 and SQ2 respectively compare to each other? In the existing solutions for CBR systems used in the health domain, a large majority were created as supplements for experts in the domain. Only one of the presented systems were made to interact directly with the user. One reason for this is that some of the systems are created for the experts, with knowledge the patient have no interest in, as in the example with the radiotherapy treatment. Another reason for this seems to be that one often need a professional to interpret the symptoms that the patient give. Also, the presentation of the diagnosis should be presented in a way that fits the patient, in addition to the fact that some people need more guidance than others when they are presented with a treatment plan.

The different solution types in health care can be divided into two groups as well, based on how easy you can verify if the system creates a correct solution. Classification and diagnosis are in the same group, where one can easily find out if the system found the correct solution or not. For the two other solution types, treatment plan and prognosis, it is harder to classify if the solution given by the system is the correct or not, as both need time to see the development of the case. In treatment planning, it is even harder to decide what the best solution is. Even though it is possible to see how the patient case develops, the same case will not appear again to compare if it is possible to get an even better solution. With the prognosis, it is possible after time to see if the solution provided is close to what the actual development is.

The difference between the adaptation approaches is that one is based more on expert knowledge while the other uses the already known knowledge in the database. The first may feel more reliable to a user, especially when it comes to health care.

Among the different adaptation techniques, the biggest difference is what kind of approach they have towards the domain knowledge modeling. Also, there is a difference in the complexity of a case and the domain they fit best. No-adaptation, generalized cases, adaptation rules and derivational adaptation being the ones that work best on not so complex cases. GAs and NNs are best for complex case bases where it is hard to find domain knowledge, while compositional adaptation, adaptation rule learning, and Naive Bayes classifier can be used with success on both complex and simpler domains.

SQ4: What is the strength of the evidence in support of the different solutions? The evaluation of the strength of evidence is based on the results of the quality criteria assessment that are presented in section 2.4.1. The general trend was that everyone passed QC1 and had a clear aim of research, in addition to all of them also at least partially passing QC2, where the studies were put into the context of earlier research and published studies. All of the studies also partly met QC5, QC9, and QC10, which makes the study algorithm possible to reuse and also that the results of the study were presented and analyzed with conclusions that matched the test results. The criteria that got the lowest average score was QC7 - *Is it clearly stated in the study which other algorithms the study's algorithm(s) have been compared with?*. This is because a few of the considered papers did not compare the solution to other algorithms, and only showed their results. Another reason for this is that some of the articles did not present an algorithm, but were instead a general article on the field. These still got points on other quality criteria that involved questions about the algorithm, but these were based on how the literature review was conducted and presented.

SQ5: What implications will these findings have when creating the new CBR system? In this section it is described how the findings presented so far can be used when developing a new CBR system.

Health system CBR is a sound technique for usage in the health care domain, and it is already used in the SELFBACK project. Thus, no other solution will be researched. The fact that most applications are made for experts and not for directly usage for the patient is something that has to be kept in mind while developing the new system. That it exists solutions that interact directly with the user shows that it is possible to do, but that it requires something that makes it reliable, and it has to be secure in the way that does not hurt the patient. For the different type of solutions, the studies that have to do with treatment planning are the most relevant ones, as this is what the new system aims to solve as well. The other studies are still relevant as they bring insight on how to structure cases, and they emphasize that CBR is a good fit for health applications.

Adaptation The main focus for the new system is how different adaptation techniques works on a given domain. The different solutions presented in this SLR were all considered based on their different traits. Two different methods found is the SLR are applied to the new system. The first method is a GA inspired approach; the other method is adaptation rules. These methods are both dependent on expert knowledge. None of the knowledge-light methods were chosen as these are dependent on more cases than the case set used for the experiments have. The case set is presented in section 3.1.3.

Limitations of this review The conduction of this review has multiple limitations, with the filtering of articles being the most apparent. The amount of articles that went through the filtering process were way too many to do a closer look at all. Since 97% of the articles were filtered out by only looking at the title, and in some cases a skim for keywords in the abstract, it is likely that some relevant articles were filtered out by this process. In addition, the time constraint for the review contributed to this. If no time constraint existed, all of the articles could have gone through a better filtering process. Another way to deal with this problem would also be to create a better method on how to search for relevant studies or create more refined search strings. In addition to this, another limitation of the review was that not all of the articles from the ICCBR seemed to be indexed correctly, and since this was realized after the filtering process of articles, only the ones that were obviously missing were added to the review. The filtering and quality assessment of the articles are also done by only one person, which makes the results biased towards that person's preferences.

Summary

In this SLR different systems in CBR have been explored. In health sciences, CBR is a method that is recognized as a good solution and accepted by the medical field as well. Several different adaptation techniques have been explored, all with positive and negative traits, which makes them suitable for different systems. Some methods work best on systems with a lot of complexity, while other have better results on more straight-forward domains. For this work, a method for both types of domains are applied, with adaptation rules fitting non-complex domains, and GAs fitting complex domains.

Chapter 3

Methods

Chapter 3 presents the case representation describing patients and exercises in the SELFBACK project, and the case base used in the experiments. The approaches used for adaptation are presented, and details of their implementations are shown.

3.1 Case Representation

The case representation is based on the SELFBACK questionnaire, as this creates the basis for the data used in the experiments. Information from the wristband is not included as this data was not available at the time of the experiments. The questionnaire answers describe the characteristics of a patient with non-specific LBP. It covers areas such as the *pain level*, their *quality of life* despite the pain, *functionality*, *coping capabilities* and their *physical activity* level. From the overall characteristics three different types of advice are generated in SELFBACK to support self-management:

- Goals for physical activity: Number of steps per day, maximum of inactive periods during hours the patient is awake.
- Education: Tailored list of educational exercises that support and reassure the patient in his/her self-management.

- Exercise: A customized list of exercises that combine clinical guidelines for LBP with past cases into action items.

In this thesis, the focus is on the generation of exercise lists based on given cases. The case representation is object-oriented, and consist of the patient characteristics and the list of exercises at a given time. The patient characteristics are used as problem description and the exercises are the solution part. These two different concepts are explained in further detail in the following sections.

3.1.1 Patient Concept

The patient concept consists of 36 attributes that describe different aspects of a patient's health. These attributes can be divided into different groups of information collected by 1) the SELFBACK questionnaire, 2) a wristband detecting physical activity worn by the patient, and 3) an interaction module in the SELFBACK app. The attributes collected by the questionnaire are a combination of important prognostic factors and outcome measures. Pain self-efficacy and beliefs about back pain have been shown to have a great impact on the future course of LBP (Fritz et al., 2001). Likewise, baseline pain and pain-related disability have a strong influence on the course of LBP, but these attributes are also important outcome measures (Costa et al., 2009). Quality of life at baseline may also influence the course of LBP, but this is mainly considered an important outcome measure (Deyo et al., 1998). An example of a patient concept as modeled in myCBR can be seen in Figure 3.1. Some fields are unknown, as this data is not included at this time, but is a part of the SELFBACK project. The patient data in this case is anonymized, as data from patients are confidential. Following is a description of the stored patient information.

Demographics For a new patient it is necessary to know some simple demographics, such as height, weight, age and gender. These are the basis for each patient, and are all easy attributes to measure. All of these attributes may influence the solution, as all attributes can be an indication of how well a patient is able to perform and follow-up on a particular exercise plan. Young people are usually stronger and more fit than older people, men are in general stronger than women, and younger people are usually able to carry out more intense physical activity or exercises than older

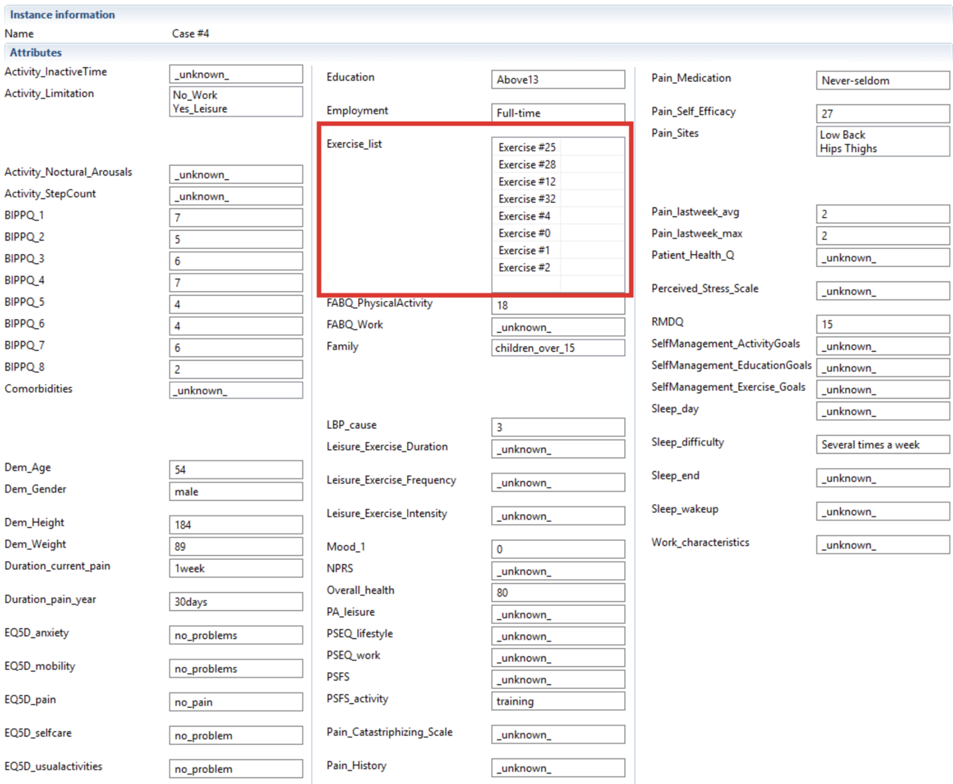


Figure 3.1: Patient example as modeled in myCBR. The highlighted exercise list consist of exercise cases.

people. Obese people may need to focus on other exercises than normal weight people.

Quality of life The impact of LBP on quality of life is another important measure of the severity and consequences of the back pain. As an additional measure, the patient also provides a score in his/her own health from 0 (worst) to 100 (best).

Pain self-efficacy and beliefs about back pain Scoring of pain self-efficacy indicates if the patient is confident that he/she can do various activities regardless of the pain and is therefore an important measure of how the patient copes with the pain. A related measure is fear-avoidance beliefs, i.e., to what extent the patient believes that physical activity will be harmful and exacerbate the back pain.

Physical activity and exercise Information about general physical activity is assessed by the SELFBACK questionnaire and the physical activity detecting wristband. The attributes assessed by the questionnaire include work characteristics (i.e., physical work demands), physical activity limitations in everyday activities (work and/or leisure) due to back pain, and level of leisure time physical activity. Physical activity information that can be derived from the wristband data includes several attributes, such as step count (including intensity [i.e., step frequency] during walking/running), and distribution of active and inactive periods during wake time. The interaction module in the SELFBACK app will ask the patient about accomplishment and adherence to the exercises prescribed in the self-management plan as well as a rating of whether the patient perceived the prescribed exercises as useful and enjoyable. All these attributes say something about how active the patient is and the coping behaviour related to his/her LBP.

Pain and pain-related disability Information about various aspects and characteristics of pain is relevant for the case, both because it can track progress and it provides an indication on how severe the case is. History of LBP provides information about whether the patient has experienced similar problems before, if it is a recurrent problem, or if it is a long-lasting ('chronic') problem. Number of pain sites reported by the patient is important to assess musculoskeletal co-morbidity while the scoring of pain-related disability provide information about how the back pain influence function.

Exercise list To connect the patient concept to the exercises, the patient has an attribute called exercise list. This attribute is a list of all the exercises the patient has. The list consists of cases on the form of the exercise concept, that is further described below.

3.1.2 Exercise Concept

The exercise concept consists of four different attributes. An example of an exercise modeled in myCBR is seen in 3.2.

Description The descriptive name and type of the exercise. The type can be a strength,

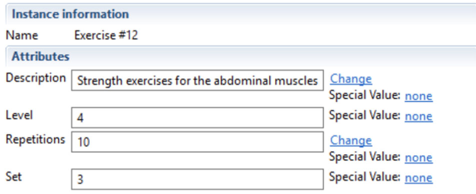


Figure 3.2: Example of an exercise as modeled in myCBR

flexibility or pain-relief exercise. All patients are encouraged to perform strength and/or flexibility exercises each week, unless they are unable because of strong pain. In general, strength and flexibility exercises are not recommended in the acute stage of a LBP episode. By performing exercises regularly the patient will increase strength and improve flexibility, which over time will prevent relapse. In the acute stage or in case of a relapse, pain-relief exercises can be recommended to help the patient to relax and reduce the most intense pain. These exercises will mainly help to relieve acute pain but will have limited relevance when the patient is pain-free.

Level An exercise can have different levels. The strength exercises used in this project have up to six different levels, where each level is a new variation of an exercise that is more demanding than the former. The patient changes levels as he/she progresses, i.e., first by increasing the number of repetitions within a level before moving to the next level. An exercise with its corresponding levels can be seen in Figure 3.3.

Repetitions Each exercise is performed in sets, with a given number of repetitions for each set. There are four levels of repetitions, 8, 10, 12 and 15 repetitions respectively. When the patient is able to perform 12-15 repetitions per exercise the patient moves up a level in the exercise.

Set The set indicates the number of times the patient should perform the given repetitions for the exercise.

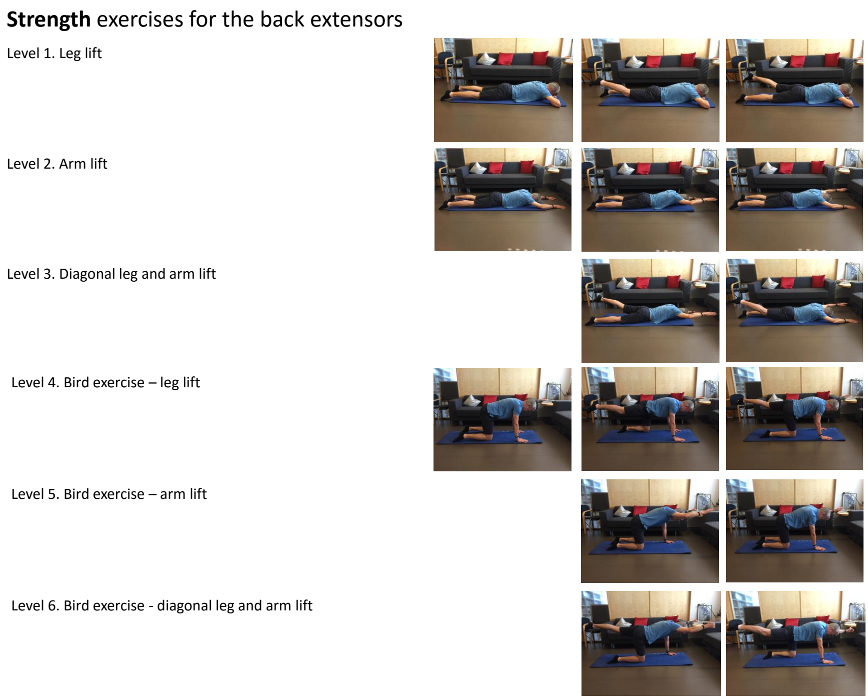


Figure 3.3: Examples of the different levels for an exercise

3.1.3 Case Base

The cases used for testing the algorithm are gathered from the SELFBACK project, and consist of data from real patients who experience LBP. A total of nine cases were created with an associated solution crafted by a medical expert. A overview of the case base is found in Table 3.1. The expert solutions was created before experiments were conducted, and these solutions work as the basis for the system generated solutions. The full cases can be found in Appendix C.

3.2 Experiment Methods

In the experiments, three different approaches are used; no-adaptation, a GA inspired approach, and adaptation rules. They are compared in regard to solution variety as well as solution quality. In the following sections, a description of how the methods are imple-

	Patient #1	**Patient #2**	**Patient #3**	**Patient #4**	**Patient #5**	**Patient #6**	**Patient #7**	**Patient #8**	**Patient #9**
Exercise #0	X	X	X	X	X	X	X	X	X
Exercise #1	X		X	X	X			X	X
Exercise #2	X		X	X	X			X	X
Exercise #3				X			X	X	
Exercise #4					X				
Exercise #5			X						
Exercise #6	X			X			X		X
Exercise #7		X							
Exercise #8						X			
Exercise #9								X	
Exercise #10				X					
Exercise #11		X							
Exercise #12	X				X		X		X
Exercise #13			X						
Exercise #14						X			
Exercise #15						X			
Exercise #16								X	
Exercise #17								X	
Exercise #18							X		
Exercise #20				X					
Exercise #22	X	X							
Exercise #24						X			
Exercise #25			X		X				X
Exercise #26								X	
Exercise #27	X	X		X			X		X
Exercise #28			X		X				
Exercise #29						X			
Exercise #30								X	
Exercise #31				X					
Exercise #32	X	X			X		X		X
Exercise #33			X						
Exercise #34						X			
Exercise #35								X	

Table 3.1: Overview of the case base

mented, and what changes were made to make the methods fit the domain, is given.

3.2.1 No-Adaptation

The first approach, and also one of the most used approaches, is the no-adaptation approach. No-adaptation is chosen as one of the methods because it is the most popular method in CBR, and it is also the method used so far in SELFBACK . The method creates a solution for the new problem by taking a direct copy of the solution for the best matching case. The challenge with no-adaptation is that it is dependent on a comprehensive case base with a high case variation to be able to provide a good solution for different patients, as the case base does not evolve over time. This approach was built out of the box from the myCBR workbench and a RestAPI for myCBR[1]. The design decisions made in this approach was the local similarity measures for the exercises. Local and global similarity

[1] https://github.com/kerstinbach/mycbr-rest-example

measures for the other attributes are taken from the SELFBACK project. For the exercises it was decided that an increase in the *level*, *set* or *repetitions* of exercises should provide a higher similarity score than a decrease of these values. An example of the modeled similarity measures is shown in Figure 3.4, with the similarity measures for the level. The similarity measures created for this approach are reused by all methods.

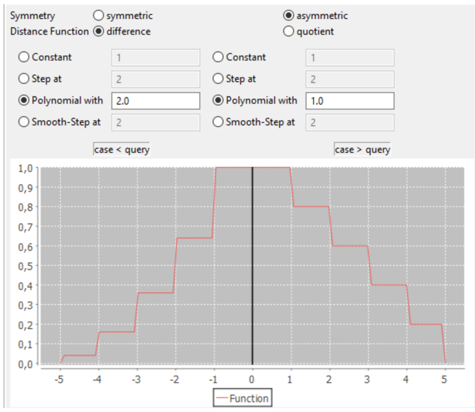


Figure 3.4: Similarity measures for the level attribute

3.2.2 Ex-Over

A GA-inspired approach was incorporated in the reuse step to perform an adaptation on the cases. The new algorithm created is hereby referred to as ex-over. The name is derived from the fact that the solution is created by doing a crossover of exercises. The method was chosen because GAs are said to create at least a sub-optimal solution on complex domains. The idea behind a GA is to retrieve the two most fit cases, and combine them to create a new case. This approach is based on how nature evolves, and the assumption behind this approach is that the combination of the two best cases will give a satisfactory solution.

General Algorithm Structure

A GA consists of different parts. It has a fitness function, i.e., a function that helps you describe how good a given specimen is. It also has a crossover function, which creates a new solution based on the two fittest individuals. The algorithm is set to stop at a termination condition, where the new solution satisfies the given condition. In the GA there is also a probability of a mutation to happen. This changes one of the attributes in the solution at random, to possibly create better solutions, and avoid getting stuck in local maxima.

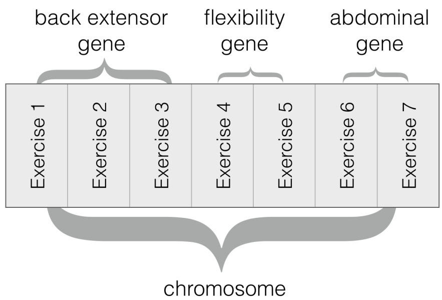


Figure 3.5: Exercise list mapped to an ex-over chromosome

Adapted Algorithm

The general structure of a GA was adapted to fit the domain, and inspired the new method ex-over. The fitness function in ex-over is based on the similarity scores between the cases, and the two fittest individuals from the population are chosen by retrieving the two most similar cases to the new problem description from the case base. The solutions from these two cases are retrieved, and from them two chromosomes of the solutions are created. The chromosomes are used in the crossover function in ex-over. A chromosome is built up such that all exercises for the same muscle group are placed inside the same gene, as each gene represents a specific trait of an individual. An example of how this mapping is done can be seen in Figure 3.5.

The description of the 4R cycle, including the ex-over method presented in this work, is seen in Figure 3.6. A new problem starts the process, and a query (Q) with the patient description as input is used to retrieve the two best matching cases (C1 and C2). The cases consist of a problem description (P(C1) and P(C2)), and the solutions (S(C1) and S(C2)). The solutions are sent to the reuse step, where is where ex-over is applied. S(C1) and S(C2) are both mapped to chromosomes to be used by the crossover. The two chromosomes representing the solution parts (S(C1) and S(C2)) are then sent to the crossover function. Here a new solution (S') is created by a crossover of the chromosomes, and it is done with a uniform crossover (Spears and De Jong, 1991). The mixing ratio is set to 0.5, because the solution is desired to have a close to equal mix of the two solutions' genes. After this, the method is revised to check if the proposed solution (S') is acceptable. Ex-over finishes after one crossover at this moment as there exists no good measures to describe how well a patient will progress before they have executed the exercise plan. Measurements on progress will be added at later iterations, but this work only address the initial creation of plans. P(Q) with its associated solution (S(Q)) is then retained in the case base.

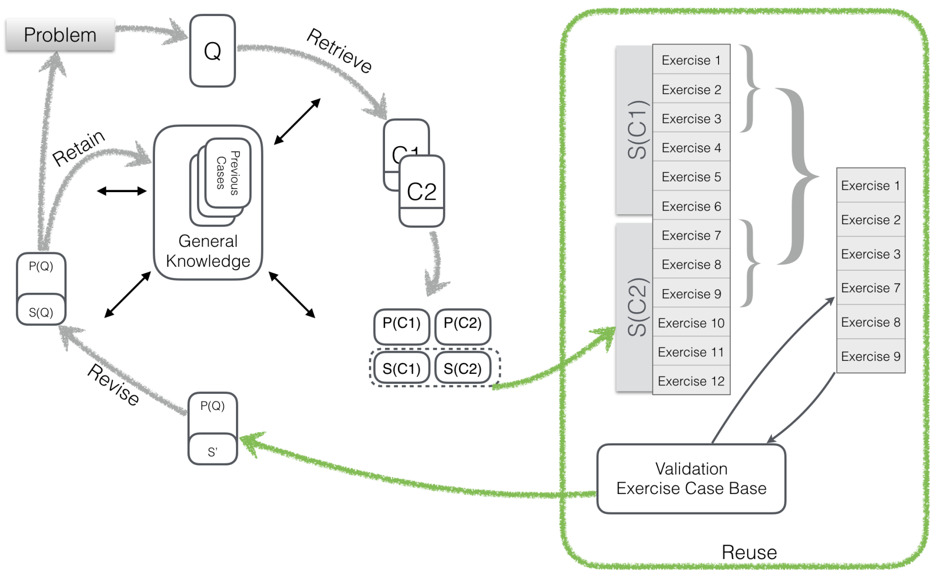


Figure 3.6: Overview of the 4R cycle (based on Aamodt and Plaza (1994)) including an adaption example of a result from a crossover between to chromosomes

The exercises have a probability of 1,5% to mutate within the reuse step. These mutations are given some restrictions, such as that the type of exercise will be kept, but the level and the number of repetitions may alter by one level. The reason for such restrictions to the mutation is so that ex-over should produce a solution that is feasible for the patient to fulfill and therefore not demotivating for the patient. Further the suggested solution should not be too easy and ensure the optimal progress for the patient. The addition of mutation helps to ensure that exercises evolves outside the exercises used in the expert solutions.

3.2.3 Adaptation Rules

Adaptation rules is the third method applied. This method is applied to see if it is possible to break down expert knowledge into rules on how to create exercise plans. The creation of rules gives a feeling of more control over the solution, and it tries to imitate how medical experts work. As a consequence of this, adaptation rules is a method that depends heavily on expert input. The rules created here are derived from guidelines on LBP. These guidelines are in general quite fuzzy, which makes it hard to create rules from them. The rules were created after a discussion with a medical expert, to get more details on how plans are created. The main points from the discussion were accumulated in the following adaptation rules, as a suggestion on how to implement guidelines on LBP (Koes et al., 2010), (Lærum et al., 2007).

1. The patient should not work out during the acute phase.
2. Each plan should consist of stabilizing exercises, exercises for back extensors, and exercises for the abdominal muscles.
3. The plan should not consist of more than six strength exercises.
4. A set of attributes affect the exercise level and repetitions.
5. Each exercise has a max level.
6. The exercises should have a more or less symmetrical number of repetitions.
7. Some exercises appear in pair.

The first rule does not need to be handled by the system, because patients in the acute phase are not referred to the program as this system only focuses on the creation of initial exercise plan suggestions. The second and third rule is already handled by CBR automatically, because the cases in the case base follows these rules. For the seventh rule some changes were done in the modeling of the exercises. The back-extensors exercises (see Figure 3.3) are examples of where exercises appear in pairs. Here level 1 and level 2 should always be given together, and level 4 and level 5 belong together. It was decided that instead of modeling them as separate levels they should be merged into one level. This results in the maximum level for back extensors being 4 in the model, where level 1 in the model represents exercise levels 1+2, level 2 represents exercise level 3, level 3 represents exercise levels 4+5 and level 4 in the model represents exercise level 6. This modeling is never shown to the user of the program, it is simply modeled that way to simplify the adaptation. The rest of the rules are used after retrieval in the adaptation to create the solution for a new patients. An example of the process can be seen in Figure 3.7.

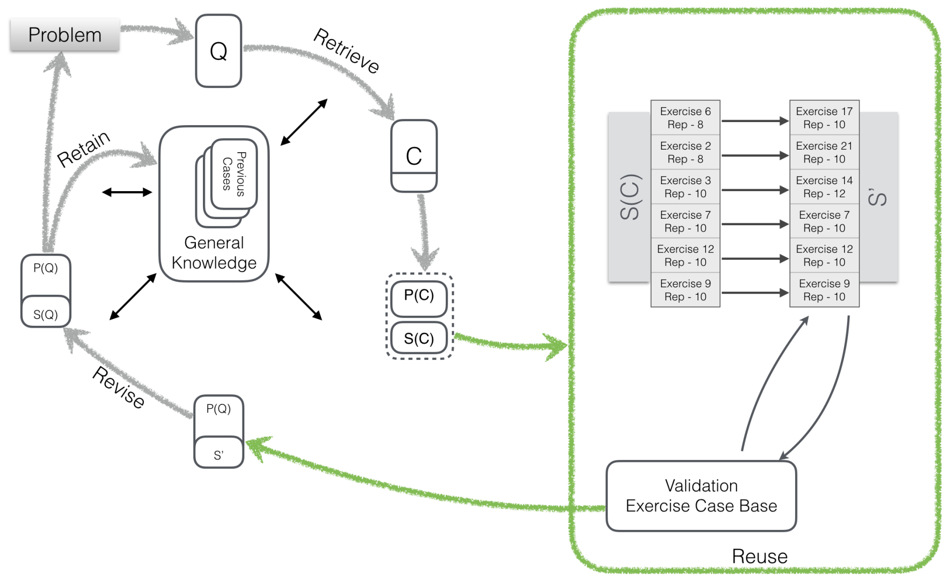


Figure 3.7: Overview of the 4R cycle (based on Aamodt and Plaza (1994)) including an adaption example of a result from adaptation rules

When a new patient is referred to the system, he is asked to answer the questionnaire in SELFBACK . This information is the new problem used as input for the system, and a query (Q) is created from the information. The closest case (C) is retrieved, consisting of a problem P(C) and solution S(C). To address rule 4, P(C) is compared to Q in terms of similarity of the attributes. The attributes of importance are attributes that say something about the pain levels, and if they have any fear of moving. To handle rule 6, the exercises are sorted ascending or descending depending on if the plans should be decreased or increased. The similarity scores are normalized between -1 and 1, and the scores are used to change the level and set of the exercises, e.g., if the patients' overall health is lower, the exercise difficulty should decrease. The max level is checked when increasing difficulty so that they are not increased past their max level. After the solution is created it is revised, and retained in the case base if the plan is accepted. The revise step was done with the help of a medical expert. A set of solutions were created by the system, and sent to the expert. The solutions was then approved.

The rules presented were made after discussions with the medical expert, and then implemented. The resulting rules and examples on how they worked were sent to an expert to verify the method. The expert accepted the rules, and thought the solutions provided were feasible for the given patients. Because the solutions were accepted, no more work were done to refine the rules further. However, it is important to remember that adaptation rules always have room for improvement. Adaptation rules is the dominating method for case adaptation, and usually provides good results given the rules are well created. For the scope of this work a solution accepted by the medical expert was deemed as sufficient to answer the main goal. This still needs to be considered when interpreting the results, where the results show how these rules work on the domain, and not how adaptation rules as a method work in general.

Chapter 4

Experiments and Results

Experiments were conducted at two stages during development. The first experiment is published in ”Evolutionary Inspired Adaptation of Exercise Plans for Increasing Solution Variety” (see Appendix A). This experiment focused on reducing the effect of the cold-start problem, and if the adaptation phase helps to increase the solution variety. The second experiment was conducted to answer the main goal of this thesis. The main focus of the experiment was on the quality of the generated exercise plans, as this thesis aims to answer if an adaptation phase will help improve the creation of personalized exercise plans. Both experiments were conducted with the case set presented in section 3.1.3, consisting of nine cases with a solution crafted by an expert.

4.1 Experiment on Solution Variety

Tests were done with ex-over to see if the approach increased solution variety, to help minimize the cold-start problem. It was compared to no-adaptation, and the solutions created by a medical expert were used to benchmark the quality of the generated solutions. The cold-start problem was originally not a part of the thesis, but was added due to the low amount of cases.

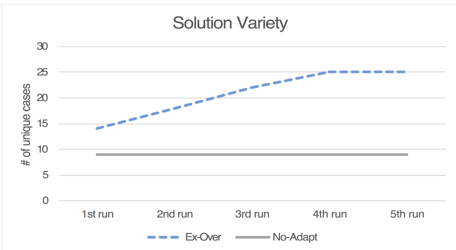
4.1.1 Setup

The experiment was performed with the Leave-One-Out Cross Validation (LOOCV) method (Feelders, 2003). In LOOCV one sample from the data set is left out, and the tests are run with the left out sample as input. LOOCV was chosen because it is seen as specifically useful on data sets of small sample sizes (Keedwell and Narayanan, 2005). While the no-adaptation method always creates the same solution, the ex-over will, because of the mixing ratio, return solutions that differ from each other with every run. As a result of this fact, the ex-over approach was tested a total of five times to see how well it performed in terms of best case, worst case, and average case. Five runs were chosen as this is sufficient to show the evolution for the newly created system. More runs would not add value because there are only five different exercises to choose from, with four or six levels, and four possible variations of repetitions, which creates a finite number of exercise combinations. Every new unique exercise plan that was created was counted, to keep track of the increase in solution variety. The solution quality was checked to make sure the generated solutions were usable. The quality of each solution was determined by comparing the generated solutions with the expert solutions. The two solutions are compared based on their similarity measures, i.e. how close the generated result is to the expert solution. This approach assumes that the expert solution is the optimal plan.

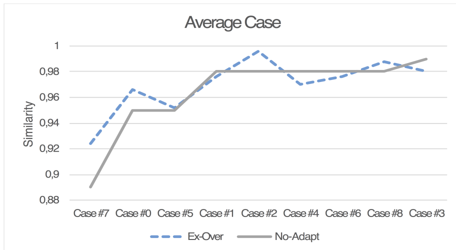
4.1.2 Results

Figure 4.1a shows the number of unique solutions created by the methods. The amount of unique solutions increases with ex-over, thus increasing the solution variety. For no-adaptation the number of solutions is constant, and the solution-variety is unchanged. It is expected that the ex-over-graph will converge with more iterations, as the variation of exercises to choose from is a finite number. The results still indicates that the use of ex-over creates a noticeable gain in terms of solution-variety.

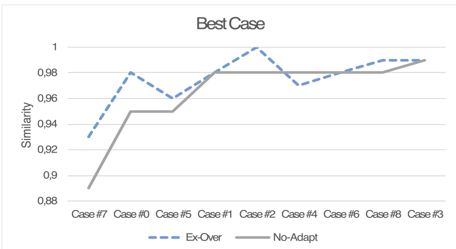
A textual example of solutions from ex-over, no-adaptation, and an expert are shown in Table 4.1 on page 46. The three solutions created for this patient are all unique, where some of the exercises are the same on all three solutions, while other exercises differ between the three solutions. The flexibility exercises recommended are for instance the same three variations of exercises in all three solutions. For the ”strong in mid-position” exercise, the solution from the expert and ex-over match, while no-adaptation suggests an exercise at a higher level but with fewer repetitions. Neither of the generated solutions match the expert solution for the ”strength exercise for the back extensors.” Here the expert solution suggests two exercises, while the two generated solutions only suggest one, and the same, exercise. Even though these variations exist, the suggested exercise plans are closely related in terms of exercises.



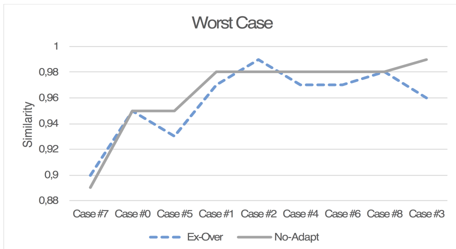
(a) Unique solutions generated over five runs



(b) Average case quality of the exercise plans



(c) Best case quality of the exercise plans



(d) Worst case quality of the exercise plans

Figure 4.1: Results from the experiment on solution variety

While the ex-over is a better solution for increasing solution variety, it only adds value to the user if the created solutions have an appropriate quality. To assure that the solutions are satisfactory they are scored by similarity to the expert solutions. The quality of the no-adaptation solutions are also scored, and the scores of the two methods are compared. Since the ex-over creates different solutions, the results show how they scored best case, worst case, and average case, out of the five runs. The three different rankings are compared to the similarity scores for the no-adaptation result, and can be seen in figures 4.1b, 4.1c, and 4.1d. The results are sorted by the similarity score for no-adaptation as this will be similar in all figures, and therefore give a better impression of the differences between

Exercise description	**Expert solution**	**Ex-over solution**	**Retrieval only solution**
Strength exercises for the back extensors	*Level:* 4 *Repetitions:* 10 *Set:* 2 *Level:* 5 *Repetitions:* 10 *Set:* 2	*Level:* 6 *Repetitions:* 10 *Set:* 3	*Level:* 6 *Repetitions:* 10 *Set:* 3
Strength exercises for the gluts and back extensors	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 2 *Repetitions:* 10 *Set:* 3
Strength exercises for the abdominal muscles	*Level:* 4 *Repetitions:* 10 *Set:* 3	*Level:* 4 *Repetitions:* 10 *Set:* 3	*Level:* 4 *Repetitions:* 10 *Set:* 3
Strength exercises for the oblique abdominals and rotator muscle in the back	*Level:* 3 *Repetitions:* 10 *Set:* 3	*Level:* 3 *Repetitions:* 10 *Set:* 3	*Level:* 3 *Repetitions:* 10 *Set:* 3
Strength "Strong in mid-position"	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 2 *Repetitions:* 8 *Set:* 3
Flexibility	*Level:* 2 *Level:* 3 *Level:* 4	*Level:* 2 *Level:* 3 *Level:* 4	*Level:* 2 *Level:* 3 *Level:* 4

Table 4.1: Textual representation of different solutions: each solution has a level, and most of them have the number of repetitions specified

the scores.

Both methods score quite well against the expert crafted solutions, ranging from 0.89-1.00 in similarity, which makes sense as all the solutions are built up with the same type of exercises. In the best case scenario for the ex-over, it scores better or equal to no-adaptation on eight out of nine cases, which suggests that this method performs better than no-adaptation. The worst case scenario gives another impression, here two cases are better on the ex-over approach, while five give a worse solution than with no-adaptation. The best results to look at to get an impression of the performance of the two solutions over time is still probably the average case. The average case shows that the ex-over performs better in five cases and worse in four. This makes the ex-over approach seem only somewhat better than without any adaptation, however, when comparing the similarity measures it shows that the solutions that score higher with the ex-over have a larger benefit compared to no-adaptation. The solutions that perform worse are quite close in scores, while the solutions that perform better have a larger gap between the scores from ex-over and no-adaptation. On average the solutions with the ex-over score 4,8% better, which indicates that in general the gain is larger with the use of this method. These results suggest that with the use of ex-over the case base will have a more varied case base with valid solutions over time, thus help solve the cold-start problem.

4.2 Experiment on Solution Quality

From the first experiment it was a small indication that the addition of ex-over increased the solution quality compared to no-adaptation. The results were not deemed as sufficient to conclude, and further experimenting on the solution quality was necessary. The second experiment was scored by three medical experts to find more evidence on the change in solution quality with the addition of an adaptation phase, and this experiment is the main evaluation method to answer RQ4. This experiment compare the quality of solutions created by ex-over and adaptation rules to the quality of solutions created by no-adaptation. The original expert solutions created for the case base were also evaluated by medical experts to see how well they performed in comparison to generated solutions from the system.

4.2.1 Setup

Experts on the domain were consulted to get an idea on how well the different methods performs regarding quality. Three medical experts were asked to help score the different exercise plans created for the patients. For each of the nine patient cases, four different exercise plans suggestions were created. The generation of plans was done in the same manner as in the first experiments, with LOOCV. Three of the exercise plans suggested were generated by the system with the use of no-adaptation, ex-over, and adaptation rules. The fourth plan was the exercise plan created by the medical expert for the case base. Comparing the solution quality of ex-over and adaptation rules with no-adaptation is the evaluation that is of most interest. The expert solution was added to see if the generated rules perform close to solutions created by an expert, or if the quality is too poor to be used in real life.

A document with information about the nine patients and the four solutions for each of them was sent to the medical experts (See Appendix C). The method used to generate the different exercise plans were anonymized, and the different solutions were color coded to separate them from each other. The anonymization was done so the medical experts would not know what method created the different plans. Attached with the exercise plan document was an explanation on how the experts should score the plans (See Appendix D), and the presentation of the exercises (See Appendix B). The evaluation was to be performed in two parts; firstly the experts should look at how the plans compared to each other, and rank the plans from 1-4 based on what plan they believed was the best fit for the patient. In the second part they should evaluate the plans only in regards to how well the plan fits the given patient, without comparing them to the other plans. The score system for the second evaluation was from 1-5, the scores are explained below:

1. Very good plan
2. Good plan
3. Ok plan
4. Poor plan
5. Very poor plan

4.2.2 Results

The results from the medical scores are divided into sections based on rank and quality score.

Ranking

All the plans were ranked by all three medical experts (ME#1, ME#2, ME#3), based on what plan they would prefer to recommend to the given patients. One of the medical experts is the expert that created the solutions for the original case set. The expert did not know his plans were a part of the evaluation at the time. Following are tables with the individual rankings from the medical experts.

The first medical expert is the one that created the expert solution. The rankings created by ME#1 is seen in Table 4.2. The expert solution is ranked as the preferred solution most

	No-Adapt	Ex-over	Rules	Expert
Patient 1	3	**1**	4	2
Patient 2	3	**1**	2	4
Patient 3	3	2	3	**1**
Patient 4	3	3	2	**1**
Patient 5	2	2	4	**1**
Patient 6	3	2	**1**	4
Patient 7	**1**	4	2	3
Patient 8	2	**1**	4	3
Patient 9	3	2	4	**1**
Average Rank	2.56	**2**	2.89	2.22

Table 4.2: Ranking done by ME#1. The best ranked plan is marked in bold. Some of the plans are rated as equals by the expert, thus having the same rank. E.g., for patient 2 the no-adapt and rules are both ranked as the second best plans.

	No-Adapt	Ex-over	Rules	Expert
Patient 1	3	2	**1**	4
Patient 2	**1**	2	3	4
Patient 3	4	2	3	**1**
Patient 4	4	3	2	**1**
Patient 5	**1**	**1**	4	3
Patient 6	3	**1**	2	4
Patient 7	2	3	**1**	3
Patient 8	3	2	**1**	4
Patient 9	3	2	4	**1**
Average Rank	2.67	**2**	2.33	2.78

Table 4.3: Ranking done by ME#2

often, being the preferred plan for patient 3, patient 4, patient 5, and patient 9. This coheres with the fact that these are the solutions the expert created as optimal at an earlier stage. Nevertheless, on average, the ex-over is ranked as more optimal than the expert solution with an average rank of 2 compared to 2.22 for the expert. Ex-over also creates the preferred generated solution more often than both no-adaptation and adaptation rules, where ex-over is preferred for three patients and the two other methods are preferred one time each. Adaptation rules create the solutions that according to ME#1 on average are least likely to be recommended, and that are optimal the fewest times(shared with no-adaptation).

The rankings from ME#2 is seen in Table 4.3. Here the plan to be most likely rec-

	No-Adapt	Ex-over	Rules	Expert
Patient 1	4	**1**	2	3
Patient 2	4	3	2	**1**
Patient 3	4	3	2	**1**
Patient 4	**1**	4	3	2
Patient 5	2	4	3	**1**
Patient 6	2	4	3	**1**
Patient 7	4	**1**	3	2
Patient 8	3	**1**	2	4
Patient 9	4	2	3	**1**
Average Rank	3.11	2.56	2.56	**1.78**

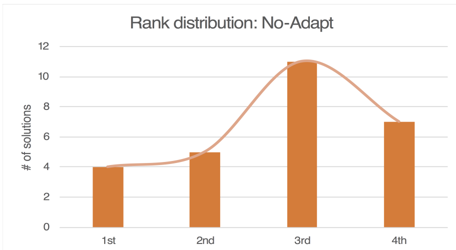
Table 4.4: Ranking done by ME#3

ommended is almost equally shared between the four presented plans, where ex-over and no-adaptation is preferred two times each, and adaptation rules and the expert solution are preferred three times each. ME#2 agreed with ME#1 by ranking ex-over as the best method on average, both giving ex-over the average rank 2. Both of the adaptation methods ranks better than no-adaptation, with no-adaptation having an average rank of 2.67 and the two generated solution scoring 2.33 and 2. The most surprising result here is that the expert solution is ranked on average as the worst solution, scoring 2.87 on average.

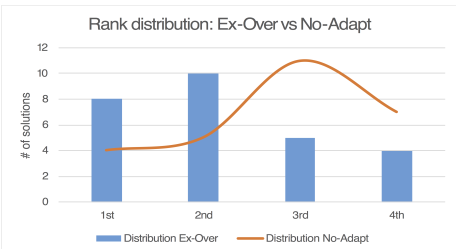
For ME#3 both adaptation methods scored the same average rank, with 2.56 as seen in Table 4.4. Ex-over is preferred as the best choice out of the generated solutions more often, being preferred three times. Still it is also ranked as the least preferable solution more often, also ending up last three times. The adaptation methods score better than no-adaptation on average, as no-adaptation only ends up at 3.11 on average rank. The expert solutions are the clearly preferred plans by ME#3, with 1.78 as the average rank.

All of the experts ranked the adaptation method ex-over as better than no-adaptation. For two of the experts, ex-over outperformed the expert solution on average as well. The rules were deemed as better ranked solutions than no-adaptation for two of the experts. These results are summarized in the average ranking for all three experts. Ex-over presents the most preferred solutions based on the average, with an average rank of 2.19. The expert solution follows with an average of 2.26, while the rules are third with the average rank 2.59. No-adaptation creates the least preferred plans on average, with 2.78.

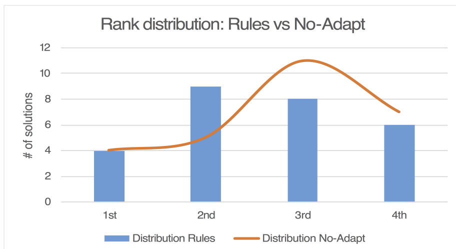
Figure 4.2a shows the distribution of how no-adapt ranked, and it is used as baseline to see how well the adaptation methods ranks. Figure 4.2b and 4.2c shows the distribution of the ranking of ex-over and adaptation rules compared to no-adaptation. The figures clearly shows that ex-over is ranked as the best or second best a lot more often than no-adaptation, being best or second best 18 times, whereas no-adaptation is best or second best only nine times. For the adaptation rules the difference is slightly less prominent, as both are preferred as the best solution four times. The ranking of the adaptation rules are higher than no-adaptation still, as solutions by adaptation rules are preferred as second best more times than no-adaptation, and ranked less times as the third and forth choice.



(a) Distribution of ranking for no-adapt



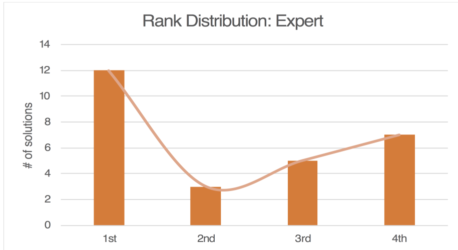
(b) Distribution of ranking for ex-over compared to no-adapt



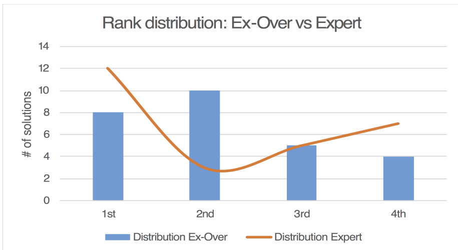
(c) Distribution of ranking for rules compared to no-adapt

Figure 4.2: Rank distributions compared to no-adaptation

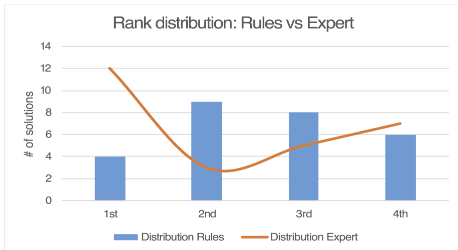
Figure 4.3a shows the distribution of how the expert solutions are ranked, and they are used as baseline to see if the generated methods have practical potential. Figure 4.3b and 4.3c shows the distribution of the ranking of ex-over and adaptation rules compared to the expert solutions. For both of the methods the expert solution is preferred considerably more often. Nevertheless, for the ex-over, the method is ranked as best or second best more often than the expert solution. Adaptation rules is preferred as best fewer times than the expert solution, although it is also ranked last fewer times than the solution created by



(a) Distribution of ranking for expert solutions



(b) Distribution of ranking for ex-over compared to expert solutions



(c) Distribution of ranking for rules compared to expert solutions

Figure 4.3: Rank distributions compared to expert solutions

the expert.

Quality Scores

The quality scores are on the scale 1-5, where 1 is the best score. An explanation of the scores is given earlier, in section 4.2.1. The solutions were scored by ME#1 and M#2. ME#3 found it hard to separate the quality of the plans, and therefore decided to give them all the score 3. These scores are taken out of the presentation of results as they do not provide any value in the evaluation of the different plans.

The quality scores from ME#1 are shown in Table 4.5. All of the suggested solutions score in the interval between ”2 - Good plan” - ”3 - OK plan” on average, which suggest all plans are acceptable for the patient. The solutions created by no-adaptation and ex-over never scores lower than three, which suggests all plans for these methods are acceptable plans. It is interesting that the expert deems the expert solution for patient 2 as a ”4 - Poor plan”, seeing it is ME#1 that created this plan two months prior to this evaluation, and at that time believed it was the optimal plan. This suggests that it is hard for an expert to

	No-Adapt	Ex-Over	Rules	Expert
Patient 1	3	**1**	3	2
Patient 2	3	**2**	**2**	4
Patient 3	2	2	2	2
Patient 4	3	3	2	**1**
Patient 5	2	2	4	**1**
Patient 6	2	2	**1**	3
Patient 7	**1**	3	**1**	2
Patient 8	**2**	**2**	3	**2**
Patient 9	3	2	4	**1**
Average Quality	2.33	2.11	2.44	**2**

Table 4.5: Quality scores given by ME#1

create the optimal solution. The expert solution scores overall best with an average of the quality being ”2 - Good Plan” according to ME#1. Out of the generated solutions, it is the ex-over that has the best average quality score with 2.11.

	No-Adapt	Ex-Over	Rules	Expert
Patient 1	3	**2**	**2**	4
Patient 2	**2**	3	3	5
Patient 3	4	3	4	**2**
Patient 4	4	4	3	**2**
Patient 5	**3**	**3**	4	**3**
Patient 6	**2**	**2**	**2**	4
Patient 7	**2**	4	**2**	4
Patient 8	**3**	**3**	**3**	4
Patient 9	4	2	4	**1**
Average Quality	3	**2.89**	3	3.22

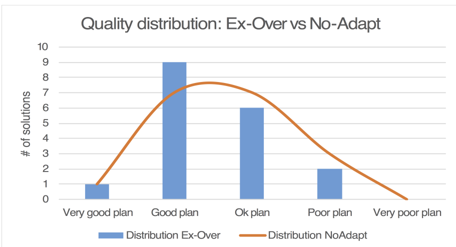
Table 4.6: Quality scores given by ME#2

For ME#2 the quality scores are shown in Table 4.6. The plans gets an average slightly lower quality score from ME#2 than ME#1, with all scores being close to ”3 - OK plan”. The expert solution is the only one that is scored as ”1 - Very good plan” for patient 9, but on the other hand it is also the only one that got the score ”5 - Very poor plan” for patient 2. The expert solutions are also, with the average score 3.22, the solutions with the lowest quality. Ex-over is deemed as the method with the highest quality overall with 2.89, while the rules and no-adaptation score the same average quality of ”3 - OK plan”.

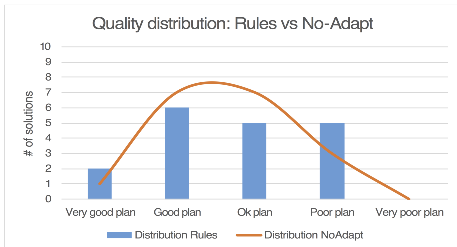
On average for both experts, all methods are in the range between ”2 - Good plan” and

"3 - OK plan". Ex-over has the highest quality score with 2.5 as average between the two experts, being exactly in the middle of a good plan and OK plan. Expert solutions follow as the second best with an average quality score of 2.61, followed by no-adapt with 2.67. Last comes adaptation rules with 2.72 as the average quality score.

(a) Distribution of quality for no-adaptation



(b) Distribution of quality for ex-over compared to no-adaptation



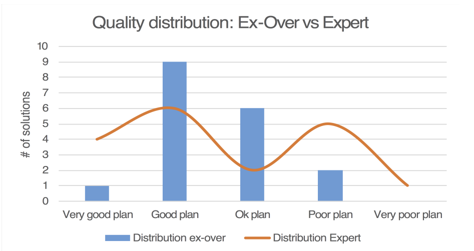
(c) Distribution of quality for rules compared to no-adaptation

Figure 4.4: Distribution of quality compared to no-adaptation

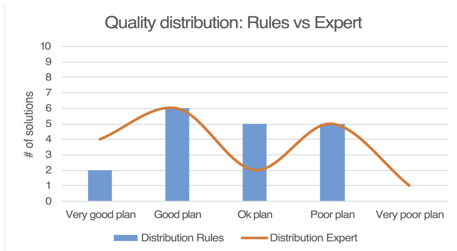
Figure 4.4 shows the distribution of scores for ex-over and adaptation rules compared to no-adaptation. Ex-over scores overall higher than no-adaptation on the good scores (1 and 2), and have fewer scores of the less good values. Adaptation rules have a higher amount of the best score, but also a higher amount of the poor plans. None of the methods have created a plan that got the worst score, a very poor plan.

Figure 4.5 shows the distribution of quality for ex-over and no-adaptation compared to the expert solutions. In comparison with the expert solutions, both of the adaptation techniques created have a lot fewer plans that receives the score of "1 - Very good plan". For the plans created by adaptation rules there are a lot more that score as "3 - OK plan". For ex-over the number of plans that score "2 - Good plan" and "3 - OK plan" increase, and the amount of plans with the score "4 - Poor plan" decreases. It is interesting that the only

(a) Distribution of quality for expert solutions



(b) Distribution of quality for ex-over compared to expert solutions



(c) Distribution of quality for rules compared to expert solutions

Figure 4.5: Distribution of quality compared to expert solutions

plan which received the score ”5 - Very poor plan” is created by the medical expert. This score was given by ME#2, which did not create the plans. However, ME#1 that created the plans rated it as a ”4 - Poor plan”. This suggests, as mentioned before, that the plans are hard to create even for experts of the domain.

Chapter 5

Discussion

This chapter will discuss the results from the experiments. In the first experiment, the expert solution was seen as the baseline for a good solution. For the second experiment, medical experts evaluated the created solutions. The expert solution used as the baseline for the first experiment was evaluated as well in the second experiment to check the validity of results from the first experiment, and to see how well generated solutions works compared to expert solutions to find out if they are applicable in real life.

5.1 Solution Variety

The first experiment focused on the increase of solution variety in the case base, targeting the cold-start problem. The cold-start problem is as mentioned when the low amount of cases in the case base makes it hard to create a good recommendation for a new user, and it is a common problem in recommendation systems. The cold-start problem was not originally a part of this thesis but had to be added because of the low amount of cases available for the experiments. For the experiments done in this work, nine cases were used. This is due to the fact that the thesis is a part of the SELFBACK project, and therefore uses the cases collected from that project. At the time of experiments for this thesis, the project had not collected more cases, thus resulting in the nine cases being used. The introduction of more solution variety in the case base will help to reduce the impacts from the cold-start problem by offering more personalized plans. Because the plans should be more personalized, it is important to check the quality of the solutions. If the solution variety is increased, but without creating valid solutions, the case base lacks quality, and the addition of more cases does not lead to the system being able to create good solutions for new cases. The solution variety is constant with no-adaptation. The number of solutions will always be equal to, or less than the number of cases in the case base with this method. The reason for this is that the solutions are simply retrieved from the case base, and no changes are made. For the SELFBACK project, the patients are supposed to increase level and repetitions in the exercises as they progress, and this will create some small variations of the solutions. However, the plans are still not as individualized as preferred. With ex-over there is a satisfactory increase in solution variety. The variety increases here as the new solution is a mix of the previous solutions. The mutation probability assures that the plans also adds some new exercise combinations that do not already exist in the case base. Nevertheless, the solution variety will converge after some time, due to finite variations of the exercises.

The quality of ex-over in the first experiment is assumed to be somewhat better than solutions created by no-adaptation. Because no-adaptation simply reuses one of the eight solutions in the case base, it does not give enough room for patients having different needs and baselines. The ex-over tries to accommodate these needs better and therefore mixes the solution from the two closest solutions. The created solutions do not differ a lot from each other, as shown in the textual example in table 4.1. They are built up this similar because all of the solutions created by the medical expert consisted of exercises for all the exercise types. The method used to score the quality of the solutions in the first experiment is not deemed as good enough to say something definitive about the solution quality. Firstly, it relies heavily on solutions created by only one medical expert, that has not been verified by other experts. Secondly, the similarity measures between the attributes are not tested to check if they represent the domain well enough. Due to this, another experiment on solution quality was performed.

5.2 Solution Quality

The evaluation of the quality of solutions was assessed by three different experts. Multiple experts were used to check if there was a general trend in preferred method among a group. The reason why it was exactly three was simply that these were recruited by the medical expert in the SELFBACK project. The experts were asked to do two types of scoring; to see both what method out of the four is preferred, but also what quality the solutions have in general. The quality is important because even though a method may be preferred, it does not verify that the solution is a good one, it may simply be the less unpleasant choice.

Ex-over got the best scores overall, both in terms of quality and ranking. Even though the plans created from this method is ranked worst in some cases, all the medical experts agree that this method ranks best out of the methods used in CBR. The expert solution is deemed as the preferred solution more often, but on average the ex-over method outperforms even the medical expert solution. This fact fits well together with the theory that GAs will create a sub-optimal solution, even though it is not always the best solution in a complex domain.

The exercise plans generated by adaptation rules ranked second worst on average. The reason for this can be explained by multiple factors. First of all the medical expert found it hard to formulate rules on the domain. The rules created were created after discussions with the medical expert, and then tried gathered into a set of rules. The method was tested on a couple of patient cases, and the results from these experiments were accepted by the medical expert. This approval led to no alternation of the method before testing all of the methods. The method could have been tested more explicitly to assure the rules worked as they should, as the results of the method are the worst. The results still fit together with the theory that a complex domain leads to the difficulty of creating explicit rules for the expert. However, these results do not verify that adaptation rules as a method that does not work on the domain, simply that the adaptation rules created at this time are not feasible. With more work invested in the creation of rules, the results could be different.

Both of the applied adaptation methods ranks better than no-adaptation on average according to all three medical experts. ME#3 is the only one that preferred no-adaptation more times than adaptation rules, but the average rank for adaptation rules was still higher.

ME#1 preferred solutions created by no-adaptation and adaptation rules the same amount of times, but on average ranked adaptation rules worse than no-adaptation. In general, the rankings are quite similar, because of the similarity of the created plans.

The expert solutions are scored as the solutions with the worst quality by ME#2. It is hard to answer why this is, but one idea could be that personal preference is of importance. Another reason could be that the experts have different experience with the creation of these plans. In addition, the guidelines for the creation of exercise plans are fuzzy and hard to derive definitive knowledge from.

None of the generated solutions were deemed as a very poor plan, only one of the expert solutions got this score. This can be explained by the fact that in the general guidelines the main advise is to be active; thus activity in general is never seen as very bad. Overall the medical experts indicated that they were satisfied with all system generated solutions.

5.3 Challenges with Evaluation

The evaluation method used in the first experiment gave some indications on quality. Still, more tests were desirable to substantiate the findings further. The challenge in the first experiment was mainly the problem with scoring the quality of the plans. The method put all trust into the solutions created by one medical expert. In the second evaluation method, several medical experts were consulted, thus removing the weakest point from the first experiment.

When creating an exercise plan there are multiple solutions that could be acceptable, and this is one of the challenges with the evaluation. This is shown where one of the medical experts actually deemed the expert solutions as the worst plans in terms of quality, and the expert who created the plans gave them the highest quality score out of the four methods. The expert who created the expert solution also rated one of his own plans as a ”poor plan”, which two months earlier was created as the optimal plan for the patient. The chosen evaluation method reduces this risk by consulting more experts, to show a general trend among experts.

All of the plans created fitted the patient in some way, as they were all similar. One of the medical experts ended up not scoring the quality of the plans, as he had a hard time separating the plans and thought they were all acceptable for the patient. The methods might have performed differently if the solutions were of larger variety. However, this would make it harder for the expert to understand the solution space, possibly resulting in a new evaluation method to be used. When confronting one of the medical experts with the results, he said that the results illustrate well that there is not a consensus on how a good exercise plan should be created. He also pointed out that in a clinical setting the medical experts would have more information about the patient than what is covered by the questionnaires, thus resulting in better exercise plans.

The evaluation methods chosen were seen as the best fitting to evaluate the created proof of concept. However, to verify that the created solutions work in real life, the solutions would need to be tested on patients to track their progression.

5.4 Main Goal and Research Questions

The findings from the SLR and the experiments are used to answer the research questions and main goal of this thesis. The main goal was to find out *how adaptation can be applied in* SELFBACK *to improve the creation of personalized exercise plans, and if an addition of an adaptation phase to the* SELFBACK *project will help to improve the quality of created exercise plans further*. The research questions are answered first to help answer the main goal.

RQ1 What are the possible adaptation techniques to apply? There are multiple adaptation techniques that could be applied to the domain. In this thesis, two adaptation techniques were applied. The ex-over is inspired by a GA, that in theory should work well on complex domains. The adaptation rules are supposed to work better on more straight forward domains. The domain here is complex, and the experts had a hard time creating rules based on fuzzy guidelines.

The theory fits with the results presented in this thesis, however, the results could be affected by the fact that the rules have room for improvement. Other adaptation techniques explored in the SLR that may be to applied to this domain includes adaptation rule learning. To create rules was a hard task for an expert, but in adaptation rule learning the case base is analyzed, and from this rules are learned. The technique could be interesting for this domain, but it would need a lot more cases to analyze than the nine used in this thesis. Generalized cases is also a technique that could be applied to the domain. This is something that the medical expert also mentioned as an interesting approach, because patients with the same set of characteristics fits the same type of solution.

RQ2 What solutions do other medical applications apply? CBR in medical solutions is widely used, and presents solutions to many different areas in medicine. Prognosis, treatment planning, diagnosis, and prescription of medicines are some of the solutions that were found in the SLR. This thesis works with treatment planning, which is a type of solution where it is hard to say something about how good a plan is. Treatment planning is dependent on information about the progression of a patient to verify the quality of a plan, and even with this information there is no guarantee the patient could not progress faster.

RQ3 How to apply different adaptations techniques to the given domain? The applications of adaptation techniques to the given domain were in this thesis dependent on input from an expert. It is possible to create adaptation techniques without the input from an expert, but this would demand a larger case base. The methods implemented in this work is explained in detail in chapter 3. The process started with exploring the technique and then asking the expert for information on the parts that needed expert input. The solutions created by the method were sent to the expert to verify that they met the guidelines for LBP patients.

RQ4 How well do the applied adaptation techniques perform compared to no-adaptation? The result shows that the applied adaptation techniques outperform no-adaptation both in terms of quality and ranking. Ex-over is the applied adaptation method that performs best in this work, but this does not mean that adaptation rules should be disregarded. As mentioned, adaptation rules can always be improved, and could be further developed to create better solutions. A more tested modeling of the similarity measures could also affect the adaptation, as these decides what solutions are retrieved. With other similarity measures, all generated solutions would have been affected, possibly ending in another result.

The answers of the research questions helps answer the main goal of the thesis. The results from the created proof-of-concept do suggest that the addition of an adaptation phase to SELFBACK will further improve the quality of exercise plans. The results from the first experiments show that the solutions created by ex-over copes better with the cold start problem since it creates a variation of solutions that are of good quality. The results from the second experiment strengthen the evidence that the created solutions are of good quality, and both approaches including adaptation are preferred to no-adaptation. Further experimenting and developing of the methods is necessary to conclude, but the results are positive.

Chapter 6

Conclusion and Future Work

This thesis has explored different adaptation techniques in CBR, and the use of CBR in medicine. Two different adaptation methods have been applied to the SELFBACK project, to try and improve the creation of exercise plans for people with non-specific LBP. More personalized exercise plans may result in the patient progressing faster and create more motivation for the patient.

6.1 Conclusion

The results suggest that adaptation improves the quality of generated exercise plans in the SELFBACK project. Both adaptation methods score higher than no-adaptation in the evaluation, and they improve solution variety. The best method in this work is ex-over, with even outperforming the solutions created by the medical expert. The results suggest that the created adaptation rules do not raise the quality of plans a lot compared to no-adaptation, but they could be further improved to possibly create a larger gain. The results show that medical experts disagree on what an optimal plan is, but that there is a trend in the exercise plans they preferred.

The created methods could be applied to other areas. Within SELFBACK the ex-over approach can be used for recommending behavioral change or educational sessions. More generally, ex-over could fit applications where some degree of creativity is possible with user feedback available. This could, for example, be exercises for other rehabilitation programs, product recommendations, or meal planning. The adaptation rules could be applied to areas where a set of attributes will change the levels in a solution in a symmetrical manner, e.g., exercises for other rehabilitation programs.

6.2 Future Work

For future work, the adaptation rules could be improved with more refining and testing to capture the medical knowledge better. The similarity measures also have room for further testing, which will affect all generated solutions as this directly affect the retrieval. Additional adaptation processes could also be explored and tried implemented to the domain. Generalized cases was an approach one of the medical experts found interesting, and that is thought to fit the domain well.

To further personalize the exercise plans, input from the patient is necessary. In order to incorporate direct feedback from patients, a web-application could be provided where they can rate the generated exercise lists. From this information, the solutions could give the patient exercises that are preferred, and remove the exercises that the patient do not like. Feedback on the progression of the patient could also be collected, to change the exercise difficulty as the patient progresses. Feedback on the progression and change in pain levels should be collected to be able to evaluate how the created solutions work in real life. The progression information could also be incorporated in the ex-over to create a better fitness function, thus creating better results.

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Appendices

6.3 Appendix A

Appendix A is the paper accepted in the main track of ICCBR2017.

Evolutionary Inspired Adaptation of Exercise Plans for Increasing Solution Variety

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Abstract. An initial case base population naturally lacks diversity of solutions. In order to overcome this cold-start problem, we present how genetic algorithms (GA) can be applied. The work presented in this paper is part of the selfBACK EU project and describes a case-based recommendation system that creates exercise plans for patients with non-specific low back pain (LBP). In selfBACK Case-Based Reasoning (CBR) is used as its main methodology for generating patient-specific advice for managing non-specific LBP. The sub-module of selfBACK presented in this work focuses on the adaptation process of exercise plans: A GA inspired method is created to increase the variation of personalized exercise plans, which today are crafted by medical professionals. Experiments are conducted using real patients' characteristics with expert-crafted solutions and automatically generated solutions. In the evaluation we compare the quality of the GA-generated solutions to null-adaptation solutions.

Keywords: Case-Based Reasoning, Similarity Assessment, Adaptation, Genetic Algorithm, Cold start problem

1 Introduction

Up to 80% in the adult population of Norway will experience low back pain during their lifetime, and a study showed that 50% of them had experienced pain during the last 12 months [18]. About 85% of these will experience non-specific low back pain, i.e., pain without a known pathomechanism [6]. As an example, back pain is the largest single cause of sickness leave in Norway, and it costs about 2% of the gross domestic product. Even though the amount of research in the area has increased, as well as the access to treatment and less physically demanding work, the costs have significantly increased over the last 30 years. General physical activity along with specific strength and stretching exercises constitute the core components in the prevention and management of non-specific low back pain.

CBR has been used in the domain of health science for a long time, because its method of using past experiences to solve a new problem lies very close to how clinical medicine is performed by specialists today. It is also a field where one often have the advantage of already having a collection of past cases to use when reviewing a new problem. The use of CBR in health sciences has proven to be so popular that over the past 10 years it has become a specialized sub-area within CBR research and application. There exist CBR-systems that are used commercially in the field of medicine, but it has still not become as successful here, in terms of successfully deployed applications, as in many other domains [5], [9].

The selfBACK project aims at creating a self-management tool for patients with non-specific low back pain, which will support them to self-manage their pain by obtaining personalized advice and continuous follow-up. After an initial screening of the patient using questionnaires, the patient gets access to a wearable and a smart phone app that is the interface to the decision support system. The wearable will be used to track activities and obtain objective measurements while the smart phone app displays feedback, shows progress in achieving the patient's goals, and obtains regular follow-up on pain, function and self-efficacy development. This includes for example whether the pain level decreases, the functionality increases and coping with pain improves. Figure 1 gives an overview of the architecture. A more thorough description of the CBR approach in selfBACK is given in [2]. This work focuses on how an adaptation phase can further improve the creation of exercise plans.

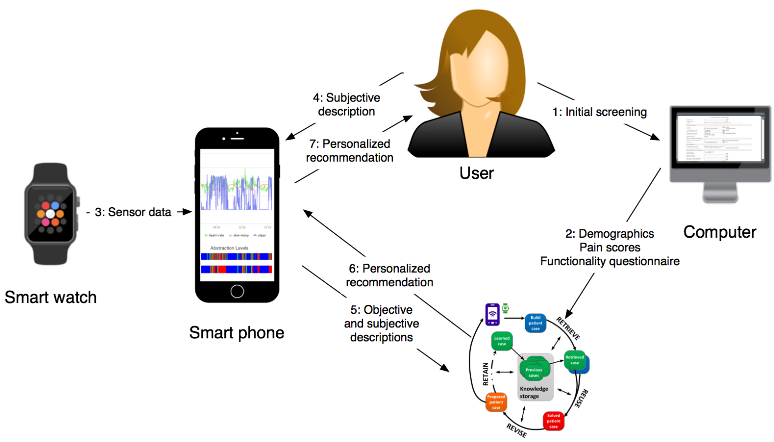

Fig. 1. The overall selfBACK architecture

1.1 Background

The adaptation part of CBR is one of most challenging issues for CBR systems in general as well as in the health sciences, where it has traditionally been carried out manually by experts of the domain. In recent years, however, the problem has been more focused. Several systems explore different approaches to automatic and semiautomatic adaptation strategies [4]. It has also been argued that the adding of adaptation is what makes the CBR system an artificial intelligence method, and that without it it can be seen as a simple pattern matcher [12]. The challenge with the adaptation phase is that it is hard to find a general strategy for case adaptation, and therefore the adaptation techniques generated are often domain specific. Adaptation is a challenge not only in the medical domain, but it is usually more complex here because cases often consist of a large number of features [22]. The reason for doing adaptation is because usually you can't reuse solutions of cases directly when you have a new case [8].

One of the reasons for the focus on adaptation in the work reported here is to deal with the cold-start problem in the beginning of the deployment of a CBR system. The cold-start problem describes the situation where the amount of cases is too low to create a good solution to the new problem [14]. Or, alternatively, if you want to introduce some variations of the solution to make a system more personalized or adaptive.

Retrieval-only Adaptation is not always necessary, and it is seen as a big challenge when creating a CBR system. Due to this, some authors skip the adaptation phase, referred to as retrieval-only. It can be justified by the fact that it is too complicated or even impossible to acquire adaptation knowledge in the given domain. Systems that are retrieval-only may just reuse the solution of the case that is closest to the problem case, or present the information of the most similar cases to the user. Some also point out important differences between the current case and similar cases. The system may present the most important information to an expert of the system, while the experts then manually will create the new solution for the current patient. This has been successfully used in systems in the field of image interpretation and organ function courses [22].

Another way to avoid the adaptation problem is to combine CBR retrieval with other reasoning methodologies [19]. The interest in these multi-modal approaches that involve CBR is increasing in different areas, including the medical domain. They can be combined in the same application, one reasoning process can be used to support the other, or the system can switch between the different reasoning processes. Rule Based Reasoning as well as reasoning form extended probabilistic and multi-relational models may be combined with CBR. A straight-forward combination is that rules and cases cooperate such that rules deal with reasonably standard or typical problems, while CBR faces exceptions, but they can be integrated in other ways [22]. Another example is to use rules or other generalized models an explanatory support to the case process [16].

Genetic algorithms Genetic Algorithms (GA) are adaptive heuristic search algorithms that are based on the natural process of evolution, known as the survival of the fittest. Systems that use GA are modeled loosely on the principles of evolution via natural selection through variation-inducing operators such as mutation and crossover. To have success you have to have a meaningful fitness evaluation and an effective GA representation. One reason to use this method is that it is capable of discovering good solutions in search spaces that are large, complex or poorly understood, where the domain knowledge is limited or the expert knowledge is difficult to encode in rules or other models. The use of GA may not find the optimal solution, but it usually comes up with a partially optimal solution [13].

1.2 Related Work

GAs have already been combined with CBR to optimise case retrieval, clean up case memory and create new and unique cases. They have also been used in the adaptation step, to achieve an adaptation technique that is not domain specific [12]. One of the most well known approaches for applying evolutionary algorithms to case adaptation is [11], in which the incremental evolution of solution candidates creates novel solutions. While this approach is general and knowledge independent, the work we are presenting in this paper includes domain knowledge from the case representation for guiding the evolution process.

Case-based reasoning is used in several health systems today, within a lot of different areas such as clinical diagnosis and treatment in psychiatry [21]. It has become a recognized and well-established method for the health sciences, and since the domain of health sciences is offering a variety of complex tasks which are hard to solve with other methods and approaches, it drives the CBR research forward. Since CBR is a reasoning process that works similarly to the reasoning of a clinician, with the use of previous experiences to solve the same or similar cases, it has become medically accepted and is also getting increased attention from the medical domain [4]. There are several advantages of using CBR in the medical domain, one is that with the use of CBR it is possible to find solutions to problems even though the complete understanding of the domain is not captured, or if the domain is very complex. The reuse of earlier solutions saves time since it is not necessary to solve every problem from scratch, and it allows learning from mistakes. The fact that cases hold a lot of information makes it usable for a number of different problem-solving purposes, compared to rules that can only be used for the purpose they were designed for [21].

Looking into previous work, we will now focus on relating our approach to existing CBR applications in the medical field and later on discuss how genetic algorithms come into play.

CASEY [17] is one of the earliest medical decision support systems that applied CBR, and it deals with heart failure diagnosis. It first retrieves similar cases, then looks at the differences between the current case and the similar case. If the differences are not too important it transfers the diagnosis of the similar case to the current one, and if the differences are too large it attempts to explain and modify the diagnosis. It falls back on a probabilistic network type of domain model if this does not work, or if no similar case can be retrieved.

Protos [3] is another well-known early medical CBR system. It addressed the problem of concpet learning and classification in weak-theory domains, such as medicine. It combined cases with a multi-relational network model used to explain case matching if features were syntactically different bu semantically related. Its domain was hearing disorders, and in the final testing it performed very well compared to clinical audiologists.

Another system that uses CBR deals with anterior cruciate ligament (ACL) injury [23], and it combines fuzzy logic with CBR. The system is not intended to interact directly with the user, but with experts such as sport trainers, coaches, and clinicians for multiple purposes in context of the ACL injury such as monitoring progress after an injury and predicting performance. It uses body-mounted wireless sensors to retrieve the input data for the case, while the solution part consists of recovery classification, treatment at different stages, as well as performance evaluation and prognosis. All the information is stored in the knowledge base with a profile of the patient and information about the recovery sessions.

One of the top fatal diseases in the world is cancer, and as part of their cancer treatment patients get diets to reduce the side-effects of the treatment, as well as making sure they get sufficient nutrition to boost the recovery cycle. This personalized diet recommendation system for cancer patients [13] makes use of the data mining techniques of CBR, and combines them with rule-based reasoning and a genetic algorithm. The CBR part of the system retrieves a set of diet plans from the case base, while the rule-based reasoning is used on this set to do further filtering of irrelevant cases. Then the genetic algorithm is used for the adaptation phase to make sure each diet menu is customized according to the patient's personal health condition. The solution part of this system consists of a menu recommendation that suggest dishes for the patient, as well as a list of specific nutritional values to be taken daily.

Radiotherapy treatment tries to destroy tumour cells with radiation, and radiotherapy treatment planning tries to make sure the radiation dose is sufficient to destroy the cells without damaging healthy organs in the tumour-surrounding area. The normal process of creating a solution to this problem can take everything from 2-3 hours to a few days, which makes it time-consuming, and it includes a group of experts in the area that you are dependent on. The Radiotherapy treatment planning CBR-system [21] was created to attempt to make the process faster and without the need to have several experts involved. The case base in the created system consists of cases made out of brain cancer patient descriptions as well as the plan used for the treatment. The treatment, i.e. the solution part, consists of the number of beams applied to the tumour and the angles of those beams. The system creates a new solution for the patient based on earlier patient cases and their treatment plans.

2 Case representation

The case representation is based on the SELFBACK questionnaire, as this creates the basis for the data used in the experiments. The questionnaire describes the characteristics of a patient with non-specific low back pain. It covers areas such as the pain level, their quality of life despite the pain, functionality, coping capabilities and their physical activity level.

From the overall characteristics three different types of advice will be generated to support self-management:

- Goals for physical activity: number of steps/day, maximum of inactive periods during hours the patient is awake
- Education: Tailored list of educational exercises that support and reassure the patient in his/her self-management.
- Exercise: A customized list of exercises that combine clinical guidelines for low back pain with past cases into action items.

In the following, we will focus on the generation of exercise lists based on given cases. Therefore our case representation consists of two different concepts, the patient characteristics and the list of exercises at a given time. The patient characteristics are taken as problem description and the exercise are describing the solution part. These two different concepts are explained in further detail in section 2.1 and 2.2.

2.1 Patient concept

The patient concept consists of 44 attributes that describe different aspects of the patient's health. These attributes can be divided into different groups of information collected by 1) the SELFBACK questionnaire, 2) a physical activity detecting wristband worn by the patient, and 3) an interaction module in the SELFBACK app. The attributes collected by the questionnaire are a combination of important prognostic factors and outcome measures. Pain self-efficacy and beliefs about back pain have been shown to have great impact on the future course of low back pain [15]. Likewise, baseline pain and pain-related disability have strong influence on the course of low back pain but these attributes are also important outcome measures [7]. Quality of life at baseline may also influence the course of low back pain but this is mainly considered an important outcome measure [10]. An example of a patient concept can be seen in figure 2. The patient data in this case is made up, as data from real patients are confidential.

Demographics With a new patient it is necessary to know some simple demographics, such as height, weight, age and gender. These are the basis for each patient, and are all quite easy attributes to measure. All of these attributes may influence the solution, as all attributes can be an indication of how well a patient is able to perform and follow-up on a particular exercise plan. Young people are usually stronger and more fit than older people, men are in general stronger than women, and younger people are usually able to carry out more intense physical activity or exercises than older people. Obese people may need to focus on other exercises than normal weight people.

Quality of life The impact of low back pain on quality of life is another important measure of the severity and consequences of the back pain. As an additional measure, the patient also provides a score in his/her own health from 0 (worst) to 100 (best).

Pain self-efficacy and beliefs about back pain Scoring of pain self-efficacy indicates if the patient is confident that he/she can do various activities regardless of the pain and is therefore an important measure of how the patient copes with the pain. A related measure is fear-avoidance beliefs, i.e., to what extent the patient believes that physical activity will be harmful and exacerbate the back pain.

Physical activity and exercise Information about general physical activity is assessed by the selfBACK questionnaire and the physical activity detecting wristband. The attributes assessed by the questionnaire include work characteristics (i.e., physical work demands), physical activity limitations in everyday activities (work and/or leisure) due to back pain, and level of leisure time physical activity. Physical activity information that can be derived from the wristband data includes several attributes, such as step count (including intensity [i.e., step frequency] during walking/running), and distribution of active and inactive periods during wake time. The interaction module in the selfBACK app will ask the patient about accomplishment and adherence to the exercises prescribed in the self-management plan as well as a rating of whether the patient perceived the prescribed exercises as useful and enjoyable. All these attributes will say something about how active the patient is and the coping behaviour related to his/her low back pain.

Pain and pain-related disability Information about various aspects and characteristics of pain is relevant for the case, both because it can track progress and it provides an indication on how severe the case is. History of low back pain provides information about whether the patient has experienced similar problems before, if it is a recurrent problem, or if it is a long-lasting ('chronic') problem. Number of pain sites reported by the patient is important to assess musculoskeletal co-morbidity while the scoring of pain-related disability provide information about how the back pain influence function.

Exercise list To connect the two concepts, the patient has an attribute that is a list of all the exercises the patient has in his solution part. This consists of cases on the form of the exercise concept that is further described below.

2.2 Exercise concept

The exercise concept consists of four different attributes. An example of how the exercise concept looks like can be found in table 1 in the results section.

Description The descriptive name and type of the exercise. The type can be a strength, flexibility or pain-relief exercise. All patients are encouraged to perform strength and/or flexibility exercises each week, unless they are unable

Feature	Example
Gender	Male
Age	45
Height	1.89m
Weight	82
BMI	23
Quality of life (EQ5D)	90
Disability (RMDQ)	9
Pain (NPRS)	8
Work type	Mostly sitting
Self-Efficacy (PSFS) activity	Prolonged standing
Self-Efficacy (PSFS) Σ	8
FABQ Physical Activity	2
Pain medication	none
Pain history	none

Fig. 2. Patient example

because of strong pain. In general, strength and flexibility exercises are not recommended in the acute stage of a low back pain episode. By performing exercises regularly the patient will increase strength and improve flexibility, which over time will prevent relapse. In the acute stage or in case of a relapse, pain-relief exercises can be recommended to help the patient to relax and reduce the most intense pain. These exercises will mainly help to relieve acute pain but will have limited relevance when the patient is pain-free.

Level An exercise can have different levels. The strength exercises used in this project have up to six different levels, where each level is a new variation of an exercise that is more demanding than the former. The patient changes levels as he/she progresses, i.e., first by increasing the number of repetitions within a level before moving to the next level.

Repetitions Each exercise is performed in sets, with a given number of repetitions for each set. There are four levels of repetitions, 8,10, 12 and 15 repetitions respectively. When the patient is able to perform 12-15 repetitions per exercise the patient moves up a level in the exercise.

Set The set indicates the number of times the patient should perform the given repetitions for the exercise.

3 Experiments

In the experiments two different approaches are used, a no-adaptation and a genetic algorithm, to see how they compare in regard to solution variety as well as solution quality. Our hypothesis is that the GA inspired approach will produce better solution variety, but it will also have to produce solutions of good quality to be useful.

3.1 Case-set

The cases used for testing the algorithm are gathered from the selfBACK project, and consist of data from real patients who experience low back pain. A total of nine cases were created with an associated solution crafted by medical professionals.

3.2 No-adaptation

The first approach, and also one of the most used approaches, is the no-adaptation approach. This approach did not require any design choices as this solution was built out of the box from the myCBR workbench and an RestAPI for myCBR[3]. This approach is dependent on a comprehensive case base with a high case variation to be able to provide a good solution for all the different patients, as this does not evolve over time. The number of solutions will always be equal to or less than the number of cases you have, and this does not give enough room for patients having different needs and different baselines. In addition, this solution does not allow the patient to increase his or her level, nor the number of exercises or the frequency of the exercises.

3.3 Genetic Algorithm

A genetic algorithm was incorporated in the CBR cycle to perform an adaptation on the cases. The idea behind the genetic algorithm is to retrieve the two most fit cases, and combine them to create a new case. This approach is based on how nature evolves, and the assumption behind this approach is that the combination of the two best cases will give a satisfactory solution.

General algorithm structure A genetic algorithm consist of different parts. It has a fitness function, i.e. a function that helps you describe how good a given specimen is. It also has a crossover function, which creates a new solution based on the two fittest individuals. The algorithm is programmed to stop at a termination condition, where the new solution satisfies the given condition. In the genetic algorithm you also have a probability of a mutation to happen. This changes one of the attributes in the solution at random, to possibly create better solutions, and avoid getting stuck in local maxima.

Adapted algorithm The general structure of a genetic algorithm was adapted to fit the domain. The fitness function in the adapted algorithm is based on the similarity scores between the cases, and the two fittest individuals from the population are chosen by retrieving the two most similar cases to the new problem description from the case base. From these two cases we retrieve their solution, the exercise list, and we create a chromosome of the solutions that is used by the genetic algorithm. The chromosome is built up such that all exercises for the same muscle group are placed inside the same gene, as each gene represents a specific trait of an individual. An example of how this mapping is done can be seen in figure 3.

[3] https://github.com/kerstinbach/mycbr-rest-example

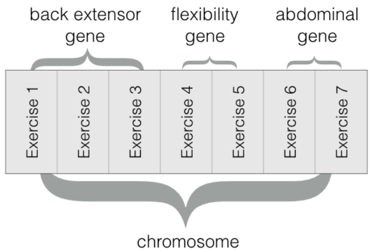

Fig. 3. The exercise list mapped to a GA chromosome

In figure 4 you see the description of the 4R cycle in this work with an adaptation example. Based on the patient description the two best matching cases are retrieved (C1 and C2). The two chromosomes representing the solution parts (S(C1) and S(C2)) are then sent to the crossover function. Here a new individual is created of the parent chromosomes, and it is done with a uniform crossover [24]. The mixing ratio is set to 0.5, since the solution is desired to have a close to equal mix of the parents' genes. The adapted algorithm finishes after one crossover at this moment as there exists no good measures to describe how well a patient will progress before they have executed the exercise plan. Measurements on progress will be added at later iterations, but in this work we only address the initial creation of plans.

The exercises also have a probability of 1,5% to have a mutation. These mutations are given some restrictions, such as that the type of exercise will be kept, but the level and the number of repetitions may alter by one level. The reason for such restrictions to the mutation is so that the algorithm should produce a solution that is feasible for the patient to fulfill and therefore not demotivating for the patient. Further the suggested solution should not be too easy and ensure the optimal progress for the patient.

3.4 Experimental Setup

Experiments were conducted in such a way that the solutions to the new problems created by the different approaches were compared to each other. Every unique solution was counted in order to check the increase in solution variety, and then the solution quality was checked. To define how good a solution is it was compared to the solution created by a medical professional. To be able to do this, the respective case to be tested was removed from the case base. The problem part of the case was fed as input to the system, and a new solution to the problem was generated. This solution, for both the no-adaptation and the GA systems, was in turn compared to the one that the medical expert had crafted. The comparison of the two solutions was done by using similarity measures to check how close the generated result was to the original solution. The

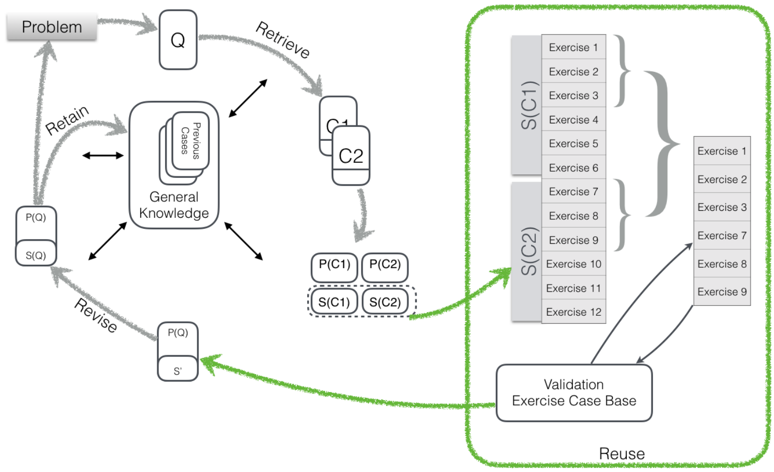

Fig. 4. Overview of the 4R cycle (based on [1]) including an adaption example of a result from a crossover between to chromosomes

no-adaptation method always creates the same solution, while the GA will return solutions that differ from each other. As a result of the fact that the GA will provide results with varied scores this approach was tested a total of five times to see how well it performed in terms of best case, worst case and average case.

3.5 Results

Regarding the cold-start problem the number of solutions in the case base will improve with the GA-approach, as hypothesized. In figure 5(a) the evolution of different solutions in the case base is presented. The number of different solutions of the no-adaptation method is, also as expected, staying constant, while for the GA the variation increases. It is expected that the GA-graph will converge with more iterations as the number of exercises to choose from is a finite number, as well as the specifications of level, repetitions and set. It still verifies that the GA-approach creates a greater solution variety when starting with a small case base.

While the GA clearly is a better solution for increasing solution variety, it only adds value to the user if the created solutions have an appropriate quality. To assure that the solutions are satisfactory they are compared to the ones created by the no-adaptation approach and the expert solutions. A textual example of the difference in results between the created solutions can be seen in table 1. Here none of the solutions created consists of exactly the same exercises. Some are the same on all three solutions, other exercises differ between the three solutions. The flexibility exercises recommended are for instance the same three variation of exercises in all three cases, while in the ”strong in mid-position” exercise we see that the solution from the expert and the GA match and that the retrieval only solution has another suggestion. If we look at the first exercise-type suggested we can see that the expert solution suggests two exercises while the two other only suggest one and the same exercise, and the suggested exercise is neither one of the one's suggested by the expert.

Exercise description	**Expert solution**	**GA solution**	**Retrieval only solution**
Strength exercises for the back extensors	*Level:* 4 *Repetitions:* 10 *Set:* 2 *Level:* 5 *Repetitions:* 10 *Set:* 2	*Level:* 6 *Repetitions:* 10 *Set:* 3	*Level:* 6 *Repetitions:* 10 *Set:* 3
Strength exercises for the gluts and back extensors	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 2 *Repetitions:* 10 *Set:* 3
Strength exercises for the abdominal muscles	*Level:* 4 *Repetitions:* 10 *Set:* 3	*Level:* 4 *Repetitions:* 10 *Set:* 3	*Level:* 4 *Repetitions:* 10 *Set:* 3
Strength exercises for the oblique abdominals and rotator muscle in the back	*Level:* 3 *Repetitions:* 10 *Set:* 3	*Level:* 3 *Repetitions:* 10 *Set:* 3	*Level:* 3 *Repetitions:* 10 *Set:* 3
Strength Strong in mid-position	*Level:* 1 *Repetitions:* 10 *Set:* 3	6 *Level:* 1 *Repetitions:* 10 *Set:* 3	*Level:* 2 *Repetitions:* 8 *Set:* 3
Flexibility	*Level:* 2 *Level:* 3 *Level:* 4	*Level:* 2 *Level:* 3 *Level:* 4	*Level:* 2 *Level:* 3 *Level:* 4

Table 1. Textual representation of different solutions: each solution has a level and most of them have the number of repetitions specified

The different suggested plans from both the no-adaptation and GA methods were scored against the exercise plan the medical expert created based on their similarity. Since the GA creates different solutions the results show how they scored in the best case, the worst case and the average case out of the five runs. The three different rankings are compared to the similarity scores for the no-adaptation result and can be seen in figures 5(b), (c) and (d). The results are sorted by the no-adaptation score as this will be similar in all figures, and therefore give a better impression of the differences between the measures. Both methods score quite well against the expert crafted solutions, which makes sense as all the solutions are built up with the same type of exercises. In the best case scenario for the GA it scores better or equal on eight out of nine cases which suggests that this method performs better than without any adaptation. The worst case scenario on the other hand gives another impression, and in this case only two cases are better on the GA approach while five actually give a worse solution with adaptation. The average case is still probably the best to look at to get a good impression on the performance of the two solutions. The average case shows that the GA performs better in five cases and worse in four. This makes the GA approach seem only somewhat better than without any adaptation, but it has another interesting trait to it. If you compare the similarity measures it shows that the solutions that scores higher with the GA have a larger benefit compared to no-adaptation, while the solutions that perform worse are quite close in scores. On average the solutions with the GA in fact score 4,8% better, which shows that in general the gain is larger with the use of this method.

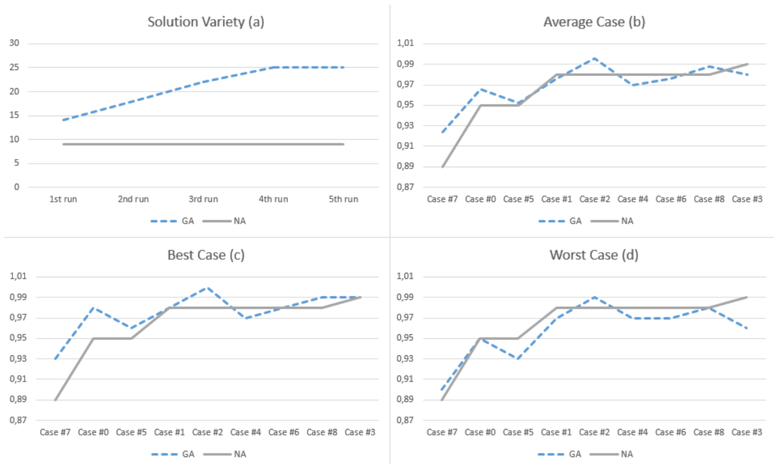

Fig. 5. The results from the experiments. Figure (a) shows the change in solution variety after testing nine different cases in five runs. The y-axis is the number of solutions created after each run. Figure (b), (c) and (d) show the quality of the exercise plans created in average case, best case and worst case respectively. Here the y-axis is the similarity score with an expert crafted solution.

4 Conclusion and Future Work

In this paper we have presented how to apply genetic algorithms for adapting cases in order to increase the solution variety, which might be necessary when deploying a new CBR system.

The results from the experiments show that the solutions created by the genetic algorithm copes better with the cold start problem since it creates a variation of solutions that are of good quality. With information obtained during the follow-up periods within the selfBACK project, we will gather more information on user preferences and outcomes in terms of pain and function.

This information will then allow us to create a better fitness function to further improve the results.

Within SELFBACK this approach can be used for recommending behavioural change or educational sessions. More generally, the approach could fit applications where some degree of creativity is possible with user feedback available. This could, for example, be exercises for other rehabilitation programs, product recommendations, or meal planning.

In our further research, additional adaptation processes will be explored. First we would like to include adaptation rules based on clinical guidelines in order to see how they compare with the genetic algorithm. As part of our CBR research more generally, we have a focus on combining CBR with general domain models beyond rules, most recently by incorporating graphical models in the form of Bayesian networks [20]. This is a line of research that will extend our work on case adaption as well as other CBR processes within the selfBACK architecture. As a further study we also plan to extend the method presented here to become not only GA-inspired, but more GA-like, as mentioned in section 3.3. In order to incorporate direct feedback from patients, we plan to provide them with a web-application where they can rate the generated exercise lists.

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6.4 Appendix B

Appendix B includes the presentation of exercises used in the SELFBACK project.

selfBACK

Back exercises

Paul Jarle Mork

This project has received funding from the European Union Horizon 2020 research and innovation programme under grant agreement No 689043

Strength exercises for the back extensors

Level 1. Leg lift

Level 2. Arm lift

Level 3. Diagonal leg and arm lift

Level 4. Bird exercise – leg lift

Level 5. Bird exercise – arm lift

Level 6. Bird exercise - diagonal leg and arm lift

Strength exercises for the gluts and back extensors

Level 1. Bridging
- Imagine lifting one vertebra at a time. Keep a straight line from your shoulders to your knees at end position
- Think of reaching your knees forward over your ankles as you hold the bridge.

Level 2. Bridging
- As 1. but with knee extension at end position

Level 3. Bridging with one leg bent
- As 1. but only pushing with one leg

Level 4. Bridging with one leg straight
- As 1. but only pushing with one leg

selfBACK

This project has received funding from the European Union Horizon 2020 research and innovation programme under grant agreement No 689043

Strength exercises for the abdominal muscles

Level 1. Forward leaning plank with arm lift
- Draw in your abdominal muscles towards your spine
- Keep upper body/hip stable and maintain a flat back
- Lift right/left arm repeatedly in a slow rhythm

Level 2. Forward leaning plank with leg lift
- As 1. but with leg lift

Level 3. Forward leaning plank with arm lift
- As 1. but with a more reclining upper body

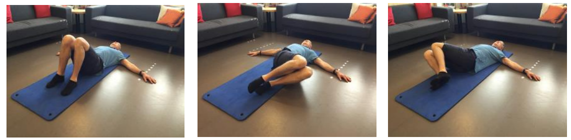
Level 4. Forward leaning plank with leg lift
- As 2. but with a more reclining upper body to increase load

Level 5. Plank with leg lift
- As 4. but standing on toes and hands

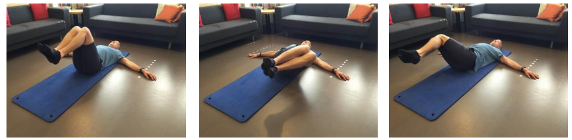
Level 6. Plank with leg lift
- As 4. but standing on toes and elbows

Strength exercises for the oblique abdominals and rotator muscle in the back

Level 1. Rotational movements with bent knees/hip
- Keep upper body stable by pushing the hands against the floor
- Keep feet's in contact with floor at all times
- Rotate slowly to about 45 degrees to each side



Level 2. Rotational movements with bent knees/hip
- As 1. but with leg lift
- Rotate slowly to about 45 degrees to each side



Level 3. Rotational movements with bent knees/hip
- As 2. but rotate until knees are 5-10 cm above floor

Level 4. Rotational movements with one leg

Level 5. Rotational movements with nearly extended legs

Level 6. Rotational movements with fully extended legs

Strength “Strong in mid-position”

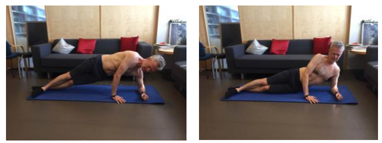
Level 1.
- Push lower back towards the floor by activating the abdominal muscles
- Extend right/left leg while keeping the lumbar spine in in contact with the floor

Level 5. Cycling
- Animation
- Push lower back towards the floor by activating the abdominal muscles
- Make cycling movement with legs while keeping the lumbar spine in contact with the floor

Level 2. Sideway bridge on knees and elbows

Level 3. Sideway bridge

Level 4. Sideway bridge



selfBACK

This project has received funding from the European Union Horizon 2020 research and innovation programme under grant agreement No 689043

Flexibility exercises

1. Stretching hamstring muscles

2. Stretching hamstring muscles

3. Stretching hip flexors

4. Stretching hip extensor/gluteus

5. Stretching back muscles/rotating spine

selfBACK

This project has received funding from the European Union Horizon 2020 research and innovation programme under grant agreement No 689043

Pain relief exercises

1. Standing knee lift

2. Standing rotation

3. "Picking pears"

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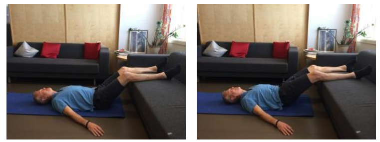
Pain relief exercises

Level 1. “Cat exercise”

Level 2. Pelvic tilting in seated position

Level 3. Pelvic tilting while lying down



Level 4. Pelvic tilting while standing

Level 3. Lateral pelvic lift while standing

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This project has received funding from the European Union Horizon 2020 research and innovation programme under grant agreement No 689043

6.5 Appendix C

Appendix C includes patient descriptions, and the four exercise plans made for each of the patients. The plans are color coded, green plans are created by ex-over, blue plans are created by rules, red plans are the expert solutions, and yellow are the no-adaptation solutions. The expert solutions was created before experiments were conducted, and are the basis for the other solutions.

Patient 1

Age	45	**BIPPQ 2**	6
Gender	Female	**BIPPQ 3**	9
Height	173	**BIPPQ 4**	2
Weight	63	**BIPPQ 5**	5
Live alone or with others?	Live with children, 6-15 and above 15	**BIPPQ 6**	0
Education	More than 13 years	**BIPPQ 7**	10
Employment	Full time	**BIPPQ 8**	1
Pain lastweek avg	1	**PSFS activity(most important activities)**	cycling/spinning
Pain lastweek max	1	**Painsites**	Neck, shoulders, low back, hips/thighs
Duration current pain	1-4 weeks	**Comorbidities**	
Duraation pain year	more than 30 days, but not every day	**EQ5D_mobility**	no problems
Activity limitation	Reduced leisure activity	**EQ5D_selfcare**	no problems
Pain medication	Never taken medication	**EQ5D_activities**	no problems
RMDQ	0	**EQ5D_pain**	slight pain or discomfort
LBP caused by physical activity	0	**EQ5D_anxiety**	no problems
FABQ	6	**Overall health**	80
Pain self efficacy	60	**Sleep difficulty**	Several times a week
BIPPQ 1	1	**Mood**	10

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	12	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	8	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Patient 2

Age	40	**BIPPQ 2**	2
Gender	Female	**BIPPQ 3**	3
Height	162	**BIPPQ 4**	5
Weight	85	**BIPPQ 5**	2
Live alone or with others?	live with spouse, children under 5	**BIPPQ 6**	5
Education	More than 13 years of schooling	**BIPPQ 7**	4
Employment	Yes, part-time employment	**BIPPQ 8**	4
Pain lastweek avg	0	**PSFS activity(most important activities)**	housework
Pain lastweek max	0	**Painsites**	low back
Duration current pain	1-4 weeks	**Comorbidities**	
Duraation pain year	8-30 days	**EQ5D_mobility**	no problems
Activity limitation	Reduced leisure activity	**EQ5D_selfcare**	no problems
Pain medication	Never	**EQ5D_activities**	slight problems
RMDQ	2	**EQ5D_pain**	no problems
LBP caused by physical activity	4	**EQ5D_anxiety**	no problems
FABQ	12	**Overall health**	70
Pain self efficacy	37	**Sleep difficulty**	sometimes
BIPPQ 1	4	**Mood**	4

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	8	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	12	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	12	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	12	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	3	Forward leaning plank with arm lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Patient 3

Age	44	**BIPPQ 2**	10
Gender	Male	**BIPPQ 3**	4
Height	183	**BIPPQ 4**	8
Weight	80	**BIPPQ 5**	6
Live alone or with others?	children under 5 years	**BIPPQ 6**	4
Education	More than 13 years of schooling	**BIPPQ 7**	8
Employment	Yes, full-time employment	**BIPPQ 8**	1
Pain lastweek avg	1	**PSFS activity(most important activities)**	Housework, standing
Pain lastweek max	2	**Painsites**	lower back, hips/thighs
Duration current pain	1-4 weeks	**Comorbidities**	Degenerative joint disease
Duraation pain year	More than 30 days, but not every day	**EQ5D_mobility**	no problem
Activity limitation	No	**EQ5D_selfcare**	no problem
Pain medication	1-2 times per week	**EQ5D_activities**	no problem
RMDQ	3	**EQ5D_pain**	moderate pain
LBP caused by physical activity	1	**EQ5D_anxiety**	no problem
FABQ	1	**Overall health**	79
Pain self efficacy	57	**Sleep difficulty**	Several times a week
BIPPQ 1	2	**Mood**	5

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	12	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	12	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	12	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	5	Plank with leg lift
abdominals and rotator muscle in the back	10	3	4	Rotational movements with one leg
Strength “Strong in mid-position”	8	3	3	Sideway bridge
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Patient 4

Age	40	**BIPPQ 2**	8
Gender	Female	**BIPPQ 3**	4
Height	166	**BIPPQ 4**	7
Weight	65	**BIPPQ 5**	7
Live alone or with others?	Live with spouse, kids over 15	**BIPPQ 6**	7
Education	10 to 12 years of schooling	**BIPPQ 7**	6
Employment	Yes, full-time employment	**BIPPQ 8**	7
Pain lastweek avg	4	**PSFS activity(most important activities)**	
Pain lastweek max	6	**Painsites**	neck, upper back, lower back, knees
Duration current pain	More than 12 weeks	**Comorbidities**	
Duraation pain year	Every day	**EQ5D_mobility**	slight problems
Activity limitation	Reduced leisure and work activities	**EQ5D_selfcare**	no problems
Pain medication	Daily	**EQ5D_activities**	moderate problems
RMDQ	14	**EQ5D_pain**	moderate problems
LBP caused by physical activity	2	**EQ5D_anxiety**	slight problems
FABQ	16	**Overall health**	45
Pain self efficacy	33	**Sleep difficulty**	Sometimes
BIPPQ 1	7	**Mood**	7

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	3	Forward leaning plank with arm lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	3	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	8	3	1	Bridging
Strength exercises for the abdominal muscles	8	3	3	Forward leaning plank with arm lift
abdominals and rotator muscle in the back	8	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	8	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	8	3	1	Leg lift
Strength exercises for the back extensors	8	3	2	Arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	2	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	1	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus
Flexibility			5	Stretching back muscles/rotating spine

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Patient 5

Age	54	**BIPPQ 2**	5
Gender	Male	**BIPPQ 3**	6
Height	184	**BIPPQ 4**	7
Weight	89	**BIPPQ 5**	4
Live alone or with others?	Child/children over 15	**BIPPQ 6**	4
Education	More than 13 years of schooling	**BIPPQ 7**	6
Employment	Yes, full-time employment	**BIPPQ 8**	2
Pain lastweek avg	2	**PSFS activity(most important activities)**	Training
Pain lastweek max	2	**Painsites**	Lower back, hips/thighs
Duration current pain	Less than 1 week	**Comorbidities**	
Duraation pain year	8-30 days	**EQ5D_mobility**	no problem
Activity limitation	Reduced leisure activity	**EQ5D_selfcare**	no problem
Pain medication	Never	**EQ5D_activities**	no problem
RMDQ	15	**EQ5D_pain**	no problem
LBP caused by physical activity	3	**EQ5D_anxiety**	no problem
FABQ	18	**Overall health**	80
Pain self efficacy	27	**Sleep difficulty**	several times a week
BIPPQ 1	7	**Mood**	0

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	8	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	8	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	8	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	8	3	4	Rotational movements with one leg
Strength "Strong in mid-position"	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	2	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	8	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Patient 6

Age	56	**BIPPQ 2**	9
Gender	Male	**BIPPQ 3**	3
Height	196	**BIPPQ 4**	8
Weight	125	**BIPPQ 5**	8
Live alone or with others?	Live alone	**BIPPQ 6**	8
Education	More than 13 years of schooling	**BIPPQ 7**	8
Employment	Yes, full-time employment	**BIPPQ 8**	9
Pain lastweek avg	4	**PSFS activity(most important activities)**	Heavy housework
Pain lastweek max	4	**Painsites**	lower back, hips/thighs
Duration current pain	More than 12 weeks	**Comorbidities**	Depression
Duraation pain year	More than 30 days, but not every day	**EQ5D_mobility**	moderate problems
Activity limitation	Reduced leisure and work activity	**EQ5D_selfcare**	slight problems
Pain medication	1-2 times per week	**EQ5D_activities**	slight problems
RMDQ	13	**EQ5D_pain**	moderate problems
LBP caused by physical activity	6	**EQ5D_anxiety**	slight problems
FABQ	24	**Overall health**	75
Pain self efficacy	40	**Sleep difficulty**	seldom or never
BIPPQ 1	7	**Mood**	7

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	12	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus
Flexibility			5	Stretching back muscles/rotating spine

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	12	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	12	3	1	Bridging
Strength exercises for the abdominal muscles	12	2	3	Forward leaning plank with arm lift
Strength exercises for the abdominal muscles	12	2	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	12	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus
Flexibility			5	Stretching back muscles/rotating spine

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	3	Diagonal leg and arm lift
Strength exercises for the gluts and back extensors	12	3	1	Bridging
Strength exercises for the abdominal muscles	12	2	2	Forward leaning plank with leg lift
Strength exercises for the abdominal muscles	12	2	3	Forward leaning plank with arm lif
abdominals and rotator muscle in the back	12	3	2	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	12	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	15	3	1	Bridging
Strength exercises for the abdominal muscles	15	2	3	Forward leaning plank with arm lift
Strength exercises for the abdominal muscles	15	2	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	15	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus
Flexibility			5	Stretching back muscles/rotating spine

Patient 7

Age	65	**BIPPQ 2**	0
Gender	Female	**BIPPQ 3**	9
Height	168	**BIPPQ 4**	10
Weight	63	**BIPPQ 5**	1
Live alone or with others?	Live with spouse	**BIPPQ 6**	0
Education	More than 13 years of schooling	**BIPPQ 7**	10
Employment	Retirement or disability pension	**BIPPQ 8**	0
Pain lastweek avg	0	**PSFS activity(most important activities)**	longtime sitting
Pain lastweek max	0	**Painsites**	elbows, wrists/hands, knees,
Duration current pain	Less than 1 week	**Comorbidities**	disease (osteoarthritis)
Duraation pain year	1-7 days	**EQ5D_mobility**	no problem
Activity limitation	No	**EQ5D_selfcare**	no problem
Pain medication	Never	**EQ5D_activities**	no problem
RMDQ	12	**EQ5D_pain**	moderate problems
LBP caused by physical activity	1	**EQ5D_anxiety**	no problem
FABQ	7	**Overall health**	95
Pain self efficacy	60	**Sleep difficulty**	Sometimes
BIPPQ 1	1	**Mood**	0

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	12	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	12	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	12	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	8	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	8	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			5	Stretching back muscles/rotating spine

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Patient 8

Age	35	**BIPPQ 2**	4
Gender	Male	**BIPPQ 3**	8
Height	193	**BIPPQ 4**	9
Weight	98	**BIPPQ 5**	2
Live alone or with others?	Live with spouse and children under 5	**BIPPQ 6**	2
Education	More than 13 years of schooling	**BIPPQ 7**	9
Employment	Yes, full-time employment	**BIPPQ 8**	1
Pain lastweek avg	2	**PSFS activity(most important activities)**	heavy lifting
Pain lastweek max	4	**Painsites**	low back
Duration current pain	1-4 weeks	**Comorbidities**	
Duraation pain year	8-30 days	**EQ5D_mobility**	no problems
Activity limitation	Reduced leisure activity	**EQ5D_selfcare**	no problems
Pain medication	Never	**EQ5D_activities**	slight problems
RMDQ	4	**EQ5D_pain**	slight problems
LBP caused by physical activity	4	**EQ5D_anxiety**	slight problems
FABQ	16	**Overall health**	85
Pain self efficacy	57	**Sleep difficulty**	Sometimes
BIPPQ 1	2	**Mood**	4

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	8	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	3	Diagonal leg and arm lift
Strength exercises for the gluts and back extensors	8	3	1	Bridging
Strength exercises for the abdominal muscles	8	3	2	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	8	3	2	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	8	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

Exercise name	**Rep**	**set**	**level**	**Description**
Strength exercises for the back extensors	12	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	15	3	1	Bridging
Strength exercises for the abdominal muscles	15	2	3	Forward leaning plank with arm lift
Strength exercises for the abdominal muscles	15	2	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	15	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	12	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus
Flexibility			5	Stretching back muscles/rotating spine

Exercise name	**Rep**	**set**	**level**	**Description**
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	3	Forward leaning plank with arm lift
Strength exercises for the oblique abdominals and rotator muscle in the	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

Patient 9

Age	45	**BIPPQ 2**	10
Gender	Female	**BIPPQ 3**	7
Height	172,82	**BIPPQ 4**	8
Weight	77,1	**BIPPQ 5**	5
Live alone or with others?	kids between 6-15 and over 15	**BIPPQ 6**	9
Education	10 to 12 years of schooling	**BIPPQ 7**	9
Employment	Yes, part-time employment	**BIPPQ 8**	9
Pain lastweek avg	0	**PSFS activity(most important activities)**	heavy housework
Pain lastweek max	0	**Painsites**	low back, ankles/feet
Duration current pain	More than 12 weeks	**Comorbidities**	
Duraation pain year	More than 30 days, but not every day	**EQ5D_mobility**	no problems
Activity limitation	No	**EQ5D_selfcare**	no problems
Pain medication	Never	**EQ5D_activities**	slight problems
RMDQ	3	**EQ5D_pain**	no problems
LBP caused by physical activity	4	**EQ5D_anxiety**	no problems
FABQ	14	**Overall health**	90
Pain self efficacy	47	**Sleep difficulty**	Sometimes
BIPPQ 1	2	**Mood**	2

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	3	Forward leaning plank with arm lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	10	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	8	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	8	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	8	3	3	Forward leaning plank with arm lift
abdominals and rotator muscle in the back	8	3	3	Rotational movements with bent knees/hip
Strength “Strong in mid-position”	8	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	3	6	Bird exercise - diagonal leg and arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	4	Forward leaning plank with leg lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	10	3	1	See exercise presentation
Flexibility			2	Stretching hamstring muscles
Flexibility			3	Stretching hip flexors
Flexibility			4	Stretching hip extensor/gluteus

Exercise name	Rep	set	level	Description
Strength exercises for the back extensors	10	2	4	Bird exercise - leg lift
Strength exercises for the back extensors	10	2	5	Bird exercise - arm lift
Strength exercises for the gluts and back extensors	10	3	1	Bridging
Strength exercises for the abdominal muscles	10	3	3	Forward leaning plank with arm lift
abdominals and rotator muscle in the back	10	3	3	Rotational movements with bent knees/hip
Strength "Strong in mid-position"	10	3	2	Sideway bridge on knees and elbows
Flexibility			2	Stretching hamstring muscles

6.6 Appendix D

Appendix D includes the evaluation information sent to the experts.

Evalueringsinformasjon

Tale Prestmo

Mai 2017

9 forskjellige caser er samlet i excel dokumentet AdaptationEvaluation. På hvert ark er det presentert informasjon om en pasient, samt fire foreslåtte treningsplaner. Treningsplanene er likt bygd opp, men har små forskjeller. Treningsplanene har en fargekode, der hver fargekode er for hvilken metode som er benyttet. Dette for å holde det skjult for dere hvilken metode som er brukt, slik at vurderingen ikke blir påvirket av det.

Jeg ønsker at planene skal evalueres på to måter. Den første er en rangering av de fire planene mot hverandre, der nr 1 er planen som er den beste planen av de foreslåtte for gitt pasient, og 4 er den dårligste planen av de foreslåtte planene. Hvis to planer er helt like så sett de opp på samme plassering. Bakgrunnen for denne evalueringen er for å se om det er en trend i hvilken metode som foretrekkes.

Den andre evaleruingsmåten går på kvaliteten til hver enkelt plan, hvor bra hver enkelt plan er for gitt pasient. Disse skal gis en poengsum fra 1-5 basert på listen under. Denne evalueringen skal brukes for å sjekke den generelle kvaliteten på treningsplanene, ettersom det ikke er sikkert at en plan er god selv om den er den beste av de foreslåtte. Det kan også hende at en plan er god, selv om den rangeres som den dårligste av de foreslåtte planene, og denne evalueringen prøver å fange opp dette.

1 - Veldig god plan for denne pasienten

2 - God plan for denne pasienten

3 - Middels god plan for denne pasienten

4 - Dårlig plan for denne pasienten

5 - Svært dårlig plan for denne pasienten

Evalueringen kan gjøres rett i excel-arket, eller i et nytt dokument. Bare husk å marker hvilken pasient det er, og hva de forskjellige poengene er for. Eksempel: **Pasient 1:** Rangering: 1. Rød, 2. Blå, 3. Grønn, 4. Gul, Poengscore: Rød: 2, Blå: 2, Grønn: 2, Gul: 5.