Dynamic knowledge assets management to interactive problem solving and sustained learning –

A collaborative CBR system in chronic and palliative care

DISSERTATRION
zur Erlangung des Grades eines Doktors
der Ingenieurwissenschaften

vorgelegt von
M.Sc. Sara Nasiri

eingereicht bei der Naturwissenschaftlich-Technischen Fakultät
der Universität Siegen
Siegen 2018

gedruckt auf alterungsbeständigem holz- und säurefreiem Papier

1. Gutachter: Prof. Dr. -Ing. Madjid Fathi
2. Gutachter: Prof. Dr. rer. nat. Rainer Brück

Tag der mündlichen Prüfung: 24.04.2018

I would like to dedicate this thesis to my beloved parents and family.

Acknowledgements

I would like to thank my advisor Prof. Dr. –Ing. Madjid Fathi, head of the Institute of Knowledge based Systems and Knowledge Management (KBS & KM) at the University of Siegen, for giving me this opportunity to serve as a research assistant, to involve in two BMBF projects (NeuroCare and MobiAssist) and also for encouraging me in my teaching roles.

I would also like to thank my second Ph.D. supervisor, Prof. Dr. rer.nat. Rainer Brück, chair of the Institute of Medical Informatics and Microsystem Design, deputy director of FoKoS (Research College), and Vice-Dean Research of School of Life Sciences at the University of Siegen. I am grateful to him for reviewing this dissertation and providing constructive feedback.

I would further like to thank Prof. Dr. Udo Kelter, chair of the Institute of Practical Computer Science and Software Engineering at the University of Siegen, and Prof. Dr. Kristof Van Laerhoven, chair of the Institute of Ubiquitous Computing at the University of Siegen for serving as my committee members. I particularly thank them for making my defense enjoyable and for their brilliant comments and suggestions.

I would especially like to thank the nurses and caregivers in the Diakonie (the social welfare organization) for spending their time in responding to several interviews and providing helpful information for mapping the ICF codes of patients. I sincerely appreciate their support in recruiting patients and collecting data for my Ph.D. thesis.

I express my thanks to all of the master's and bachelor's students whose willingness and dedication to work on their topics from a variety of perspectives contributed to this research especially who have taken part in the student group project of MedAusbild (Medical educational systems).

I would also like to thank all of my friends and colleagues who supported me directly or indirectly in performing this research and who provided me with incentive to keep striving towards my goal especially Marjan, who is my best friend and colleague from the very beginning of this long journey.

I am grateful to Prof. Dr. Gabriele Kern-Isberner, chair of Computer Science (Logic in Computer Science-LS1), at the Technische Universität Dortmund (TU Dortmund) for her insightful guidance and also for the constructive comments in reviewing my paper.

My acknowledgment would be incomplete without thanking my most significant source of strength: my family. Words cannot express how grateful I am to my mother and father for all of the sacrifices that they have made on my behalf. I salute them for their selfless love, care and pain that has sustained me thus far. I would also like to thank my brothers for their support and valuable prayers and my husband, who has, in his way, kept me on my path to success, assisting me per his ability in whatever manner possible and ensuring that the good times keep flowing. To my beloved daughter, Baran, I would like to express my thanks for being such a good girl and always cheering me up. I appreciate her supporting me in everything and, in particular, cannot thank her enough for encouraging me throughout this experience.

Finally, I thank my God, for giving me patience through all the difficulties. I have experienced Your guidance day by day; You are the one who let me finish my degree. I will keep on trusting You for my future; thank You for Your endless ripple of kindness.

Abstract

Knowledge management is a decision-making approach for facilitating the development and application of a variety types of knowledge assets. There are a number of key questions in the field, including “how can we gather knowledge assets?” and “How can we evaluate knowledge management initiatives planned for improving user experiences?”. The identification of the key knowledge asset value drivers and their relations allows stakeholders to define priorities. It is also important to utilize existing knowledge effectively in the proper knowledge management of knowledge-based assets. Accordingly, building a knowledge-based system to solve new and similar problems is a research challenge that this thesis aims to address.

Although search engines and question-answering systems already serve as crucial tools for knowledge workers, understanding texts and using knowledge obtained from the texts for problem-solving is far from routine. Thus, this work addresses the problem of developing a collaborative knowledge-based system that can learn from user experience and knowledge assets.

The research described in this dissertation involved an investigation of the use of word association strength based on the statistical cohesions between words to build a semantic profile of a text. This approach in the retrieval of relevant information can provide reasoning information from a text in a manner that has traditionally required the use of human experts; this information then be reused in the analysis of new problems. In developing an artificial intelligence (AI)-based problem-solving technique, this study investigated the use of case-based reasoning (CBR), a methodology in which data representing information on solved problems is stored for reuse in new problem-solving processes. The choice of past cases to be reused is based on similarity measures in the retrieval process as extracted from all stored cases in the case base. Each similarity measure characterizes a set of heuristics for approximating the unidentified utility of a case, and the quality of similarity measures can be improved by integrating as much knowledge regarding the specific application domain as possible into them. Features relations from ontology and fuzzy logic can also be integrated into CBR similarity measures to handle the ambiguities and uncertainties that are characteristically present in knowledge-intensive processes.

The system developed in this research – DePicT CLASS – is based on the DePicT concept, in which diseases are detected and predicted using image classification and text information from personal health records. DePicT CLASS was developed to serve as a collaborative case-based system to support caregivers and patients' relatives by preparing relevant references and learning material to help them understand the patients' medical issues. The main characteristics of DePicT and DePicT CLASS are demonstrated in this work using instances from two disease domains: dementia and melanoma.

Zusammenfassung

Wissensmanagement ist ein Ansatz der Entscheidungsfindung, um die Entwicklung und Anwendung von Wissensressourcen unterschiedlicher Art zu erleichtern. Es gibt eine Reihe von Schlüsselfragen in diesem Bereich, einschließlich „Wie können wir Wissensressourcen sammeln?“ und „Wie können wir Initiativen zum Wissensmanagement bewerten, die zur Verbesserung der Benutzererfahrungen geplant sind?“. Die Identifikation der wichtigsten Wissensbestandswerttreiber und deren Beziehungen ermöglichen es den Stakeholdern, Prioritäten zu definieren. Darüber hinaus ist es wichtig, vorhandenes Wissen effektiv für das richtige Wissensmanagement von wissensbasierten Beständen zu nutzen. Dementsprechend ist der Aufbau eines wissensbasierten Systems zur Lösung neuer und ähnlicher Probleme eine Forschungsherausforderung, die mit dieser Dissertation angegangen werden soll.

Obwohl Suchmaschinen und Frage-Antwort-Systeme bereits als entscheidende Werkzeuge für Wissensarbeiter dienen, ist das Verstehen von Texten und das Verwenden von Wissen, das aus den Texten zur Problemlösung gewonnen wird, weit von einer Routine entfernt. Daher befasst sich diese Arbeit mit dem Problem der Entwicklung eines kollaborativen wissensbasierten Systems, das von Benutzererfahrungen und Wissensressourcen lernen kann.

Die in dieser Dissertation beschriebene Forschung beinhaltete eine Untersuchung der Verwendung von Wortvereinigungsstärke basierend auf den statistischen Zusammenhängen zwischen Wörtern, um ein semantisches Profil eines Textes aufzubauen. Dieser Ansatz bei der Suche nach relevanten Informationen kann aus einem Text aufschlussreiche Informationen liefern, die traditionell den Einsatz von Experten erfordern. Diese Informationen werden dann bei der Analyse neuer Probleme wiederverwendet. Bei der Entwicklung einer auf künstlicher Intelligenz beruhenden Problemlösungs-Technik untersuchte diese Studie die Verwendung von fallbasiertem Denken (CBR), eine Methodik, bei der Daten, die Informationen zu gelösten Problemen darstellen, zur Wiederverwendung in neuen Problemlösungsprozessen gespeichert werden. Die Auswahl der zu verwendenden Fälle in der Vergangenheit basiert auf Ähnlichkeitsmaßen im Abrufprozess, die aus allen gespeicherten Fällen in der Fallbasis extrahiert werden. Jedes Ähnlichkeitsmaß charakterisiert eine Menge von Heuristiken zur Approximation des nicht identifizierten Nutzens eines Falls, und die Qualität von Ähnlichkeitsmaßen kann verbessert werden, indem so viel Wissen wie möglich

in die spezifische Anwendungsdomäne integriert wird. Eigenschaften-Relationen aus Ontologie und Fuzzy-Logik können auch in CBR-Ähnlichkeitsmaße integriert werden, um die Mehrdeutigkeiten und Unsicherheiten zu bewältigen, die charakteristisch in wissensintensiven Prozessen vorhanden sind.

Das in dieser Studie entwickelte System – DePicT CLASS - basiert auf dem DePicT Konzept, bei dem Krankheiten anhand von Bildklassifikationen und Textinformationen aus persönlichen Gesundheitsakten erkannt und vorhergesagt werden. DePicT CLASS wurde entwickelt, um als kollaboratives fallbasiertes System zur Unterstützung von Angehörigen und Angehörigen von Patienten zu dienen, indem relevante Referenzen und Lernmaterialien erstellt werden, die ihnen helfen, die medizinischen Probleme der Patienten zu verstehen. Die Hauptmerkmale von DePicT und DePicT CLASS werden in dieser Arbeit anhand von Beispielen aus zwei Krankheitsdomänen demonstriert: Demenz und Melanom.

Table of contents

List of figures

List of tables

List of Abbreviations

AD	Alzheimer's disease
AHIMA	American Health Information Management Association
AI	Artificial Intelligence
CBR	Case-based Reasoning
CCBR	Conversational Case-based Reasoning
CM	Change Management
CTC	Caregiver-to-Caregiver
CTD	Caregiver-to-Doctor
DePicT	Detect and Predict diseases using image classification and Text information
DePicT CLASS	Detect and Predict diseases using image classification and Text information via Case-based Learning Assistant System
DKAM	Dynamic Knowledge Assets Management
EHR	Electronic Health Record
EMR	Electronic Medical Record
FIS	Fuzzy Inference System
HIMSS	Healthcare Information and Management System Society
HIP	Health Information Profile
HSV	Hue-Saturation-Value
IC	Incoming Case
ICF	International Classification of Functioning, Disability, and Health
ICT	Information and Communication Technology

ISIC	International Skin Imaging Collaboration
IT	Information Technology
KDT/KDD	Knowledge Discovery from Text/Data
k-NN	k Nearest Neighbor
KM	Knowledge Management
KMS	Knowledge Management System
KP	Knowledge Portal
KPI	Key Performance Indicator
NCCN	National Comprehensive Cancer Network
PHR	Personal Hearth Record
PIP	Personal Information Profile
PM	Project Management
POI	Points of Interest
PTC	Patient-to-Caregiver
PTD	Patient-to-Doctor
PTP	Patient-to-Patient
RGB	Red-Green-Blue
ROI	Region of Interest
SVM	Support Vector Machine
TCBR	Textual Case-based Reasoning
TEL	Technology Enhanced Learning
VET	Vocational Education and Training
WAS	Word Association Strength
WHO	World Health Organization

Chapter 1

Introduction

In this section the background and motivation of this thesis are described. The key insight applied in this work is the focusing of artificial intelligence (AI) methods into a knowledge management (KM) approach to problem-solving using explicit knowledge modeling utilizing case-based reasoning (CBR). This approach enables an enhanced understanding of information through the extraction and storing of explicit and implicit knowledge as a collection of cases in knowledge base. It is understood that knowledge-based models for developing competent and robust systems that can tackle complex problems must be compound in nature, i.e., they must be able to capture and utilize the various available types of knowledge assets needed to build a knowledge-based system and control the problem solving and learning processes.

1.1 Motivation

The Healthcare Information and Management System Society (HIMSS) broadly defines e-health "as information technology (IT)-enabled healthcare system that improves the access, efficiency, effectiveness and quality of clinical and business processes" [116]. Healthcare organizations, physicians, and patients apply e-health to achieve purposes that include cost-cutting, improving patient satisfaction, and furthering the overall development of medical care. Haughom [108] posited that healthcare gains significantly through the implementation of the following key Deming principles:

- *Quality improvement is a science of process improvement.* Healthcare is widely understood to be very complicated and to contain many interconnected processes.

By focusing upon separate care processes independently, it is possible to address the challenges facing healthcare in principally “game-changing” manner. Based on Pareto’s 80/20 principle, 80% of the impact will come from 20% of the process application; here,the challenge is identifying the 20%.

- *If you cannot measure it, you cannot improve it*. Significant quality improvement must be data-driven. Data are therefore critical in obtaining meaningful impacts on healthcare.

- *Managed care means managing the processes of care, not managing physicians and nurses*, as these personnel are best prepared to work out how to improve the process of care progressively.

- *The right data in the right format at the right time in the right hands*. Approximately, 259,000 health-related apps[1] are currently available, with over 59,000 mHealth app publishers worldwide producing for the main app stores. Based on reporting by Flurry Analytics, the daily use of health apps increased by 62% from December 2013 to June 2014, as compared to a 33% increase in the use of mobile apps in general [253].

- *Engaging the “smart cogs” of healthcare*. As illustrated in Fig. 1.1, McKinsey surveyed a large number of physicians (more than 1,402 U.S. physicians), whom they referred to as "smart cogs", and found that the majority (84%) were willing to change when given a compelling argument for such change [181].

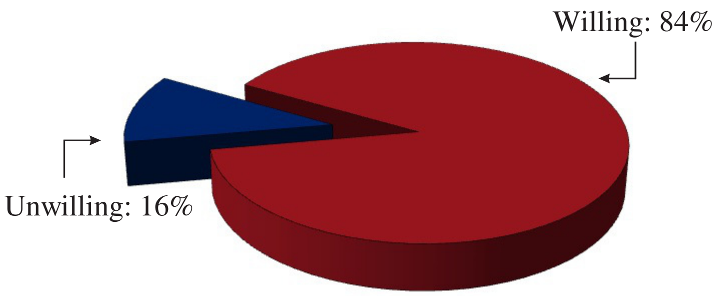


Fig. 1.1 Physicians willingness to change.

KM is currently held up as a savior of healthcare organizations suffering from information overload [136]. The use of IT enables knowledge-centric views that e-health solutions must begin to take advantage of. Accordingly, the healthcare industry is attempting to embrace

[1] Medium.com: mHealth Apps Market: Situation, Trends & Projections

KM–enabled technologies and applications to improve the access and transfer of e-health information and knowledge at all levels (e.g., physicians, nurses, therapists, diagnosticians, and pharmacists) [119],[43], and KM-enabled healthcare systems are an important new trend in e-health. In the context of processing healthcare data and generating information, it is crucial to support health services in terms of, e.g., clinical decision making. Healthcare data can be drived from administrative, basic healthcare, or clinical complexes in forms of, e.g., diagnoses, procedures, evolutions, comparatives, and assessments [187]; however, the proper application of KM in healthcare organizations requires well-structured and well-managed information.

Building a sharing culture and capacity for the use and application of scientific and experiential knowledge is also of great importance [271], and KM techniques will eventually help to build a sharing culture that through processes of tacit and implicit knowledge discovery will pave the way for the reapplication of scientific and experiential knowledge.

Explicit knowledge is acquired using documentary sources, both internal and external. Tacit knowledge is present in individuals and groups as a result of experience, while implicit knowledge results from the working practice of healthcare professionals. The main knowledge sources in the area of healthcare are health professionals who own their tacit knowledge intrinsically, and this sort of knowledge has the greatest value in the KM process [187]. The KM process can be subdivided further into, for example, creating internal knowledge, acquiring external knowledge, storing knowledge in documents versus storing it in routines, and updating the knowledge and sharing it internally and externally [119],[16].

KM activities can supply the healthcare industry with enhanced quality of care and, as a result, the industry is increasingly becoming a knowledge-based community [119]. Utilizing KM systems (KMSs) to manage medical information and healthcare knowledge to support the full spectrum of knowledge has made the use of electronic health records (EHRs) important for patients and professionals. EHR is "a longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting. Included in this information are patient demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data and radiology reports. The EHR automates and streamlines the clinician's workflow. The EHR has the ability to generate a complete record of a clinical patient encounter - as well as supporting other care-related activities directly or indirectly via interface - including evidence-based decision support, quality management, and outcomes reporting" [116]. Therefore, EHR must include:

- A longitudinal collection of electronic health information for and about persons
- Immediate electronic access to person- and population- level information by authorized, and only authorized, users

- Provision of knowledge and decision support that enhances the quality, safety, and efficiency of patient care, and

- Support of efficient processes for health care delivery [116].

Owing to the vast amount of data and information that can be stored in EHRs, it is always a very complex task to find relations between different instances of data, information and knowledge, and it would be a significant help if these could be presented to target groups in line with their respective needs and demands; enabling this is the main motivation of this thesis. Such KMS would also help in the more effective sharing of knowledge. It would also be useful to devise a model that could satisfy every healthcare stakeholder, from patients to physicians.

A question posed in [192] “How is it possible to establish an EHR which is enriched with data from a personal health record (PHR) and data from social network communication between patients, caregivers and doctors contributing to a better understanding of the patient’s background for the doctor?” outlines our interest in developing a method for better understanding patient records. Several discussions can be found in the literature on the use of EHR in all areas of healthcare science. Effectively managing such data at high levels and for all patients is a very challenging task because of the large amounts of data an individual will generate in the form of different data types such as texts, statistics, images, or a combination of all three [192]. The use of EHRs for accessing patient history, conducting lab tests, and performing imaging can have significant benefits in the healthcare field. The PHR, a concept similar to EHR, has been defined by the American Health Information Management Association (AHIMA) as “an electronic, universally available, lifelong resource of health information needed by individuals to make health decisions. Individuals own and manage the information in the PHR, which comes from healthcare providers and the individual. The PHR is maintained in a secure and private environment, with the individual determining rights of access. The PHR is separate from and does not replace the legal record of any provider” [53]. Patients can also leverage shared patient data to manage their own data, find other patients who share similar disorders or symptoms, and discover relevant clinical trials [227].

1.2 Problem statement and research goals

Organizations can experience changes in three states, namely, the current, transition, and future state. Each of these states involves combinations of technologies, processes, systems, tools, documentation, networks, and also roles and responsibilities. Under a current situation, staff is prepared for or against change, while change management teams attempt to identify all affected processes, users, and systems before change occurs. In a transition state, the interrelation of systems and processes can cause a minor change in one component of a system or process to produce major impacts on the other components. Integration of KM activities into transition processes can aid in control and administrate knowledge flow among knowledge professionals and stakeholders. Furthermore, the application of a knowledge-based recommendation approach can improve knowledge use. Finally, once the change has been applied and the future state has been reached, a change management team can reinforce the change by collecting and analyzing feedback from staff to reduce gaps between the new current and desired future states and ensure continuous improvement.

Electronic patient information systems improve the quality of patient information transmitted to health professionals and can also control costs through improved efficiency [282]. The phrase “creating change” is selected intentionally here, as many health leaders are now expected to create change instead of simply managing it [76]. Decision-makers in modern health systems must constantly confront changes from many perspectives, including:

- changes forced by shifts in the surrounding environment (i.e., sociological, economic, political, or technological);
- changes inherited from other policy makers’ decisions within the health system; and
- self-determined changes.

It is the decision maker’s job to assure that the unavoidable changes with which they much deal are addressed in a positive and productive manner [76].

There are two approaches for dealing with challenges such as these. Under a system-oriented approach, monitoring of the current system identifies gaps and problems relatives to the desired future. Then, based on an understanding of the requested change, a change plan for the transition state can be created. One of the best monitoring methods with respect to healthcare systems is process mining, which can be used to identify current operations and activities and people who perform such activities. This can be used to identify gaps (e.g., between the current and desired systems), by identifying needed changes in systems, products and/or personnel and then to redesign the process and improve it. For example, a clinic with a data collection or patient record system seeking to implement knowledge-based EHR can first design a process model and then, based on the current gaps and the desired EHR structure, create a new process model. The new model can then be designed and implemented via a “change creation system” to help the clinic workers go through the transition.

The second approach is patient-oriented and involves improving patient experience and enabling better communication. This study considers the use of these approaches in conjunction with CBR, based on patient records to create the case/knowledge-based system. This system would allow patients to build upon their experiences in monitoring and controlling their condition. We also feel that it is important to address change in terms of new features of cases (e.g., symptoms) and the new cases (e.g., diseases) so that similar cases can be identified and categorized. correspondingly, two primary steps are used in our approach: creating a system core based on patient records, with CBR used as a "knowledge-based system" for problem-solving; and continuous learning via "change creating" to help patients and clinic workers (e.g., caregivers) during the progression of patient's condition.

After explaining these problem statements and challenges in dealing with changes in a patient-oriented approach, and based on the proposed method for care process improvement using problem-solving, the main contribution of this research is the design and development of DePicT and DePicT CLASS. DePicT is a concept for **D**etecting and **P**redicting diseases using **i**mage **c**lassification and **T**ext information from patient health records, while DePicT CLASS is a recommender system employing a **C**ase-based **L**earning **A**ssistant **Sys**tem that applies CBR. In this context, the following chapters addresses several main research questions and points:

i) How can we extract knowledge from healthcare stakeholders to create the desired system in consideration of changes needed to solve their problems?

ii) How is it possible to establish an assistant system that utilizes data from patients, caregivers, and physicians to obtain a better understanding of their challenges?

iii) How can we solve the users' problems and improve their experience and sustained learning using a case-based systems?

iv) How can we extract/organize the important features from references and domain experts (e.g. how can we extract structured cases from texts)?

v) How can we evaluate similarities and adaptation mechanisms based on the image classification and word association strength given the following features of such mechanisms?

   - Each new similarity measurement contains different local similarity measures.
   - Each new proposal based on adaptation of the most similar cases can be followed by a word association profile. The practicalities of this will be discussed in detail later in this thesis.
   - The system can learn from the case base updating and from the opinions of users on the automatic adaptation of similar references retrieved from the case base

(e.g. the learner can rank the best references). In the context of similarity and adaptation, this can compared to the:

- o information extraction using domain expert and stakeholders;
- o information extraction using references (images and texts);
- o statistical approaches (e.g., values of word association profile and image features);
- o statistical approaches enhanced by learned knowledge. (e.g., ranking grades).

Accordingly, two main hypotheses are considered in this thesis:

i) Applicability

- Can words-association profiles be used to construct similar cases to record adapted references?
- Can adapted/selected cases be captured automatically from similar cases?

ii) Quality

- Does the reuse of cases lead to acceptable results?
- Is the quality of such recommended results comparable to the quality of reference results acquired by experts?

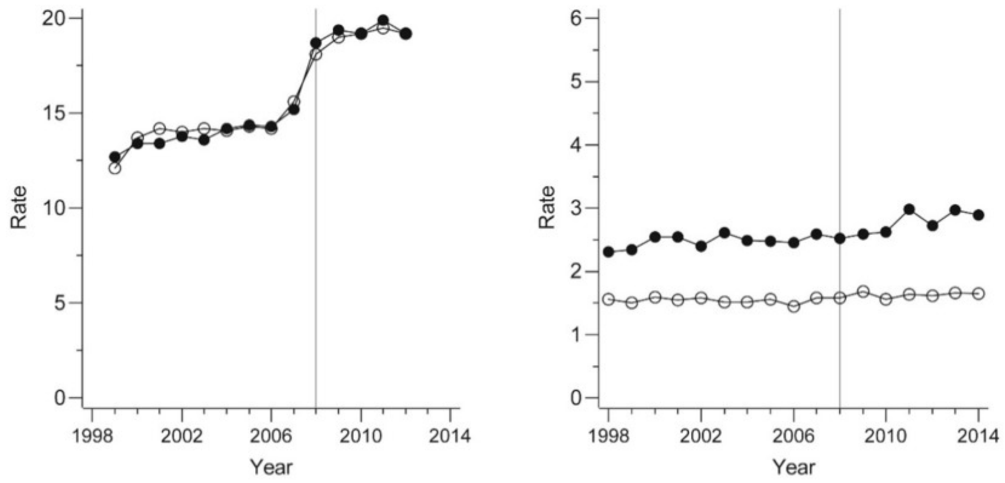
In the following chapters, these questions and points will be addressed.

1.3 The main contribution of thesis

This study looks first at the preliminary concept of DePicT and then the development of the DePicT CLASS recommender system for problem solving. In developing the preliminary concept, we focus on the the use of collaborative CBR based on the combination of textual and conversational functionalities that utilizes the DePicT Profile Matrix of word association to find the word association strengths between identified keywords reflecting case title and case features, respectively.

DePicT [197] is a case-based concept for the identification and diagnosis of diseases. It utilizes the graphical and textual similarity measurements of non-image and image information. DePicT CLASS [198] is a case-based learning assistant system embodying a complete cyclic CBR system implementation of the DePicT concept. DePicT CLASS can search for references based on a comparison of word association profiles of identified keywords to find the most similar references for a requested problem. DePicT CLASS represents an integrated process of solving problems by revising similar solutions and learning from retained experiences. In this work, by using k-nearest neighbor (k-NN) and support vector machine (SVM), images are classified and stored in cases. The DePicT Profile Matrix is used to enrich the knowledge base of DePicT CLASS. In the following chapters, the DePicT CLASS retrieval procedure system involving the use of such features as attributes is explained in detail, following which there is discussion as to how requested user information is refined and used in the case-matching and selection processes. Finally, as discussed in the case reuse and revise phases (See Chapter 3), solutions for recommendation are adapted based on similar cases. DePicT CLASS attaches references and learning materials related to the problem and solution to the case as a case description and a case recommendation, respectively. Reference images are tagged word association profiles based on impact factors defined by domain experts. DePicT CLASS utilizes a system of collaborative recommendation in which tagged keywords, references, and learning materials are ranked for significance by users.

The main characteristics of DePicT CLASS are demonstrated in this work based on instances from two disease domains: melanoma and dementia. As reported by the American Cancer Society, melanoma is the cause of the vast majority of skin cancer deaths. In 2016, there were an estimated 3,520 deaths from other types of skin cancer and around 10,130 deaths (in 2017, this was an estimated 9,730 deaths), even though melanoma accounts for only 1% of all types of skin cancer [24]. The survival rate for melanoma from the early to the terminal stages varies between 98% and 18%, respectively, with figures of 98% for the localized stage, 62% for regional stage, and 18% for the distant stage [24]. Thus, early detection is vital in surviving melanoma, and any new skin lesion particularly one that appears unusual, or any progressive change in a lesion's appearance (in terms of, e.g., size, shape, or color) should be assessed promptly by a dermatologist [24]. Even following treatment, it is necessary for patients to maintain their medical history and records [24]. The European Standard Population incidence and mortality rates of skin melanoma in Germany (per 100,000 person-years) [247] are shown in Fig. 1.2. DePicT CBMelanom and DePicT Melanoma CLASS are utilized by patients who have skin problems. These CBR systems apply the textual-conversational approach in which users who are not necessarily able to formulate questions in machine-readable form for input into a CBR system can use a conversational CBR interface that provides a question dialog to guide users to describe their problems incrementally through a series of questions and answers. DePicT CBMelanom and DePicT Melanoma CLASS both utilizes melanoma datasets (ISIC Archive; Publicifsv-Melanoma; PH2Dataset) to build case bases for supporting patients in the early stages of melanoma skin cancer (See Chapter 4).



a) Incidence (199-2012) b) Mortality (1998-2014)

Dots: men; Circles: women; Vertical line (year 2008): indicates the start of the nationwide skin cancer screening program.

Fig. 1.2 Incidence and mortality rates of skin melanoma in Germany.

DePicT Dementia CLASS is used and updated by caregivers and domain experts. It enables caregivers and patients' relatives to find their learning materials and references that address the problems for which they are seeking answers. Dementia covers a range of neurological illnesses distinguished by memory loss and cognitive impairment. In 2015, an estimated 47 million people worldwide were affected by dementia, a figure that is expected to climb to nearly 131 million in 2050 [279]. Dementia estimates for this time-frame in European countries based on [225] are shown in Fig. 1.3.

In 2012 and again in 2015, the World Health Organization (WHO) produced reports in which they contended that Alzheimer's disease (AD) and other dementias should be considered as a global public health priority [279]. Meanwhile, under the umbrella of the International Classification of Functioning, Disability, and Health (ICF) [270], initiative several research groups have carried out projects to develop systems for classifying the *ICF* codes of specific health conditions and disorders.

DePicT Dementia CLASS uses the DePicT Profile Matrix, which contains association strengths between title phrases and identified keywords of cases representing dementia-related diseases and *ICF* parameters, respectively. In this analysis, references and learning materials with high-valued keywords from word association profiles from the most similar cases are recommended for use in selected cases. A new case-matching and adaptation methods for medical vocational educational training using the calculated word association

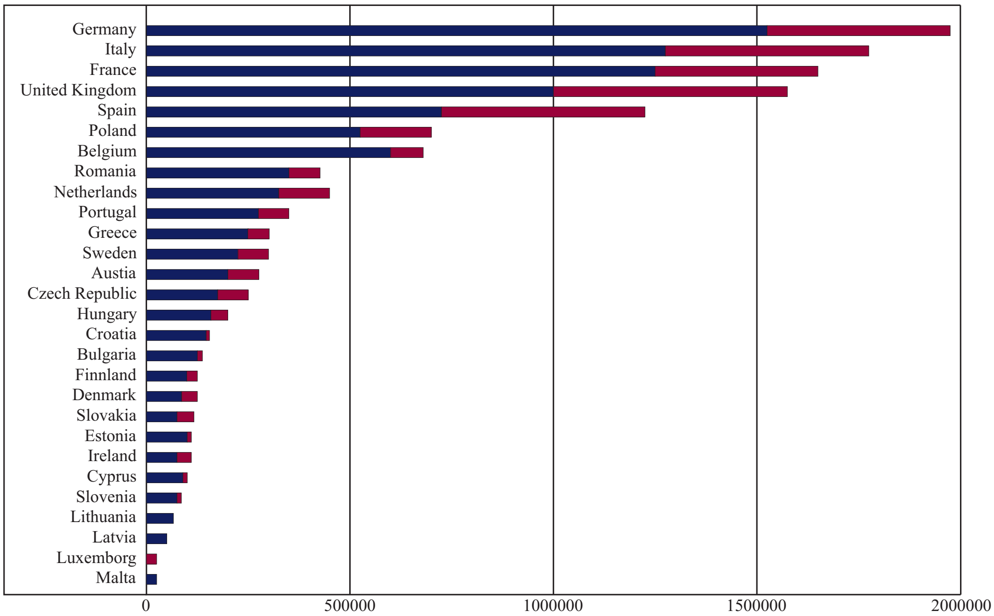


Fig. 1.3 Dementia estimate for EU28 countries 2015 and 2050.

strength of the DePicT Profile Matrix is proposed [198]. DePicT Dementia CLASS, which is used and updated by caregivers and domain experts, enables caregivers and patient's relatives to find relevant learning materials and references to answer question they may have. In the case formation process, requested keywords are identified and their values assigned based on the DePicT Profile Matrix. 110 *ICF* parameters are searched from thirty-three dementia and caregiving books and handbooks to create a large document for use by the DePicT Profile Matrix in developing the feature values (See Chapter 4). Other parameters relevant to caregiving e.g., challenges and task difficulties, are considered in the DePicT Dementia Onto-CLASS which is also referred to recommendation. DePicT Dementia Fuzz-CLASS improves on the results obtained from DePicT Dementia CLASS by distinguishing the stages of dementia.

These prospects of improving knowledge-based systems was a primary motivation in undertaking the current study, and explanations of the concepts, system designs, and development of the applications for achieving these goals are given in the following chapters.

1.4 Overview of the methodology chosen

Many medical assistant systems have been developed over the past few decades, with interest in computer-aided problem-solving in the medical and healthcare fields continuing to grow. Most of the software, applications, and systems developed for use in this domain focus on decision support and the recommendation of effective medications for patients. A combination of statistical analysis and CBR can facilitate better medical diagnosis, and the feature selection and similarity measurement capabilities employed by the case comparison mechanism of CBR can play an important role in the case-retrieval process.

Rather than a specific technology, CBR is a general methodology for building AI agents [266]. Over the years, research on CBR has led to a large number of applications [96]. CBR methodology addresses new states by first using an intelligent agent to retrieve similar experiences from similar stored situation, then reusing such past experience in the framework of a new situation by producing a new solution, and finally retaining the new experience obtained from the new situation in knowledge-base [96].

The DePicT methodology used in this study employs image interpretation and word association for feature selection and recommendation of medical solutions. Gathered patient records are stored in relational databases in structured, or closed-format (e.g., parameters and statistics), or unstructured, or open-format (e.g., texts and images). As an example of the latter, images of areas affected by a melanoma skin cancer can contribute to and support early-stage monitoring and diagnosis. In addition, further information obtained through answered questions or written statements on a patient's health condition can be added to the case base. Domain experts are used to validate and verify the collected information and also to update the case base to correct patient data records. To assist in detection and predict disease occurrence, results from the fields of vocational education and training (VET) and technology enhanced learning (TEL) [132] are used continuously. The DePicT CLASS CBR system also enriches cases using learning materials such as reference images and textbooks. Improving the learning environment using an education plan is considered in a dynamic environment and in dealing with new changes (e.g. references and courses). This involves the use of smart (case-based) and accessible systems to provide both vocational educational learning opportunities and achieving higher education. Having a universal framework for use by educational organizations both enables future systematic change and organizes, guides, and monitors the new modifications [92].

1.5 Overview of thesis and structure of the work

This section provides an overview of this study. The main processes proposed by this thesis are illustrated in Fig. 1.4 and explained in the following.

This dissertation comprises five main parts, including this introduction (Chapter 1) which in turn comprises seven sub-chapters that provide an overview of the thesis, background, and motivation.

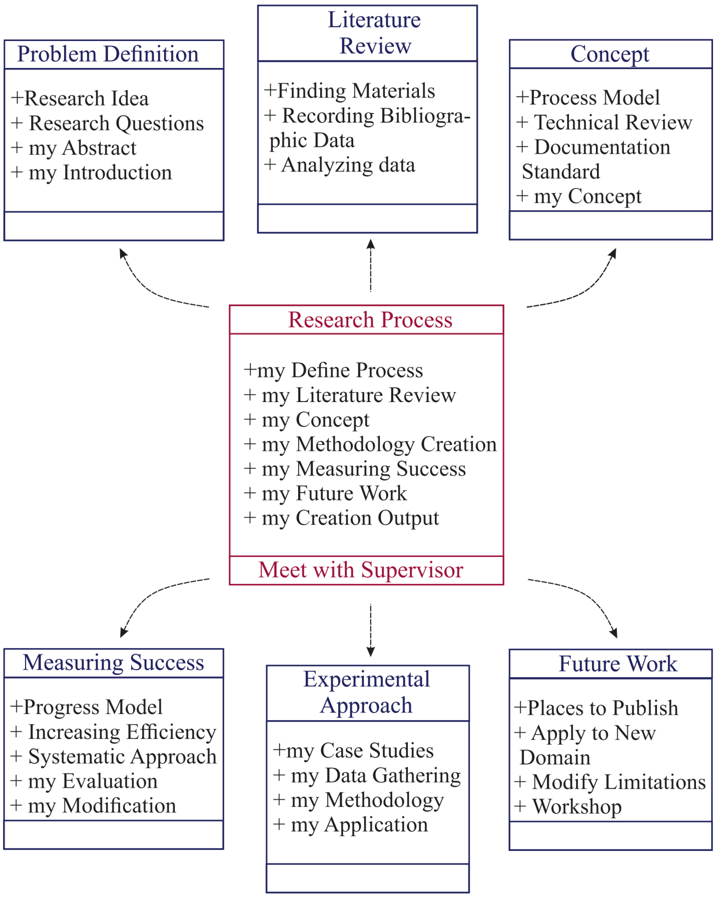


Fig. 1.4 Research processes of the current work.

Chapter 2 describes the state-of-the-art in the field and presents related works. In this chapter, a background of the field and a technical review of existing approaches that address the problems of dynamic knowledge assets, knowledge-based e-health, and case-based reasoning in problem-solving and sustained learning are given. In addition, a requirement analysis of knowledge acquisition is provided and the results of an experimental survey for understanding user knowledge concerning EHR and the use of web searching for problem solving is presented. Existing relevant medical CBR systems, textual CBR methods, conversational CBR applications, fuzzy CBR and collaborative CBR recommender systems are all discussed. The advantages and disadvantages of these current systems in relation to the objectives and characteristics of this research and its methodology are explored.

Chapter 3 develops a collaborative, case-based reasoning methodology and provides a system overview with a description of the proposed DePicT and DePicT CLASS conceptual models along with an overview of the developmental design and methodologies of these systems. The architecture and components of these systems and their main processes are explained. A more detailed description of the knowledge representation, case retrieval, adaptation, and retain phases of the proposed problem solving and learning method is given.

Chapter 4 describes the implementation of the proposed systems in the selected domains. It first explains the domain of applications—melanoma skin cancer and dementia disease—and then describes the systems that have already been developed for application in these domains, DePicT CBMelanom and DePicT Melanoma CLASS, respectively.

Examples of how DePicT is used to develop and maintain a system for detecting and predicting melanoma cancer are provided. In this case, the specific problem of focusing and representing the design of DePicT to recognize and treat melanoma symptoms is addressed. A specific characteristic of treatment of this cancer is that the task of symptom- and feature-finding is interleaved with the treatment task. As another example, the DePicT Dementia CLASS is presented as a conceptual modification of DePicT CLASS based on the development of a vocational educational training system for dementia caregivers and further developed in two other approaches as DePicT Dementia Onto-ClASS and DePicT Dementia Fuzz-CLASS.

Chapter 5 presents the evaluation and conclusion of this work. Opening with a comparison of the characteristics of the proposed evaluation procedure with defined evaluation scores, it follows this discussion by evaluating DePiCT Melanoma CLASS and DePicT Dementia CLASS following the analyzed approach. Finally, the thesis is completed by discussing the strengths and limitations of the proposed methodology and developed systems and suggesting directions for future research.

Five appendices are attached to these chapters. Appendix One presents the nine questions used in our survey for obtaining our initial understanding of EHR for this study. Appendix Two provides a literature review from 1988 to the present on medical CBR systems. In Appendix Three, the references which are used for calculation of word association strengths between melanoma and dementia-related diseases and their symptoms are showed. It also include the sample tests for the evaluation procedure. In Appendix Four, the WHO *ICF* code results for samples of dementia (Alzheimer) in the early, middle, and late stages used in the application are given. Appendix Five provides screenshots of the applications which are developed in these two domains.

This chapter also presents a list of the publications used in the development of this thesis and a list of the submitted publications (See next Section) prepared based on this work.

1.6 Publications of the thesis

1. Sara Nasiri, Katharina Klingauf, Dan Li, Jan Ortmann, and Madjid Fathi, DePicT Dementia CLASS: Medical CBR Learning Assistant System, In Proceedings of the video competition at the 25th International Conference on Case-Based Reasoning, Best Student Video Nominee (Top three) http://sce.carleton.ca/ mfloyd/ICCBRVC2017/, Trondheim, Norway, 26-28 July, p. 291, (2017).

2. S. Nasiri and M. Fathi, Case Representation and Similarity Assessment in a Recommender System to Support Dementia Caregivers in Geriatric and Palliative Care, In Proceedings of the Workshop on Process Oriented Case-based Reasoning at the 25th International Conference on Case-Based Reasoning, Trondheim, Norway, 26-28 July, pp. 157–166, (2017).

3. S. Nasiri, I. Allayarov, M. Fathi, Developing a Prototype of Case-based System Utilizing Fuzzy Sets to Detect Faults of Injection Molding Process, 7th German workshop of Experience management(GWEM2017) in 6th Conference "Professional Knowledge Management - knowledge management in the digital era" in Karlsruhe, Germany from 5-7 April, pp. 92–96, (2017).

4. S. Nasiri, J. Zenkert, M. Fathi, Improving CBR adaptation for recommendation of associated references in a knowledge-based learning assistant system, Journal of Neurocomputing, 250, pp. 5–17, (2017).

5. S.Nasiri, B. Aslan, S. Geller, M. Fathi, A Prototype of Case-based Skin Cancer Detector for Android Phones based on DePicT Concept: CBMelanom 2016 International Conference on Computational Science and Computational Intelligence (CSCI'16), Symposium on Health Informatics and Medical Systems, 15-17 December, Las Vegas, USA, pp. 98–103, (2016).

6. S. Nasiri, J. Zenkert, M. Fathi, A Medical Case-based Reasoning Approach using Image Classification and Text Information for Recommendation Springer I. Rojas et al. (Eds.): IWANN 2015, Part II, Lecture Notes on Computer Science (LNCS 9095), Palma de Mallorca, Spain, pp. 43–55, (2015).

7. El Moussaoui, C. Reuter, M. Wiegel, S. Unkauf, T. Wießmann, M. Dornhöfer, M. Fathi, S. Nasiri, NeuroCare: Digitalisierte Früherkennung leichter kognitiver Einschränkungen In 8. Deutscher AAL-Kongress, Frankfurt am Main, 30 April, (2015).

8. S. Nasiri, S. Dienst, M. Dornhöfer, M. Fathi, Knowledge Based Platform to Manage Home Care and Advanced Mutual Communications (NeuroCare Portal) 2014 IEEE Global Humanitarian Technology Conference (GHTC), San Jose, California USA, 10-13 October, (2014).

9. S. Nasiri, M. Fathi, Toward an Integrated e-Health based on Acquired Healthcare Knowledge, 2014 Middle East Conference on Biomedical Engineering (MECBME), 17-20 February, IEEE Press, pp.301–304, ISBN: 978-1-4799-4799-7, (2014).

10. M. Khobreh, S. Nasiri, M. Fathi, E-Nursing: Experience Platform for Improving Nursing Performance, Journal of Geoinformatics, 10 (1):57–63 (2014).

11. S. Nasiri, M. Dornhöfer, M. Fathi, Improving EHR and Patient Empowerment based on Dynamic Knowledge Assets, Informatik 2013: 43.Jahrestagung der Gesellschaft für Informatik, Lecture Note in Informatics (LNI), Köllen Druk+Verlag, Matthias Horbach (Ed.), September 16-20, Koblenz, Germany, pp. 402–413 (2013).

12. S. Nasiri, F. Ansari, M. Fathi, Dynamics of knowledge assets and change management perspectives, the 2013 IEEE International Conference on Electro/Information Technology (IEEE EIT), Rapid City, SD, USA, May 9-11, IEEE Press, pp.1–6, ISBN: 978-1-4673-5207-9, (2013).

13. S. Nasiri, M. M. Sepehri, M. Khobreh, Utilizing Acquired Healthcare Knowledge, based on Using Electronic Health Records, in Information Quality in e-Health, Lecture Notes in Computer Science, Holzinger, A. and Simonic, K.M.(Eds.), Springer, November 25-26, Graz, Austria, pp. 429–439, (2011).

1.7 Submitted publications:

14. S. Nasiri, M. Jung, J. Helsper, M. Fathi, Detect and Predict Melanoma utilizing TCBR and Classification of Skin lesions in Learning Assistant System, In book: Bioinformatics and Biomedical Engineering, DOI: 10.1007/978-3-319-78723-7_46, (2018).

15. S. Nasiri, G. Zahedi, S. Kuntz, M. Fathi, Knowledge Representation and Management based on an Ontological CBR System for Dementia Caregiving, Submitted (2018).

16. S. Nasiri, M. Fathi, Advanced Retrieval Process utilizing Fuzzy logic in a Dementia CBR System, Submitted (2018).

Chapter 2

Background and technical review

This chapter provides an overview and technical review of the CBR and related works on CBR approaches in medical systems. It begins with an experimental survey for assessing general understanding of EHR and how health information is assessed online. It then continues with a discussion of dynamic knowledge assets management and an integrated knowledge-based e-health proposed by the author in [190] and [192]. The focus then turns to problem-solving, CBR methodologies, and its textual, conversational, and fuzzy approaches befor the chapter is concluded with a review of the literature on medical and learning CBR systems from 1988 to the present.

2.1 Experimental survey

The use of the internet to obtain health-related information continues to increase worldwide. A population-based survey of seven European countries found a growing use of online health information, with an average increase between 2005 and 2007 of 11.4% (from 42.1% to 53.5%) in the seven countries examined (Denmark, Norway, Germany, Poland, Latvia, Portugal, and Greece) [179]. According to the population-based survey by Kummervold et al.[144], Germany has seen the greatest increase in the access of health information via the internet, rising from 44.4% of the population in 2005 to 56.6% of the population in 2007 [179]. Their study also found that people are interested in texting or emailing images relating to their health problems to doctors to aid in their diagnosis; it was found that 15% of German population had done so in 2011, a figure projected to rise to 35% in the future [179]. In this manner, the patient's role has changed gradually from being simply informed to being actively involved in all stages from diagnosis to treatment.

Starting in January 2014 Germany has tested an EHR system in a few cities [249]. However, many people remain unclear as the functionalities of this system. In this chapter, the results of an experimental survey of 222 volunteers are discussed to gain a better insight into public awareness and understanding of EHRs, PHRs, and users' experiences in sharing and accessing information online [37]. A similar, but short (three-question), survey relevant to this topic was previously carried out in [118]. Our survey, which centers on the acceptance of the EHR by the German public and their awareness of its functions, comprised nine questions with five answer choices for each [37]. Of the 222 people who participated in this survey, 58.11% were female and 41.89% were male, 5.41% were under 18 years of age, 72.97% were between 18-39 years in age, 18.02% were between 40-65 years in age, and 3.65% were older than 65 (See Fig. 2.1).

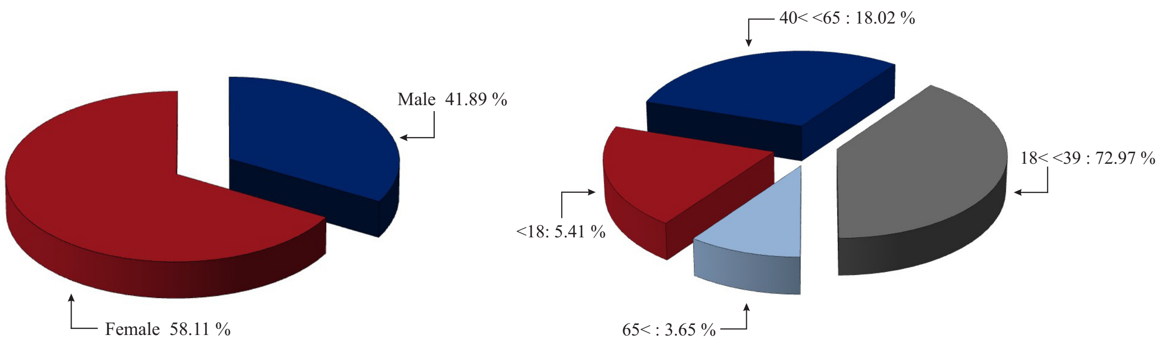


Fig. 2.1 Demographic participants in EHR survey.

The first question was "Do you have any information about the EHR - a patient point of view", with five choices, ranging from a firm yes to a firm no, available as answers. Only 54% of the participants were aware of the EHR, while 32% had never heard anything about it. Of the participants older than 65, 62 % were completely unaware of it. The results of this question are shown in Fig. A.1.

The second question was "How often do you collect your medical data?" Only 9% of the participants always collected their health information in the form of e.g., receipts or diagnoses. More than 30% never collected their medical information, while 35% usually collected it. Figure A.2 shows the results of the second question.

The third question is "Would you like to get your medical records online?" 55.9% of the participants did not want to download their medical information from the internet, as compared to 25% who did and another 18.92% who were unsure. The results of this question are shown in Fig. A.3.

The fourth question was “Would you like to edit your medical records?” 46% of the participants did not want to edit their medical information, while 29% did. Figure A.4 shows the results.

The fifth question was “Would you like your doctors to be able to access your electronic health/medical records?” 50% of the participants wanted their physicians to access their medical records, while only 29% did not, and another 22% were unsure. The results are shown in Fig. A.5.

The sixth question was “Would you like to determine which physician / physiotherapist can view which data?” 74% of the participants wanted this power, although 37, 5% of the participants older than 65 years did not, as shown in Fig. 2.2.

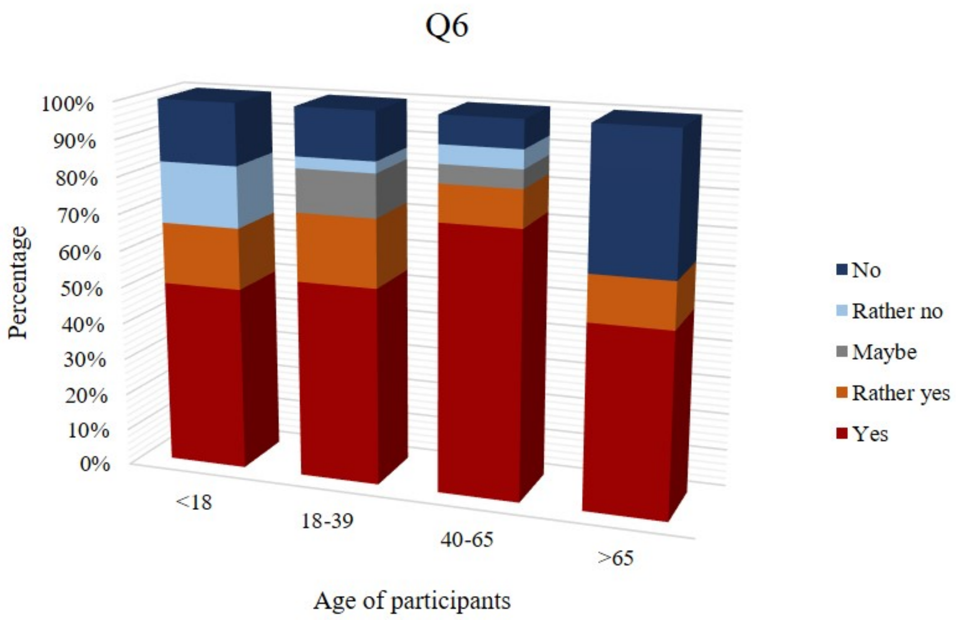


Fig. 2.2 Q6 - Determination of physicians accessing to patient data.

The seventh question was “Do you search about your symptoms in Google?” 63% of participants always searched their symptoms, while another 20% never did so. The main reason stated for not doing so was the perception that information found on the internet is not trustworthy. The results of this question are shown in Fig. 2.3.

The eighth question was “Suppose you had a serious illness, would you like to exchange the records with people who have the same disease?” While non of the under-18 participants answered affirmatively, more than 50% of the participants who were older than 65 expressed

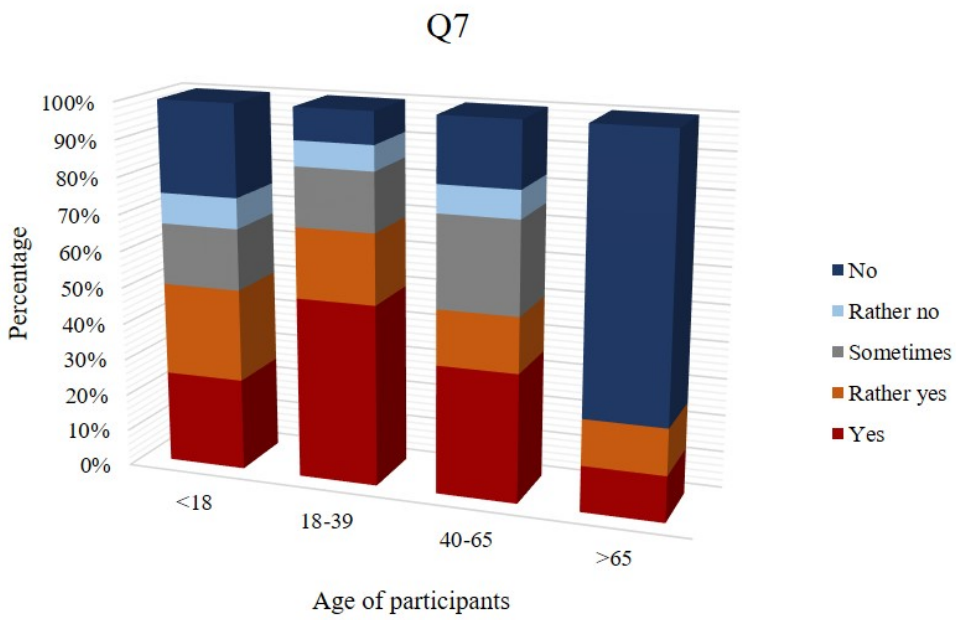


Fig. 2.3 Q7 - Searching in Google.

interest in such an information sharing scheme, as shown in Fig. A.6. Females were more likely (86%) than males (76%) to wish to communicate information on their condition.

The ninth question was "Do you inform sufficiently about the electronic health record from health insurance and the German Ministry of Health?" 63% of the participants felt that their health insurance provider had not given them sufficient information on the EHR and that they wished to have more. Figure A.7 shows the results of the last question.

It is apparent that much of the public is unaware of the EHR system and their functions. The survey results here suggest that, although the bulk of the German population never collect their medical information, more than 50% want to be able to download it, a result indicating the general lack of reference to personal health records. Generally, only those aged 65 years and older want to be able to edit their records; most want their doctors to be able to check their health records but do not want to otherwise share information. This suggests a general lack of awareness of the EHR's functions. However, the answers to the seventh question indicates that most people want to know more about their condition, with more than 63% engaging in internet symptoms searches. The fact that many of those who do not engage in internet research feel that they cannot trust online resources suggests the potential for creating a reliable and personalized assistant system as the essential result of this survey.

2.2 Dynamic knowledge assets management

During the past few decades there have been a very large number of changes in many aspects of human life. Increased awareness, knowledge-sharing, and the creation of new ideas in new and innovative ways have proven to be the key factors to successful change in competitive environments. Today, there is a greater need than ever to acquire, utilize, and share knowledge and particularly to improve the geographic mobility of knowledge in supporting a large number of organizations and practices. The value of effectively capturing, sharing, circulating, protecting, and appraising organizational knowledge has been increasingly apparent over the last two decades [160], with the exploitation of intangible knowledge becoming much more critical than managing tangible assets [73]. This issue has also been anticipated by policy makers as a major aspect of, for instance, VET and TEL policies for improving skills and competencies in the European labor market [83].

By managing its knowledge assets, an enterprise can improve its competitiveness and adaptability and, therefore, its chances of success [231]. By definition of Boisot, knowledge assets are as “stocks of knowledge from which services are expected to flow for a period of time that may be hard to specify in advance” [40]. In dealing with change in particular, managing the dynamics of knowledge is the top strategic agenda of a variety of companies that recognize the critical role of KM and its effects on their future success [231]. Managers particularly strategic managers are challenged to maintain a competitive edge in their market while leading their organization through constant change. To proactively address change instead of simply accepting a situation while systematically coordinating their employees’ transition to new ways of doing things, managers need an edge. Providing this “edge” underlies the approaches of Lewin [156], Kotter and Cohen [143], Hiatt and Creasy [114], Hiatt [113], and Bridges [46], the main leaders in the field of change management (CM).

The CM models of CM John Kotter and William Bridges are similar from many structural and organizational aspects. Both envision change as ocuuring in three phases, namely, *current, transition,* and *future*. In Kotter’s model, these phases can be understood to represent, respectively, creating a climate of change, engaging and enabling the organization, and implementing and sustaining the change [143]. This model relies heavily on communication and information sharing to facilitate the acceptance of change, primarily because it sees each person as needing to accept change on his/her individual level before it is implemented. In Bridge’s model, the three phases are interpreted as the endings, the neutral zone, and the beginnings [143]. He also emphasized the need for communication down to the individual level to overcome individual challenges in terms of acceptance [157]. Wijethilake et al. further defined CM as fostering the achievement of the most successful outcome by managing the "people side" of change utilizing process, tools, and techniques when a new technology or process is introduced into an organization or system [273].

In the paradigm suggested by these studies, everyone in an organization (including management) experiences change under the three main phases of CM as current, transition, and future states. In the current state, preparations are made or for the change, and the CM team and its strategy are identified. In the transition state, the project team conducts the shift carrying out the CM plans. Finally, in the future state the change is reinforced via collection and analysis of feedback. In this manner, the CM process supports the people side, while a project management (PM) process is used to administer the technical side of the change. In this regard, the Prosci Change Management Learning Center [217] defined CM as the process of helping employees transition from the current state to the future (desired) state, as defined by the change plan, in a manner that limits productivity loss and negative customer impact while at the same time maximizing the speed of adoption and decisive utilization of the change throughout the organization. To achieve this, communication and coaching are used to help employees make their personal transitions.

2.2.1 Knowledge management reinforces change management

CM requires two perspectives: 1) an individual standpoint (i.e., how people experience a change); and 2) an organizational perspective (i.e., how groups can be managed through a change). For individuals or groups to make a change successfully (as characterized by Prosci's ADKAR model [113],[217]), they need:

- awareness of the necessity of the change;
- a desire to participate in and support the change;
- knowledge of how to change;
- an ability to implement the required skills and behaviors; and
- reinforcement to sustain the change.

According to our approach, a third perspective can be additionally defined as: 3) a systematic approach (i.e., how processes, tools, or systems can be deployed to support successful management and implementation of the organizational change). In this context, the organizations must consider knowledge assets that are generated, (re)-used, stored, exchanged, or delivered during processes and projects. Monitoring people and organizational knowledge assets during the change must be considered in light of potential technological or non-technological risk, loss, and resistance of individuals against change [250]. As stated by Gray and Larson, addressing risk in the form of uncertain events or conditions will have a positive effect on project purposes [147]. Risk management, a key to project success, is a well-defined ongoing process that should be integrated into all project processes and continues throughout the life cycle of a project [250]. In this context, loss and resistance are risks based on human factors that affect CM, i.e., human reactions in response to changing events. There are three main types of resistances: emotional (psychological), cultural, and rational (behavioral) resistance [157] and [260]. KM can support the elimination of these, particularly rational or behavioral resistance, because they stem from misunderstanding or lack of information. A typical example discussed in [157] and [260] is misunderstanding the finer details of a project, which can lead to an assumption that change is unnecessary and an expectation that it will raise negative consequences.

In this manner, the gap between the PM, or technical side, and CM, or the people side, can be bridged in consideration of stakeholder values, performance objectives, process mining, and monitoring and control of knowledge assets. This leads to better management of each change event, which in turn enhances system adaptation. The role of KM in reducing or even eliminating gap between CM and PM is illustrated in Fig. 2.4 [190].

Fig. 2.4 The role of KM in compensating the gap between CM and PM.

A large part of the KM literature suggests the consideration of KM implementation under three broad perspectives: strategic, managerial, and operational [106], [287], [130] and [170]. According to the three-dimensional model of Wijnhoven [274] these perspectives can be describes as follows:

- the strategic perspective, which is supported by the strategic mainstream, highlights the strategic importance of the knowledge and its management to an the organization's success. It further considers sets of approaches for connecting the organization's strategy with KM.

- the managerial perspective comprises the set of approaches and methodologies for assessing an organization's intellectual capital in implementing the KM processes. It covers all models for motivating managers in the assessment and management of knowledge processes [56].

- the operational perspective comprises the set of organizational and managerial activities and projects (e.g., teamwork, meetings, benchmarking of best practices, communities of practice, etc.), implemented with the goal of using and developing an organization's knowledge assets.

To implement KM effectively, a combination of strategic, managerial, and operational approaches is required.

2.2.2 Dynamics of knowledge assets

Integration of KM activities into knowledge-intensive business processes leads, on one hand, to control and administrate knowledge flows among knowledge professionals and stakeholders and, on the other hand, to potential improvements in the use of knowledge assets. Such assets can be differentiated based on knowledge type as explicit, tacit, or latent. Polanyi [214] and Nonaka and Takeuchi [201] defined these three types of knowledge and made distinctions between them. Here we use the definition provided in [274]:

- explicit knowledge is knowledge expressed without attenuation (e.g., personal, independent, and documented knowledge);

- tacit knowledge is not and cannot be expressed (e.g., personal skills and experiences);

- implicit knowledge can be expressed, but is not because of inherent difficulties in expressing it without attenuation (e.g., informal norms and values).

Despite its advantages, the principal question of how to measure the success rate of KM activities remains. The monitoring and evaluating of KM activities require the application of process- and result-oriented metrics and indicators. In other words, after applying KM in an organization, a next step is required in the development process, namely, developing and implementing a reliable method for monitoring and evaluating KM activities (i.e., a feedback mechanism). The use-case scenarios for most KM activities involve knowledge-intensive business processes that can be characterized as specific business processes with increased need for expert knowledge in the fulfillment of single-, multi-, or interdisciplinary domains tasks [99]. Feedback from evaluation can assist the knowledge officer in improving business processes in terms of output quality, process runtime or fulfilling customer demand.

Although strategic and managerial KM are both essential, the success of KM is primarily realized at the operational level, particularly as a result of the proper performance of KM tools (e.g., agent technology, search engines, knowledge discovery systems for databases) and systems (e.g., document- or content management systems). These are either used by or applied to organizations. However, it is important to determine the rate of success. In this context, the European Committee for Standardization [84] has defined the main bottlenecks resulting from either absence or inefficient use of KM in organizations, particularly in small and medium enterprises (SMEs), as follows:

- knowledge tends to be tacit/informal/not recorded;
- know-how might not be valued as highly as it should be;
- it might be difficult to explicitly acknowledge lack of know-how;
- short-term approaches to knowledge gaps can work appropriately and thus make change appear unnecessary;
- know-how can easily be lost if the owner sells the business or retires.

The success of KM becomes concretely apparent when evaluating the impact of KM on the development and use of organizational knowledge assets [170]. Such assets include humans, structural, and customer capitals. As explained earlier, KM assigns different types of tools or systems in processing organizational knowledge. The proper performance of KM tools or KMSs in the utilization of organizational knowledge crucially requires monitoring and evaluation. Alon these lines, Franceschini et al. pointed out that testing the effectiveness and efficiency of a process through monitoring requires the identification of specific activities, responsibilities, and indicators [88]. Efficiency can be defined as doing tasks correctly, while effectiveness is concerned with performing the correct tasks. Alternatively, efficiency can be defined as getting the most output per unit input people or products, while effectiveness can be defined in terms of setting the right goals and making sure to accomplish them [88]. Based on this definition, effectiveness is primarily result-oriented and is therefore measured by comparing achieved results against target objectives, while efficiency is process-oriented and concerned with links between process performance and the resources employed.

To monitor and evaluate KM, two principal objectives are focused upon:

- process quality, or the efficiency of a target tool or system (e.g., the usage rate of organizational knowledge assets by a KMS);
- product quality, or the effectiveness of a target tool or system (e.g., usefulness or appropriateness of results produced or delivered by a KMS).

The efficiency and effectiveness of KM tools or KMSs are validated by using metrics and indicators. Despite similarities in concept and application fields, in some of the literature a slight difference is seen between these two terms. In general, metrics are quantitative information that is processed relative to the specific needs of business analysis and control and characterized as being able to represent a situation in concentrated format [115]. By contrast, indicators imply an indirect measurement approach and do not map to facts that can be directly measured [115]. Although this difference points out important differences between the two terms, in the concept proposed in this thesis “indicator” is utilized for both measurement approaches.

Operational KM is not only simple but also a potentially critical decision tool for distinguishing between process and product quality, as the two concepts are strictly interconnected. This connection is revealed in, e.g., knowledge discovery. Explicit knowledge detection employs the three core activities of retrieval, search, and discovery (browsing) [86]. In this sense, a successful measuring and evaluation method requires essentially concrete measurement objectives that are considered in a comprehensive and customizable measurement framework.

In other words, the measurement of KM activities requires both performance and the use of documented and personal knowledge. In addition, interconnections and interrelations between indicators need to be properly determined.

2.2.3 Knowledge management system enriches DKAM

The discussion so far on the co-operation of KM and CM in the deployment of knowledge assets and on the dynamics of such assets over time points to the design of a conceptual model for dynamic knowledge assets management (DKAM) [192]. DKAM addresses the major aspects of CM through the implementation of KM (See Fig. 2.5). It is a modular model comprising the main states of the CM process (the current, transition, and future states), which are colored as red, yellow, and green, respectively, in the figure. It also encompasses PM, stakeholders, and a new component that replaces the traditional iterative processes known as KM. This enables entire procedures and processes that considering the dynamics of organizations or systematic knowledge assets to use CM in support of each of the states, thereby guaranteeing a successful approach to managing change. Stakeholders provide value dimensions as inputs into the CM strategy developed during the current state; the strategy is then delivered to the KM team for identification of knowledge assets and change factors that influence (i.e., update, create, and reuse) the knowledge assets within the CM. Applying KM to PM allows for the identification of knowledge assets relevant to process objectives and project procedures and also enables the application of specific experience, knowledge, tools, and expertise to the project. In this context, knowledge assets represent the completing pieces of the “technical” and “people” puzzle discussed earlier. Through the application of KM, the gap between the technical (PM) and people (CM) sides is bridged through the input of stakeholder values and the use of performance objectives, process mining, and the monitoring and control of knowledge assets.

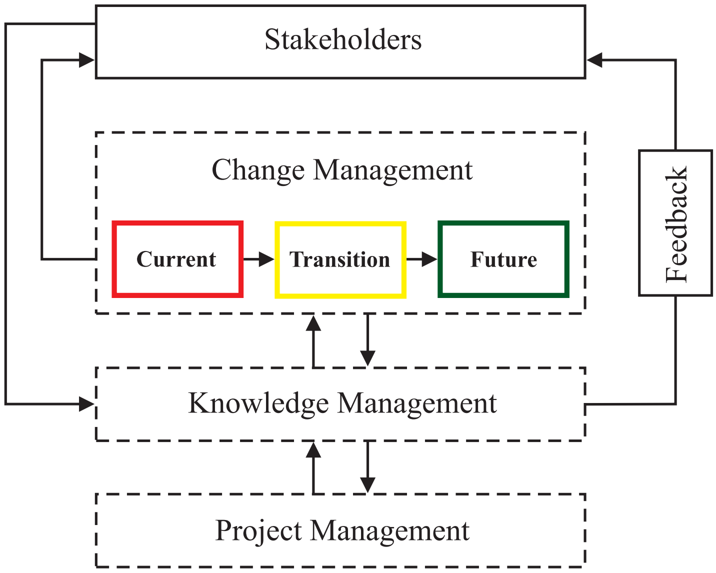


Fig. 2.5 DKAM Conceptual Model.

During the current state, a CM strategy and set of guidelines relevant to the size, scope, type and amount of needed change is created and the capacity for change as well as the adaptability to change are examined. These activities lead to the development of a sponsor model (See Fig. 2.6) and enable stakeholders to play a role in defining the organizational values. In this step, the desired state in terms of the stakeholders’ value requirements, as illustrated in Fig. 2.6, basic resources (e.g., project management resources), and current/changed knowledge assets are identified. Knowledge assets in particular are modified based on the amount of risk and the resistance to the modification and change management strategy. KM is applied to support functions or systems within the organization (or system). In the transition state, the CM team, in collaboration with the PM team, develops CM plans for communication, supervisory coaching, training, and readiness management. In this state, the role of KM (i.e., KMS) is crucial. As explained earlier, misunderstanding of the finer details of a project can occur from the employees' point of view in the presence of unstructured, dynamic, or varied types of knowledge. To avoid this, KMS is used to share correct knowledge (or information) in a timely manner for use by the right people. It is the role of KM to bridge the gap between technically oriented PM and people-oriented CM in enhancing the rich interconnectivity of the DKAM based on domain expert activities.

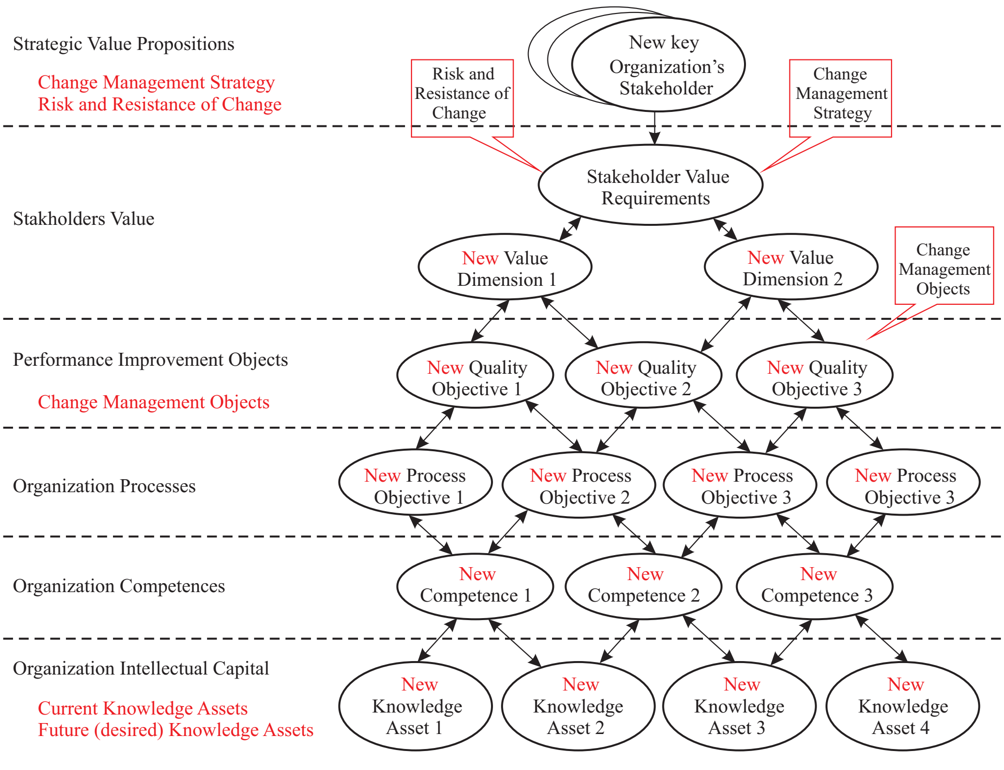


Fig. 2.6 Desired knowledge Assets, adopted from [235].

DKAM based on KMS (See Fig. 2.7) comprises sets of knowledge-based systems that can facilitate the transition state by considering the current knowledge model and key requirements, as illustrated in Fig. 2.6. The challenges in building and maintaining knowledge-based systems are generally referred to as the knowledge acquisition problem. Knowledge acquisition is a cyclic process that runs through the entire lifetime of a system. Broadly speaking, knowledge acquisition can be split into two main tasks [2]:

i) Initial knowledge modelling, in which the initial competence model of domain knowledge is developed based on current and desired knowledge assets, problem solving strategies, and reasoning methods. The objective of this task is to capture, within a computing system, the relevant knowledge that a human being would use to solve problems within the domain (e.g., the stakeholder's values and objectives). Given that this model is somewhat incomplete, the process is also called the knowledge acquisition bottleneck. Initial knowledge modeling establishes the knowledge environment in which problem-solving initially occurs and from which consequent learning methods obtain support.

ii) Knowledge maintenance, in which modification of the initial knowledge model and discovery of new knowledge assets is accomplished. The objectives of the task are:

- to correct errors, and improve the quality of knowledge to reinforce the change;
- to improve performance efficiency by applying the new quality objectives; and
- to adjust to a changing external environment in light of new competences and new or desired knowledge assets.

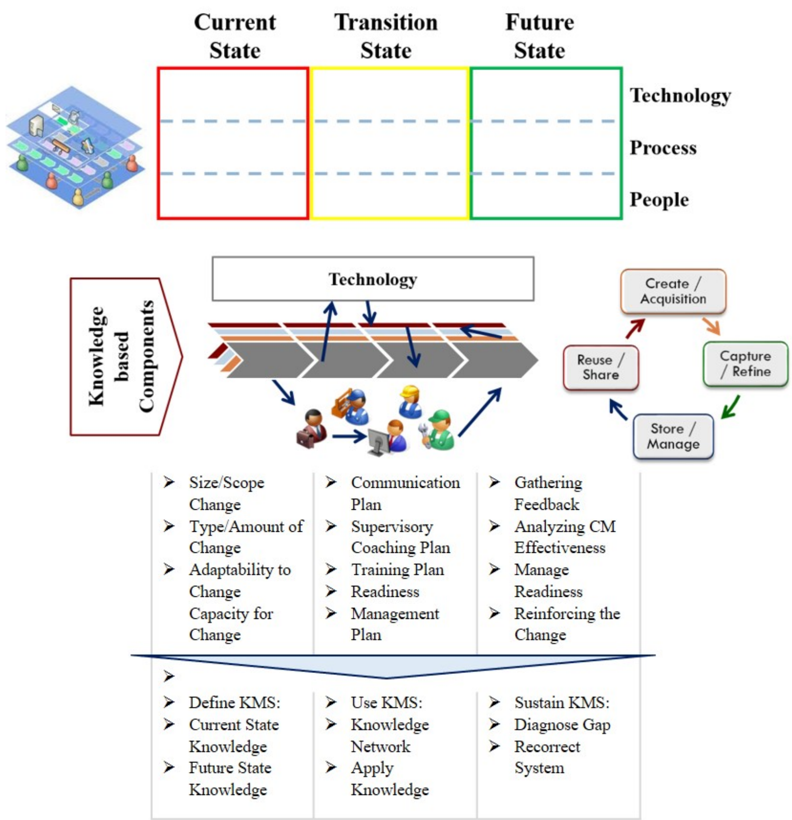


Fig. 2.7 DKAM based on KMS.

2.3 An integrated, knowledge-based e-health

Several tools were used to develop the integrated e-health system, as will be discussed in this section. Some of these tools, including knowledge portals (KPs), make knowledge accessible to users and support them in the exchange of knowledge. KPs are useful to knowledge-seeking users as a type of KMS in which a single point of access is provided to the represent the knowledge of an organization [164]. The KPs examined in this research (i.e., EHR and PHR) are used to improve the recording and analysis of patient profiles from internal networking systems as well as other social medias. Several accounts have been produced on how the objectives and roles of KPs are defined.

In addition to the KPs, apps are used to provides synchronous collection and gathering of data and for extracting knowledge. Based on a study conducted by the IMS institute for healthcare informatics, there were around 165,000 mobile health applications available on the marketplace in 2015; these could be classified into the two main categories of treatment/wellness management and disease [182] (See Fig. 2.8).

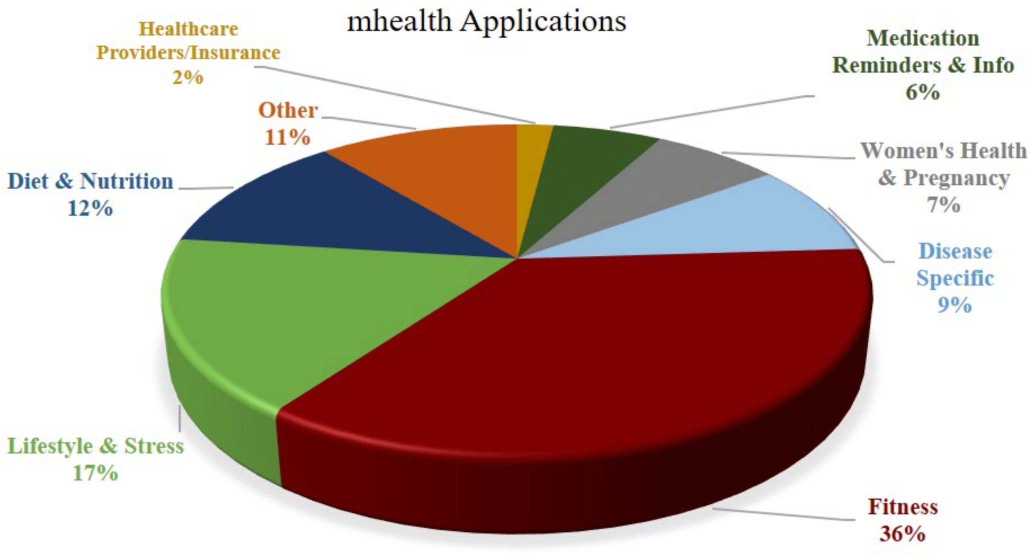


Fig. 2.8 Mobile health applications.

A study conducted by eClinicalworks (ten physicians) in the United States that 93% of the 649 physicians surveyed felt that connecting a health app to an EHR could provide value, especially in terms of appointment management and medication provision [233]. It was also found that 89% of the physicians were likely to recommend a mobile health app to a patient, while 93% relied on improvements provided by such systems to ensure patient health outcomes [233]. These results stress on the usability of the medium and suggest the usefulness of developing mobile apps for different healthcare purposes. Using clinical apps, datasets, and medical records can help clinicians manage growing amounts of information [65]. In addition, communications between colleagues and patients is enhanced through the use of apps and they can provide for better information management and access. mHealth is a growing area in e-health involving the use of mobile technologies in interactive data collection. Such technologies can be fully utilized in the management or dispersal of electronic patient information such as electronic medical records (EMRs) and EHRs by defining standards in place for using electronic records and their interoperability. Smartphone or mobile apps are also being increasingly used in daily practice.

Under our approach, the key to managing knowledge-based e-health is focusing on knowledge integration. Knowledge assets can be classified based on a distinction between stakeholders' resources and basic resources. Structural knowledge assets include, for instance, standards, best practices, patents, methods, and intellectual property, while stakeholder knowledge assets include capabilities and relations, experiences, skills, creativity, and innovation [55].

An integrated knowledge-based e-health system should be designed to support and enable knowledge extraction and creation, storage and retrieval, sharing and transfer, and knowledge integration (i.e., the processes of KM) by providing access to relevant knowledge artifacts.

Whereas gathered patient records are generally well-structured, documented, and storable in relational databases, internet-based records are generally unstructured. In addition, most formal and informal data primarily include text. Thus, record content should be analyzed with a particular eye for extracting knowledge elements. Knowledge discovery from text/data (KDT/KDD) has become an increasingly important area of study in the field of KM, leading to a number of advanced KDT and KDD methods. Knowledge sources stored in text documents can be obtained, even if there is sparse or lacking information regarding the text, through detection of the most prominent or often used words in the text. Such methods, which are called keyword extraction or keyword detection, focus on the automated location and extraction of the most characteristic words of a text [137]. However, it is more useful to analyze text documents based on the number and content of the sub-topics, and the corresponding computation and assessment of the associations between words is the most challenging task in text-mining methods [137]. Using such methods to extract knowledge and information from various sources enables their utilization in an integrated manner of knowledge-sharing and transfer through direct interaction between knowledge stakeholders and experts. Collaboration and communication tools also provide functionalities for identifying and connecting experts based on their expertise.

2.3.1 EHR data management

In the past few years, manufacturers have found the health sector to be a significant market for new and advanced products and services aimed at the improvement of patient treatment, observation, and collaboration. In addition to "hardware" products, services related at the ambient assisted living care at home or in social media have increased significantly. The patient's role has changed from one of being merely informed to being actively involved in all stages from diagnosis to treatment. In the literature, the products and services that have been developed are given various names and categories such as Health 2.0, Medicine 2.0, or both relating to Web 2.0, or eHealth for electronic health. Varying definitions are available for each technology- see, e.g., [85]. Bos et al. [42] defines Health 2.0 in their work on Patient 2.0 Empowerment as the use of information and communication technology (ICT) by patients to enable them to become active and responsible partners in their own health and care pathways. The title of a source often reveals the new roles played by patients in healthcare. While formerly the practitioner held all of the knowledge regarding the diagnosis and treatment of a patient, it is now expected that the patient will use ICT services to gain information on what is happening to them. Hughes et al. define Medicine 2.0 as personalized health care in which a specific set of web tools (e.g., blogs) are used to generate content by healthcare actors (e.g., doctors and patients), with a focus more on the technical point of view [124]. Eysenbach sees a strong correlation between Medicine 2.0 and PHR 2.0, whereas PHR 2.0, which builds communities around certain health topics and issues by allowing patients to access their EHRs and share some of the data with others [85]. A short web search will reveal a multitude of apps for tracking patient fitness, recording former diseases, providing medication, reminders, heart rate measurement via smartphone, eye examinations, and, of course diet apps for a healthier nutrition, to name only a few categories. The characteristics of certain types of apps particularly those that build on the patient's motivation (e.g., dieting or fitness) allow interaction with other users or for direct sharing of scores via social media services. Although the mobile apps market is booming, in 2012 Google decided to shut down its web-based health application "Google Health" which was used by both patients and professionals [48], owing to a lack of widespread use. The competition provided by Microsoft in the form of HealthVault [110] and World Medical Card [281] offer support for apps and connection to APIs or social media, with, for instance, HealthVault allowing users to login via their Facebook authentication.

Thus, the role of social media and mobile access to healthcare services have both increased significantly. In the context of IT, industry, and business, the general use of social media services focuses primarily on marketing via social media and is initiated by the companies; by contract, the use of social media in healthcare occurs on a more personal and private level. In most social media channels, any stakeholder can initiate a topic for discussion; however, in a medical context a patient might hesitate to ask questions in cases of personal or related illness owing to embarrassment, even though they are seeking support. For healthcare professionals, the use of social media is no easier, as a desire to provide support in specific cases might be hampered by ethical constraints restricting the discussion of related cases or patients whom they are treating. A related question is why professionals should undertake the extra work of communicating with patients via social media. Lau et al. answered this by noting that professionals actually find knowledge sharing and learning to be a significant good in terms of improving their own skills and delivering a higher quality of medical service [148]. While their definition is more focused on the application for the interaction between practitioners, it also applies to fostering better understanding between practitioners and patients.

The approach of using social networks for the exchange of information between doctors and patients furthers the already established concept of EHRs, which summarize patient information and medical histories into single records. Although EHRs are an established concept, in reality, patients are still often obliged to manually transfer certain information or test results between healthcare institutions and doctors.

2.3.2 EHR enriched by networks data

Following a basic overview of healthcare, this section focuses on creating an EHR that is enriched with data from PHRs and networking, specifically from social network communication, which integrates productive knowledge assets into the EHR. Enriching an EHR with PHR and social media data offers a more universal basis for medical decision making. Based on the definition of HIMSS, EHRs can generate complete patient record-related data that can be accessed directly or indirectly via an interface [116]. The EHR content, comprising administrative and medical or clinical data, should be comprehensive and expressive and address all aspects of the healthcare process for all related disciplines and authorities. There should be no restrictions on the type of data that can be entered into the EHR [141]. Clinical data should include patient medical history, physical examinations, clinical orders, pathology reports, consultations, operative data, monitoring data, observations, etc. Ideally, it will include all available patient data, irrespective of its source, and be capable of providing medical professionals with meaningful views on these data [196].

The use of EHRs offers significant benefits in healthcare. Direct access to patient history, lab tests, and images from the point of care eliminates the delay faced by the medical attendants in dispatching and retrieving physical records from dispersed physical locations. A dynamic for patient knowledge is necessary, necessitating an approach that can help in understanding the relations among the diverse data acquired by the enriched EHR while providing the right information to the right person at the right time, particularly within the network context. Based on user role, different views and requirements for knowledge assets (e.g., organizational, personal, structural) must be available.

2.3.3 EHR interoperability and dynamic knowledge assets

Patients can participate in social media to manage their data, find other patients who share similar disorders or symptoms, and discover relevant clinical trials by leveraging shared patient data [227]. The definition by Dobrev et al. of interoperability as continuous change management in a long-term endeavor suggests a model for successfully establishing and maintaining eHealth interoperability [77]. Dobrev et al. also highlighted that EHR interoperability must interpret "patient and other health information knowledge" independently of the source and that eHealth interoperability is divided into different levels of exchange and sharing of information and knowledge.

The integration of knowledge management activities into knowledge-intensive business processes leads, on the one hand, to controlled knowledge flows among knowledge professionals and stakeholders while, on the other hand, knowledge management improves the utilization of knowledge assets [190]. Knowledge assets are classified based on the distinction between stakeholder and basic resources. In this context "DKAM, enables the entire procedures and processes considering the dynamics of organizational or systematically knowledge assets through change management, to support each of the states and guarantee a successful approach to the change" [190]. Stakeholders provide value dimensions in terms of plan modification, which allows knowledge management teams to identify knowledge assets and factors that influence changes (i.e., update, create, reuse) in knowledge assets within the change states. They can also identify knowledge assets for meeting process objectives and undertaking project procedures. Knowledge assets are the completing pieces of the "technical" and "people" puzzle, bridging the "gap between the technical side and people side," while considering different factors like performance objectives and indicators [190].

Based on research of Rebuge and Ferreira, healthcare processes in general can be seen to have the characteristics of dynamic process changes and to have dependencies owing to the complexities in medical decisions, the amounts of data, multi-disciplinarily within a healthcare network, the use of ad-hoc decisions and individual processes, and the requirement for log data management, making the application of process mining to such processes challenging [221]. The final aspect, log data management, is particularly interesting, as the availability and quality of data are the key to the ability to apply process mining techniques. The concept of process mining involves extracting knowledge from system event logs. According to the authors, process mining focuses the process, organizational, and the case perspectives [262]. Caron et al. posited that most organizations and their stakeholders have very incomplete information on what is happening their own business processes and that process mining could be used to address this problem [57]. The application of process mining techniques in healthcare has been highlighted by the Process Mining Manifesto [125], which was created by a group of more than 75 people representing more than 50 organizations. Healthcare has increased in complexity, and medical procedures and processes are changing continually. Although the structural of healthcare processes is limited by their use of expertise, intuition, and creativity, there is still significant opportunity and potential for improvement (Spaghetti process improvement) in terms of learning and interconnecting among users [262].

2.4 Problem solving and CBR

CBR can solve new problems by adapting stored solutions previously used to solve similar problems [140][224]. CBR is a potential approach for understanding intelligence based on two assumptions: problems have a tendency to repeat, and similar problems tend to have similar solutions. CBR is an effective reasoning strategy if these two conditions apply [150][96]. The creative problem-solving process typically involves iterative phases of problem formulation, preparation, idea generation, evaluation, and selection [19]. CBR has been formalized for the purposes of computer reasoning as a four-step process [5] (Fig. 2.9): These four step is as follows:

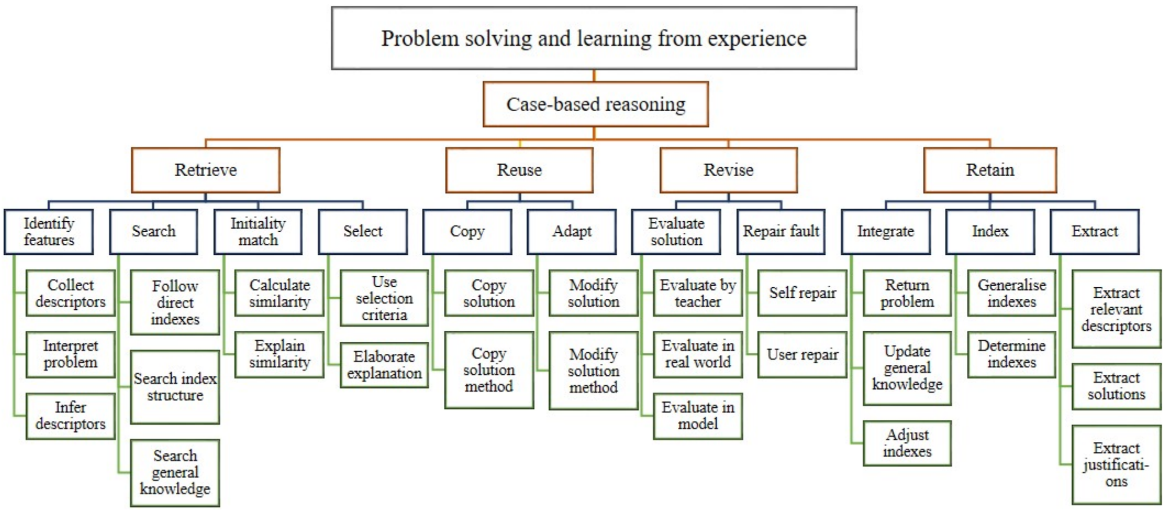


Fig. 2.9 Task-method decomposition of CBR.

1. Retrieve: Given a requested problem, retrieve information from existing related cases to solve it. A case comprises of a problem, its solution, and, typically, comments about how the solution should apply. For instance, suppose I want to make "Texas lasagna". The most relevant experience which I had as a novice cooker, is successfully making pasta tortellini with chicken. Therefore, the steps I have for making tortellini, including explanations for a new cook, comprise my retrieved case.

2. Reuse: Use the solution from the previous case and refine it to the requested problem in a manner that fits the new situation. Coming back to the lasagne example, I should adjust the retrieved solution to the new recipe containing lasagna.

3. Revise: Test the application of the previous solution to the new situation by simulating or even performing it, and then adapt it. Assume that I adapted the tortellini solution by simply mixing chicken with lasagna, producing a sub-optimal lasagna prepared without the layer step. Thus, an adaptation involving adding separate layers of lasagne, chicken, and sauce cream into the pot is required.

4. Retain: After the adaptation step is implemented, the experience obtained in solving the requested problem as a new case should be store in the case base for future use. Through this process, I have developed a new recipe for making lasagne and can apply this experience to obtain better cooking results in the future.

Collaborative CBR focuses on the use of retained cases in a problem-solving by a multi-agent CBR system comprising individual agents (users) [180]. Collaborative CBR differs from other federated peer learning cooperation models in that each requested problem that is locally solved by an agent is retained for future problem solving. If a given agent does not have the solution to solve a requested problem, they can call upon the problem-solving experience of other agents [180].

2.4.1 Textual and conversational CBR

Although many types of research have been done in the CBR domains, there remains a practical gap between the investigation and application of CBR. Textual and conversational cases are easily understood by humans but still requires structures for automatic processing. In CBR systems, problem formulation is the very first step in the CBR process model and is usually a prerequisite to the remaining steps and, as is true for other methodological procedures, there is no specific method for how this should be done [223].

Textual CBR (TCBR) is a subfield of CBR in which some or all of the knowledge sources are available as a texts [268]. The goal of TCBR is to apply an automated/semiautomated approach in the use of textual knowledge for problem-solving. Over the years, there has been significant progress in developing methods for importing textual knowledge sources into structured case bases. TCBR research often depends on representations of information retrieval from bag-of-words representations that ignore relations between words, e.g., vector space models (VSMs). Such methods represent documents as vectors with words as elements and word frequencies as values. TCBR systems utilize word occurrence for retrieving and reviewing the textual components of cases, as shown in 2.10. Many TCBR systems accomplish tasks similar to document retrieval and classification tools, e.g., [154][52][87][49][72][280][50][206][4][45][244][41][245]. The difference between these tasks in general and TCBR is that TCBR systems are designed to support problem-solving and are often developed with a specific domain and task in mind. Therefore, TCBR systems are often developed by modifying general retrieval and classification methods for a target domain and task.

Conversational CBR (CCBR) systems require the problem descriptions, which are initially prepared as brief free-text descriptions by users. As a results, CCBR queries are often constructed as problem specifications [6]. Examples of CCBR and related systems and tools are presented in [7]. Weber et al. presented a CCBR system which is called CBR Flow that enables users to reuse represented cases exceptions to workflow rules concerning process schemas [267]. For users who cannot formulate a problem in a machine-readable form usable by standard CBR system, CCBR provides a question dialog that can provide user guidance in describing their problem incrementally through an process of questions and answers [103]. CCBR is applied in a number of fields and domains [267], [243] and has been successfully improved the overall field of problem solving. It allows users to see question lists concerning relevant features and can answer questions to create new problem descriptions. Users can also examine entire sets of similar cases. The question list and cases are revised and new information is added to the case base each time a question is answered [149]. As users generally obtain multi-stage solutions in their decision-making, they require a recommender mechanism that can provide a suggestion package with detailed action recommendations for each stage [265].

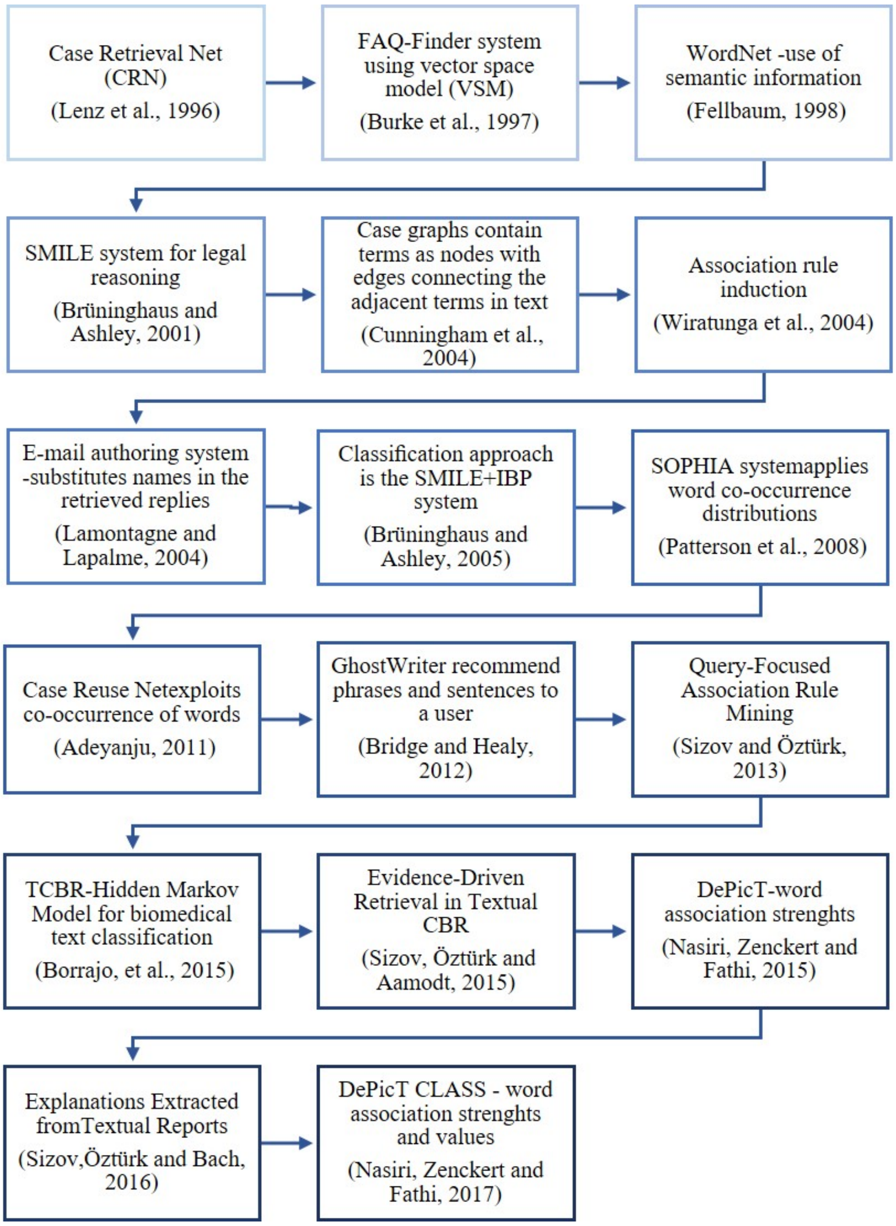


Fig. 2.10 Textual CBR overview of last decades.

2.4.2 Medical and learning CBR

Medical CBR applications have primarily been developed as mechanisms for making decisions based on previous cases. Using data sets of illnesses, corresponding symptoms, and suggested drugs, such systems attempt to imitate the examination of a patient's illness by a medical expert such as a doctor or specialist and provide advice as the output of expert knowledge from the system's knowledge base. CBR is applied in various problem-solving domains; in medicine, it can be useful integrate such systems to achieve explicit experience, cognitive adequateness, and objective/subjective knowledge duality and to extract subjective knowledge [122]. Only a few medical systems have been developed based on the complete CBR method. For this thesis, the literature on CBR systems from 1988 was reviewed (the sources are listed in chronological order in Appendix B). Based on this literature review, Figure 2.11 shows a classification of medical CBR systems according to objective. The review was adapted from that in [62] with the addition of:

i) the review of literatures in particular from 2016 and 2017 in six categories;

ii) similarity measurement of these medical applications or approaches; and

iii) datasets of reviewed medical CBR, if present.

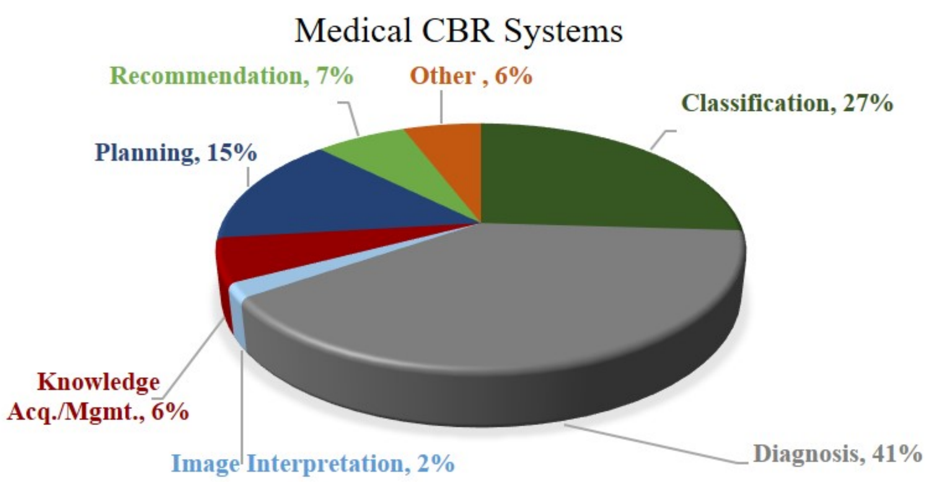


Fig. 2.11 Classification of medical CBR systems for the last three decades.

The CBR system mentioned in [197] compares features of an unsolved cases to those from a compendium of existing cases in a database to produce related recommendation such as CASY[142] and ICON [236]. Another system is also used in an ambient assisted living services to enable user interaction with the environment [59]. Marling et.al presented four different CBR systems: CARE-PARTNER [38], which assists in the long-term follow-up care of stem-cell transplantation patients; the Malardalen Stress System [8], which provides decision support for the diagnosis and treatment of stress; retrieval of HEmodialysis in NEphrological Disorders (RHENE) [185], which supports physicians working in the domain of end-stage renal disease; and the 4 Diabetes Support System, which assists patients with type-1 diabetes and their professional caregivers [175]. Van den Branden et.al, developed

ExcelicareCBR to support clinical decision-making through the harvesting of electronic patient records to enable the reuse of clinical experience [261]. The latest designs and developments in this area focus on the integration of data mining into CBR systems in, for instance, a proposed model for the prognosis and diagnosis of chronic diseases [122]. CBR is also used for the diagnostic screening of children with developmental delay [59]. Hybrid case-based architectures can improve the learning of newly adapted knowledge and can be applied in multiple disease diagnosis [120]. Hybrid CBR is also applied in other fields. For instance, Han and Cao presented an improved hybrid CBR method based on fuzzy c-mean clustering, mutual information, and SVMs to improve weight calculation in basic oxygen furnace endpoint prediction [105]. Yan et al. adapted CBR to establish a model for soft-sensing dissolved oxygen concentrations. Their model uses a genetic algorithm (GA) to optimize the weights in group decision making and case retrieval [284]. The combination of statistical analysis and case-based reasoning can facilitate many types of research related to hybrid CBR approaches in which CBR is combined with forms of AI. Teodorovi´c proposed a CBR-BCO model enriched by bee colony optimization and tested it on a real data set of patients with thyroid cancer containing 120 examples of a physicians' decisions [251]. Within the case comparison mechanism of CBR, feature selection and similarity measurement play an important role in determining retrieval cases. Medical CBR is applied in knowledge-based medical decision support systems; for instance, in [18] a system for diagnosing levels of intoxications caused by the administering of drugs was developed. The main goal of this system was the reduction of time used and the improvement of decision making, particularly in emergency cases [18]. L´opez et al. developed a tool called eXiT*CBR, comprising a framework for case-based medical diagnosis development and experimentation [165]. In eXiT*CBR Version 2.0, Pla et al. distributed a case-based reasoning tool for medical prognosis in the form of a tool for designing multi-agent cooperative CBR systems for which several vocabularies, cases, and weights can be provided. Optionally, information on agent relevance (collaborative data) can be provided or otherwise learned [213].

The combination of statistical analysis and CBR has facilitated much research on approaches to hybridizing CBR with related AI methods. Wilson and O'Sullivan developed standardized vocabularies and medical ontologies for representation of images in which keyword and medical expressions are used in developing visual image features to improve understanding by medical practitioners [278].

In developing a method for learning and educational CBR recommendation, Craw et al. utilized introspective learning adaptation knowledge acquired by exploiting the original knowledge from a problem solving case base. In their study, different learning algorithms were explored and used to demonstrate tablet formulation in a demanding component-based pharmaceutical design task [71]. Thistlethwaite et al. explored and analyzed the evidence relating to the effectiveness of case-based learning (CBL) to achieve defined learning outcomes in health professional prequalification training programs [252]. From their description given at the Queen's University Centre for Teaching and Learning (Ontario, Canada), "Using a case-based approach engages students in discussion of specific situations, typically real-world examples. This method is learner-centered and involves intense interaction between the participants" [252]. Bousbahi and Chorfi proposed a system which is called MOOCs-Rec that recommends appropriate courses from sets of massive open online courses (MOOCs) in response to specific learner requests [44]. The cases are created from a set of attributes-values with five features—course title (keywords), fees, course availability, language, and location of the Open University—with respective weight values. In this system, similar cases are found based on feature values, with the most similar solution recommended without modification [44].

He [109] presented a novel online cost estimation framework for course production based on the integration of work breakdown structure with CBR techniques. The proposed framework provides users with courses based on characteristics such as subject, course level, credits, and estimated development time based on a cost estimate process involving the reuse of previously recorded similar experiences [109].

The adaptation process is a complex and significant phase of CBR and is generally domain-dependent. As shown by the results of our review in Fig. 2.12, most medical CBR systems do not perform an adaptation phase. A number of algorithms and approaches have been proposed for adaptation in CBR. Kolodner defines three types of adaptation [140]: substitution replaces new values of new problem with values from retrieved solutions; transformation changes a retrieved solution to suit a new problem; and special methods apply specialized heuristic knowledge to repair a retrieved solution. The other four successful adaptation techniques are discussed in [239]. This include: i) adaptation rules and operators, which are applied if no similar case can be found or, if adaptation fails, use a few general rules for adaptation; ii) constraints, which reduces a list of solutions using constraints; iii) compositional adaptation, which computes weighted averages for the solution attributes determined by similarity to the current case; and, iv) abstraction, which generates additional abstract cases for the medical domain for situations in which each case is characterized by a long list of features and there are too many differences between current and similar cases for adaptation to take into account. Wilke and Bergmann developed a five-value classification of adaptation methods, including: null adaptation to describes the simplest methods; methods applying structural changes to the structure of solutions; generative methods requiring the generation of a problem solver; compositional methods, which are mentioned above,

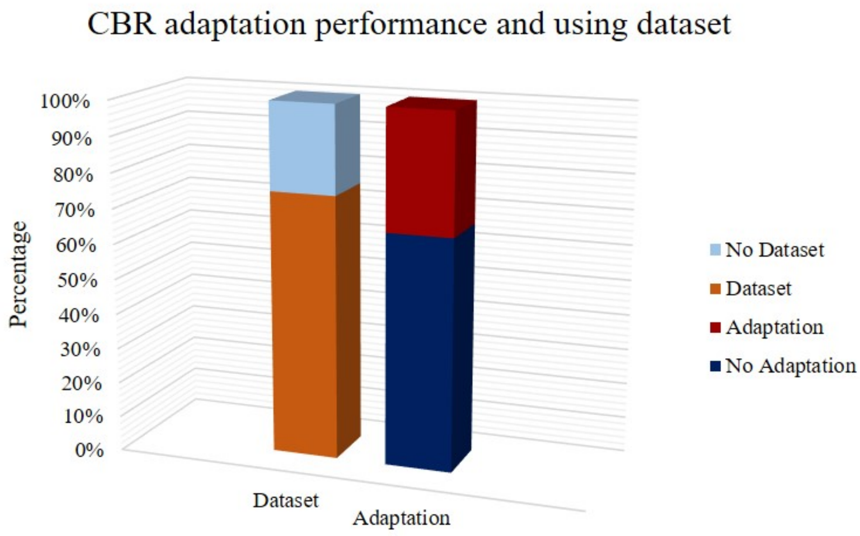


Fig. 2.12 Medical CBR systems contribution in terms of adaptation performance and using dataset.

involving the composition of multiple solutions of cases; and hierarchical methods with several levels of abstraction [275]. Lieber added to these conservative adaptation, which involves shifting from the source to a target context to operate a minimal changes [159].

There remains a lack of research on adapting textual cases. The goal of textual adaptation is to address semantic words or processes which are divided into case adaptations for use in a single numerical adaptation and in data sets stored according to the forms of the solution [291]. Amailef and Lu presented case adaptation based on a classification system involving comparison of an object of an incoming case with those in existing cases and then distinguishing the former from the classified objects [23]. Lamontagne and Lapalme introduced an approach for adapting solutions in which the case base contains past messages (e-mails) organized into cases comprising requests and responses [146], with the retrieved response used to address the unmatched aspects of the request modified and adapted. Arshadi and Badie presented a compositional adaptation approach for designing a tutoring library by combining solutions from multiple cases to produce a new composite of corresponding solutions (book chapters) [26]. Using the compositional approach, Sizov et al. produced an improved adaptation method by combining explanations from more than one case and and evaluating them using an incident analysis task [246].

2.4.3 Fuzzy CBR

There is not a lot of information in the literature on CBR systems incorporating fuzzy logic techniques. Although the use of hybrid fuzzy CBR technologies has drawn a significant amount of attention from the academic community, to date its use in applied systems has been sparse, and most operational CBR systems applying fuzzy methods incorporate fuzzy logic only in the similarity assessment undertaken as part of the retrieval stage.

If CBR is to be an effective problem-solving methodology, it must deal with some inherent degree of fuzziness and uncertainty, as these are often encountered in addressing complex applications. However, the standard, non-fuzzy methodologies of CBR engines are not sufficiently powerful to fully address such uncertainties. Previously, Choudhury and Begum reviewed the role of fuzzy logic in CBR [63]. In 1965, Zadeh introduced fuzzy set theory [288], inspiring Yager to suggest a fundamental similarity between CBR and fuzzy sets for integration and additional in use [283].

Fuzzy case-based reasoning has been successfully developed by researchers and has been confirmed to be extremely fruitful in some applications, e.g., [8], [215], [166], [91] and [128], involving the case-based identification of problems and solutions by CBR. Problems in which some attribute-values have fuzzy characteristics can themselves be fuzzified and similarity measurements can be developed with respect to these features [223]. Using fuzzy logic in the indexing and retrieval phases of CBR has some advantages, including [129] [63]:

i) easier transfer of knowledge across domains;

ii) the use of term modifiers to increase flexibility in retrieval;

iii) the conversion of numerical features to fuzzy terms to simplify comparison; and

iv) multiple indexing of a case using a single feature with varying degrees of membership.

Thus, fuzzy logic can be useful in cases with quantitative attributes. Case directories defined using fuzzy sets can be arranged for retrieval and also make available, from a range of features, symbolic information for higher level abstraction [263]. There are several methods for calculating similarities between cases, including calculation of numeric combinations of feature vectors, representing known cases, using different combination rules and rule-based similarity assessments, and using the similarity of structured representations and goal-driven similarity assessments [204]. The retrieval process will also require fuzzy treatment if quantitative attributes are involved. Following the definition in [129], the fuzzy retrieval process comprises three steps:

i) quantitative attributes are converted into fuzzy terms based on membership functions defined in the fuzzifier;

ii) the resulting combinations of fuzzy terms and known qualitative attributes are used as keys for searching similar cases; and

iii) matched cases are retrieved as candidates, with the candidate with the highest similarity used to construct a solution to the new case.

2.5 Chapter conclusion

In this chapter, the use of CBR in many medical applications and for a variety of tasks including diagnosis, classification, treatment planning, and knowledge management was discussed. The results of the survey made us aware that the hybridization of CBR with other AI techniques such as ontology, rule-based reasoning, fuzzy logic, and neural networks and with techniques involving probabilistic and statistical computing is a promising avenue to enhancing CBR systems by incrementing them to manage the increasingly large, complex, and uncertain data sets in clinical environments.

We will discuss how word association strengths are used in defining our TCBR for constructing structured cases from texts, and how ontological and fuzzy CBR approaches can enrich the retrieval process. In the next chapters, we will also describe how two classifiers can be used to retrieve images from image inputs cases—another technique that is used in our proposed methodology.

Chapter 3

System overview and architecture

This chapter presents the theoretical model applied in this study and describes the contribution of the proposed new conceptual model and methodology for an assistant system to facilitate the in-depth analysis of a CBR system. Previously, we published some part of the proposed model as the DePicT concept in [197] and its methodology as the DePicT CLASS in [198]. This section focuses on case creation by DePicT CLASS and how graphical and textual information are used as a feature within the processes of case representation, matching, selection, and adaptation procedure. First, we describe how these types of data can be used to enrich the knowledge-base of DePicT CLASS. Then, we discuss how gathered user data can contribute to the case matching and selection process. This chapter is organized as follows. Section 3.1 introduces a conceptual model of the proposed system. The DePicT concept is explained in Section 3.2, while Section 3.3 presents the DePicT CLASS concept. Sections 3.4 to 3.7 describes the methodology and, finally, Section 3.8 summarizes the chapter.

3.1 Conceptual model

The conceptual model considering dynamic knowledge assets is based on the three-layers architecture shown in Fig. 3.1. Using DKAM enables both the implementation of changes and the maintenance of sustained long-term healthcare advantages. Under the proposed concept, the knowledge assets are knowledge elements contained in the EHR and PHR of a patient. Such records can be updated on the results of examination, laboratory tests, indications of changes in medication, or the commencement of therapies; as such, they continuously expand and change. In addition, practitioner processes also change continuously. The use by practitioners of internal expert networks is therefore only possible when the dynamic expansion of knowledge assets in a patient file is transparent, as otherwise the practitioner would not be able to support the patient via a social network or answer specific questions regarding, e.g., the latest examination results.

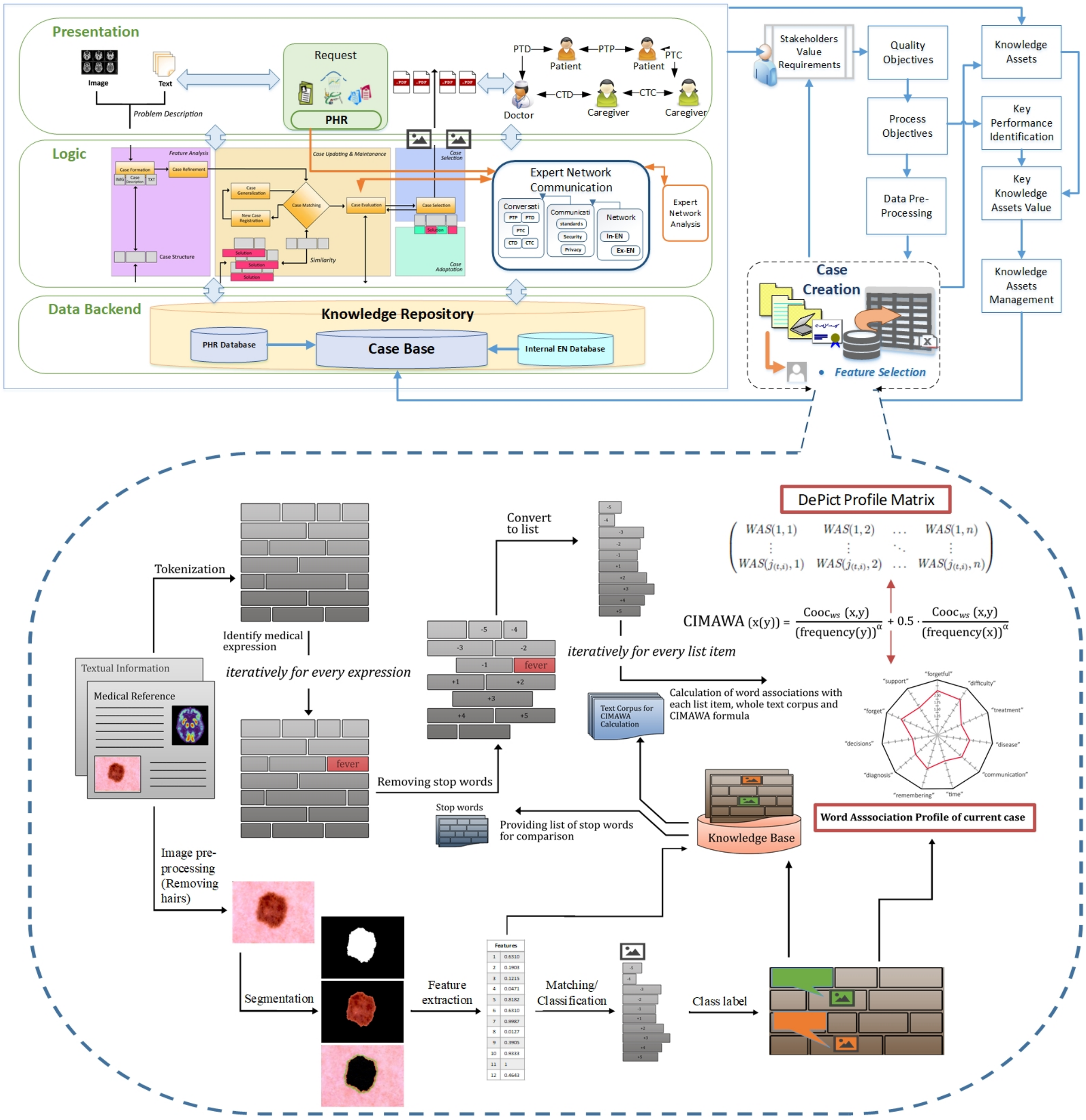


Fig. 3.1 Overview of the conceptual model.

Process mining of EHRs can now be used to discover information, make comparisons for confirmation, and enhance processes [262]. Model analyses to represent the output of the mining of EHR processes can lead to further EHR process improvements. In our conceptual model, as illustrated in the right side-bar of Fig. 3.1, related key performance indicators (KPIs) are identified according to the process objectives. Significant KPI factors are specified through the use of process mining and comparison among KPIs. A matrix of knowledge assets and performance targets is used to find knowledge assets values. Based on the definition provided by Carlucci and Schiuma, knowledge assets are listed in rows and classified in accordance with a knowledge assets map, while explicitly defined performance objectives are listed in columns [55] based on new value dimensions as defined by stakeholders, new objectives (i.e., quality and process), new competencies, and new knowledge assets (See Fig. 2.6). Knowledge assets are valued depending on the level of performance objectives achieved compared to a set of predefined performance objectives. Key competencies are used to manage and measure knowledge assets. Various knowledge asset measurement models based on the classification by Malhotra are compared and analyzed using indicators. Knowledge management activities, process improvement, and the promotion of stakeholder relationships and satisfaction are all used in the creation of objective indicators [173].

The PHR does not serve as a substitute for the legal records of any provider [77]. The proposed approach enriches EHRs with patient-managed data from PHRs and input data representing, for instance, conversations or communication between patients and doctors on medication issues or side effects [192]. This relation is illustrated in Fig. 3.2. To use a social network, a personal profile is required. A user can add health-related information to their profile to enrich their PHR. Each health information profile stores user health information regarding, e.g., allergies, conditions, and medicines as well as other parameters such as work environment, job risk, lifestyle, and level of interpersonal support used to better understand the user's background [230]. Such data can also be stored in connection with the personal information profile.Here, we define health-related and personal user information (applicable in this case to a patient or caregiver) as the health information profile (HIP) and personal information profile (PIP), respectively. The social network can be a hospital internal social network or a network established via a health collaboration between different institutions. Public social media services such as Facebook or Twitter can also be used in the modern hospital; however, although patients might use these in their free time, willingness to share medical information via these media is likely to be slim. The HIP and PIP include primary patient information and are created by patients directly for their PHRs. Like patients and caregivers, a practitioner can access the EHR system as well as the network, allowing for direct exchange between the most relevant stakeholders during the treatment of a patient. In establishing such a network, patient access should be voluntary, i.e., they should not be required to use this medium to communicate with assigned practitioners. However, use of the

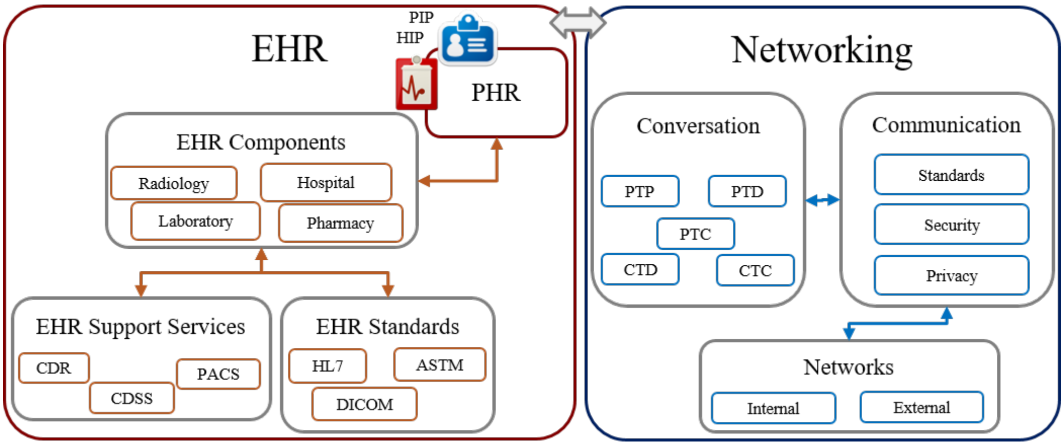


Fig. 3.2 EHR data management.

network should be mandatory for all hospital practitioners, as otherwise the service would not be consistent and the goal of transparency in the treatment process would be thwarted. The internal network can facilitate communication in the following forms:

- patient-to-patient (PTP);
- patient-to-doctor (PTD);
- caregiver-to-caregiver (CTC);
- caregiver-to-doctor (CTD); and
- patient-to-caregiver (PTC).

Such communication can occur with one hospital or in a hospital collaboration; the latter would probably offer more interaction but require more openness between hospitals. In particular, PTD and CTD communication must be handled in a secure and private manner, meaning that communication between a doctor and patient or (e.g., cases of patients with dementia) between a caregiver and doctor must be confined to them and not visible to other members of the network. If a patient and/or caregivers wish to communicate with the doctor or the doctor wants to add another expert to the conversation, they will have to register such additions as communication points to ensure that those involved in a conversation are always visible. Ideally, the practitioner assigned to a patient in "real life" will also be the one communicating with them or with their caregiver via the internal network. This requires a logic for assigning the patient to a specific doctor, defining roles and a rights concept, and flexibility in adding more experts or caregivers to conversations. To make previous communications between practitioner and patient visible to, e.g., a newly assigned doctor, the conversation should be stored and archived as an attachment to the EHR in the form of a protocol. For this approach to work in practice, matching terms of service need to be established and agreed upon by the patient and/or caregiver. These terms of service benefit the practitioner, as s/he can produce a documented conversation with the patient/caregiver in the event that trouble arises during treatment. The above complexities indicate some of the difficulties in developing patient networks relative to public networks.

Unlike the PTD or CTD data, the PTP, PTC, and CTC communication content are entirely independent of the EHR and are not stored in connection to it. This allows patients to freely connect to others in similar situations without in a manner that is invisible to the practitioner. The network design must show clearly which parts of the conversation are visible to all members in the network and which are only visible as PTD, CTD, or private 1:1 communication between patients or caregivers. One difficulty in this context is asynchronicity of communication, as a practitioner might not reply to a question on the same day it is asked, during which time the patient might have already asked a new question or sent a reply to their original message. Additionally, the practitioner must be able to find and restructure a conversation in the EHR after it has occurred. Thus, metadata should be associated with conversations to aid practitioners in finding particular information. Furthermore, patient rights and communication standards must be considered in the creation of the PIP and HIP.

In addition to the above technical issues, medical staff participation is another potential problem area, particularly during busy hospital days. Thus, participating medical institutions should promote a process change for their employees to provide them with, e.g., a fixed time slot each week for "remote" consultation and patient service. However, the additional burden of the remote system should be offset by its provision of EHR-enriched data, which will enhance practitioner decision-making during, e.g., diagnosis or further treatment of the patient.

Considering the growing number of useful home-based self-care tools, the proposed concept can also empower patients with conditions requiring long-term care to, for example, reduce their care expenses. Many activities utilizing EHR data and dynamic knowledge discovery from other stakeholders and different processes can be related to EHR knowledge assets, enabling the application of enriched EHR data to more dynamic interaction of stakeholders' knowledge. Such a process can also be applied to improving performance during treatment as well as that of the overall hospital.

The first layer of the proposed network is the presentation layer, which contains a variety of views as various participants require different knowledge assets. Participants in the network include medical staff, patients and their relatives, and caregivers. Doctors focus on the enriched EHR and communication within the network, while patients answer questions and add information to their PHRs in the form of, e.g., images of affected areas. The logic layer visualizes the functionalities and roles above and is used to enrich PHRs using the CBR recommender approach through comparison of cases within the case base and by using expert network communication and data from user feedback (if available). The data backend comprised various databases (PHR, internal expert network, additional knowledge assets), which are joined via the logic layer and used to build the case base. Case base creation (illustrated at the bottom of Fig. 3.1) is adapted from [192] and [197] in an expanded form. Its data comprise two primary input types from users: texts and images, as explained in the next chapter (Chapter 4).

3.2 DePicT concept

DePicT is a knowledge-based system for the identification and diagnosis of illness by applying a CBR recommendation approach to graphical and textual data sources [197]. The system in practice employs image interpretation and text-mining methods as well as the suggestions of medical experts in its feature analysis process. The concept of DePicT is illustrated in Fig. 3.3.

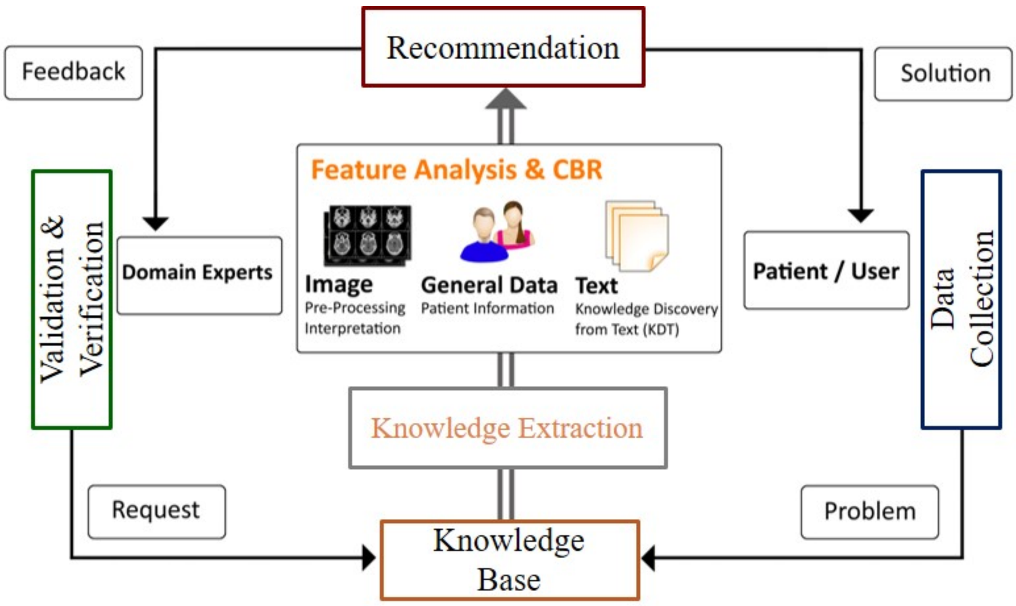


Fig. 3.3 DePicT concept idea.

The main innovation and advantage of DePicT is a combination of different data sources in a single knowledge-base system; this leads to multi-dimensionality and flexibility in medical problem-solving. In the process of patient examination and continuous health monitoring, data are entered into the knowledge base as PHRs. The DePicT database holds textual and graphical descriptions of patient health conditions stored into three major components. The PHR data, which include patient images and predefined information such as personal and health status as well as personal statements by patient in text form, image interpretations of the records, and a current word association profile of each record obtained via KDT. All gathered patient records are stored in relational databases as structured or closed-format files containing, e.g., parameters and statistics or unstructured or open-format files containing, e.g., texts and images. The latter type is particularly useful as, for instance, photographs of melanoma-affected areas can support early-stage diagnosis. Further information obtained from answered questions or from written statements on patients' health conditions, especially concerning affected zones, can be added to the knowledge base as useful data for describing current cases. Domain Experts can then validate and verify collected information and update or correct patient data records. Knowledge extraction can be used to pre-process patient data for use by a CBR recommendation system employing feature selection and analysis. In a history-based, learnable approach to detection and prediction, new images are pre-processed through comparison with existing (clustered) images in the case base to help classify a disease and compare it to existing cases. DePicT utilizes statistical methods such as knowledge discovery tools and algorithms used in data and text-mining techniques to gather and extract knowledge from recorded images and texts and information from connected databases to create a knowledge base. The resulting data are further classified and analyzed using systematic and standard diagnostic methods employed by domain experts. Finally, to provide recommendations to users (i.e., patients or caregivers) based on the type and severity of detected cases, DePicT collects and manages a variety of patient data and records, as illustrated in Fig. 3.4.

Such recommendations are automatically generated based on patient analysis, reference records from textbooks, and the evidence-based consideration of domain experts. These recommendations can facilitate early diagnosis, assist in home care by caregivers and relatives, and ultimately guide patient visits to specialists. Recommendations include summaries of findings based on analysis of patient records and treatment plans based on consideration by domain experts. Recommendation techniques are typically based on knowledge sources, which can used to obtain "the knowledge of other users' preferences" or "ontological or inferential knowledge about the domain, added by a human knowledge engineer" [51]. As mentioned above, DePicT utilizes a case-based recommendation approach. Under this recommendation framework, the system does not gather user ratings but rather provides recommendations and referrals to determined domain knowledge regarding how particular features meet users' requirements and preferences. The procedure of recommendation used by DePicT System, which is described in detail in the following section, involves the use of cyclic CBR and integrated processes of problem-solving, as illustrated in Fig. 3.4.

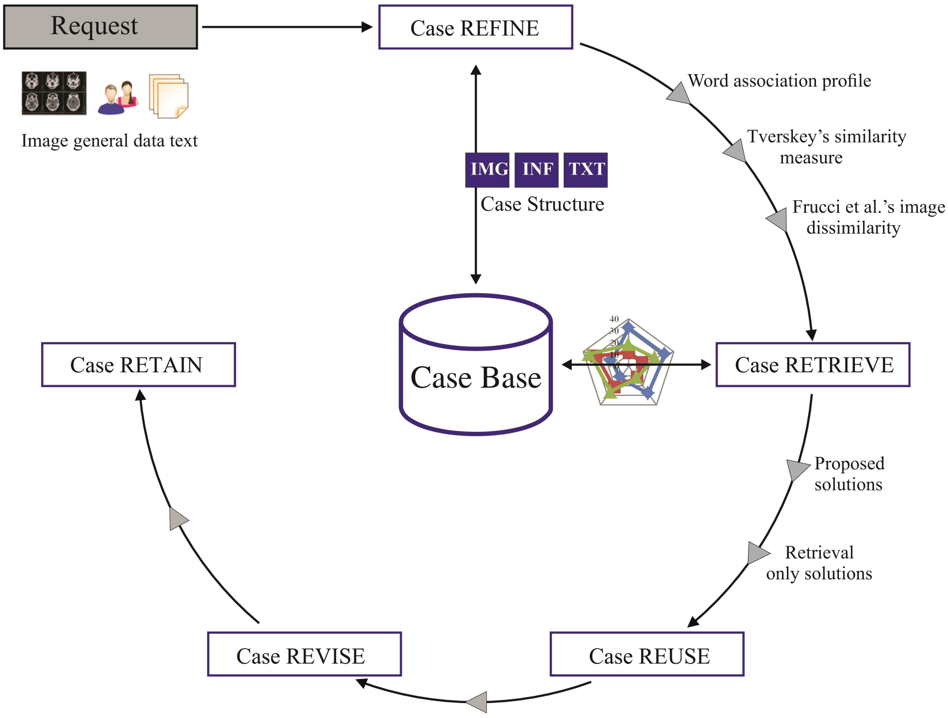


Fig. 3.4 DePicT concept.

The next section focuses on the recommendation process of DePicT and how it uses graphical and textual information as a feature within the CBR case-matching and selection process. After describing how these types of data can be used to enrich the knowledge base of DePicT, the section discusses how gathered patient data can contribute to the case matching and selection process. To produce a good recommendation, it is necessary to construct a set of cases find the appropriate similarity measure for the problem and finally match the cases to determine the best similar case to recommend as a solution. The solved case can then be added to the knowledge base. Fig. 3.5 shows the structure of cases within DePicT. In addition to image and text information, general patient data are included for problem description.

The recommendation procedure of DePicT is illustrated in Fig. 3.6. Starting with a request, images, text, and general patient data are combined into a case in the case formation process. As DePicT uses personal data, each patient must agree to the conditions of the PHR. For patients supplying requests for recommendations, DePicT will refine their data in

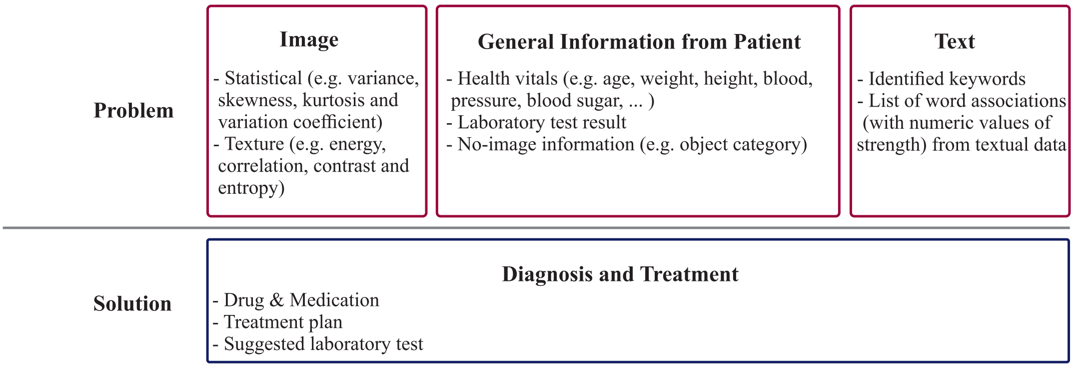


Fig. 3.5 DePicT case structure.

the case formation process based on the case structure as predefined by the case base. The problem description of the case summarizes information on symptoms and reference images and test results. When a new case is refined, DePicT checks its similarity to existing cases in the case matching and retrieval process step to find the closest case. This case is then selected and its solution is presented as a recommendation in response to the user's request.

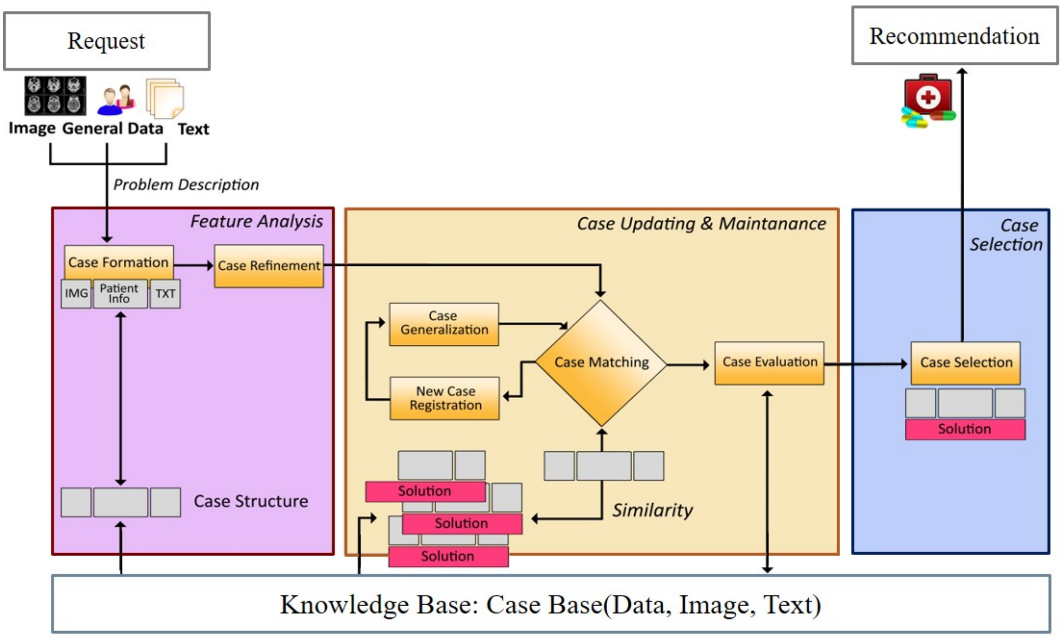


Fig. 3.6 DePicT recommender procedure.

3.3 DePicT CLASS concept

Vocational educational training (VET) and technology enhanced learning (TEL) [132] are part of an ever-growing field involving the improvement of the learning environment based on education plans within the context of dynamic environments in which there is constant change in terms of, e.g., references and courses. Searching and finding the most appropriate learning resources is therefore of great significance in TEL and VET. Two primary objectives in developing learning systems are quality of learning materials and the ability to upgrade and update the system.

The purpose of Detect and Predict diseases using image classification and Text information in Case-based Learning Assistant System (DePicT CLASS) is to present cases that are enriched with the input of learning materials (e.g., reference images and textbooks). The tool is used and updated by both learners and domain experts [198]. DePicT CLASS has enabled medical students, young medical staff, and also novice physicians to locate learning materials and references related to problems they are seeking to address. As mentioned in Chapter 2, CBR methodologies can be a useful approach in the medical application recommendation process, particularly in the context of medical assistant systems. However, CBR systems generally use the most similar case as the only related solution while ignoring other useful similar-case solutions in the adaptation process. In this study, we address the problem of facilitating the finding of references through the use of a particular retrieval and adaptation mechanism based on the word association profiles of requests. Using textual CBR, DePicT CLASS recommends the highest-value associated references from the set of most similar cases. As illustrated in Fig. 3.7, DePicT CLASS is a complete cyclic CBR system and integrated process for solving a problem by revising similar solutions and learning from retained experiences.

In dynamic environments, CBR systems are used to learn and revise through the resolving of problems. In this thesis, we focus on a textual and structural case-based reasoning method combining k-NN/SVM for image classification with word association to find the association strengths of keywords (See Fig. 3.1). In this section, DePicT CLASS, a case-based learning assistant system, is introduced. This tool is an extension of the DePicT concept, which was explained in the previous section as a preliminary concept. DePicT CLASS is a case-based reasoner that interacts with learners to share knowledge and experience. Based on the word association profiles of identified keywords, the system is able to search for text and images to learn more about diseases and their treatment. The target group of DePicT CLASS is medical students in the final stages of their training and novice medical staff. It can also be useful in helping novice physicians and caregivers decide cases within time periods shorter than would otherwise be possible given a lack of experience or a specialty outside of

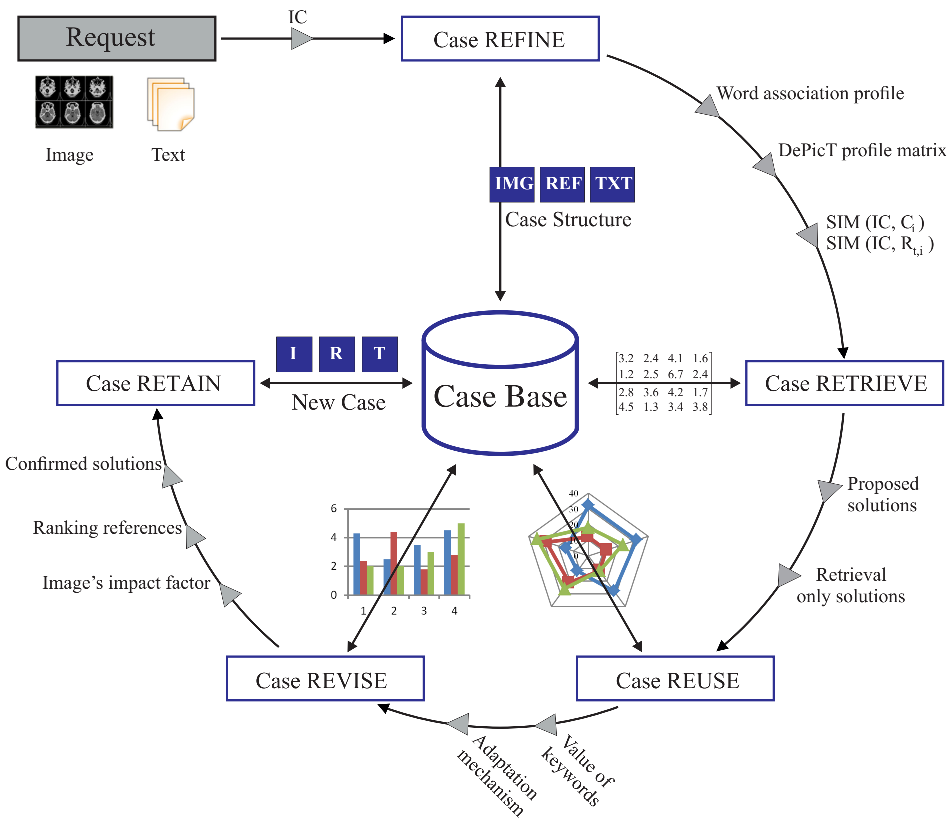


Fig. 3.7 DePicT CLASS concept.

their particular domain. The proposed implementation provides a learning/training assistant system to identify diagnoses and treatment plans. Fig. 3.8 shows the structure of cases within DePicT CLASS, in which references related to problems and their solutions are attached to cases as case descriptions and recommendations, respectively.

This section focuses on the recommendation process of DePicT CLASS and how textual information is used as features within the CBR case-matching and adaptation procedure. The main objective in developing the learning system is ensuring the quality and availability of learning materials.

There are five main steps in the CBR recommender system:

i) Case formation: identifying the requested keywords and assigning values to them based on the DePicT Profile Matrix. As explained in the next section, this process involves characterizing a case base and ascertaining how incoming cases are refined for retrieving.

ii) Case matching: retrieving incoming cases using previous cases in the case base.

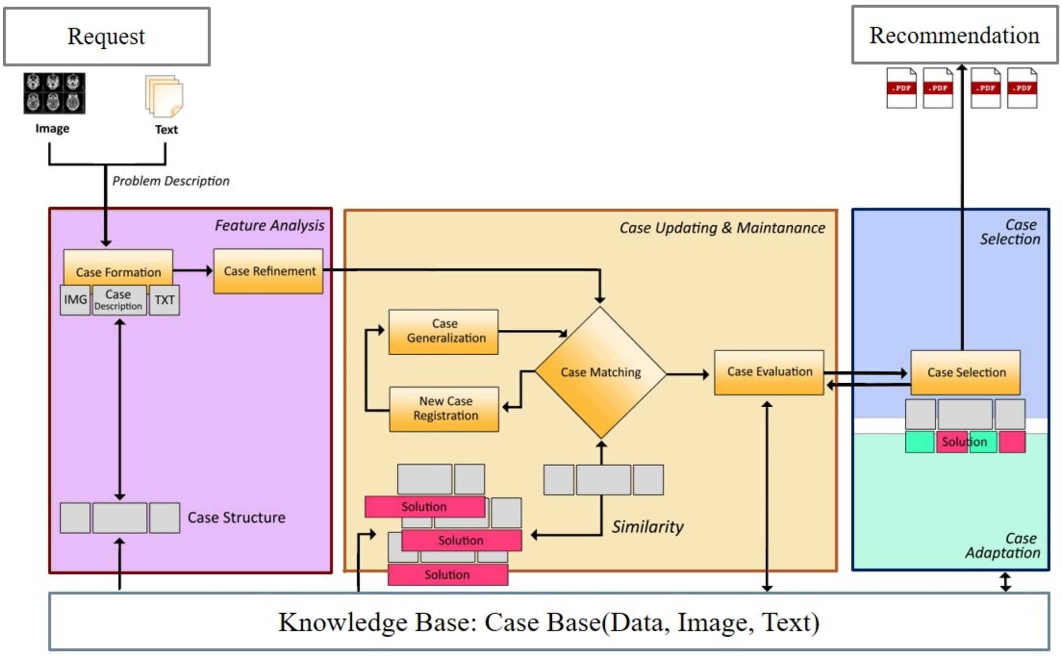


Fig. 3.8 DePicT CLASS recommender procedure

iii) Case adaptation: revising the solutions of most similar cases for application to requested problems.

iv) Case selection: recommending the solutions and associated references of selected cases for application to new cases.

v) Case evaluation and retaining: verifying the adapted solutions of new problems and storing them in the case base for future use.

When a new case is refined as an incoming case, DePicT CLASS checks the similarity between the incoming case and actual cases from the case base to find the most similar cases and references. The adapted solution of the selected case is then presented as a recommendation in response to the user's request. The adaptation phase plays the principal role of selecting appropriate references following the recommendation procedure of DePicT CLASS, as explained in the next section.

3.4 Case representation

This section focuses on the case creation process of DePicT/DePicT CLASS and how graphical and textual data are used as features within the CBR case matching, selection, and adaptation procedures. After describing how these types of data can be used to enrich the knowledge base of DePicT, the process through which gathered user data can contribute to the case matching and selection processes is discussed. To enable recommendation, cases need to be created and an appropriate similarity measure applied, with the resulting solutions adapted based on similar cases. Figure 3.9 illustrates the structure of cases within DePicT CLASS. In addition to image and text information, a general description of the condition is included in the case as a problem description. References related to a problem are attached to its description, while references linked to its solution are appended to the case recommendation.

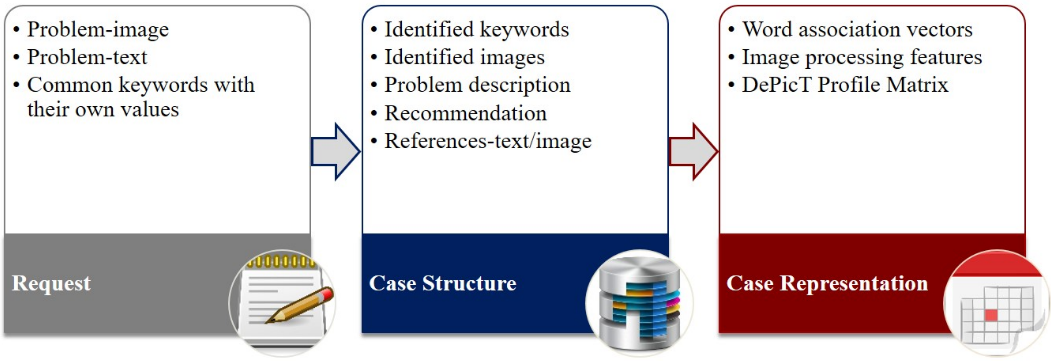


Fig. 3.9 DePicT CLASS case representation.

The structure of a case is predefined by the case base of DePicT CLASS. The case structure summarizes information on symptoms, reference images, disease information, test results, and identified keywords and images. The DePicT Profile matrix is used to encode word association vectors and image processing features. When a new case is refined during the case matching and retrieval process step, DePicT CLASS checks the similarities between the incoming case and current cases from the case base to find the most similar cases. The adapted solution of the selected case is then presented as a recommendation in response to a user's request. In the following subsection, we will explain the methodology of case matching and retrieval; that is, the methodology for finding the strength of word associations between the most relevant keywords for, e.g., diseases, symptoms, treatment, and drugs as text features of cases.

3.5 Case retrieval

In the DePicT case matching process, the criteria for comparing existing and new cases are determined. For integrated medical systems to successfully function, it is necessary to provide a level of standardization for image diagnosis and retrieval in addition to patient information. The matching procedure implemented in DePicT involves the prioritization and weighting of features depending on the data source of the request. Under the concept of matching features, all features contain both critical and insignificant features, both of which should be defined.

3.5.1 Visual information from image representation

Image interpretation is the process of mapping a numerical representation of an image onto a logical representation. Image interpretation systems generally use a bottom-up control structure [209] involving a complex, four-step process of: i) image pre-processing, ii) image segmentation, iii) image analysis, and iv) image interpretation. The image interpretation component identifies each object by finding the object it corresponds to from among the models of the object class [209]. Surveys of approaches involving medical imagery in CBR have shown that clinical patient information such as prescriptions in text format, patient data, images, and structured reports in DICOM format can be used to enrich cases [278]. The segmentation and classification problems play a significant role in determining the best classifier, and segmentation algorithms have been used to label image regions with the output of classifiers [89]. Image and non-image features (which are called general information in DePicT) obtained in different steps can be used to classify images in the case base; for instance, textural features (18 RGB and 18) extracted from different regions of interest can be used to form cases in two separate case bases [278] [90]. Similarity measures for image representation are defined into various classes as: i) pixel matrix-based (iconic); ii) feature-based (numerical, symbolic, or mixed-type); or iii) structured similarity measures. However, the use of new similarity measures for specific goals and different types of image interpretation has been proposed [208]. For DePicT features, there are three similarity measures: image information, background (non-image), and text information. General information is defined with respect to application and includes patient-specific parameters such as age and gender. While general patient data will be present in all cases, case components can be initially compared for similarity based on the non-image information shown Eq. (3.1). To find the similarity in terms of non-image information between a new or incoming case (IC) and a case C_i already in the case base, Teverskey's similarity measure can be applied [256]:

$$SIM = S(C_i, IC) = \frac{|A_i|}{\alpha|A_i| + \beta|D_i| + \gamma|E_i|} \quad , \quad \alpha = 1\,, \beta = \gamma = 0.5 \tag{3.1}$$

where A_i are the features common to both C_i and IC, D_i are the features that belong to C_i but not to IC, and E_i are the features that belong to IC but not to C_i. To determine the similarity in terms of image information between images O and U, we can use Frucci et al.'s image dissimilarity measure [89]:

$$dis_{OU} = \frac{1}{z}\Sigma_{v=1}^{z} w_v \left| \frac{C_{vO} - C_{vmin}}{C_{vmax} - C_{vmin}} - \frac{C_{vU} - C_{vmin}}{C_{vmax} - C_{vmin}} \right| \tag{3.2}$$

where w_v is the weight of the v^{th} feature, with $w_1 + w_2 + ... + w_v + ... + w_z = 1$ (thus, in different cases different values can be assigned to the weights), C_{vmax} and C_{vmin} are the maximum, and minimum value, respectively, of the v^{th} feature in all images, and C_{vO} and C_{vU} are the values of the v^{th} feature of O and U, respectively.

Developing standardized vocabularies and medical ontologies for representation is a significant challenge. In particular, it is necessary to use a vocabulary that can provide meanings to medical imagery that are generally understandable by medical practitioners [278]. In the following sub-section, word association profiles and text information similarity measures are discussed.

3.5.2 Strength of word associations between disease, symptoms, and drugs

A high frequency of word co-occurrence at different levels of text is a good indication of a direct relation between selected words. To estimate the semantic relationships of textual content, we use the concept of imitation of the human ability to word-associate [259]. This method, which is designed to imitate human word association (HWA) over a large collection of texts, is called CIMAWA [2] and was developed in the KBS & KM institute by [258]. As an output, CIMAWA produces the following equation as a final result for text mining application [259]:

$$CIMAWA_{ws}^{\zeta}(x(y)) = \frac{Cooc_{ws}(x,y)}{(frequency(y))^{\alpha}} + \zeta \times \frac{Cooc_{ws}(x,y)}{(frequency(x))^{\alpha}} \tag{3.3}$$

The hybrid character of Eq. (3.3) makes it possible to measure symmetric and asymmetric word associations with a damping factor larger than zero. Co-occurrences ($Cooc_{ws}$) of two words x and y within a defined text window size *ws* are measured over a large document corpus. In previous studies, the best results were achieved using a text window size of 10 and a damping factor of 0.5 [137](Klahold, et al., 2014). As a final result, all word associations

[2] Concept of imitation of the human ability of word association

with a selected word, x, within a document collection can be listed and ordered using the numeric values produced by CIMAWA. We applied this methodology of word associations in a medical context to evaluate textual data from the knowledge base of DePicT. Substitutions of word x in Eq. (3.3) with medical expressions of diseases, symptoms, and drugs resulted in lists of word associations and corresponding numeric strength values that could be combined to build a semantic profile of the current textual data record of the case. The algorithm is visualized in Fig. 3.10 [197].

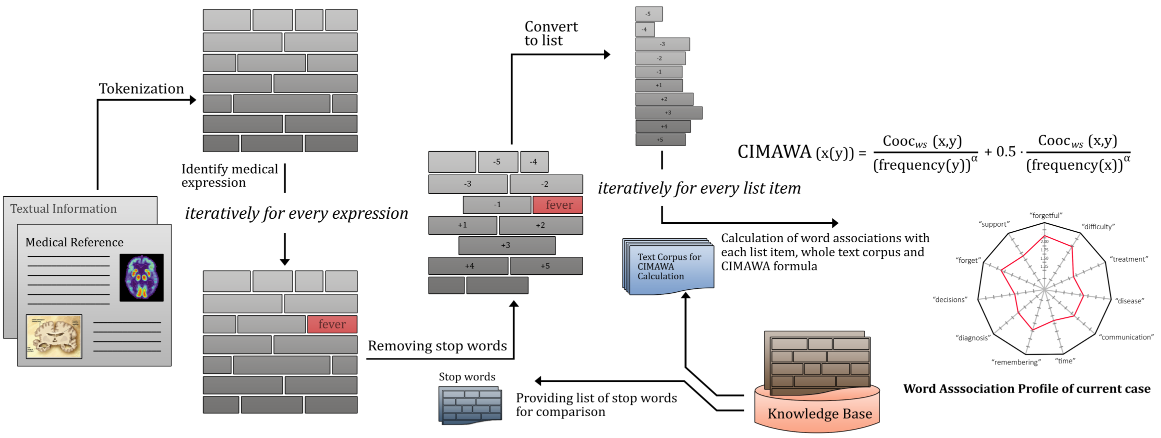


Fig. 3.10 Visualization of the DePicT word association profiles for cases.

In the first step, all text information is tokenized, stop words are removed, and all medical expressions are iteratively identified by a list of words from medical references within the knowledge base of DePicT. When a medical expression is found, a short list of text neighbor words within the text window (*ws*) is created. For each short list item, the CIMAWA equation in Eq. (3.3) is iteratively applied. This process leads to numerical values of all word association strength between medical expressions and other types of words (e.g., diseases, symptoms, and drugs). In the final step, all word associations are summarized to create an association profile of the current case. This profile is stored in the related case from the knowledge base (case base). Using this classification, the system can compare the strengths of word associations of a new case to existing cases and their specific word associations in the knowledge base. A high similarity degree is assigned if the profile of strengths of word association related to disease, symptoms, and drugs are similar in terms of CIMAWA numeric values of to those of an existing profile. DePicT can use such medical expressions and tag images related to cases by adding the identified word associations as keywords to each case. As a consequence, the system is able to search its knowledge base for cases with similar text expressions and find similar images. These case image interpretation and textual problem descriptions are considered in the second step of the search, i.e., after ordering and selecting cases from the knowledge base with similar patient information (e.g., patient age and gender). Using this implementation of the similarity measure for image interpretation (which is explained in more detail in Chapter 4) and a comparison of word association profiles created using Eq. (3.3), an incoming case can be compared to existing cases in the knowledge base. Using a method adopted from [197], the word association profile added to cases for which there are textual data in the problem description can be compared existing case profiles of cases (Fig. 3.11).

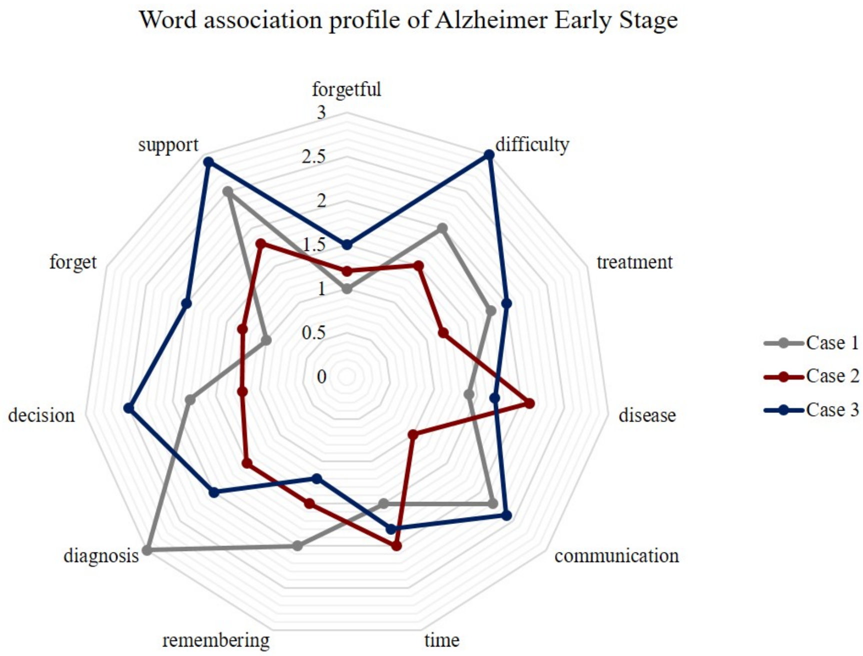


Fig. 3.11 Case matching of word association profiles.

The matching process can skip either the graphical or the textual similarity measure if relevant data are missing from the request. The case from the knowledge base that best fits to the current patient data, the textual problem description, and/or the graphical interpretation of the patient's image is selected and the solution from the case is presented as a recommendation. If no case matches with the current case, a new case is created in the DePicT knowledge base for validation by the domain experts.

3.5.3 Local similarity measures

In DePicT CLASS, adding the identified word associations as keywords to each case enables the system to use these features for checking the case-matching, which is described in this section as the local word association measure. This similarity measure is also used to find similar images based on the profile of word association strengths related to disease, symptoms, treatments, and drugs. In each case, reference images are tagged with the word association profiles of identified keywords. To find similarities in image information, keywords for all reference images in a case are weighted by domain experts during the case base creation phase. Using these keywords, the system is able to search the knowledge base for cases with similar text expressions, keywords, and similar images. In this section, these word association profiles are compared to the similarity measurement of fuzzy and relational features based on local similarities. As shown in Fig. 3.12, three local similarity measures are considered and defined in this research which are as follows:

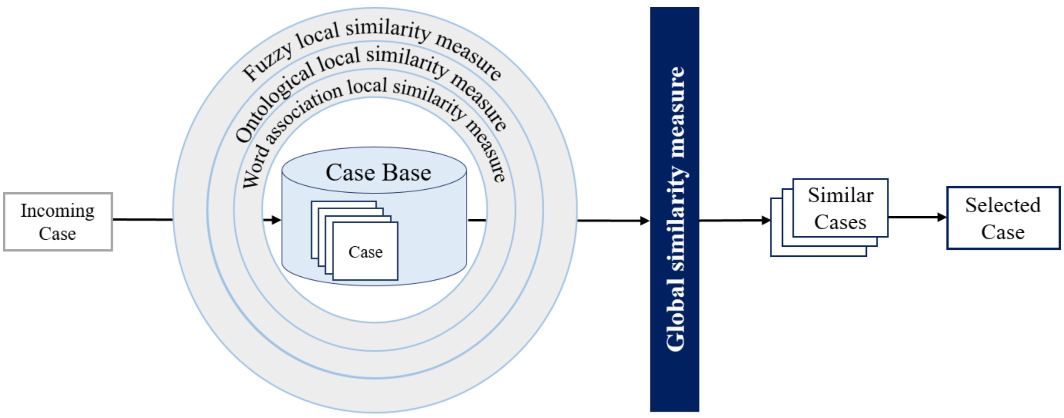


Fig. 3.12 Local-global similarity measures.

- **Local ontological similarity measure:**

Each case has specific attributes. In modelling cases with an ontology, it is useful to consider the use of local similarity measures [36] for attributes (numerical and symbolic) and the relations between attributes and the classes as follows.

i) Numerical attributes can be modeled using:

$$sim_a(a_j^{IC}, a_j^{C_i}) = sim_a(a_j^{C_i}, a_j^{IC}) \tag{3.4}$$

$$sim_a(a_j^{IC}, a_j^{C_i}) = 1 - \frac{|a_j^{C_i} - a_j^{IC}|}{\max d} \quad \text{with } \max d = |a_j^{max} - a_j^{min}| \tag{3.5}$$

where $sim_a(a_j^{IC}, a_j^{C_i})$ is the local similarity between the attributes of case i and incoming case IC. This measure compares the value of attribute j of incoming case $IC(a_j^{IC})$ with the value of attribute j of the case i $(a_j^{C_i})$ from the case base, where $a_j^{C_i} \in \{a_1^{C_i}, a_2^{C_i}, ..., a_J^{C_i}\}$, $a_j^{IC} \in \{a_1^{IC}, a_2^{IC}, ..., a_J^{IC}\}$, $j \in \{1, 2, ..., J\}$ and J is the total number of attributes.

ii) Relations:

The variables $insIC$ and $insC_i$ are the instances which are related the incoming case IC and the i^{th} case from the case base with the relation values r_h^{IC} and $r_h^{C_i}$.

$$sim_a(r_h^{IC}, r_h^{C_i}) = \Sigma_{l=1}^{E}(w_l \, . \, sim_a(a_l^{insIC}, a_l^{insC_i})) \tag{3.6}$$

where $sim_a(r_h^{IC}, r_h^{C_i})$ is the local similarity between the relations of the case i and the incoming case IC. This measure compares the value of the relation h of the case $i(r_h^{C_i})$ from the case base with the value of the relation of the incoming case $IC(r_h^{IC})$. Here, $r_h^{C_i} \in \{r_1^{C_i}, r_2^{C_i}, ..., r_H^{C_i}\}$, $r_h^{IC} \in \{r_1^{IC}, r_2^{IC}, ..., r_H^{IC}\}$ and $h \in \{1, 2, ..., H\}$, E is the total number of instances (or attributes value of non-integer attributes) and H is the total number of classes.

iii) Classes:

For calculation of the local similarity between classes, the number of attributes, S, in each class should be counted:

$$S = \frac{\text{total number of atttibuts}}{\text{number of common atttibuts}} \times \frac{1}{\text{number of nodes}} \tag{3.7}$$

where $sim_c(c_h^{IC}, c_h^{C_i})$ is the local similarity between the classes. The attributes of class h of the case $IC(c_h^{IC})$ are $\{A_1^{IC}, A_2^{IC}, ..., A_L^{IC}\}$, the attributes of the class h of case $i(c_h^{C_i})$ are $\{A_1^{C_i}, A_2^{C_i}, ..., A_L^{C_i}\}$, and L is the total number of attribute sets of the class.

$$sim_c(c_h^{IC}, c_h{}^{C_i}) = \begin{cases} 1 & \text{if} \quad c_h^{IC} = c_h^{IC} \\ S & \text{if} \quad \{A_1^{IC}, ..., A_L^{IC}\} \cap \{A_1^i, ..., A_L^i\} \neq \{\} \\ 0 & \text{if} \quad \{A_1^{IC}, ..., A_L^{IC}\} \cap \{A_1^i, ..., A_L^i\} = \{\} \end{cases} \tag{3.8}$$

- **Local word association similarity measure:**

Each case has a word association profile based on its main keywords and defined by the domain experts as well as other identified keywords, which are extracted from the case description and case references. The word association strength (WAS) between the case title and case features (identified keywords) are combined within the DePicT Profile Matrix.

$$\text{DePicT Profile Matrix}_{WAS} = \begin{bmatrix} WAS(1(0,1),1) & \dots & WAS(1(t,i),i) & \dots & WAS(1(t,z),z) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ WAS(j(t,1),1) & \dots & WAS(j(t,i),i) & \dots & WAS(j(t,z),z) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ WAS(m(q,1),1) & \dots & WAS(m(q,i),i) & \dots & WAS(m(q,z),z) \end{bmatrix} \quad (3.9)$$

where z is the total number of cases, m is the total number of identified keywords in case i and q is the total number of references in case i. $WAS(j(t,i),i)$ is the numeric value of CIMAWA between the title phrase of the case i and the j^{th} identified keyword of the t^{th} reference extracted from the references and learning materials associated with case i. The case title phrase is a combination of the keywords into text string. To find the similar keywords and extract commonalities from the text, the system needs a similarity measure SIM. The local similarity measure of word association is calculated based on the vectors of each case (C_i) and incoming case IC:

$$sim_{was}(WAS_j^{IC}, WAS_j^{C_i}) = (WAS_j^{C_i} . WAS_j^{IC}) \quad (3.10)$$

where C_i is the word association profile vector of i^{th} case that is as follows:

$$C_i = (WAS_{1,i}, ..., WAS_{j,i}, ..., WAS_{m,i}) \quad (3.11)$$

where $WAS_{1,i}$ is the feature value of the first word association strength of the i^{th} case. Assume that the problem description, IC, is expressed as follows:

$$IC = (W_1, ..., W_m) \quad (3.12)$$

where W_1 is the feature value of the first word association strength of the input case, which takes a value 1 for the request keyword appearance and 0 for its absence.

- **Local fuzzy similarity measure:**

Each case has membership functions for which the local fuzzy similarity measure can be calculated as follows:

$$sim_\mu(\mu_j^{IC}, \mu_j^{C_i}) = min[\mu_j^{C_i}(Level_j), \mu_j^{IC}(Level_j)] \quad (3.13)$$

where $sim_\mu(\mu_j^{IC}, \mu_j^{C_i})$ is the local similarity between the membership functions of the case i and the incoming case IC. This measure compares the degree of the membership function of the attribute j based on the level of impairment of this function which is $Level_j$ from the case $i(\mu_j^{C_i}(Level_j))$ to the degree of the membership function l of the attribute a from the incoming case $IC(\mu_j^{IC}(Level_j))$. Here, $\mu_j^{C_i}(Level_j) \in \{\mu_1^{C_i}, \mu_2^{C_i}, ..., \mu_M^{C_i}\}, \mu_i^{IC}(Level_j) \in \{\mu_1^{IC}, \mu_2^{IC}, ..., \mu_M^{IC}\}, j \in \{1, 2, ..., M\}$, and M is the total number of membership functions.

As an example, in the medical domain we can define and use the intersection or union of the membership functions of mild and moderate impairment are as follows:

$$Mild\text{ - }Impairment \cap Moderate\text{ - }Impairment \leftrightarrow \forall ICF \in U,$$

$$\begin{aligned}&\mu_j^{Mild-Impairment \cap Moderate-Impairment}(ICF) = \\ &\min[\mu_j^{Mild-Impairment}(ICF), \mu_j^{Moderate-Impairment}(ICF)]\end{aligned} \tag{3.14}$$

$$Mild\text{ - }Impairment \cup Moderate\text{ - }Impairment \leftrightarrow \forall ICF \in U,$$

$$\begin{aligned}&\mu_j^{Mild-Impairment \cup Moderate-Impairment}(ICF) = \\ &\max[\mu_j^{Mild-Impairment}(ICF), \mu_j^{Moderate-Impairment}(ICF)]\end{aligned} \tag{3.15}$$

where ICF is the patient's functioning and its membership functions are used to assess the severity of each function, with higher scores corresponding to higher degrees of danger. Our goal in this study of enriching global similarity with local fuzzy similarity measure is explained using an example in Chapter 4.

3.5.4 Global similarity measure

$SIM(IC, C_i)$ checks the similarity between incoming case IC and existing cases C_i based on the weights of identified keywords (w_{ij}). The similarity equation between IC and C_i is defined as follows:

$$SIM(IC, C_i) = \Sigma_{j=1}^{n} \frac{w_{ij}\,\mathrm{sim}(C_i, IC)}{n} \tag{3.16}$$

where n is the total number of common keywords between the case $i(C_i)$ and incoming case (IC), and $sim(C_i, IC)$ is the local similarity that should be replaced based on the related similarity measure, as explained in the previous sub-section.

The weights of identified keywords are determined based on the within-case counting frequencies in cases which are as follows:

$$w_{ij} = \frac{f_{ij}}{N} \tag{3.17}$$

where f_{ij} is the frequency of word j in the case i and N is the total number of identified keywords including their frequencies, in case i. The matching process can skip either the graphical or the textual similarity measure if relevant data are not present in the request. Each reference has a word association vector for each relevant keywords in the reference. DePicT CLASS checks the similarity of these vectors to the new vector created with the selected keywords input via the user request.

The similarity measurement for each case based on its references is given as:

$$SIM(IC, C_i(R_{t,i})) = \Sigma_{j=1}^{Q} \Sigma_{t=0}^{q} \frac{w_{tj} \times w_{ij} \times sim(R_{t,i}, IC)}{q} \tag{3.18}$$

where q is the total number of references in case i, where Q is the number of common keywords between the reference t $(R_{t,i})$ of i^{th} case (C_i) and incoming case (IC), and $R_{t,i}$ is the word association profile vector of the t^{th} reference from case i, which given by

$$R_{t,i} = (WAS_{1,(t,i)}, ..., WAS_{j,(t,i)}, ..., WAS_{r,(t,i)}) \tag{3.19}$$

where $WAS_{j,(t,i)}$ is the feature value of the word association strength of the j^{th} identified keyword of the t^{th} reference of the i^{th} case, r is the total number of words in the t^{th} reference, and w_{tj} is the weight of identified keyword j in the reference t, which is expressed as follows:

$$w_{tj} = \frac{f_{tj}}{Q} \tag{3.20}$$

i) Here, f_{tj} is the frequency of word j in reference t and Q is the total number of common keywords between reference t and IC.

ii) For the reference image t, f_{tj} is the impact factor of word j in the reference t and Q is the sum of impact factors of all common keywords between the reference image and incoming images.

Each reference has a word association vector for each relevant keywords in the reference. DePicT CLASS checks the similarity of this vector with the new (incoming) vector created by input keywords selected from a user request. In addition, the DePicT Profile Matrices (w_i) and (w_t) which are filled based on Eqs. (3.17) and (3.20), respectively to define the weights in each case and reference, respectively.

$$\begin{bmatrix} w11 & ...w1j... & w1n \\ \vdots & \ddots & \vdots \\ wz1 & ...wzj... & wzn \end{bmatrix} \tag{3.21}$$

$$\begin{bmatrix} w11 & ...w1j... & w1k \\ \vdots & \ddots & \vdots \\ wq1 & ...wqj... & wqk \end{bmatrix} \tag{3.22}$$

The DePicT CLASS similarity measure calculates the similarity degree of cases based on requested problems. After defining the *IC*, the similarity measurement (Eq. (3.16)) is used to calculate the similarity between *IC* and each case using the references for the common keywords. The similarity degrees of all cases are then sorted and the most similar cases are obtained. Based on the retrieval-only approach, cases with the highest similarity degree are selected to provide a recommended solution to the request.

By adding the identified word associations as keywords to each case, DePicT CLASS can use these features for checking case-matching, as will be described with an example in the next chapter. In this manner, a global similarity measure to replace the local similarity measures depending on the type of attribute is applied to find the most similar cases.

3.6 Case adaptation

Liao et al. [158] presented four types of adaptation methods: i) nonadaptation, which can be used for cases with simple solutions but complex conditions; ii) manual case adaptation, which can be utilized for cases which complicated mechanisms and complicated relationships between the problems and solutions (complex-solution cases); iii) methods involving combination with another artificial intelligence methods (e.g., genetic algorithms or artificial neural networks) to provide adaptation; and iv) knowledge-light adaptation methods, which do not require a significant amount of additional knowledge acquisition because they use the knowledge within a system [276]. In addition, there are three types of adaptation, as defined by Kolodner [140]: i) substitution, which replaces the new values of a new problem with values from the retrieved solution; ii) transformation, which changes retrieved solutions to make them applicable to new issues; and iii) special methods, which apply specialized heuristic knowledge to repair the retrieved solutions. However, many CBR systems avoid adaptation, although some studies have focused on case adaptation based on different types of case inputs (data, images, and text) [291]. Adaptation for cases with pictures is usually applied during examinations and photo-taking color design and quick calculation [219].

Textual adaptation aims to address semantic words or processes and can take the form of case adaptations for a single numerical adaptation or adaptation for data sets according to the solution form [291]. Amailef and Lu presented a case adaptation method based on a classification system involving comparison of object within the incoming case with those in existing cases to distinguish the former from classified objects [23].

The general model of the adaptation in CBR can be described in terms of the transformation of solution of the most similar case to the solution of the incoming case *IC* representing the most appropriate solution. This process is illustrated as follows:

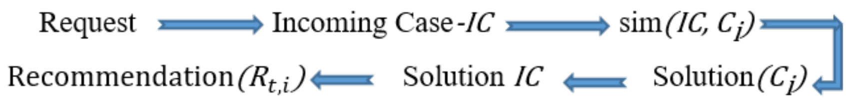


Fig. 3.13 General adaptation model.

Our approach differs from this standard approach as it proposes a new adaptation method for medical vocational educational training based on the word association strength of the DePicT Profile Matrix (Eq. (3.9)). This approach uses a domain-independent adaptation design. Based on the definition of Kolodner [140], DePicT CLASS adaptation is categorized as substitution, because it replaces the values of retrieved references with new values from newly requested problems. As it also employs the collaborative recommendation of users who rank references, add the image tags, suggest image impact factors, and send the feedback to contribute to the reference collection, it can also be classified as a special type of adaptation. Finally, it also utilizes abstraction adaptation to characterize each case based on the references list associated with each disease and compositional adaptation to compute a value for each reference from the set of most similar cases. Accordingly, the DePicT CLASS adaptation mechanism represents a combination of value comparison methodologies based on requested word association profiles with manual adaptation based on user collaborative recommendation, e.g., learners can rank the best references based on their understanding and requirements with a attract rate defined based on the ratio of their value to their rank. In this manner, DePicT CLASS compares reference rankings enhanced by the earned knowledge of users and employs the reference value calculated in Eq. (3.23).

Using Eqs. (3.9), (3.12), and (3.18), DePicT CLASS creates reference word association profile based on keywords recognized from the incoming case (*IC*)) in the most similar cases. The process of comparing word association profiles between references is described in detail the next chapter. In this analysis, references with a high keyword value in the word association profiles of similar cases are recommended as better solutions to the selected case. The value of each keyword is compared to the values of each profile from the set of retrieved case references and is defined from Eqs. (3.19) and (3.20) as follows:

$$V_j(R_{t,i}) = f_{tj} \times WAS_{j,(t,i)} \tag{3.23}$$

$$\text{attract rate} = \frac{V_j(R_{t,i})}{Rank_j(R_{t,i})} \tag{3.24}$$

where $Rank_j(R_{t,i})$ is the rank of reference t for the identified keyword j.

In addition to the attract rate, the adaptation rate (adapt rate), defined as the ratio of retrieval-only references to the total number of associated references, is also used to assess adaptation results.

$$\text{adapt rate} = \frac{\text{retrieval-only references}}{\text{total number of associated references}} \tag{3.25}$$

The DePicT CLASS adaptation mechanism is described using an example in the next chapter.

3.7 Case retain

The learning phase of a CBR system is its retain phase. The typical form of learning that occurs in a CBR system occurs through the addition of revised cases to the case base. In this manner, the new problem-solving experience is retained for reuse in future problem-solving circumstances as the set of features that proved relevant during problem-solving and the solution, i.e., the category that successfully classified the problem. Problems successfully solved by CBR will be stored if it has features that differ significantly from those of previous cases. No learning occurs from failed justification attempts. One problem with this system is that the continuous increase of the case base size results in utility problems that can manifest as decreased retrieval efficiency. Thus, explicit competence models have been developed to enable selective retention of cases.

Specific methods for learning similarity measures have been also developed. While early approaches were restricted to learning feature weights, recent methods address the more difficult problem of learning local and global similarity functions, e.g., learning new cases according to the caregiver inputs. In our cases, the user plays an active role in the overall learning process. The system uses a typical learning apprentice that attempts to solve problems and learn from the experience on its own but relies on an expert or skilled user to supply the necessary explanation when an attempt fails or feedback is given. Users serving as informal caregivers provide ratings to implicitly or explicitly catalog items, and users with given tastes in the past are expected to have similar tastes in the future.

In this manner, collaborative filtering allows the evaluation of such features; however, the integration of CBR and collaborative filtering in the context of compositional recommendation systems presents two drawbacks:

i) The first is related to the choice of case reference, in that a case description cannot be associated with a single user because the experience is represented by a word association profiles. Each profile can be considered to be a reference for which the goal of collecting a set of keywords following a given criterion has been achieved. Looking at single references as single cases is one of our working assumptions; at the same time, from a collaborative filtering perspective we can consider the single word association profile as the profile of a virtual user request.

ii) The second drawback related to the rating of references. Generally, collaborative filtering techniques rely on the correlation between sets of two user profiles based on the use of ratings to assess their similarities. In the case of references, an explicit rating is available in the form of the average of users' opinions, and we can simply recommend all references belonging to the cases with the highest ratings.

3.8 Chapter conclusion

After detailing our concept of a collaborative CBR system for use in medical systems. The question of its applicability remains. The basis for implementing the proposed concept in a real medical environment requires not only technical changes regarding the management of EHRs but also process changes that must be undertaken by the institution, practitioner, and patient. Therefore, the next step will be a prototypical implementation of the concept within medical institutions of different sizes. As it will not be possible to integrate the prototype directly into a real-time environment, a test using a limited number of test candidates is proposed.

CBR methodology is the approach used in the recommendation process of our medical assistant system. The current section explained the four-phase methodology of DePicT CLASS, namely, case representation, retrieval, adaptation, and retaining.

A DePicT CLASS for medical VET was developed based on this methodology and applied in two domains, which are described in the next section. Using an example, the performance and features of the developed applications are presented in Chapter 4.

Chapter 4

Applications domain and development

A CBR methodology is an approach to the recommendation process in medical applications, pericularly medical assistant systems [29] [11] [237] [197] [62]. Figure 4.1 shows the disease types identified in medical CBR systems based on Table B.1.

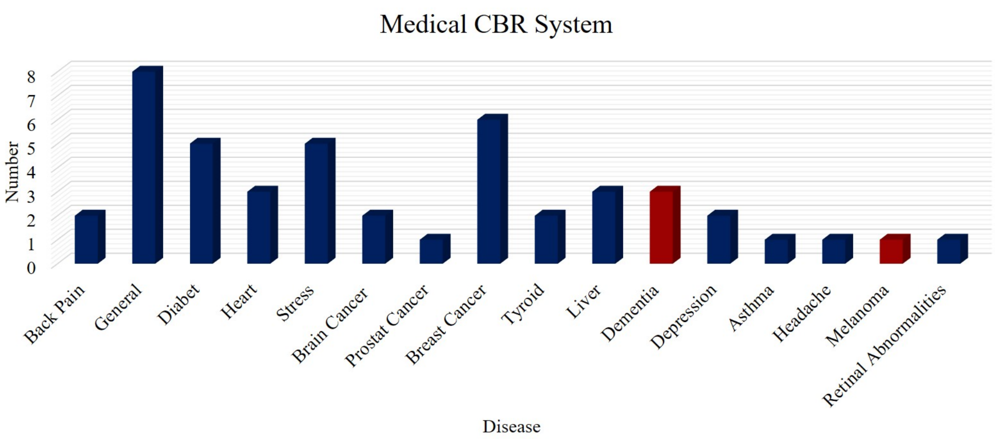


Fig. 4.1 Disease types of reviewed medical CBR systems.

Case-based reasoners have characteristics appropriate for use in a medical domain, particularly in situations in which a clear conception of the case definition exists and in which cases are used comprehensively in medical research via case description and case collection of diseases.

In this study, the concept of DePicT/DePicT CLASS [197] [198] was applied in two domains: i) the dementia domain, based on the patient functionality and the enrichment of cases with dementia learning materials (e.g., reference images and textbooks); and ii) the skin cancer domain, in the development of an early melanoma detector that interacts with users to assess their skin problems using, e.g., skin images and then recommended related solutions.

4.1 Dementia and ICF framework

As we discussed in previous chapters, DePicT CLASS is a case-based learning assistant system for detecting and predicting disease using image classification and text information. DePicT CLASS was adapted to caregiver use as DePicT Dementia CLASS [193] in the MedAusbild[3] project undertaken by the Institute of Knowledge Based Systems & Knowledge Management (KBS & KM) at the University of Siegen. DePicT Dementia CLASS was developed as an XML-based tool [138], and an Android version of the application [139] is also launched in November 2017[4]. It will be applied in the MobiAssist[5] project funded by the German Federal Ministry of Education and Research (BMBF), with which KBS & KM has also partnered to create an educational caregiving system. DePicT Dementia CLASS is used and updated by caregivers and domain experts, and it enables caregivers and patients' relatives to find learning materials and references to address problems and answer questions. As such, the location of appropriate learning materials is a significant component of the system. The increasing prevalence of dementia poses a major challenge to global health at multiple levels [126] and, to date, CBR has been applied three times in the treatment of dementia: in the Auguste project, an effort to provide decision support for planning the ongoing care of AD patients [177]; in the GerAmi system, which creates a distributed, intelligent environment (ambient assisted living) that helps healthcare facilities and providers deal with the increasing challenges of caring for Alzheimer's patients, the elderly, and people with other disabilities [69]; and in GRACE tool, the attributed-labelled graph model represented a domain knowledge as cases dementia unit (DU) of Frontotemporal dementia patients [131].

Based on the increasing number of people worldwide who are affected by dementia, in 2012 and 2015 the World Health Organization (WHO) suggested that Alzheimer's Disease (AD) and other dementias should be regarded as a global public health priority [279]. In WHO's international classification system, health conditions (diseases, disorders, injuries, etc.) are categorized principally in the International Classification of Diseases, Tenth Re-

[3]MedAusbild, https://www.eti.uni-siegen.de/ws/projekte/medausbild/index.html.en?lang=en
[4]https://play.google.com/store/apps/details?id=com.DePicT_Dementia_CLASS.app
[5]MobiAssist, http://mobiassist.info/

vision (ICD-10), which provides an etiological framework. Functioning and disabilities associated with health conditions are classified under International Classification of Functioning, Disability, and Health, known (*ICF*). Users are given support in the combined use of these two components of the WHO set of international classifications, with ICD-10 providing "diagnoses" of diseases, which are enriched by additional information given by *ICF* on functioning to provide a meaningful picture of the health of individuals and populations for use in decision making. The structure of *ICF* is illustrated in Fig. 4.2.

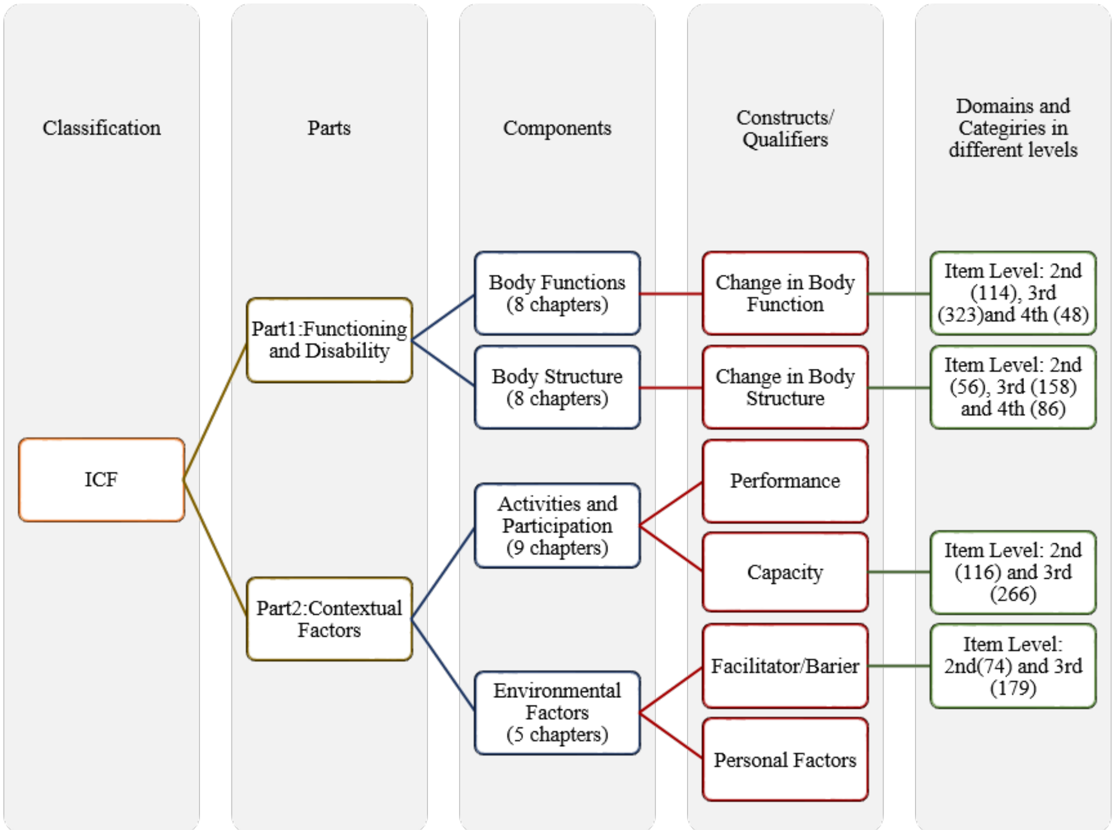


Fig. 4.2 *ICF* Framework.

At the first level, the maximum number of codes per person is 34 and covers eight bodily functions, eight body structures, nine performance codes, and nine capacity codes. The number of codes increases to 362 at the second level and up to 1,424 at more detailed levels [234]. Since the development *ICF* framework [270], several research groups have undertaken projects to develop core sets of *ICF* codes for specific health conditions and disabilities to, for instance, match older adults suffering from dementia with technology [234], to illustrate the use of the *ICF* in the cognitive-communication disorders of dementia [117], to analyze the communication of Alzheimer-related disorders [30], to provide a detailed description of the *ICF* as it relates to the language and communication changes experienced by individuals with AD that are found stressful by family caregivers [54], and to analyze the prevalence of functional impairments, activity limitations, and participation restrictions [171]. *ICF* is a multipurpose classification tool used to assist various disciplines and in different areas. Its particular objectives can be summarized as follows [270]:

- "to provide a scientific basis for understanding and studying health and health-related states, outcomes, and determinants;
- to establish a common language for describing health and health-related states to improve communication between different users, such as healthcare workers, researchers, policy-makers and the public, including people with disabilities;
- to permit comparison of data across countries, health care disciplines, services and time; and
- to provide a systematic coding scheme for health information systems."

These aims are interconnected, as the need for and uses of *ICF* call for a meaningful and practical system that can be utilized by multiple consumers in the fields of health policy, quality assurance, and outcome evaluation across different cultures. In this work, we have a specific objective of helping caregivers and patients' relatives by facilitating the location of references and learning materials using DePicT CLASS's retrieval and adaptation mechanism, which is based on request word association profiles. The preliminary objective here is to use word association strengths to define the features of a case. The case formation process identifies requested keywords and assigns values to them based on the DePicT Profile Matrix. The method used for characterizing case bases and ascertaining how incoming cases are refined for retrieving will be explained in the next section. Because *ICF* is inherently a health and health-related classification, it is used as: i) a clinical tool in needs assessment for matching treatments with specific conditions, vocational assessment, rehabilitation, and outcome evaluation; and as ii) an educational tool in curriculum design and for raising awareness and undertaking social action. Development of the *ICF* Core Set for older adults with dementia involved a formal decision-making and consensus process that integrated evidence gathered from preliminary studies by Scherer et al. [234] using focus groups of health professionals, a systematic review of the literature, and empirical data collected from patients and caregivers. They considered 110 *ICF* codes for dementia, as classified in Fig. 4.3 and illustrated in Table 4.1.

Eight dementia-related diseases are considered as ceases in this study: i) Alzheimer's dementia, ii) Vascular dementia, iii) Parkinson's disease, iv) Frontotemporal dementia (Pick),

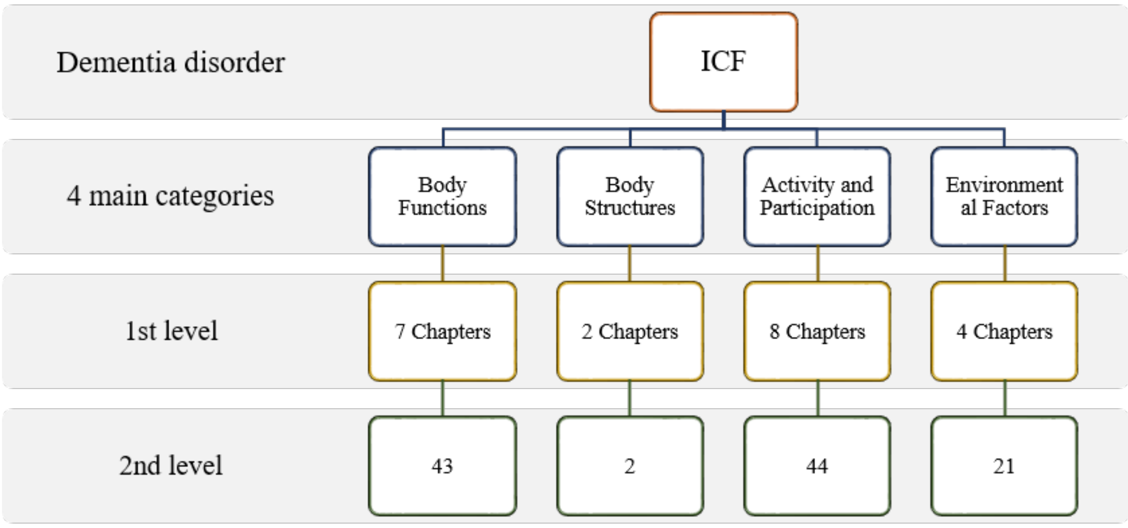


Fig. 4.3 *ICF* structure of dementia.

v) Huntington's disease, vi) Dementia with Lewy bodies (DLB), vii) Creutzfeldt-Jakob disease (CJD), and viii) Meningitis. Based on the 110 dementia *ICF* parameters, we have defined 270 keywords that contain relevant synonyms. In this study, the 110 parameters were utilized as case features, as illustrated in Table 4.1, searched from thirty-three dementia and caregiving books and handbooks (See Appendix C), including [27] [183] [155] [107] [167] [255], to create a large document for building the case base and DePicT Profile Matrix based on the word association strengths calculated between the eight dementia-related diseases and the 270 keywords. Twenty-four text samples based on the eight types of dementia disease extracted from different websites were created for application testing. The resources from which these text samples were extracted are also provided in third appendix (See Andixppendix C).

Table 4.1 Dementia *ICF* codes.

ICF Codes for Older Adults with Dementia

Second level	Chapter	Comp.
b110 Consciousness functions b114 Orientation functions b117 Intellectual functions b130 Energy and drive functions b140 Attention functions b144 Memory functions b147 Psychomotor functions b152 Emotional functions b156 Perceptual functions b160 Thought functions b164 Higher-level cognitive functions b167 Mental functions of language b172 Calculation functions b176 Mental function of sequencing complex movements b180 Experience of self and time functions	1: Mental Functions (15)	Body functions
b210 Seeing functions b215 Functions of structures adjoining the eye b230 Hearing functions b235 Vestibular functions b260 Proprioceptive function b240 Sensations associated with hearing and vestibular function b265 Touch function	2: Sensory Function and pain (7)	
b320 Articulation functions b330 Fluency and rhythm of speech functions	3: Voice and Speech Function (2)	
b410 Heart functions b415 Blood vessel functions b420 Blood pressure functions b430 Hematological system functions b435 Immunological system functions b440 Respiration functions	4: Functions of Cardiovascular Hematological, Immunological Respiratory Systems (6)	

Second level	Chapter	Comp.
b525 Defecation functions b540 General metabolic functions b545 Water, mineral and electrolyte balance functions b555 Endocrine gland functions	5: Functions of Digestive Metabolic and Endocrine Systems (4)	Body functions
b620 Urination functions	6: Genitourinary and Reproduc-tive Functions (1)	
b735 Muscle tone functions b740 Muscle endurance functions b750 Motor reflex functions b755 Involuntary movement reaction functions b760 Control of voluntary movement functions b765 Involuntary movement functions b770 Gait pattern functions b780 Sensations related to muscles and movement functions	7: Neuromusculoskeletal and Movement-related Functions (8)	
s110 Structure of brain	1: Structures of Nervous System	Body structures
s410 Structure of cardiovascular system	4: Structures of the Cardiovas, cular, Immunological and Respiratory Systems	
d130 Copying d135 Rehearsing d160 Focusing attention d163 Thinking d166 Reading d170 Writing d172 Calculating d175 Solving Problems d177 Making decisions	1: Learning and Applying Knowledge (9)	Activities and participation
d210 Undertaking a single task d220 Undertaking multiple task d230 Carrying out daily routine	2: General Tasks and Demands (3)	

Second level	Chapter	Comp.
d310 Communicating with receiving spoken messages d315 Communicating with receiving nonverbal messages d325 Communicating with receiving written messages d330 Speaking d335 Producing nonverbal messages d345 Writing message d355 Conversation d360 Using communication devices and techniques	3: Communication (8)	Activities and participation
d410 Changing basic body position d415 Maintaining a body position d440 Fine hand use (picking up, grasping) d450 Walking d460 Moving around in different locations d475 Driving	4: Mobility (6)	
d510 Washing oneself d520 Caring for body parts d530 Toileting d540 Dressing d550 Eating d560 Drinking	5: Self-Care (6)	
d620 Acquisition of goods and services d630 Preparation food d640 Housekeeping d650 Household tasks d660 Assisting others	6: Domestic Life(5)	
d710 Basic interpersonal interactions d720 Complex interpersonal interactions d750 Informal social relationships d760 Family relationships d770 Intimate relationships	7: Interpersonal Interactions and Relationships (5)	
d910 Community life d920 Recreation and leisure	9: Community, Social and Civic life (2)	

Second level	Chapter	Comp.
e110 Products or substances for personal consumption e115 Products and technology for personal use in daily living e120 Products and technology for personal indoor and outdoor mobility and transportation e125 Products and technology for communication	1: Products and Technology (5)	Environmental factors
e225 Climate e240 Light e245 Time-related changes	2: Natural Environment and Human Made Changes to Environment (3)	
e310 Immediate family e315 Extended family e320 Friends e325 Acquaintances, peers, colleagues neighbors and community members e330 People in position of authority e340 Personal care providers and personal assistants e355 Health professionals	3: Support and Relationships (7)	
e410 Individual attitudes of immediate family members e420 Individual attitudes of friends e425 Individual attitudes of acquaintances peers, colleagues, neighbors and community members e440 Individual attitudes of personal care providers and personal assistants e450 Individual attitudes of health professionals e460 Societal attitudes	4: Attitudes (6)	

4.2 DePicT Dementia CLASS

Using the above methodology, a DePicT Dementia CLASS for medical VET was developed. This section presents this DePicT CLASS using an example. The composite character of Eq. (3.3) makes it possible to measure symmetric and asymmetric word associations with a damping factor ζ larger than zero. Co-occurrences ($Cooc_{ws}$) of two words x and y in a defined text window size (ws) are measured in a large document corpus, with the damping factors and window size altered depending on the domain. In this case, in developing a normalized word association strength between 0 and 1 we found that the best results were achieved by using 0.68 and $0,5$ for α and ζ, respectively and a text window size of 40, with twenty words on both the left and the right of the selected keyword (we have tested with different α like 1,5 and 2). The proposed method considers the identified *ICF* parameters and its synonyms and calculated the word association strength based on the thirty-three surveyed dementia books. From the list of the *ICF*-identified keywords, the word association strength between "Alzheimer" and "memory loss", which is the b144 Memory function from the *ICF* second level qualifier, is calculated based on the following description from Alzheimer's Association [22]: "Alzheimer is the most common form of dementia, a general term for memory loss and other cognitive abilities serious enough to interfere with daily life. Alzheimer disease accounts for 60 to 80 percent of dementia cases. Alzheimer is a progressive disease, where dementia symptoms gradually worsen over a number of years. People with memory loss or other possible signs of Alzheimer may find it hard to recognize they have a problem." In this example, the frequency, Eqs. (3.3) and (3.9) with $ws = 10$ are used to calculate the co-occurrence and *WAS* of these words based on two different values for α as follows:

$$frequency(\text{Alzheimer}) = 4 \tag{4.1}$$

$$frequency(\text{memory loss}) = 2 \tag{4.2}$$

$$Cooc_{10}(\text{Alzheimer, memory loss}) = 1 \tag{4.3}$$

$$WAS(\text{Alzheimer, memory loss}) = \frac{1}{2^2} + 0.5\frac{1}{4^2} = 0.28125 \tag{4.4}$$

$$WAS(\text{Alzheimer, memory loss}) = \frac{1}{2^{0.68}} + 0.5\frac{1}{4^{0.68}} = 0.8189 \tag{4.5}$$

To implement of this formula, the large text created based on the *ICF* parameters for each dementia-related diseases is first defined as a long string or string array. In the second step, the frequency of keywords and their co-occurrence within forty words (the window size, ws) is calculated. In this process, the *WAS* values are calculated for all keywords in each case as cells of the DePicT Profile Matrix$_{WAS}$ and then implemented. The DePicT CLASS similarity measure calculates the similarity degree of cases based on requested problems, as illustrated on the right side of Fig. 4.4. After defining the *IC*, the similarity measurement (Eq. (3.16)) is used to calculate the similarity between *IC* and each case with its references for the common keywords. The similarity degrees of all cases are sorted to obtain the most similar cases. Based on this retrieval-only approach, the case with the highest similarity degrees are selected and their solutions recommended to the requester. Incoming case vector is refined according to word association profile of each case (the calculation used in the case retrieval process is described in the next sub-section). Various types of references can be assigned to a solution or problem description for each case, as shown in Fig. 4.4. Image references also have word association profiles containing impact factors defined by domain experts and tagged to the images. To update or propose different synonyms of tagged words, users can send feedback to the system. Each impact factor is calculated and highlighted as an Impact Factor based on collaborative recommendation.

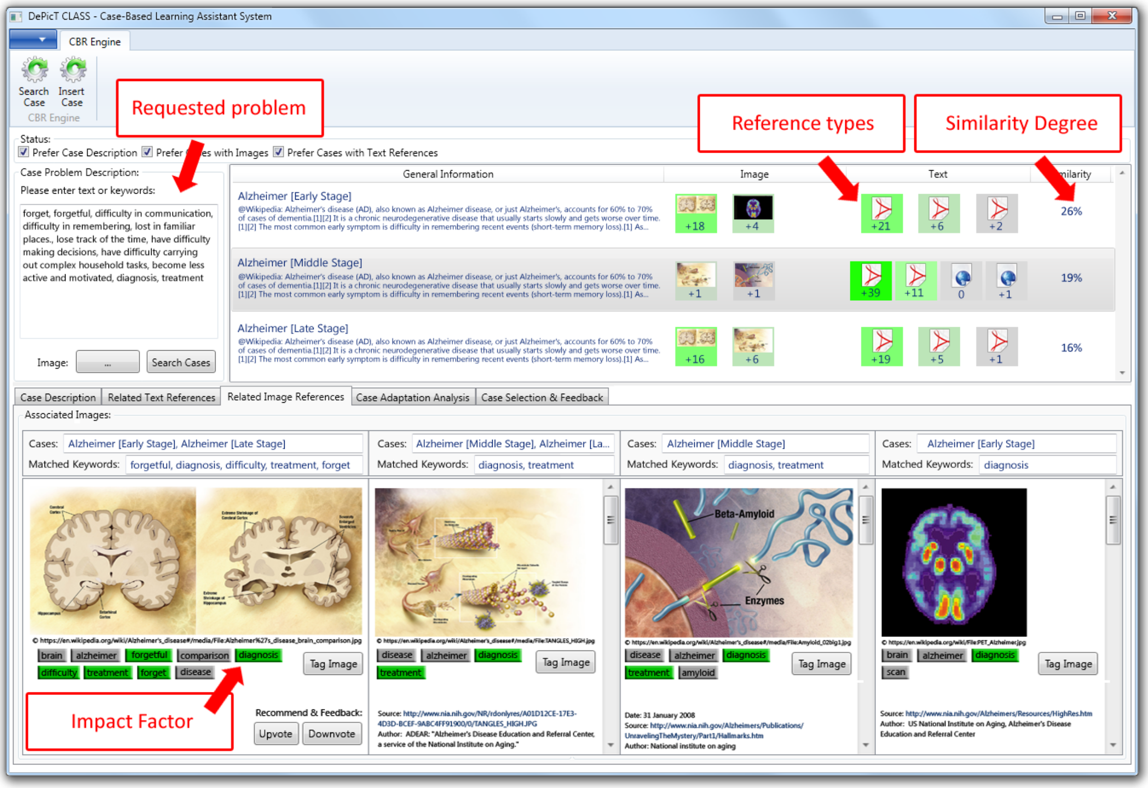


Fig. 4.4 DePicT CLASS similar cases with related image references.

Table 4.1 Initial DePicT CLASS experimental data

Case No.	Case Title	q	N	Q	*"common"*	f_{tj}	*"difficulty"*	f_{tj}	*"forgetful"*	f_{tj}	*"diagnose"*	f_{tj}
1.1	*"Alz. Early St."*	6	453	136	3.24		2.93		5.87		2.68	
	$R_{0,1}$			24	3.24	5	2.93	8	5.87	4	2.68	7
	$R_{1,1}$			26	3.24	12	2.93	2	5.87	7	2.68	5
	$R_{2,1}$			25	3.24	7	2.93	11	5.87	5	2.68	2
	$R_{3,1}$			25	3.24	4	2.93	8	5.87	10	2.68	3
	$R_{4,1}$			18	3.24	11	2.93	2	5.87	1	2.68	4
	$R_{5,1}$			18	3.24	9	2.93	3	5.87	5	2.68	1
1.2	*"Alz. Early St."*	4	323	103	3.24		2.93		5.87		2.68	
	$R_{0,2}$			30	3.24	3	2.93	11	5.87	12	2.68	4
	$R_{1,2}$			21	3.24	5	2.93	8	5.87	1	2.68	7
	$R_{2,2}$			28	3.24	4	2.93	7	5.87	8	2.68	9
	$R_{3,2}$			24	3.24	6	2.93	3	5.87	7	2.68	8
1.3	*"Alz. Early St."*	4	302	94	3.24		2.93		5.87		2.68	
	$R_{0,3}$			20	3.24	5	2.93	5	5.87	6	2.68	4
	$R_{1,3}$			26	3.24	12	2.93	1	5.87	8	2.68	5
	$R_{2,3}$			16	3.24	8	2.93	4	5.87	3	2.68	1
	$R_{3,3}$			32	3.24	10	2.93	12	5.87	8	2.68	2
2.1	*"Alz. Middle St."*	5	372	116	3.49		2.89		4.63		5.68	
	$R_{0,4}$			24	3.49	7	2.89	5	4.63	4	5.68	8
	$R_{1,4}$			27	3.49	10	2.89	3	4.63	5	5.68	9
	$R_{2,4}$			22	3.49	8	2.89	1	4.63	6	5.68	7
	$R_{3,4}$			16	3.49	3	2.89	2	4.63	8	5.68	3
	$R_{4,4}$			27	3.49	9	2.89	3	4.63	10	5.68	5
2.2	*"Alz. Middle St."*	4	522	170	3.49		2.89		4.63		5.68	
	$R_{0,5}$			40	3.49	7	2.89	10	4.63	11	5.68	12
	$R_{1,5}$			42	3.49	9	2.89	8	4.63	13	5.68	12
	$R_{2,5}$			48	3.49	15	2.89	13	4.63	15	5.68	5
	$R_{3,5}$			40	3.49	13	2.89	8	4.63	9	5.68	10
2.3	*"Alz. Middle St."*	2	135	62	3.49		2.89		4.63		5.68	
	$R_{0,6}$			24	3.49	8	2.89	11	4.63	2	5.68	3
	$R_{1,6}$			38	3.49	12	2.89	2	4.63	6	5.68	18
2.4	*"Alz. Middle St."*	4	405	133	3.49		2.89		4.63		5.68	
	$R_{0,7}$			39	3.49	5	2.89	16	4.63	7	5.68	11
	$R_{1,7}$			28	3.49	1	2.89	15	4.63	4	5.68	8
	$R_{2,7}$			32	3.49	13	2.89	10	4.63	1	5.68	8
	$R_{3,7}$			34	3.49	19	2.89	5	4.63	4	5.68	6
3.1	*"Alz. Late St."*	4	472	151	4.98		3.78		2.45		3.45	
	$R_{0,8}$			29	4.98	4	3.78	11	2.45	5	3.45	9
	$R_{1,8}$			44	4.98	21	3.78	5	2.45	9	3.45	9
	$R_{2,8}$			38	4.98	15	3.78	2	2.45	18	3.45	3
	$R_{3,8}$			40	4.98	12	3.78	11	2.45	8	3.45	9
3.2	*"Alz. Late St."*	3	382	120	4.98		3.78		2.45		3.45	
	$R_{0,9}$			36	4.98	8	3.78	13	2.45	9	3.45	6
	$R_{1,9}$			41	4.98	18	3.78	6	2.45	8	3.45	9
	$R_{2,9}$			43	4.98	11	3.78	13	2.45	10	3.45	9
3.3	*"Alz. Late St."*	6	421	127	4.98		3.78		2.45		3.45	
	$R_{0,10}$			19	4.98	4	3.78	2	2.45	4	3.45	9
	$R_{1,10}$			19	4.98	10	3.78	1	2.45	2	3.45	6
	$R_{2,10}$			20	4.98	5	3.78	5	2.45	2	3.45	8
	$R_{3,10}$			21	4.98	7	3.78	6	2.45	4	3.45	4
	$R_{4,10}$			29	4.98	5	3.78	3	2.45	12	3.45	9
	$R_{5,10}$			19	4.98	7	3.78	6	2.45	2	3.45	4

The initial data used in this thesis to present the proposed approach in DePicT CLASS are shown in Table 4.1, which has four main columns (extracted the common keywords from request and case-features) corresponding to cases, word association strengths of identified keywords, frequencies, and total number of keywords used, respectively. In this chapter, various references are applied to these ten cases to illustrate how the system computes the case similarity degree and the values of most similar cases, as described in the following subsections.

4.2.1 Calculation of DePicT CLASS retrieval

This section examines the performance of the proposed CBR approach. As an illustration of the calculation of the case similarity degree, the incoming case *IC* is first created based on the input keywords. For each keyword in the problem description of the incoming case, *IC* is given a value of 1 if the keyword is matched to a keyword in the word association profile of the reference, and a value of 0 otherwise. To refine the incoming case, an *IC* vector and DePicT Profile Matrix is created. The case problem description box Requested problem in Fig. 4.5 provided an example of request: “forget, forgetful, difficulty in communication, difficulty in remembering, lost in familiar places, lose track of the time, have difficulty making decisions, have difficulty carrying out complex household tasks, become less active and motivated, diagnosis, treatment.” Each term is handled as one element in a list of tokens, with the example is represented as follows:

[forget] [forgetful] [difficulty] [in] [communication] [difficulty] [in] [remembering] [lost] [in] [familiar] [places] [lose] [track] [of] [the] [time] [have] [difficulty] [making] [decisions] [have] [difficulty] [carrying] [out] [complex] [household] [tasks] [become] [less] [active] [and] [motivated] [diagnosis]. According to the identified keywords of the case base, common keywords from requested problem are recognized. Therefore, the *IC* vector is: Based on the identified keywords of the case base, common keywords are recognized from requested problem, producing the following *IC* vector:

$$IC \in \{communication, difficulty, forgotful, diagnose\} = [0,0,1,0,1,0,0,1,0,1,0] \quad (4.6)$$

then, based on the word association profile of $Case1.1$ from Table 4.1, DePicT Profile Matrix (Eq. (3.9)) is created. This matrix has three columns containing the word association strengths of the four keywords in each case (these three cases) and four rows containing the word association strengths of each keyword in all cases.

For example, the elements of the first column of matrix are: $WAS(communication(Alzheimer\, early\, stage))$, $WAS(difficulty(Alzheimer\, early\, stage))$, $WAS(forgetful(Alzheimer\, early\, stage))$ and $WAS(diagnose(Alzheimer\, early\, stage))$ and have the following respective association strengths: 3.24, 2.93, 5.87, and 2.68. The elements of the first row of the matrix are: $WAS(communication(Alzheimer\, early\, stage))$, $WAS(communication(Alzheimer\, middle\, stage))$, and $WAS(communication(Alzheimer\, late\, stage))$ and have the following association strengths: 3.24, 3.49, and 4.98 respectively.

$$\begin{pmatrix} 3.24 & 3.49 & 4.98 \\ 2.93 & 2.89 & 3.78 \\ 5.87 & 4.63 & 2.49 \\ 2.68 & 5.68 & 3.45 \end{pmatrix} \quad (4.7)$$

Based on this, and utilizing the similarity measure (Eq. (3.18)), the similarity between *IC* and each case in terms of its references is calculated. The calculation of $SIM(IC,R(C_1))$ based on the related data of the four keywords in *Case 1.1* is illustrated below ((4.8)-(4.14)):

$$SIM(IC,R_{0,1}) = \frac{48}{453}\cdot\frac{5}{24}\cdot 3.24 + \frac{34}{453}\cdot\frac{8}{24}\cdot 2.93 + \frac{32}{453}\cdot\frac{4}{24}\cdot 5.87 + \frac{22}{453}\cdot\frac{7}{24}\cdot 2.68 = 0.2208 \tag{4.8}$$

$$SIM(IC,R_{1,1}) = \frac{48}{453}\cdot\frac{12}{26}\cdot 3.24 + \frac{34}{453}\cdot\frac{2}{26}\cdot 2.93 + \frac{32}{453}\cdot\frac{7}{26}\cdot 5.87 + \frac{22}{453}\cdot\frac{5}{26}\cdot 2.68 = 0.2811 \tag{4.9}$$

$$SIM(IC,R_{2,1}) = \frac{48}{453}\cdot\frac{7}{25}\cdot 3.24 + \frac{34}{453}\cdot\frac{22}{25}\cdot 2.93 + \frac{32}{453}\cdot\frac{5}{25}\cdot 5.87 + \frac{22}{453}\cdot\frac{2}{25}\cdot 2.68 = 0.2620 \tag{4.10}$$

$$SIM(IC,R_{3,1}) = \frac{48}{453}\cdot\frac{11}{28}\cdot 3.24 + \frac{34}{453}\cdot\frac{8}{25}\cdot 2.93 + \frac{32}{453}\cdot\frac{10}{25}\cdot 5.87 + \frac{22}{453}\cdot\frac{3}{25}\cdot 2.68 = 0.2595 \tag{4.11}$$

$$SIM(IC,R_{4,1}) = \frac{48}{453}\cdot\frac{11}{28}\cdot 3.24 + \frac{34}{453}\cdot\frac{2}{18}\cdot 2.93 + \frac{32}{453}\cdot\frac{1}{18}\cdot 5.87 + \frac{22}{453}\cdot\frac{4}{18}\cdot 2.68 = 0.2627 \tag{4.12}$$

$$SIM(IC,R_{5,1}) = \frac{48}{453}\cdot\frac{9}{18}\cdot 3.24 + \frac{34}{453}\cdot\frac{3}{18}\cdot 2.93 + \frac{32}{453}\cdot\frac{5}{18}\cdot 5.87 + \frac{22}{453}\cdot\frac{1}{18}\cdot 2.68 = 0.2733 \tag{4.13}$$

$$SIM(IC,R_{C_1}) = \frac{1}{6}(0.2208 + 0.2811 + 0.2620 + 0.2595 + 0.2627 + 0.2733) = 0.2601 \tag{4.14}$$

The similarity degrees of the other cases are also calculated in the same manner, with the most similar cases obtained as shown in Fig. 4.5.

In the traditional CBR case retrieval process, the case with highest similarity degree is selected and its solution is recommended to the requester. By contrast, DePicT CLASS selects the highest value references of the most similar cases for recommendation. In the

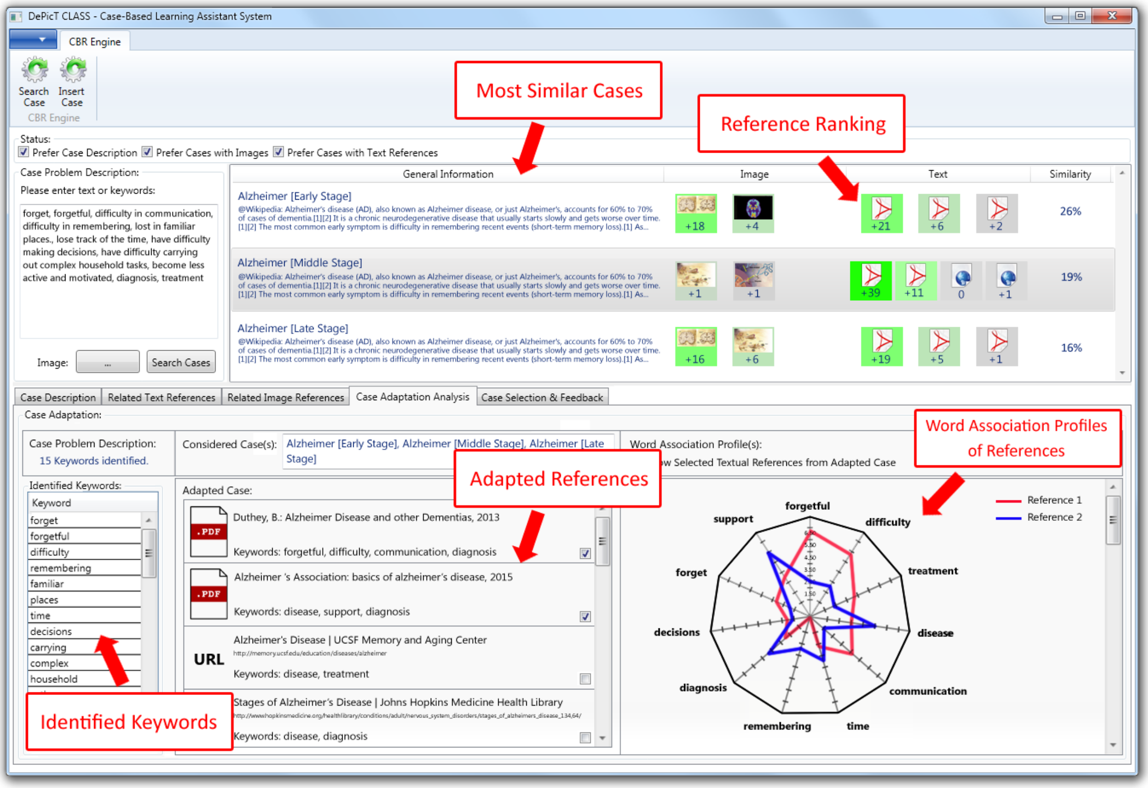


Fig. 4.5 Case adaptation and selection in DePicT CLASS.

following sub-section, a comparison of retrieval-only and adapted references approach is presented.

4.2.2 Comparison of retrieval-only and adapted references

The comparison of references values for most similar cases is illustrated in Fig. 4.6. In this analysis, a combination of high-value references is recommended as an adapted solution (reference) of the selected case. The diagram is created based on the values of the keywords shown in Table 4.1. These keywords are compared to each reference and the highest value references selected. Table 4.2 contains the three most similar cases, including their references with Frequencies / Impact Factors and values of the keywords calculated based on Eq. (3.23). The value calculation of the keyword "communication" in the six references of *Case 1.1*, Alzheimer's Early Stage, is given as follows:

$$V_{communication}(R_{0,1}) = 5 \times 3.24 = 16.02 \sim 16 \quad (4.15)$$

$$V_{communication}(R_{1,1}) = 12 \times 3.24 = 38.88 \sim 39 \tag{4.16}$$

$$V_{communication}(R_{2,1}) = 7 \times 3.24 = 22.68 \sim 23 \tag{4.17}$$

$$V_{communication}(R_{3,1}) = 4 \times 3.24 = 12.96 \sim 13 \tag{4.18}$$

$$V_{communication}(R_{4,1}) = 11 \times 3.24 = 35.67 \sim 36 \tag{4.19}$$

$$V_{communication}(R_{5,1}) = 9 \times 3.24 = 29.16 \sim 29 \tag{4.20}$$

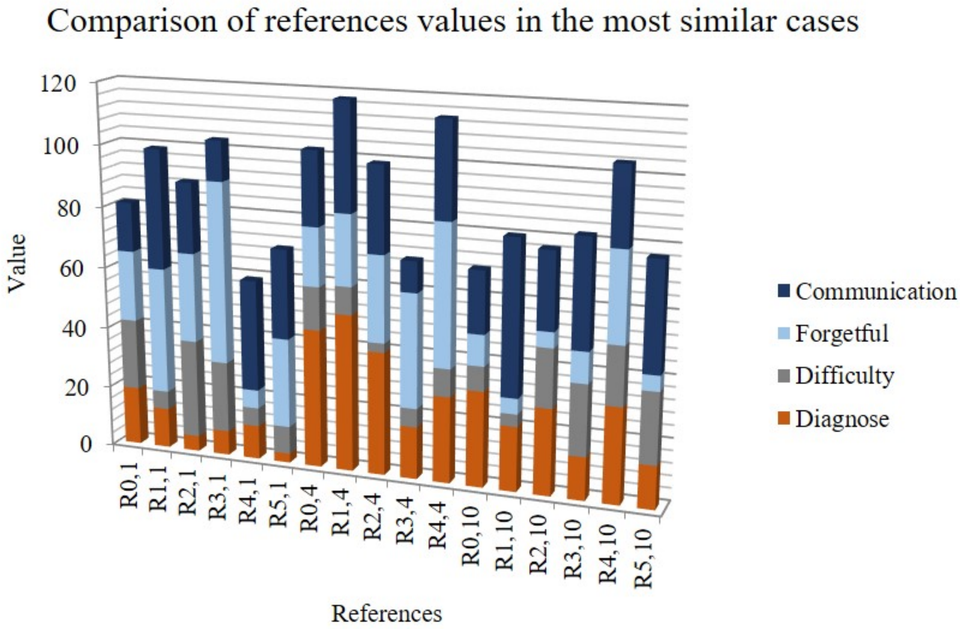


Fig. 4.6 Comparison of references values in the most similar cases.

The values of the other keywords and references are obtained according to their respective frequencies in each reference. They can also be acquired based on the impact factors of the tagging keywords in each reference image. A diagram of the highest values of references for all three most similar cases of keywords from Table 4.1 is shown in Fig. 4.6. In these comparative diagrams, collaborative recommendation ranking is also illustrated. Users can also recommend their selected references to other users by ranking them via the system's feedback module. Under the first method, the system shows a ranking of references (Fig. 4.7) from the most similar cases to users who can then follow other users' recommendations.

Under the second method, users can update the case base by sending new references and suggestions to domain experts (Fig. 4.8). The recommendation of selected cases is therefore arranged based on a combination of high-value references, as shown in Fig. 4.5.

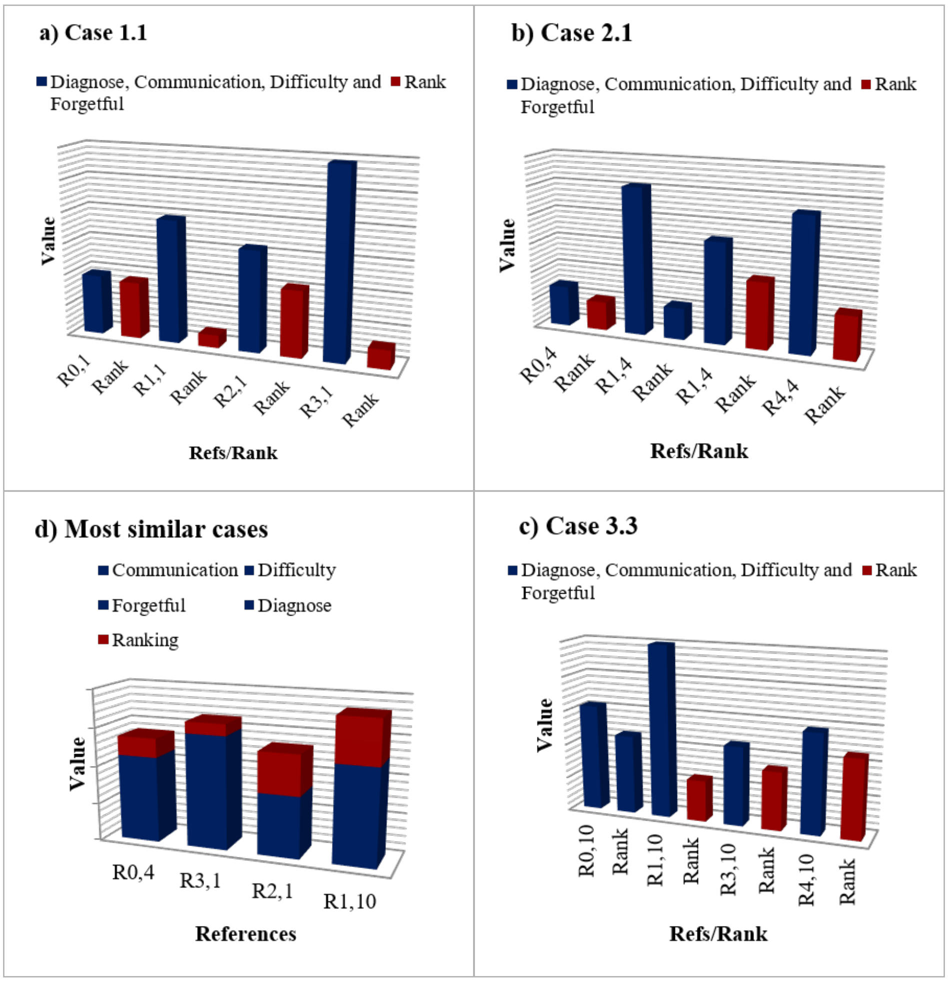


Fig. 4.7 Associated references and collaborative recommendation ranking, a) Case 1.1 b) Case 2.1, c) Case 3.3, and d) Highest value associated references of most similar cases.

The attract rates of associated references are calculated based on the ratio of their values to their ranks (Eq. 3.24): for $R_{1,10}$, $R_{2,1}$, $R_{3,1}$, and $R_{0,4}$, these are 46%,66%,1%, and 22% respectively. A Comparison of retrieval-only references for most similar cases based on DePicT CLASS adapted references for the three most similar cases is shown in Fig. 4.7. This comparison shows which references are more valuable for respective requested keywords. In this case, DePicT CLASS has revised half of the references relative to the case shown in the diagrams in Fig. 4.9. Accordingly, this case study results in an adaptation rate (adapt rate, Eq. 3.25) of 50%, reflecting the ratio of (two) associated references to (four) retrieval-only references. User can see the matched references and select them as a learning material (See Fig. 4.5). In the feedback component, which is illustrated in Fig. 4.8, useful material such as summarized book chapters, related images, or text references can be added or uploaded to

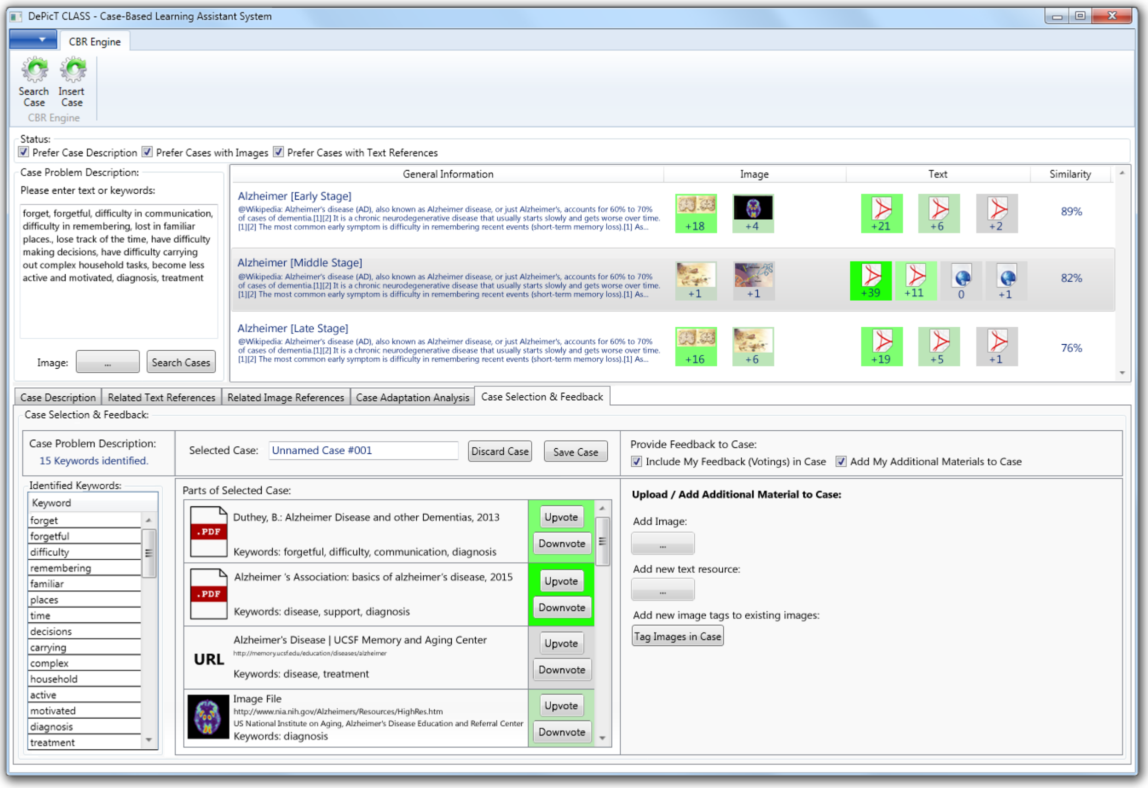


Fig. 4.8 Case retain & feedback in DePicT CLASS

the case base. Users can also suggest tagging keywords for image reference via the system. Such new material is then verified by domain experts and added to the case base. This method of case adaptation can be applied to extend the case base, which is useful in obtaining better references. It also improves the availability and selection of associated references. However, the method only considers identified keywords and does not take into account different keyword meanings. Future research will involve the calculation of word association strength in a very large medical text corpora and also how to add synonyms and topic-related keywords to the word association profiles.

Table 4.2 The DePicT CLASS adaptation data.

Recommended Cases

Value/IF	Case 1.1						Case 2.1					Case 3.3					
communication	16	39	23	13	36	29	24	35	28	10	31	20	50	25	35	25	35
difficulty	23	6	32	23	6	9	14	9	3	6	9	8	4	19	23	19	23
forgetful	23	41	29	59	6	29	19	23	28	37	46	10	5	5	10	29	5
diagnose	19	13	5	8	11	3	45	51	40	17	28	31	21	28	14	31	14
Impact Factor	Case 1.1						Case 2.1					Case 3.3					
communication	5	12	7	4	11	9	7	10	8	3	9	4	10	5	7	5	7
difficulty	8	2	11	8	2	3	5	3	1	2	3	2	1	5	6	3	6
forgetful	4	7	5	10	1	5	4	5	6	8	10	4	2	2	4	12	2
diagnose	7	5	2	3	4	1	8	9	7	3	5	9	6	8	4	9	4

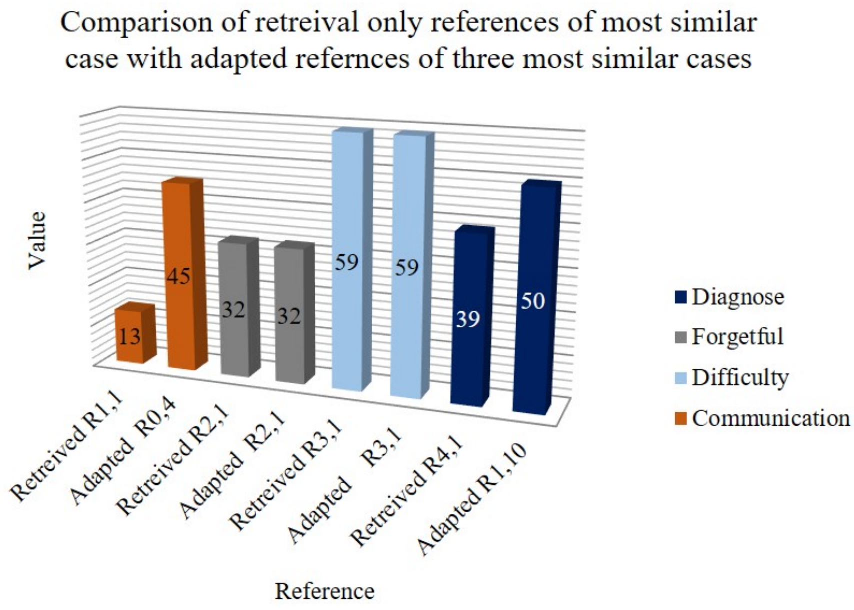


Fig. 4.9 Retrieval-only and adapted references.

The main contribution of this study is case representation and retrieval of using DePicT CLASS. As the system is used, its learning materials are ranked and updated by learners and domain experts. In the case-matching process, DePicT CLASS can make recommendations that make it possible to search for similar cases through the evaluation of text, patient information, and/or images.

4.2.3 Calculation of ontological retrieval

The system methodology involves the use of knowledge-intensive ontological CBR. Ontologies are used in our knowledge model for case representation, and storage, and to set the case base. Using the WHO *ICF*, dementia ontologies such as ADO and systematic reviews of quantitative and qualitative studies on the needs of informal caregivers for patients suffering from related disorders can be used in the development and integration of the caring recommender system. This methodology relies on the dependencies that occur among concepts or relationships and on the explicit identification of these relationship properties. Here, an ontological CBR system utilizing protégé [6] and myCBR [7] open source tools is proposed. Under this system, users (e.g., patients' relatives) can answer *ICF* queries related to their

[6]https://protege.stanford.edu/
[7]http://www.mycbr-project.net/

understanding of the patient's situation to obtain information to help address their challenges. This knowledge model provides a realistic representation and ensures the essential strength relationships of the model.

The ontology comprises three superclasses: "Clinical," "Diseases," and "Caregiving," which are divided into subclasses (See Fig. 4.10). The "Diseases" class comprises dementia and its related diseases. The "Diagnose," "Assessment," and "Treatments and Training" classes cover concepts that have contributed to understanding the pathology, diagnosis, and treatment options for dementia, and each is divided into subclasses. The "Caregiving" class covers information regarding the needs of informal caregivers in handling challenges they face in dealing with patients.

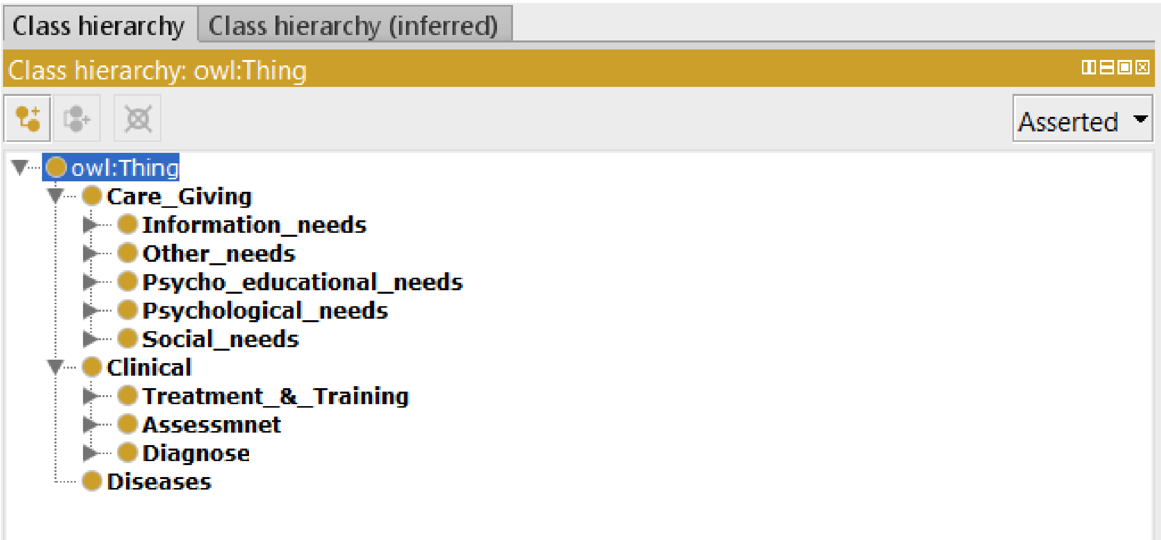


Fig. 4.10 Ontology-main classes.

A preliminary collection of terms and concepts related to the clinical part of dementia and focusing on various aspects of the disease, such as aspects of diagnosis and treatment, was obtained through web-based searches of resources such as [22]. In addition, the published version of the ADO ontology [172] was used to acquire clinical features, treatments, and risk factors in the area of Alzheimer's disease. Symptoms of dementia were extracted using the ICF dementia-related codes of [270] [234]. The other resources which are used to build the ontology is shown in Table 4.3.

The case-base ontology has 193 concepts, six object properties, 115 datatype properties, eight datatypes, and 288 instances [289]. The ontology was evaluated using Hermit and also based on the reasoning of myCBR, with caregivers validating the obtained results. The ontology comprises three main topics relevant to clinical (diagnosis and therapy), sports, and

Table 4.3 Resources for DePicT Dementia Caregiving Ontology.

Ontology	Class	
	Clinical	Caregiving
Resources	[234],[172],[33],[100],[277],[22]	[202],[168],[80],[95],[79],[3],[20],[21],[272]

caregiving aspects of dementia; here, we focus on *ICF* codes reflecting caregiving. Below, the performance of the proposed ontological CBR retrieval process in DePicT Dementia Onto-CLASS is demonstrated through an example using two patients (patient 1 and 2), who are 77 and 86 years old, respectively. Their queries based on the *ICF* codes are filled as IC_1 and IC_2, respectively. In this example, the similarity degrees for the two patients in the class of "Mental function" are calculated. To do this, the values of each feature or attribute of the Mental function class for *ICs* from 0-5, reflecting the patients' situations, are filled. The relevant features are listed in Table 4.4, along with attributes of the other cases for the sixteen features.

Table 4.4 Attributes values of the mental function class for the case base and two incoming cases.

Attributes of Mental Function	IC_1	IC_2	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*
Consciousness functions	4	2	3	4	2	4	2	1	3	5
Orientation functions	4	1	4	4	4	5	4	3	3	5
Intellectual functions	2	4	2	3	4	5	4	3	2	5
Energy and drive functions	2	3	2	2	1	5	3	2	2	5
Attention functions	2	3	2	3	1	3	5	1	3	4
Memory functions	2	4	4	4	3	4	5	2	3	5
Psychomotor functions	2	4	1	2	1	2	4	2	2	4
Emotional functions	2	4	1	1	1	1	2	1	2	2
Perceptual functions	4	2	5	4	3	4	3	1	3	4
Thought functions	4	3	3	3	4	5	4	2	3	5
Higher-level cognitive functions	4	2	4	4	4	4	4	2	2	5
Mental functions of language	5	2	3	3	2	5	4	2	2	5
Calculation functions	5	2	3	4	3	5	5	3	3	5
Mental function of sequencing complex movements	4	4	1	3	2	4	3	3	2	5
Experience of self and time functions	5	3	5	5	5	5	4	3	3	5
Age	77	86	68	72	70	80	74	60	69	88

Next, the similarity between *IC* and each case is calculated using the local similarity measures for classes, relations, and attributes (See Fig. 4.11). In this example, age is a numerical attribute that is calculated based on the Eq. (3.4), with the results shown in Table 4.5.

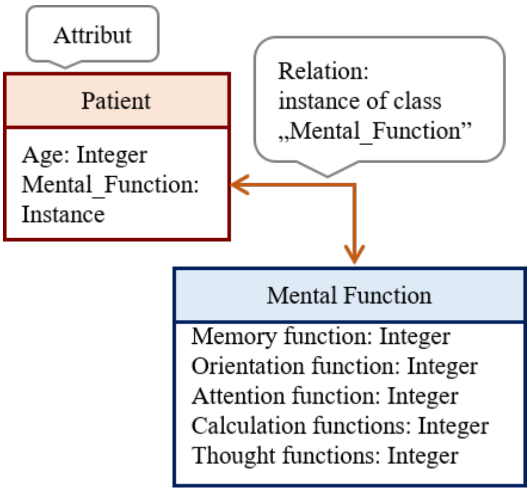


Fig. 4.11 Example of ontological similarity measure-mental function.

Table 4.5 Local similarity measure of the numerical attribute *age*.

Local similarity of attribute *age*	
$sim_a(a_{age}^{IC_1}, a_{age}^{C_A}) = 1 - \frac{\lvert 77-68 \rvert}{88-60} = 0.67$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_A}) = 1 - \frac{\lvert 86-68 \rvert}{88-60} = 0.35$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_B}) = 1 - \frac{\lvert 77-72 \rvert}{88-60} = 0.82$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_B}) = 1 - \frac{\lvert 86-72 \rvert}{88-60} = 0.5$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_c}) = 1 - \frac{\lvert 77-70 \rvert}{88-60} = 0.75$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_c}) = 1 - \frac{\lvert 86-70 \rvert}{88-60} = 0.42$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_B}) = 1 - \frac{\lvert 77-72 \rvert}{88-60} = 0.82$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_B}) = 1 - \frac{\lvert 86-72 \rvert}{88-60} = 0.50$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_D}) = 1 - \frac{\lvert 77-80 \rvert}{88-60} = 0.92$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_D}) = 1 - \frac{\lvert 86-80 \rvert}{88-60} = 0.78$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_E}) = 1 - \frac{\lvert 77-74 \rvert}{88-60} = 0.85$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_E}) = 1 - \frac{\lvert 86-74 \rvert}{88-60} = 0.57$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_F}) = 1 - \frac{\lvert 77-60 \rvert}{88-60} = 0.39$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_F}) = 1 - \frac{\lvert 86-60 \rvert}{88-60} = 0.07$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_G}) = 1 - \frac{\lvert 77-69 \rvert}{88-60} = 0.71$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_G}) = 1 - \frac{\lvert 86-69 \rvert}{88-60} = 0.39$
$sim_a(a_{age}^{IC_1}, a_{age}^{C_H}) = 1 - \frac{\lvert 77-88 \rvert}{88-60} = 0.60$	$sim_a(a_{age}^{IC_2}, a_{age}^{C_H}) = 1 - \frac{\lvert 86-88 \rvert}{88-60} = 0.92$

The class similarity degree of "Mental function" for the two patients is then calculated based on the Eq. (3.8) as follows:

$$S = (\frac{15}{15}) \times 1 = 1 \tag{4.21}$$

$$sim_c(c_{Mental function}^{IC}, c_{Mental function}^{C}) = 1 \tag{4.22}$$

Table 4.6 Local similarity of relation for the first incoming case IC_1 and the case A.

Local similarity between IC_1, C_A	
$sim_a(a_1^{IC_1}, a_1^{C_A}) = 1 - \frac{\lvert 4-3 \rvert}{5} = 0.8$	$sim_a(a_2^{IC_1}, a_2^{C_A}) = 1 - \frac{\lvert 4-4 \rvert}{5} = 1$
$sim_a(a_3^{IC_1}, a_3^{C_A}) = 1 - \frac{\lvert 2-2 \rvert}{5} = 1$	$sim_a(a_4^{IC_2}, a_4^{C_A}) = 1 - \frac{\lvert 2-2 \rvert}{5} = 1$
$sim_a(a_5^{IC_1}, a_5^{C_A}) = 1 - \frac{\lvert 2-2 \rvert}{5} = 0.75$	$sim_a(a_6^{IC_2}, a_6^{C_A}) = 1 - \frac{\lvert 2-4 \rvert}{5} = 0.42$
$sim_a(a_7^{IC_1}, a_7^{C_A}) = 1 - \frac{\lvert 2-1 \rvert}{5} = 0.8$	$sim_a(a_8^{IC_2}, a_8^{C_A}) = 1 - \frac{\lvert 2-1 \rvert}{5} = 0.8$
$sim_a(a_9^{IC_1}, a_9^{C_A}) = 1 - \frac{\lvert 4-5 \rvert}{5} = 0.8$	$sim_a(a_{10}^{IC_2}, a_{10}^{C_A}) = 1 - \frac{\lvert 4-3 \rvert}{5} = 0.8$
$sim_a(a_{11}^{IC_1}, a_{11}^{C_A}) = 1 - \frac{\lvert 4-4 \rvert}{5} = 1$	$sim_a(a_{12}^{IC_2}, a_{12}^{C_A}) = 1 - \frac{\lvert 5-3 \rvert}{5} = 0.6$
$sim_a(a_{13}^{IC_1}, a_{13}^{C_A}) = 1 - \frac{\lvert 5-3 \rvert}{5} = 0.6$	$sim_a(a_{14}^{IC_1}, a_{14}^{C_A}) = 1 - \frac{\lvert 4-1 \rvert}{5} = 0.4$
$sim_a(a_{15}^{IC_1}, a_{15}^{C_A}) = 1 - \frac{\lvert 5-5 \rvert}{5} = 1$	

Finally, the relations are calculated using Eq. (3.8), with the resulting local similarity of relation for the attributes IC_1 and C_A shown in Table 4.6.

$$sim_r(IC_1, C_A) = \frac{1}{15} \times (0.8 + 1 + 1 + 1 + 1 + 0.6 + 0.8 + 0.8 + 0.8 + 0.8 + 1 + 0.6 + 0.6 + 0.4 + 1) = 0.81 \tag{4.23}$$

The global similarity can also be calculated for this example, based on the ontological CBR approach as follows:

$$sim_g(IC, C_i) = \sum_{j=1}^{J} (w_j \,.\, sim_a(a_j^{IC}, a_j^{C_i})) + \sum_{h=1}^{H} (w_h \,.\, (\sum_{l=1}^{E} w_l \,.\, sim_r(a_l^{insIC}, a_l^{insC_i}))\,.\, sim_c(c_h^{IC}, c_h^{C_i})) \tag{4.24}$$

Thus, the similarity between the IC_j and case A can be calculated based on the ontological CBR approach (See Table 4.5 and Eq. 4.23) as follows:

$$sim_g(IC_1, C_A) = \frac{1}{2}(0.67) + \frac{1}{2}(0.81 \times 1) = 0.74 \tag{4.25}$$

4.2.4 Calculation of advanced fuzzy retrieval

There are several methods for calculating the similarities between cases, including: numeric combination of feature vectors; representation of known cases; using different combination rules and rule-based similarity assessment; assessing the similarity of structured representations; and goal-driven similarity assessment [204]. In this section, our contribution to the study and development of fuzzy similarity relations in our DePicT Dementia Fuzz-CLASS CBR system is described. Dementia patients experience the stages of dementia differently and the symptoms individually. The membership degree of a symptom to a fuzzy set can thus be seen as the degree of resemblance between the symptom and prototypes of the fuzzy set. Therefore, we can use the capabilities of fuzzy membership functions to define similarity degrees between the *ICF* codes of patients in different stages of dementia. If quantitative attributes are involved, the retrieval process will also require fuzzy treatment. Following the definition of [129], the fuzzy retrieval process comprises three steps :

i) first, quantitative attributes are converted into fuzzy terms based on membership functions defined in the fuzzifier;

ii) the resulting fuzzy terms can be combined with known qualitative attributes for use as keys for searching similar cases; and

iii) matched cases are retrieved as candidates, with the case with the highest similarity used to construct a solution to the new case.

In this study, we applied these steps in the retrieval process of DePicT Dementia CLASS using fuzzy membership functions defined for each feature. These membership functions were used to calculate the local similarity measurement ($sim(C_i, IC_1)$) between the existing cases(C)) and the incoming case(IC) as will explain in this section. Feature classification is significant in defining the similarity measure related to each feature. In this case, we introduced feature similarities based on a set of linguistic terms (level of impairment) and their fuzzy membership functions. To find the fuzzy similarity of each *ICF* function, we first set linguistic terms as reference contexts defined based on the *ICF* report. Fuzzy membership functions were then calculated for each feature. In the *ICF* codes (Table 4.7), patient bodily functions are categorized into eight types. The membership degree of an element "f" from the *ICF* function of the i^{th} function within the fuzzy set "Impairment" indicated by $\mu_{ICF}^{Impairment}(f)$ is assigned a value in the interval [0,1]. In identifying the grade of each *ICF* code for a particular patient, five levels of impairments are used as follows [270]:

- Level 1: which means the person has no problem;
- Level 2: which means a problem that is presently less than 25% of the time, with an intensity a person can tolerate and which rarely happens over the last 30 days;
- Level 3: which means that a problem that is presently less than 50% of the time, with intensity, which is interfering in the persons day to day life and which occasionally happens over the last 30 days;

- Level 4: which means that a problem that is presently more than 50% of the time, with intensity, which is partially disrupting the persons day to day life and which frequently happens over the last 30 days; and
- Level 5: which means that a problem that is presently more than 95% of the time, with intensity, which is disrupting the persons day to day life and which happens every day over the last 30 days.

The *ICF* descriptions are used to assess the severity of each function, with higher scores corresponding to higher degrees of danger. This approach was used based on the fuzzy aspects of age and depression, by Zekri et al., who created the ontology for the representation and manipulation of knowledge and data relating to the diagnosis and management of the AD [290]. In this study the fuzzy inference system of mental function is calculated using fifteen related mental functions (See Table 4.7) as inputs and one membership function representing the stage of dementia as an output.

Although most of the patients share common symptoms, the disease progresses differently and, in some cases, very rapidly. The effects of dementia depend on the patient and there are distinct symptoms values for each patient. Figure 4.12 shows the *ICF* codes for two patients and their average as mean (blue curve) in the early stage of Alzheimer's disease (main dementia related disease) based on the observations of caregivers according to the severity of each function, from 0 to 5, which is the severity levels of problem (impairment).

For instance, the ratings of dementia patient *B* for all these fifteen features are as follows:

$$C_B \in [\text{Concsiousness, Orientation, Intellectual; Energy and drive; Attention; ...}] \quad (4.26)$$

$$C_B = [3;3;2;2;3;3;2;2;3;3;2;2;3;2;3] \quad (4.27)$$

In this system, measured *ICF* codes are represented within their respective membership functions as curves on a graph on which the x-axis represents values representing the range of impairment-which in the case of this study is from 0 to 5-while the y-axis represents the membership degree, which takes values in the range [0,1]. The membership function of a fuzzy set can be represented in different forms, e.g., trapezoidal, triangular, left-shoulder (L-functions), or right-shoulder (R-functions), all of which can be used to identify membership degrees. The type of fuzzy membership function used in this in this system for *ICF* parameters is a generic trapezoidal function, as illustrated in Fig. 4.13.

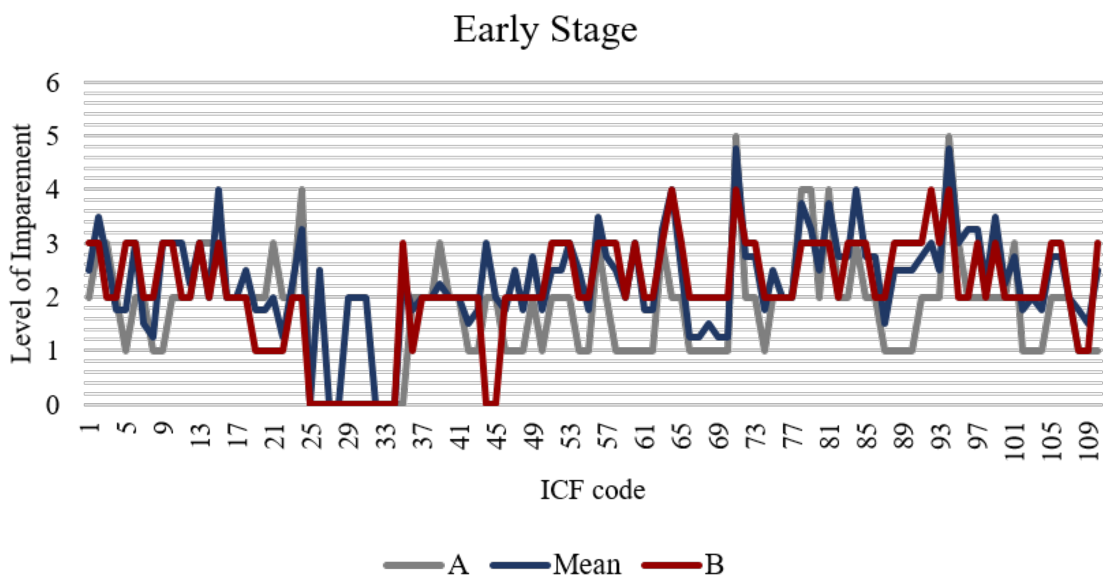


Fig. 4.12 Sample of *ICF* values (impairment) for the patients at the early stage of Alzheimer's disease.

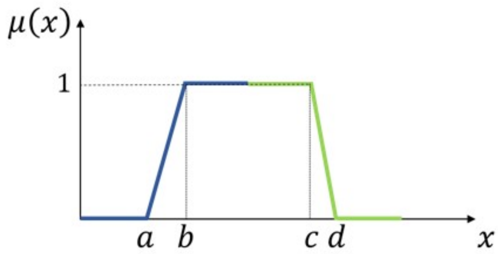


Fig. 4.13 Membership functions-trapezoidal: L-functions and R-functions.

The membership function has four parameters, $a,b,c,d \in \cup$, with $a < b < c < d$ which can be presented as [a, b, c, d], and is defined as follows:

$$\mu(x) = \begin{cases} \frac{x-a}{b-a} & \text{if} \quad a \leq x \leq b \\ 1 & \text{if} \quad b \leq x \leq c \\ \frac{-x+d}{d-c} & \text{if} \quad c \leq x \leq d \\ 0 & \text{else} \end{cases} \tag{4.28}$$

Triangular functions are used when the constraints $a < b = c < d$ are used, while *L-functions* (See Fig. 4.13, blue curve) arise in the case $(0\, if\, x \leq a) \wedge (\frac{x-a}{b-a}\, if\, a < x < b)$, and *R-functions*

Table 4.7 Membership functions of the dementia *ICF* functions-b1 (from the category of "Body function" and its sub-category of "Mental function").

ICF Codes-b1:Mental Function (15 functions)	$\mu^{ICF}(f) \in [0,1]$
b110 Consciousness functions	$\mu_{Consciousness}$
b114 Orientation functions	$\mu_{Orientation}$
b117 Intellectual functions	$\mu_{Intellectual}$
b130 Energy and drive functions	$\mu_{Energy-drive}$
b140 Attention functions	$\mu_{Attention}$
b144 Memory functions	μ_{Memory}
b147 Psychomotor functions	$\mu_{Phsychomotor}$
b152 Emotional functions	$\mu_{Emotional}$
b156 Perceptual functions	$\mu_{Preceptual}$
b160 Thought functions	$\mu_{Thought}$
b164 Higher-level cognitive functions	$\mu_{High-cognitive}$
b167 Mental functions of language	$\mu_{Language}$
b172 Calculation functions	$\mu_{Calculation}$
b176 Mental function of sequencing complex movements	$\mu_{Seq-movement}$
b180 Experience of self and time functions	$\mu_{Self-time}$

(See Fig. 4.13, green curve) correspond to $(1\, if\, x \leq c) \wedge (0\, if\, x \geq d) \wedge (\frac{-x+d}{d-c}\, if\, c < x < d)$. These functions allow for the determination of fuzzy concrete features as structures of crisp concrete features. The representation of the fuzzy membership function for *ICF* codes is given as follows:

$$ICF = \{ICF_1, ..., ICF_m\}, Level_{ICF_m} \in U = \{1,2,3,4,5\} \tag{4.29}$$

$$\mu \triangleq \{(ICF_1, \mu_{ICF_1}^{Impairment}(Level_{ICF_1})), ..., (ICF_m, \mu_{ICF_m}^{Impairment}(Level_{ICF_m}))\} \tag{4.30}$$

For instance, from the concrete impairments, we can define the fuzzy concrete feature "Consciousness" as a vector of impairment's membership functions in different level of impairment, where:

$$\mu_{Consciousness}^{Impairment}(ICF) = (\mu_{Consciousness}^{No-Impairment}(ICF), \mu_{Consciousness}^{Mild-Impairment}(ICF), \mu_{Consciousness}^{Moderate-Impairment}(ICF),$$
$$\mu_{Consciousness}^{Severe-Impairment}(ICF), \mu_{Consciousness}^{Complete-Impairment}(ICF)) \tag{4.31}$$

and these membership functions are as follows:

$$\mu^{No-Impairment}_{Consciousness}(ICF) = \begin{cases} 1 & \text{if} \quad ICF < 0.5 \quad \text{or} \\ \frac{-ICF+1}{1-0.5} & \text{if} \quad 0.5 < ICF < 1 \quad \text{or} \\ 0 & \text{if} \quad 1 \leq ICF \end{cases} \tag{4.32}$$

$$\mu^{Mild-Impairment}_{Consciousness}(ICF) = \begin{cases} \frac{ICF-0.5}{1-0.5} & \text{if} \quad 0.5 <= ICF < 1 \quad \text{or} \\ 1 & \text{if} \quad 1 <= ICF <= 3 \quad \text{or else } 0 \end{cases} \tag{4.33}$$

$$\mu^{Moderate-Impairment}_{Consciousness}(ICF) = \begin{cases} \frac{ICF-2}{2.5-2} & \text{if} \quad 2 <= ICF < 2.5 \quad \text{or} \\ 1 & \text{if} \quad 2.5 <= ICF <= 3.5 \text{ or} \\ \frac{-ICF+4}{4-3.5} & \text{if} \quad 3.5 < ICF <= 4 \quad \text{or else } 0 \end{cases} \tag{4.34}$$

$$\mu^{Severe-Impairment}_{Consciousness}(ICF) = \begin{cases} \frac{ICF-3.5}{4-3.5} & \text{if} \quad 3.5 <= ICF < 4 \quad \text{or} \\ 1 & \text{if} \quad 4 <= ICF <= 4.5 \text{ or} \\ \frac{-ICF+5}{5-4.5} & \text{if} \quad 4.5 < ICF <= 5 \quad \text{or else } 0 \end{cases} \tag{4.35}$$

$$\mu^{Complete-Impairment}_{Consciousness}(ICF) = \begin{cases} \frac{ICF-4.5}{5-4.5} & \text{if} \quad 4.5 <= ICF < 5 \quad \text{or} \\ 1 & \text{if} \quad ICF = 5 \quad \text{or} \quad \text{else } 0 \end{cases} \tag{4.36}$$

Figure 4.14 shows the membership functions of the feature “Consciousness” in terms of the five labels “No-Impairment,” “Mild-Impairment,” “Moderate-Impairment,” “Severe-Impairment,” and “Complete-Impairment.” For instance, the fuzzy membership function of “Moderate-Impairment” is a trapezoidal function (See Fig. 4.13) represented as Eq.(4.34).

By observing and estimating the values of these parameters, caregivers or patients' relatives can define the level of their “Impairment.” As described at the beginning of this sub-section, these parameters are based on duration and number of occurrence of the patient state over the proceeding month. Therefore, a result for which $f \in [1,3]$ 25% of the time indicates that this function range rarely occurred over the proceeding 30 days. Similarly, the levels of impairment for “Moderate-Impairment” and “Severe-Impairment” can be defined in the range of (2,4] and (3,5], respectively. All feature values are associated with at least one linguistic label and also match one *ICF* value as well as two membership degrees. For instance, in the example of Fig. 4.14, “Consciousness” impairment level 3 (impairment range on the x-axis) is common to “Moderate-Impairment” and “Mild-Impairment.” Thus, we can define the local similarity based on the fuzzy membership functions for each *ICF* function is

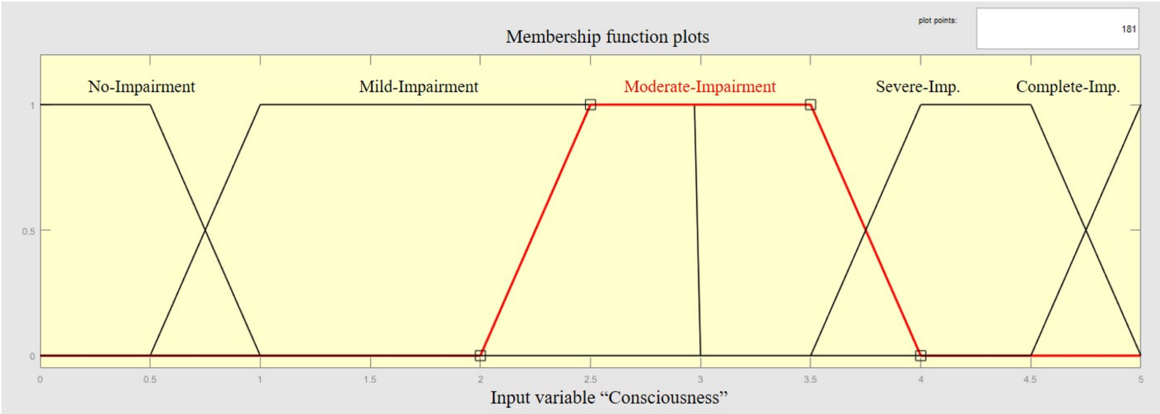


Fig. 4.14 Membership function of feature "Consciousness"- Moderate-Impairment.

as follows:

$$sim_{Impairment}(C_i(Level_{ICF}), IC(Level_{ICF})) = \min[\mu_{ICF}^{Impairment}(C_i(Level_{ICF})), \mu_{ICF}^{Impairment}(IC(Level_{ICF}))] \tag{4.37}$$

where

$$C_i(Level_{ICF}) = (Level_{ICF\,1,i}, ..., Level_{ICF\,j,i}, ..., Level_{ICF\,m,i}) \tag{4.38}$$

is the vector of ICF function degree of the i_{th} common features and $f_{j,i}$ is the feature value of the ICF function degree of feature j in case i. For instance, the local similarity of the feature "Consciousness" from the ICF function for the "Mental function" is as follows:

$$Mild-Impairment \cap Moderate-Impairment \leftrightarrow \forall \quad Level_{ICF} \in U, \mu_{ICF}^{Mild-Impairment \cap Moderate-Impairment}(Level_{ICF}) = \min[\mu_{ICF}^{Mild-Impairment}(Level_{ICF}), \mu_{ICF}^{Moderate-Impairment}(Level_{ICF})] \tag{4.39}$$

Based on an ICF sample we obtained for eleven dementia patients (in the early, middle, and late stages), the fuzzy membership function of all ICF codes was calculated and stored in our case base for using the local similarity measure. To explain the performance of the fuzzy retrieval process as applied to our updated case base (which contains the fuzzy membership function of each feature), the local similarity measurement of an incoming case of mental function for a dementia patient in the early to middle stage (patient D) is calculated using Eq. (4.37) for all fifteen features. The IC of patient D is given as follows:

$$IC \in [Consciousness; Orientation; Intellectual, ...] \tag{4.40}$$

$$IC = [3;4;2;2;2;4;1;1;5;3;4;3;3;1;5] \tag{4.41}$$

For instance, the local similarity of the feature "Consciousness" between *IC* and the first case(Alzheimer's) from the the fuzzy membership functions of "Impairment" (See Fig. 4.13) is given as follows:

$$\begin{aligned}&\text{sim}_{No-Impairment}(C_1(Level_{Consciousness}), IC(Level_{Consciousness})) =\\ &\min[\mu^{No-Impairment}_{Consciousness}(C_1(3)), \mu^{Impairment}_{Consciousness}(IC(3))] = 0\end{aligned} \tag{4.42}$$

$$\begin{aligned}&\text{sim}_{Mild-Impairment}(C_1(Level_{Consciousness}), IC(Level_{Consciousness})) =\\ &\min[\mu^{Mild-Impairment}_{Consciousness}(C_1(3)), \mu^{Impairment}_{Consciousness}(IC(3))] = 1\end{aligned} \tag{4.43}$$

$$\begin{aligned}&\text{sim}_{Moderate-Impairment}(C_1(Level_{Consciousness}), IC(Level_{Consciousness})) =\\ &\min[\mu^{Moderate-Impairment}_{Consciousness}(C_1(3)), \mu^{Impairment}_{Consciousness}(IC(3))] = 1\end{aligned} \tag{4.44}$$

$$\begin{aligned}&\text{sim}_{Severe-Impairment}(C_1(Level_{Consciousness}), IC(Level_{Consciousness})) =\\ &\min[\mu^{Severe-Impairment}_{Consciousness}(C_1(3)), \mu^{Impairment}_{Consciousness}(IC(3))] = 0\end{aligned} \tag{4.45}$$

$$\begin{aligned}&\text{sim}_{Complete-Impairment}(C_1(Level_{Consciousness}), IC(Level_{Consciousness})) =\\ &\min[\mu^{Complete-Impairment}_{Consciousness}(C_1(3)), \mu^{Impairment}_{Consciousness}(IC(3))] = 0\end{aligned} \tag{4.46}$$

Using the above mentioned eleven-patient *ICF* sample, the membership functions of all *ICF* codes were calculated. Table 4.8 lists the membership functions for fifteen *ICF* codes.

We can also calculate the local fuzzy similarity between two values, f_1 and f_2, of a feature using the same fuzzy sets applied to the feature "Consciousness" with the linguistic term (fuzzy set) "Moderate-Impairment" as follows:

$$\begin{aligned}&\text{sim}_{Moderate-Impairment}(C_1(f_1(Consciousness)), C_2(f_2(Consciousness))) =\\ &1 - \left|\mu^{Moderate-Impairment}_{Consciousness}(f_1) - \mu^{Moderate-Impairment}_{Consciousness}(f_2)\right|\end{aligned} \tag{4.47}$$

Table 4.8 Membership functions of the dementia *ICF* functions-b1 for five categories of impairment (no, mild, moderate, severe and complete).

$\mu_{ICF}(ICF_m)$	Impairment				
	No	Mild	Moderate	Severe	Complete
$\mu_{Consciousness}$	$[0,0,0.5,1]$	$[0.5,1,3,3]$	$[2,2.5,3,4]$	$[3.5,4,4.5,5]$	$[5,5,5]$
$\mu_{Orientation}$	$[0,0,0.5,1]$	$[1,2,3,3.5]$	$[3.5,4,4.5]$	$[4,4.5,5,5]$	$[5,5,5]$
$\mu_{Intellectual}$	$[0,0,0.5,1]$	$[1,2,3,3.5]$	$[3,,3,4,4.5]$	$[4.5,5,5]$	$[5,5,5]$
$\mu_{Energy-drive}$	$[0,0,0.5,1]$	$[0.5,1,2,3]$	$[2,3,5]$	$[4,5,5]$	$[5,5,5]$
$\mu_{Attention}$	$[0,0,0.5,1]$	$[0.5,1,3,3.5]$	$[2.5,3,4,4.5]$	$[3.5,4,4.5]$	$[5,5,5]$
μ_{Memory}	$[0,0,0.5,1]$	$[1,2,3,3.5]$	$[3.5,4,5,5]$	$[4.5,4.5,5,5]$	$[5,5,5]$
$\mu_{Phsychomotor}$	$[0,0,0.5,1]$	$[0.5,1,2,2.5]$	$[2,2,4,4.5]$	$[3,4,5]$	$[4,5,5]$
$\mu_{Emotional}$	$[0,0,0.5,1]$	$[0.5,1,2,2.5]$	$[0.5,1,2,2.5]$	$[1.5,2,2.5]$	$[2,3.5,5,5]$
$\mu_{Preceptual}$	$[0,0,1,1.5]$	$[0.5,1,3,3.5]$	$[2.5,3,4,4.5]$	$[3,4,5]$	$[4,5,5]$
$\mu_{Thought}$	$[0,0,1,1.5]$	$[1.5,2,3,3.5]$	$[2.5,3,4,4.5]$	$[4,5,5]$	$[5,5,5]$
$\mu_{High-cognitive}$	$[0,0,1,1.5]$	$[1,2,3]$	$[3,4,5]$	$[4,5,5]$	$[5,5,5]$
$\mu_{Language}$	$[0,0,1,1.5]$	$[1,2,3]$	$[2.5,3,4,4.5]$	$[3,4,5]$	$[4,5,5]$
$\mu_{Calculation}$	$[0,0,1.5,2]$	$[2,3,4]$	$[3,4,5,5]$	$[4,5,5]$	$[5,5,5]$
$\mu_{Seq-movement}$	$[0,0,0.5,1]$	$[1,2,3,4]$	$[2,3,4.5]$	$[3.5,5,5]$	$[5,5,5]$
$\mu_{Self-time}$	$[0,0,1.5,2]$	$[2,3,4]$	$[3,4,5,5]$	$[4.5,5,5]$	$[5,5,5]$

For instance, for patients *A* (See Fig. 4.12) and *D* (See Eq. (4.41)), the local similarity between the feature of "Consciousness" based on their respective fuzzy membership functions (See Fig. 4.14) is calculated as follows:

$$\begin{aligned} &\mathrm{sim}_{Moderate-Impairment}(C_B((2),C_D(3) = \\ &1-\left|\mu^{Moderate-Impairment}_{Consciousness}(2)-\mu^{Moderate-Impairment}_{Consciousness}(3)\right| = 1-|0-1| = 1 \end{aligned} \tag{4.48}$$

We calculate global similarity utilizing fuzzy rules and sets (See Table 4.9), but in this research, the global similarity is calculated based on the enriched similarity measure Eq. (3.16) by replacing the local fuzzy similarity measure Eq. (4.37) as follows:

Table 4.9 Fuzzy membership functions of Alzheimer stages.

	Early stage	Early to Middle	Middle stage	Middle to Late	Late stage
$\mu^{Alzheimer}_{Stage}$	$[2,3,4]$	$[2.5,3.5,4.5]$	$[3,4,5]$	$[3.5,4.5,5]$	$[4,5,5]$

$$SIM(IC,C_i) = \Sigma^{k}_{j=1}\frac{w_i\,.\,sim_{Impairment}(C_i(Level_{ICF}),IC(Level_{ICF}))}{k} \tag{4.49}$$

Calculation of all local similarities between the *IC* of patient *D* (Eq. (4.49)) and the Alzheimer's case produced similarity degrees of the *IC* for the early, middle, and late stages of 53%, 53%, and 13%, respectively. For better explanation, we can calculate the similarity of three *ICs* which are early, middle and late based on the membership functions of Table 4.8 and global similarity measure (Eq. (4.49)). The queries of these three *ICs* and its similarity degrees are illustrated in Table 4.10. The similarity degree of the first query is calculated as follows:

$$SIM(IC_{Early}, C_{Early}) = \frac{1+1+1+1+1+1+1+1+1+1+1+1+0+1+0}{15} = 0.86 \tag{4.50}$$

$$SIM(IC_{Early}, C_{Middle}) = \frac{0+0+0+1+1+0+1+1+0+1+0+0+0+0+0}{15} = 0.33 \tag{4.51}$$

$$SIM(IC_{Early}, C_{Late}) = \frac{0+0+0+0+0+0+0+1+0+0+0+0+0+0+0}{15} = 0.06 \tag{4.52}$$

Table 4.10 Similarity degrees of three *IC* queries in the early, middle, and late stages Alzheimer's disease.

Query	Mental Function															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	$SIM(IC, C_i)$
Early	1	1	2	3	2	2	2	2	2	3	2	2	2	2	1	**0.86**, 0.33, 0.06
Middle	3	3	4	4	4	4	2	3	4	4	4	4	4	4	3	0.26, **0.72**, 0.23
Late	5	5	5	5	5	5	2	5	5	5	5	5	5	5	3	0.13, 0.20, **0.50**

4.2.5 Experimental results and validation-dementia

DePicT Dementia CLASS achieved appropriate results. Its performance considering the comparison of its evaluation scores (precision, recall, f-score and accuracy) for identified keywords and their package of synonyms based on WAS and k-NN is shown in Table 4.11. For evaluating the textual part of requested problem, we have defined some samples from dementia related diseases home pages (See Appendix C).

DePicT Dementia Fuzz-CLASS achieved better results in distinguishing the stages of Alzheimer more than DePicT Dementia Onto-CLASS which is shown in Table 4.12. Therefore, the combination of these local similarity measures has better results for recommendation with higher accuracy.

For evaluating the results of ontological similarity measure, we have assumed that similarity degrees more than 70% are accepted and we have just counted these similarity

Table 4.11 The comparison of the evaluation scores (precision, recall, f-score, and accuracy) of DePicT Dementia CLASS.

Local sim	Evaluation Score										
	TP	TN	FP	FN	Pre.	Rec.	F-m.	Acc.	k=1	k=3	k=5
WAS k-NN	4	4	20	7	0.16	0.36	0.22	0.22	0.25	0.29	0.20
WAS k-NN (p)	5	7	5	3	0.50	0.62	0.55	0.605	–	–	–
WAS k-NN (p)	10	11	5	14	0.41	0.66	0.51	0.52	0.37	0.37	0.2

Table 4.12 Similarity degrees of three queries of the incoming cases.

Query	Onto-CLASS								Fuzz-CLASS		
	EtM	M	EtM	MtL	M	E	E	L	E	M	L
Early	0,66	0,65	0,73	0,62	0,66	0,76	0,74	0,61	0.86	0.33	0.06
Middle	0,69	0,69	0,66	0,67	0,70	0,57	0,63	0,72	0.26	0.72	0.23
Late	0,60	0,61	0,55	0,64	0,60	0,45	0,496	0,69	0.13	0.20	0.50

degrees as true positive (TP). For evaluating the results of fuzzy similarity measures, we have calculated the global similarity degrees for all of test incoming cases based on the fuzzy membership functions of these three stages and counted the true positive (TP), true negetive (TN), false positive (FP) and false negetive (FN). Thus, the evaluation scores based on our dataset (samples) is illustrated in Table 4.13.

Table 4.13 The comparison of the evaluation scores (precision, recall, f-score, and accuracy) of DePicT Dementia Onto-CLASS and DePicT Dementia Fuzz-CLASS.

Local sim	Evaluation Score							
	TP	TN	FP	FN	Pre.	Rec.	F-m.	Acc.
Ontological relation	3	17	2	2	0.6	0.6	0.6	0.83
Fuzzy membership function	5	11	1	1	0.83	0.83	0.83	0.88

4.3 Melanomic skin cancers

Melanoma results in the vast majority of skin cancer deaths; in 2016, there were an estimated 3,520 deaths from other types of skin cancer and approximately three times more around 10,130 deaths from melanoma, even though this disease accounts for only 1% of all instances of skin cancer [24]. The survival rates of melanoma from early to terminal stages vary more than 50% [17]; therefore, having the right information at the right time via early detection is essential to surviving this type of cancer. Accordingly, developing decision support systems has become a major area of research in this field [178]. The best path to early detection is recognizing new or changing skin growths, especially those that appear different from other moles [24]. Even after treatment, it is very important that Patients to keep up on their medical history and records. The National Comprehensive Cancer Network (NCCN) creates helpful reports and resources to serve as guidelines for informing patients and other stakeholders about cancer [68]. The NCCN guideline for patients on melanoma, which is endorsed by the Melanoma Research Foundation [188] and Aim at Melanoma [15], explains which cancer tests and treatments are recommended by melanoma experts. Although CBR has been applied in a number of medical systems, only a few system has been developed for melanoma, e.g., [199]. This CBR system used rules to answer medical questions based on the knowledge extracted from image data [199].

Various skin lesions classification have been developed using SVMs and k-NN-like interactive object recognition methodologies to perform border segmentation [229], extract global and local features and apply Otsu's adaptive thresholding method [133]. Sumithra et al. utilized SVM and k-NN for skin cancer classification based on region-growing segmentation with results of 46 and 34%, respectively [248]. Although convolutional networks outperform other methods in many recognition tasks and in the classification of particular melanomas [228] [82], deep networks generally requires thousands of training samples. In this study, DePicT CLASS was used to classify melanoma images using region growing method (utilizing SVM and k-NN) to support patients and health providers in managing the disease.

4.4 DePicT Melanoma CLASS

This section describes the development of a textual-conversational case-based system for melanoma classification and treatment based on the DePicT CLASS. In the proposed system, text and image references and learning materials related to the disease and its treatment are attached to individual cases as case descriptions and a case recommendations, respectively. Problem requests submitted as free text, images from the affected areas, and filled-out questionnaires are compared with the existing cases from the case base, with the solution of the most similar case considered as the recommendation. In the following, it is explained how DePicT CLASS can be applied to the detection of melanoma through enrichment by an image processing algorithm. DePicT Melanoma CLASS was developed for use in the MedAusbild project, an initiative of the Institute of Knowledge Based Systems & Knowledge Management (KBS & KM) at the University of Siegen [111].

The case base of melanoma is built based on the AJCC [8] staging and melanoma skin cancer information data base [9]. Each case has a word association profile for main keywords extracted from melanoma textbooks and reports (fourteen melanoma-related papers and books, see Appendix C) from which case descriptions and references are built. The case structure (Fig. 4.15) comprises a case description and recommendation including image features, segmentation processes, identified keywords, and a word association profile.

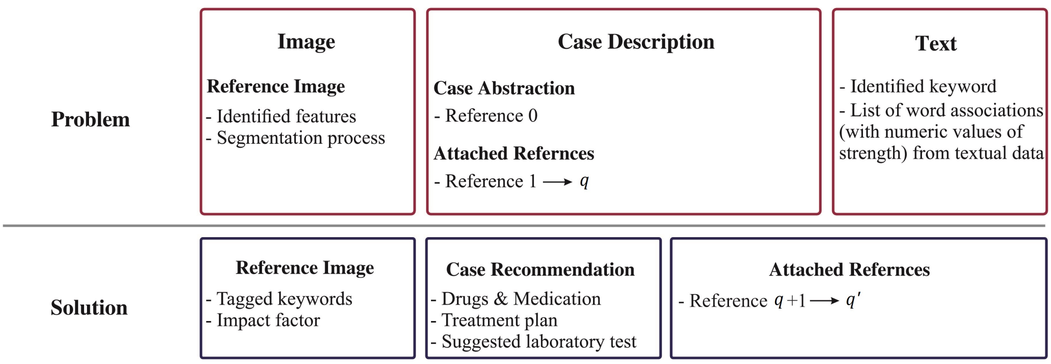


Fig. 4.15 Case structure of DePicT Melanoma CLASS.

[8] American Joint Committee on Cancer: Melanoma of the Skin Staging

[9] American Cancer Society, https://www.cancer.org/cancer/melanoma-skin-cancer.html

4.4.1 DePicT Profile Matrix of melanoma

The DePicT Profile Matrix of melanoma has 260 (5×52) elements for five cases as melanoma stages and 52 identified keywords as features. To describe the procedure of DePicT CLASS, a problem request is needed. An example of such a request is given as follows: [A few months ago, I discovered a strange spot on my arm. At first I did not mind, but now it is itching. Strangely I was burned by the sun in the same region last summer. I was exposed to massive UV radiation there. The spot seems to have changed in the last weeks. Its shape seems awkward now. Now some lymph nodes are swollen.]

From this example, the system recognized the following keywords: UV, lymph, and arm. Instead of comprising a problem, the user can also answer to the questions, with the answers to the questions used to generate input features for the incoming case. Table 4.14 shows our DePicT Profile Matrix based on these three common keywords for five cases.

Table 4.14 DePicT Profile Matrix of melanoma for the requested problem.

Keyword	ID	C_1	C_2	C_3	C_4	C_5
UV	15	5.6	6.4	7.7	10.4	4.4
lymph	22	0	25.2	26.2	29.2	13.1
arm	34	4.5	6.9	13.7	17.5	8.7

Thus, based on the identified keywords, common keywords from the requested problem are recognized, and an *IC* vector created based on three (out of 52) common keywords:

$$IC \in [...;\mathrm{UV};...;\mathrm{lymph};...;\mathrm{arm};...] \tag{4.53}$$

$$IC = [0;0;0;0;0;0;0;0;0;0;0;0;0;0;1;0;0;0;0;0;0;1;0;0;0;0;0;0;0;0;0;0;0;1\\ ;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0;0] \tag{4.54}$$

After defining the *IC*, the similarity measurement is calculated using (Eq. (3.18)) to represent the similarities between *IC* and each case with their respective references for the three common keywords. The similarity degrees of all cases are considered and the most similar cases obtained. To demonstrate the performance of the case retrieval process, the similarity degree of the first case from this example is calculated below:

$$
\begin{aligned}
&SIM(IC, C(R_{3,3})) = \\
&(5.6 \times 0.6 \times 0.8) + (5.6 \times 0.4 \times 0.8) + (5.6 \times 0.3 \times 0.8) \\
&+ (0 \times 0.8 \times 0.4) + (0 \times 0.6 \times 0.4) + (0 \times 0.5 \times 0.4) \\
&+ (4.5 \times 0.2 \times 0.2) + (4.5 \times 0.2 \times 0.2) + (4.5 \times 0.3 \times 0.2)/3 = 3.2
\end{aligned} \tag{4.55}
$$

4.4.2 Image processing and classification

The first clinical signs of melanoma are called the lesion area, which denotes the affected area and corresponding spots on the skin. There are two classes of melanoma-malignant and benign-and the recognition process comprises five main steps (which are illustrated as a pipeline in Fig. 4.16):

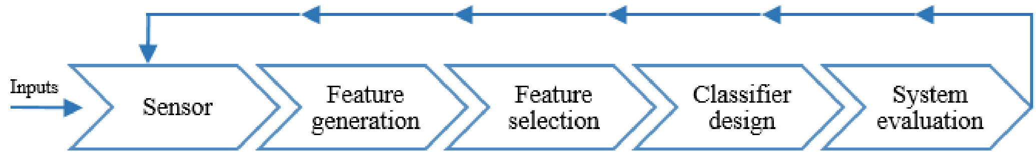


Fig. 4.16 Image processing pipeline.

- *Sensor*: The input data used for image processing comprises images and respective points of interest (POI). The image data should be in RGB format with a minimum resolution of 200×200 pixels, and images should include the skin spot to be examined. If there is more than one spot, the relevant spots must be marked as POIs.

- *Feature generation*: Features are developed to distinguish the spots based on their respective characteristics. The spots can then be divided into the categories malignant or benign.

- *Feature Selection*: After feature creation, the features are tested, with those that significantly improve detection selected and used while the rest are removed.

- *Classification*: Data input data using the selected features are categorized into the above two classes.

- *System evaluation*: After the system has been implemented, evaluation metrics are used to assess the performance of the system.

- **Image pre-processing**

Image pre-processing is the crucial step in the use of image data. Scaling is performed to bring images from datasets to a correct resolution. Spots images often contain noises such as hairs or dermatological markers. In this study, a DullRazor [10] algorithm was used to perform a three-steps: i) first, the position was determined using a morphological closing operation; ii) then, neighboring hairs were replaced using bilinear interpolation pixels; and finally iii) the remaining pixels were smoothed using an adaptive median filter [153].

- **Feature selection and region growing segmentation**

Region growing is a method for identifying similar areas on an image and then selecting them as a whole. As an initial step of this procedure, one or more seed points are selected. The color values of the neighboring pixels are then compared with those of the seed points; if they are sufficiently similar, the compared pixels are also selected and similarity comparisons are then performed with their neighbors. The algorithm terminates when there are no more sufficiently similar pixels. The image is then converted into a gray-value image as the first step. A 3×3 median filter (a modified decision-based unsymmetrical trimmed median filter) is used for noise reduction based on a received set of values—in this case, the gray values of the nine pixels—which are sorted, with the middle value selected as the new value for the current pixel. In the case of a border pixels, missing values are filled with zeros. The brightness is adjusted to increase the contrast. The histogram of the gray values is rearranged to take advantage of the complete color space. To segment the lesion region of interest (ROI), POIs are indicated within the relevant skin regions; these are used as "seeds" for a region-growing algorithm that compares each pixel of the ROI to its neighbors for similarity. If the similarity is higher than a threshold, the pixel is added to the region. The method terminates if no further pixels can be recursively added. To remove remaining smaller elements, a complementary image is formed and an opening process is used to close existing holes. Based on the characteristics of the skin spots occurring as a results of melanoma, Table 4.15 presents twelve features considered in terms of the categories of color and shape.

Because skin spots can be sharply differentiated or categorized by their color composition, the color values of the segmented images are examined in both the RGB and HSV color spaces. The average values of all three channels of the two color spaces (for features 1-6) are formed as follows:

$$FV_d = \frac{1}{P}\Sigma_{b=1}^{p} CV_b \quad , \quad d \in \{1,2,3,4,5,6\} \tag{4.56}$$

where p is the number of pixels in the segmented region and CV_b is the pixel color value.

[10] http://www.dermweb.com/dull_razor/

Table 4.15 Image processing features.

Category	Name	Inputs	Feature numbers
Color	Average RGB Channel	3	1-3
	Average HSV Channel	3	4-6
	Color Structure Descriptor	1	7
	Color Layout Descriptor	2	8-9
Shape	Principal Component Ratio	1	10
	Filled Fitted Ellipse	1	11
	Unfilled Fitted Ellipse	1	12

The distance between the maximum and minimum values in HSV color space is calculated and used as feature 7 $(FV_7 = FV_{max} - FV_{min})$. For the classification of skin spots, both the color value distribution around a spot and the different color values within the spot are generally relevant. For this reason, three regions are defined for the next two features: R_s is defined as the region surrounding the ROI, R_o represents the outside of the region, and R_i represents the core of ROI. Accordingly, features 8 and 9 are calculated as follows:

$$FV_8 = \left| \frac{ACV_{Ri}}{P_{Ri}} - \frac{ACV_{Ro}}{P_{Ro}} \right| \tag{4.57}$$

$$FV_9 = \left| \frac{ACV_{Ro}}{P_{Ro}} - \frac{ACV_{Rs}}{P_{Rs}} \right| \tag{4.58}$$

where ACV_{Ri} is the average color value in the inner region of the ROI, ACV_{Ro} is the average color value outside the ROI, and ACV_{Rs} is the average color value in the ROI nighborhood (See Fig. 4.17). P_{Ro}, P_{Ri}, and P_{Rs} represent the total number of pixels in each region. The tenth feature is the principal component ratio. Benign melanomas tend to have much more circular or elliptical shape than malignant melanomas; accordingly, an ellipse is fitted around the ROI and the percentages of ROI pixels on the ellipse and outside of the ROI are used as features 11 and 12, respectively. To compare all twelve features, they are normalized (0,1) and stored in a feature vector for use in classification.

This methodology can be demonstrated by visualizing its steps as a process of selecting two 1600×900 pixel images from a dataset representing a benign (See Fig. 4.18-a1) and a malignant (see Fig. 4.19-a2) melanoma, respectively. For the benign image, the POI dimensions were set to $x = 828$ and $y = 420$, while the malignant image dimensions were set to $x = 943$ and $y = 506$. The pre-processing and segmentation processes described above was performed, with the results shown in Figs. 4.18 and 4.19, respectively. Expert segmentation for these examples is illustrated in Fig. 4.20. The values of all features from these test data are specified in Table 4.16.

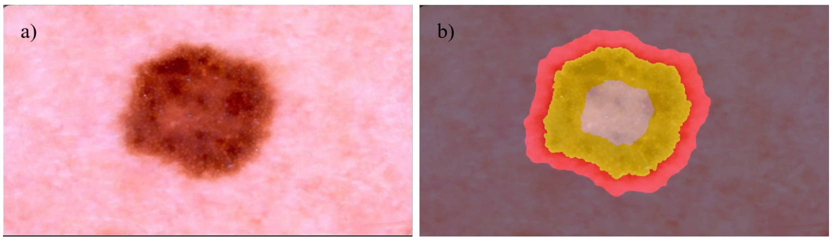


Fig. 4.17 Color layout descriptor a) Input field (ISIC Archive) b) Color layout descriptor regions, Ro: red, Rs: yellow, Ri: white.

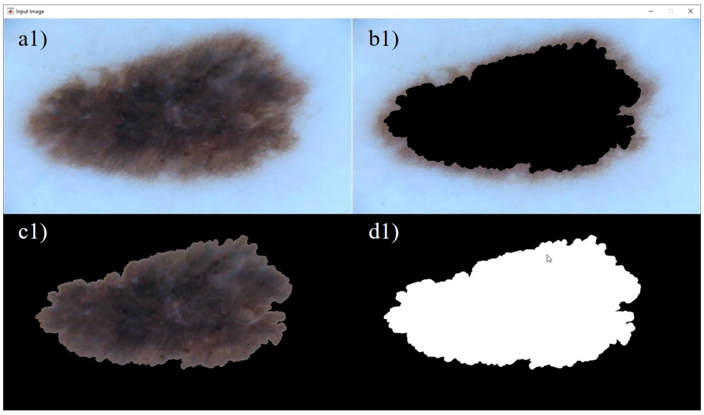


Fig. 4.18 Segmentation of benign image.

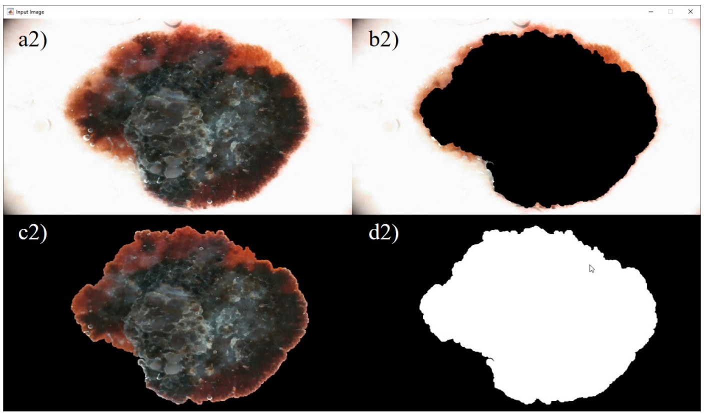


Fig. 4.19 Segmentation of malignant image.

The result of the current example is illustrated in Table 4.17. with the 100% accuracy for k-NN and 50% accuracy for SVM.

Table 4.16 Feature values of experimented images.

Nr.	Benign	Malignant	Min	Max
1	0.2730	0.3054	0.1720	0.9127
2	0.2327	0.2491	0.0408	0.7341
3	0.2472	0.2219	0.0242	0.6632
4	0.7317	0.2044	0.0265	0.9436
5	0.1614	0.2741	0.0900	0.9579
6	0.2758	0.3158	0.1853	0.9134
7	0.9948	0.9977	0.0366	0.9989
8	0.0985	0.0335	0.0018	0.2101
9	0.3473	0.6485	0.0060	0.6358
10	0.4941	0.7431	0.3101	0.9933
11	0.9577	0.9787	0.3412	1
12	0.4491	0.4650	0.1600	0.9918

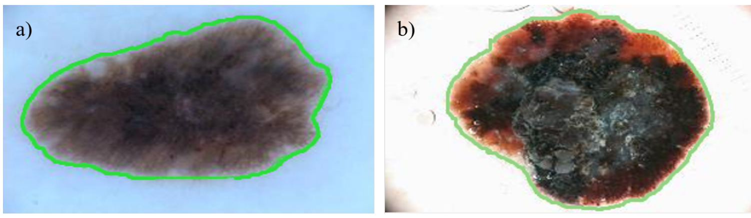


Fig. 4.20 Expert segmentation- a) benign melanoma and b) malignant melanoma.

Table 4.17 Result of described example.

Input (sample image)	Classification Method	
	k-NN	SVM
Benign	correct	correct
Malignant	correct	incorrect

4.4.3 Tools and dataset

Matlab (2017a) was utilized to develop DePicT Melanoma CLASS, in particular with the use of Image Processing Toolbox, Parallel Computing Toolbox, Matlab Compiler and Coder, and App Designer. The ISIC Archive dataset [11] containing images of benign and malignant melanoma was used for image-processing (300 images for training and 100 images for testing).

[11] https://www.isic.or https://isic-archive.com/

4.4.4 Experimental results and validation-melanoma

DePicT Melanoma CLASS achieved appropriate results. Its performance in terms of comparison of its evaluation scores (precision, recall, f-score and accuracy) for k-NN, SVM, and WAS is shown in Table 4.18. In training 300 images and testing 100 images for k=1, 64% of the inputs were classified correctly (Euclidean), while the accuracy obtained using SVM was 62%. In evaluating the textual components of requested problems in the form of nineteen samples extracted from melanoma forums [12], it outperformed with an accuracy of 63%.

Table 4.18 The comparison of the evaluation scores (precision, recall, f-score, and accuracy) of DePicT Melanoma CLASS.

Classification and Local sim	Evaluation Score							
	TP	TN	FP	FN	Pre.	Rec.	F-m.	Acc.
KNN	30	34	16	20	0.65	0.6	0.62	0.64
SVM	25	37	13	25	0.66	0.5	0.57	0.62
WAS	8	4	7	0	0.42	0.53	0.47	0.63

4.5 Chapter conclusion

In this chapter, dementia-related diseases and melanoma skin cancer were discussed as domains of current research. The main parameters and datasets for case creation were also discussed. In addition, the process of case representation and retrieval by our applications (DePicT Dementia CLASS and DePicT Melanoma CLASS) were described using an example.

We tested the performance of our proposed dementia disease fuzzy retrieval process for use in the early, middle, and late stages based on input from related cases. All cases included *ICF* function grades, which we used to evaluate the similarity measurement performance by comparing retrieved cases with the actual patient conditions. In these assessments, we looked primarily at *ICF* membership functions, in particular, the word association profile. The results confirm our assumption that similar diseases can be shown to be consequent from similar patient functions as long as the functions are combined into an appropriate fuzzy membership function within the local similarity measurement. Thus, an essential characteristic of our modified system is its fuzzy non-linear local similarity measure that calculates the similarities between cases to retrieve bodily and structural functions based on the *ICF* standard. The

[12] MRF, Melanoma Research Foundation, https://www.melanoma.org and MIF, Melanoma International Foundation, http://melanomainternational.org/

nature of the fuzzy retrieval process allows aggregation of the membership degree with regards to a particular feature (the *ICF* code) to compute an accurate representation of the overall similarity. The DePicT Dementia Fuzz-CLASS results were therefore compared to DePicT Dementia CLASS results produced by the DePicT Profile Matrix, which represents local similarity, DePicT Dementia Onto-CLASS which is our ontological approach, and the k-nearest neighbor method. These experimental results are presented in the next section; we note here, however, that use of fuzzy local similarity measurement to define the stage of dementia based on eleven patient cases produced improved results.

Early melanoma detection is one of the key objectives in skin cancer treatment. We proposed a case-based system for utilizing collected cases to support patients and healthcare providers through the early detection of melanoma. We used both k-NN and SVMs to classify incoming images and word association profiles obtained from requests in the form of text queries or filled-in questionnaires. Analysis of the results obtained by testing a melanoma dataset suggests that our case-based system for detecting malignant melanoma is fit for the purpose of supporting users by providing relevant information. Further would involve extending the image processing phase by selecting more relevant features and using more testing images. The text-mining phase could also be further developed by enriching the case base with packages of synonym words, more descriptions and references.

Chapter 5

Conclusion and future works

The motivation of the research conducted in this thesis was to explore ways of managing knowledge assets extracted from patient health records, in particular, images, and texts obtained from unstructured sources, in helping to solve patient's problems. We presented the concept of a case-based reasoning system containing knowledge that can be used in the identification of problems and in the description of the related solutions based on knowledge extracted from narratives that describe how particular problems are solved. The design and development of DePicT, a system used to **D**etect and **P**redict diseases using **i**mage **c**lassification and **T**ext Information from patient health records, and DePicT CLASS, a **C**ase-based **L**earning **A**ssistant **Sys**tem that uses the local-global similarity measures and adaptation mechanism, in particular, using the DePicT Profile Matrix of the association strength between title phrases and identified keywords of cases, are the main contributions of this research. To validate our research and the proposed recommender system, we focused on skin and brain diseases in extending our initial concept to develop the DePicT Melanoma CLASS patient assistant systems and the DePicT Dementia CLASS caregiver learning assistant system, respectively. In this context, the following chapter addresses the key findings of this research and its proof of concept, system strengths and weakness, continued system development, system evaluations, and future research directions.

5.1 Conclusion and key findings of the research

The primary objective of the research presented in this work was to design and develop a CBR system for applying knowledge assets extracted from textbooks and image references to new problem-solving processes. We answered five cumulative research questions to achieve this goal. As this was a relational study, we developed descriptions by observing and measuring each of the features of the cases we were trying to relate; as it was also a causal study, we described both the causes and effects of cases as features-values of the problems and solutions that they were related to each other. For our given research goals and objectives, we obtained results for which: i) the empirical data demonstrated improved outcomes; ii) qualitative feedback demonstrated positive experiences; iii) the CBR system demonstrated benefits in terms of problem-solving; and iv) the proposed system perspective is able to aid users in reflection andin attaining further improvement. The key findings of this work are focused on:

1. Developing a case-based system to improve user (e.g., patients, relatives, and caregivers involved in chronic and palliative care situations) experience.
2. Testing a new proposal that word association profiles can solve requested problems by utilizing local-global similarity measures and applying adaptations based on the most-similar cases.
3. Developing a system for guiding the manual adaptation of similar references retrieved from a case base (e.g., a learner can rank the best references).
4. Extracting knowledge using domain experts and stakeholders (e.g., caregiver observations of new patients).
5. Enhancing statistical approaches using learned knowledge through the use of, for example, ranking grades (See point 3 above) and new ICF functions (See point 4).

The limitations of this study and some methodological considerations are given as follows:

1. Calculation of word association strengths is domain-based.
2. Timing is not always ideal but dictated by circumstances.
3. Access to the domain experts should be expanded.
4. The interview data were not fully processed and knowledge extraction from experts was difficult.
5. It was difficult to obtain survey responses from caregivers.
6. There was challenges in finding relevant and helpful references to build the case base.

7. Ethical considerations restricted the development of the patient-oriented system.
8. Limiting the thesis scope was difficult as the work touched upon many interesting and related topics.

There are several relevant discussions in the literature on AI research in general [67] and case-based reasoning research in particular, [66]; these topics have also addressed in some dissertations, e.g., [1]. In this section, we consider five questions from [66] and [1] that should be answered by researchers in presenting AI methods (e.g, CBR) and how they were addressed in this study.

1. What are the metrics for evaluating the method?

In dementia case study, we evaluated the proposed case base and retrieval function using ontological, textual approach (association strength), and fuzzy approaches; in the melanoma case study, we used a textual approach and image classification.

The evaluation scores of the methodologies for these applications were calculated as follows:

$$\text{Precision} = \frac{\{\text{relevant refrences}\} \cap \{\text{adapted refrences}\}}{\{\text{adapted references}\}} = \frac{\text{TP}}{\text{TP+FP}} \tag{5.1}$$

$$\text{Recall} = \frac{\{\text{relevant refrences}\} \cap \{\text{adapted refrences}\}}{\{\text{relevant references}\}} = \frac{\text{TP}}{\text{TP+FN}} \tag{5.2}$$

$$\text{F-score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \tag{5.3}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{5.4}$$

$$\text{Sensitivity} = \frac{\text{number of correctly predicted malignant lesions}}{\text{number of malignant lesions}} = \frac{\text{TP}}{\text{TP+FN}} \tag{5.5}$$

$$\text{Specificity} = \frac{\text{number of correctly predicted benign lesions}}{\text{number of benign lesions}} = \frac{\text{TN}}{\text{FP+TN}} \tag{5.6}$$

The measures are computed by utilizing the equation explained with the following conventions as follows:

- *TP* (True Positive): positive samples classified as positive.
- *TN* (True Negative): Negative samples classified as negative.
- *FP* (False Positive): Negative samples classified as positive.
- *FN* (False Negative): Positive samples classified as negative.

Regarding the factors of recall and precision illustrated in Fig. 5.1, the retrieval scenario shows instances of references (e.g., texts and images) and the task is to return a set of relevant references given a requested problem or, more precisely, to assign each reference to one of two categories: relevant and not relevant. In this case, relevant references are simply those that belong to the relevant category. In this context, precision is defined as the number of relevant references retrieved by a requested problem divided by the total number of references retrieved by the problem, whereas recall is defined as the number of relevant references retrieved by a requested problem divided by the total number of existing relevant references.

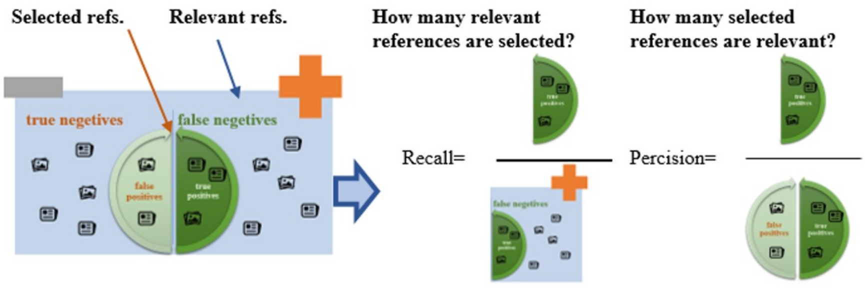


Fig. 5.1 Precision and recall score.

Based on these two scores, an f-score can be calculated. To determine accuracy, we can define sensitivity and specificity, which are calculated, respectively, as the number of correctly predicted malignant lesions divided by the total numbers of malignant lesions and the number of correctly predicted benign lesions divided by the total numbers of benign lesions.

The overall performance of the DePicT Dementia CLASS was evaluated based on the testing of matched cases using 24 sample texts as problem requests and eleven samples and the *ICF* data from observed patients. The domain experts (caregivers) had already validated the built case base in terms of its completeness and correctness of each function (*ICF*) and the main features (*ICF* codes) had been used to create the case base. The performance of DePicT Melanoma CLASS was evaluated using 100 images from the ISIC archive and nineteen samples. The testing and evaluation procedure has six steps:

- Step 1: A comparison with k-NN DePicT Dementia CLASS local word association similarity measure results obtained using identified keywords from the *ICF* codes set as features using their word association strengths (DePicT Profile Matrix$_{WAS}$) and constant weights.

- Step 2: A comparison with k-NN of DePicT Dementia CLASS local word association similarity measure results obtained using identified keywords from the *ICF* codes and the synonym package of keywords as features based on their word association strengths (DePicT Profile Matrix$_{WAS}$) and constant weights.

- Step 3: Mapping patient situations to ICF codes by assigning values from 1 to 5 using DePicT Dementia Onto-CLASS results obtained based on the local ontological similarity measure, using with *ICF* codes used to build the ontology and as features with numerical values from provided by caregivers' observations (mapping patient situation to *ICF* codes by assigning the value from 1 to 5).

- Step 4: Building membership functions of *ICF* codes in terms of the level of impairment in each stage for each feature by applying DePicT Dementia Fuzz-CLASS to produce local fuzzy similarity measures based on fuzzy sets.

- Step 5: Applying DePicT Melanoma CLASS based on the local word association similarity measure for identified keywords and synonym packages of keywords as features using word association strengths (DePicT Profile Matrix$_{WAS}$) and constant weights.

- Step 6: A comparison with k-NN and SVM-based methods of DePicT Melanoma CLASS results based on an application of the image classification method involving training and testing of 300 and 100 images, respectively.

2. How is the method an improvement, an alternative, or a complement to existing technologies? Does it account for more situations, or produce a wider variety of desired behaviors, or is it more efficient in time or space, or model humans better?

There is always a room for improvement; for current research in particular, we mention four improvement approaches in the next sub-section (future research directions). The fact that detection and diagnosis of dementia and melanoma is very difficult even by experts leads to many challenges and aspects for consideration. Providing the right information at the right time is an important goal. The methodology proposed in this work of case acquisition from raw data that includes both texts and images to build explainable CBR systems that can support interactive explanation functionalities for users that propose solutions using a transparent reasoning process can go a long way toward meeting this goal. In this study, different tools for building CBR systems were applied and successfully tested in two domains, which suggests that the methodology could also be applied in other domains.

3. What are the underlying architectural assumptions? Are all design decisions justified? Do the methods rely on each other?

An example of “problem request” is required to explain the performance of DePicT CLASS. In the previous sections, we provided concrete examples of all of the proposed systems utilizing each type of local similarity measure and applied the methodology of word associations in a medical context to evaluate textual data obtained from the knowledge base of DePicT. Substitutions for words x in Eq. (3.3) using medical expressions for diseases, symptoms, and drugs results in lists of word associations and corresponding numeric strength values that can be combined to build a semantic profile of the current textual data record of a case. The hybrid character of Eq. (3.3) makes it possible to measure symmetric and asymmetric word associations with a damping factor larger than zero. Co-occurrences ($Cooc_{ws}$) of two words, x and y, within a defined text window size (ws) are measured over a large document corpus. In previous studies, best results were achieved using a text window size of 10 (ws=10) and a damping factor of 0.5 ($\alpha = 0.5$). Our method achieved best results by defining a text window size of 40 ($ws = 40$, with 20 keywords each to the right and left of the target keyword) and a damping factor of 0.68 ($\alpha = 0.68$). As a final result, all identified word (e.g., $ICFcodes$) associations from a set of selected words (e.g., types of diseases given as case titles) within a document collection can be listed and ordered in the DePicT Profile Matrix of calculated numeric values (*WAS*). We also assessed two additional factors, $\beta = \gamma = 0.001$, to help in considering additional conditions [269] based on the size of the used resources (e.g., textbooks) as follows:

$$\frac{Cooc_{ws(x,y)}}{(Frequency(y))^{\alpha}} = \begin{cases} \frac{Cooc(x,y)}{(Frequency(y))^{\alpha}} & \text{if} \quad Frequency(y) > \beta * Q \\ \frac{Cooc(x,y)}{\gamma * Q} & \text{if} \quad Frequency(y) \leq \beta * Q \end{cases} \tag{5.7}$$

$$\frac{Cooc_{ws(x,y)}}{(Frequency(x))^{\alpha}} = \begin{cases} \frac{Cooc(x,y)}{(Frequency(x))^{\alpha}} & \text{if} \quad Frequency(x) > \beta * Q \\ \frac{Cooc(x,y)}{\gamma * Q} & \text{if} \quad Frequency(x) \leq \beta * Q \end{cases} \tag{5.8}$$

where $\beta = \gamma = 0.001$ and Q is the total number of keywords.

To explain these conditions, we provide an example using cases Alzheimer’s disease and vascular dementia. From the list of keywords of *ICF* codes, we select the function of “eating” (Essen in German) from category 76. Table 5.1 shows the improvement of accuracy based on the use of these conditions obtained by calculating the word association.

4. What is the scope of the method? How extendible is it? Will it scale up? Does it exactly address the task, or portions of the task, or a class of tasks? Could it or parts of it be applied to other problems? Does it subsume some other method?

Table 5.1 Accuracy improvement of *WAS* - example of "eating function" in Alzheimer's disease and vascular dementia.

eating (Essen)	Alzheimer	Vascular
WAS calculation	Cooc (Alzheimer, eating) = 3 Frequency (Alzheimer) = 119 Frequency (eating) = 9 $\frac{3}{(9)^{1.5}} + 0.5 \times \frac{3}{(119)^{1.5}} =$ $0.11111 + 0.00115 =$ $0.11226 \sim 0.11$	Cooc (Vascular, eating) = 2 Frequency (Vascular) = 165 Frequency (eating) = 1 $\frac{2}{(1)^{1.5}} + 0.5 \times \frac{2}{(165)^{1.5}} =$ $2 + 0.00094 =$ $2.00094 \sim 2$
CIMAWA conditions	$Q = 7444$ $\beta \times Q = 7.444$ $\gamma \times Q = 7.444$	$Q = 5788$ $\beta \times Q = 5.788$ $\gamma \times Q = 5.788$
WAS calculation regarding conditions	Cooc (Alzheimer, eating) = 3 Frequency (Alzheimer) = 119 Frequency (eating) = 9 Frequency (Alzheimer) = 119 $>$7.444 $\wedge$ Frequency (eating)=9 > 7.444 $\rightarrow$ $\frac{3}{(9)^{1.5}} + 0.5 \times \frac{3}{(119)^{1.5}} =$ $0.11111 + 0.00115 =$ $0.11226 \sim 0.11$ $\rightarrow$ $\frac{3}{(9)^{0.68}} + 0.5 \times \frac{3}{(119)^{0.68}} =$ $0.67335 + 0.0.05817 =$ $0.73152 \sim 0.73$	Cooc (Vascular, eating) = 2 Frequency (Vascular) = 165 Frequency (eating) = 1 Frequency (Vascular) = 165 $>$5.788 $\wedge$ Frequency (eating)=1 ≤ 5.788 $\rightarrow$ $\frac{2}{5.788} + 0.5 \times \frac{2}{(165)^{1.5}} =$ $0.3455 + 0.00094 =$ $0.3464 \sim 0.35$ $\rightarrow$ $\frac{2}{5.788} + 0.5 \times \frac{2}{(165)^{0.68}} =$ $0.3455 + 0.03105 =$ $0.37655 \sim 0.38$

The results of our work are explained in this section with the goal of assessing the degree to which our research addressed the problems that we sought to address. To measure the relevance of selected references and how many relevant references are selected by the proposed method, the precision, recall, and f-scores obtained from DePicT's two-step construction of similarity measurement using the 24 dementia samples described above are shown in Fig. 5.2.

The k-nearest neighbors (k-NN) algorithm was used to evaluate and successfully validate the retrieval process. K-NN characterizes one of the simplest and intuitive statistical discrimination techniques of using a distance metric to measures the closeness of two requests (in this case, from the problem descriptions for diseases). The K-NN results for the tested samples for three values of k are shown in Fig. 5.3.

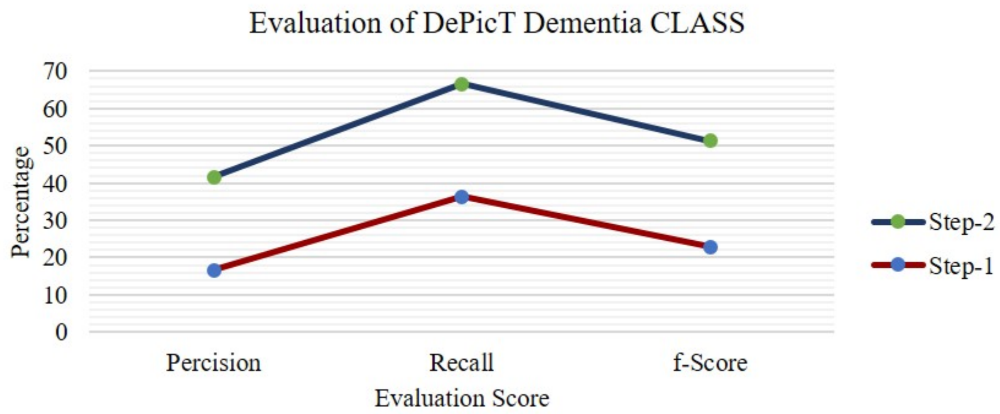


Fig. 5.2 Comparison of the evaluation scores (precision, recall and f-score) of DePicT Dementia CLASS in the first two-steps.

Although we could test the performance of the word association retrieval process for general case of Alzheimer' disease, we chose to test the performance of the fuzzy and ontological retrieval processes based on related cases for dementia diseases in the early, middle, and late stages. Although each case has its own word association profile (with specific words and strengths), functions grades are assigned for each based on the level of impairment as measured by caregiver. A diagram of visualized *ICF* mental functions based on cases for eight patients is shown in Fig. 5.4. While all of the cases include *ICF* function grades, we were able to evaluate the similarity measurement by comparing each case retrieved from the set of existing cases with the actual patient situations.

At the third step of our testing procedure (described above), the ontological similarity measure results for the *ICs* of three additional patients in the early, middle, and late stages of Alzheimer's were tested against the results for the eight original cases, as shown in Fig. 5.5.

The result produced by this retrieval process for patient *D* (early-to-middle stage), which we described in the previous section to demonstrate the performance of the fuzzy similarity measure, are listed Table 5.2.

Table 5.2 Results of the ontological retrieval process for patient *D* (early-to-middle stage of Alzheimer's disease).

Patient D	Similarity Digree		
	Early Stage	Middle Stage	Late Stage
Ontological relation	0.65	0.65	0.61
Fuzzy membership function	0.53	0.53	0.13

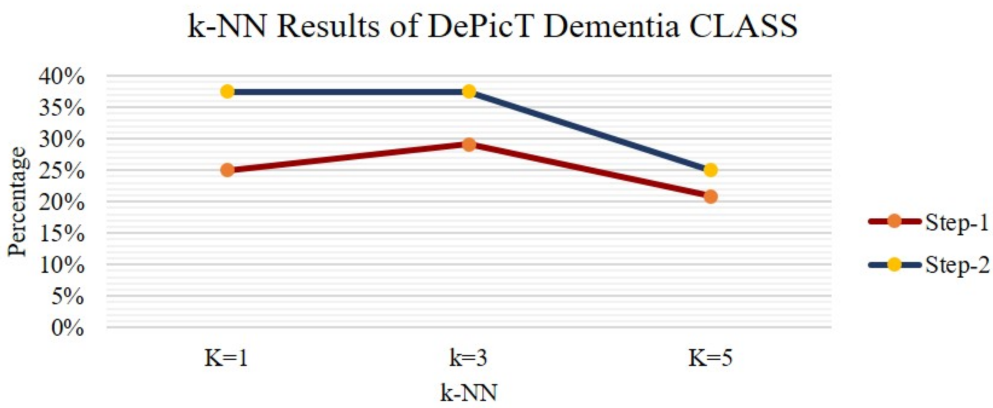


Fig. 5.3 Comparison of the results of k-NN (k=1,3,5) test for the first two-steps.

In these experiments, we looked primarily at the *ICF* membership functions, with particular attention paid to attribute distances and word association profiles. The results (fourth step) confirmed the assumption that similar diseases can be found to be consequent from similar patient functions as long as these functions are combined into an appropriate fuzzy membership function in the local similarity measure. Thus, an essential characteristic of our modified system is its use of a fuzzy non-linear local similarity measure that calculates similarities between cases to retrieve patient bodily and structural functions based on the *ICF* standard. The nature of this fuzzy retrieval process allows for aggregation of the membership degrees with respect to individual features (*ICF* codes) in computing an accurate representation of the total similarity.

The fuzzy similarity measure (DePicT Dementia Fuzz-CLASS) results were compared with the DePicT Dementia CLASS word association similarity measure produced by the DePicT Profile Matrix, DePicT Dementia Onto-CLASS, using the ontological similarity measure and the k-nearest neighbor method. The experimental results (Table 5.3), which were obtained using DePicT's case base, reveal that the use of fuzzy local similarity measurement improved classification of the stages of dementia. As we explained in the previous chapter (See Table 4.12), the evaluation scores calculated based on our assumption for 70% acceptance rate of similarity degree (See Fig. 5.5).

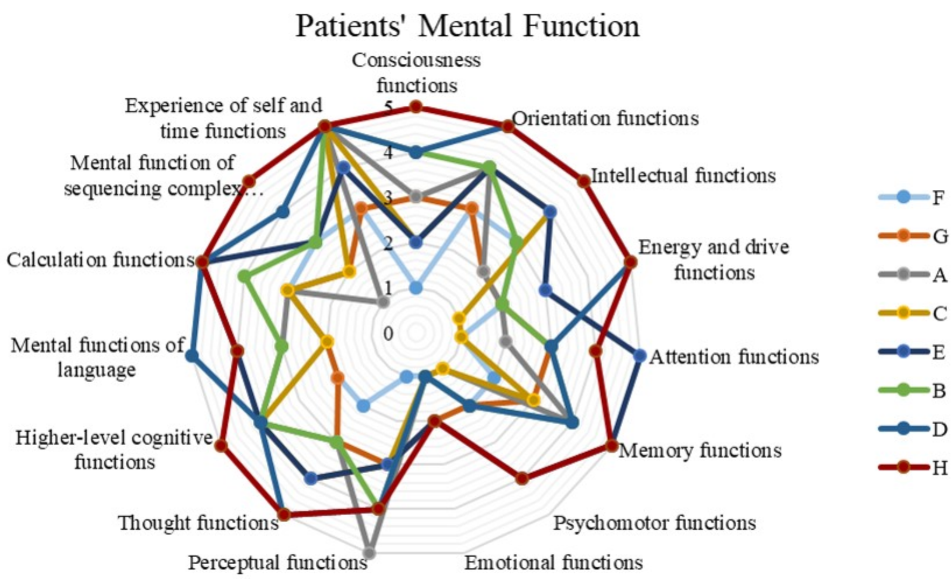


Fig. 5.4 *ICF* mental functions from eight cases for dementia patients.

Table 5.3 Experimental results of DePicT Dementia CLASS based on the different local similarity measures.

	Evaluation Result		
Local sim	Fuzzy Membership	Ontological Relation	DePicT Profile Matrix
Precision	83%	60%	41.6%
Recall	83%	60%	66%
F-Score	83%	60%	51%
Accuracy	88.8%	83%	52%

Precision was calculated for retrieval-only cases with single weights set for each case and reference feature in terms of the accuracy of comparison between the various local similarity measurements produced by each method. DePicT Melanoma CLASS achieved appropriate results, and a comparison of its evaluation scores for WAS, k-NN, and SVM in the fifth and sixth steps is shown in Fig. 5.6. In the image classification domain, we also applied the sensitivity and specificity comparison metrics. Figure 5.7 shows the sensitivity and specificity results of DePicT Melanoma CLASS for k-NN and SVM.

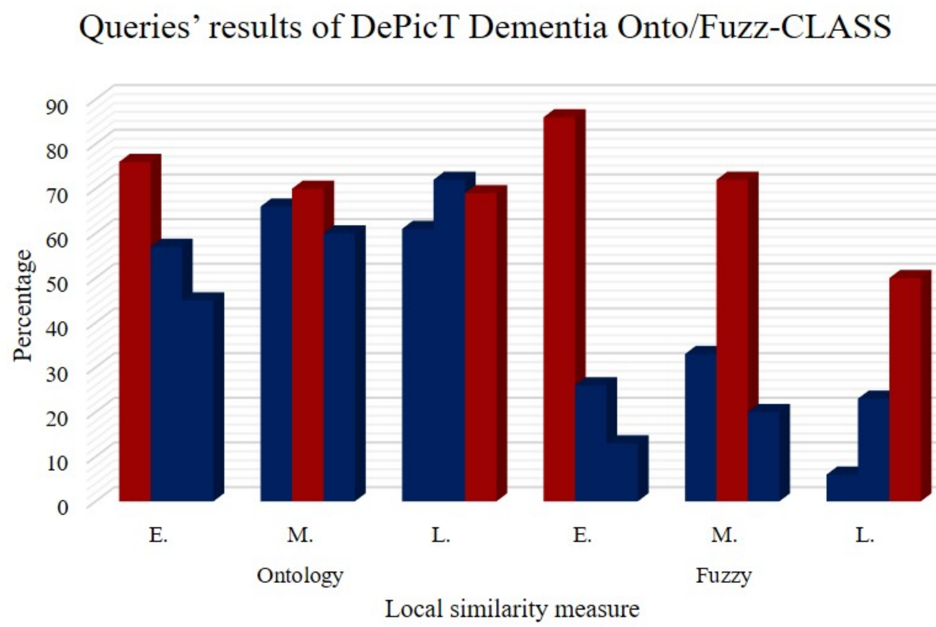


Fig. 5.5 Result of ontological and fuzzy similarity measures for three queries of patients in early (E.), middle (M.), and late (L.) stages of Alzheimer's disease (selected cases are in red).

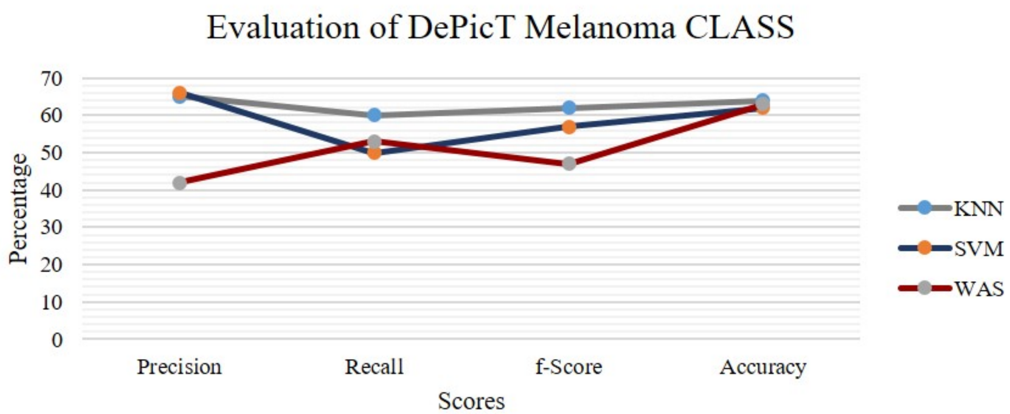


Fig. 5.6 Comparison of the evaluation scores (precision, recall, f-score and accuracy) of DePicT Melanoma CLASS in the fifth and sixth steps.

5. Why does the method work (or not work)? Under what circumstances won't it work. Are the limitations of the method inherent, or simply not addressed?

Our adaptation of combining the four approaches which of word association, ontological feature relation, fuzzy membership functions, and image classification to the case-based rea-

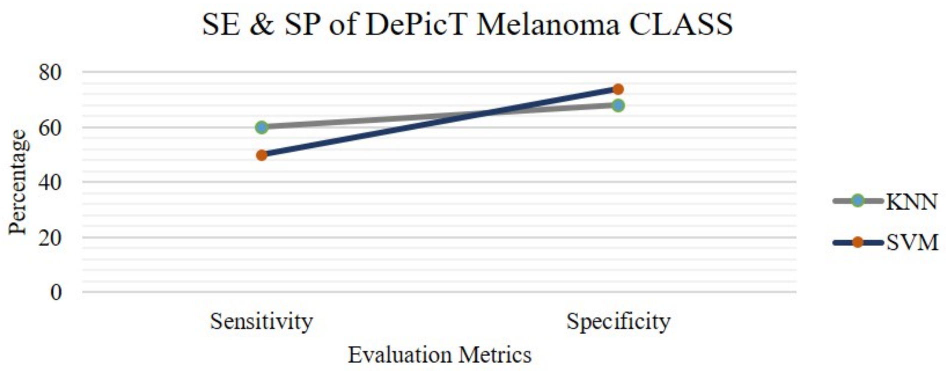


Fig. 5.7 Comparison of the evaluation (sensitivity and specificity metrics) of DePicT Melanoma CLASS in the sixth step.

soning methodology used in our three models was based on the fact that textual, ontological, and fuzzy CBR approaches have all been shown to work. As we presented in our review, a significant number of systems have been successfully built based on these methods (See Section 2.4 and Appendix B). Following the basic concept of this study, the integration of different local similarity measures and image classifiers has enabled to develop an integrated system that improves on the respective limitations of the respective methods. As we hypothesized and found in our results, the essential component for successfully calculating word association strengths is the quality of textual case resources, which is domain-dependent. The successfully evaluation of our methods establishes their appropriateness for recommendation and classification following learning.

5.2 Future research directions

Based on the results and findings of this study, several future research directions appear to be promising from the author's point of view:

i) There is room for further development of the proposed concept in light of current evaluation results and based on the new features and cases.

For instance, we believe that there is room for improving the performance of our DePicT Dementia Fuzz-CLASS system to enable the use of fuzzy rules in the calculation of the global similarity measure of cases, as a significant advantage of utilizing a fuzzy CBR approach is the ability to learn fuzzy rules from a case base. In addition, the functionality of adding new cases to a case base to obtain continuous improvements in system performance can be explored as means of learning feature values and degrees in fuzzy functions. One example of membership function output revealing the stages of dementia is the valuable fusion of *ICF* parameters obtained by combining different patient behaviors, e.g., early-to-middle or middle-to-late stages. By gathering more information from more patients, it will be possible to propose increasingly appropriate rules for recommending proper output from the inferences produced by the hybrid system. Figure 5.8 shows the FIS output of "mental function," which is presented for the early, middle, and late stages of dementia. This output is achieved by using rules that are defined with regards to the input conditions. One example involves the logical concatenation of 15 *ICF* codes for mental function: ***if*** (Consciousness is Mild-Impairment) and (Orientation is Mild-Impairment) and (Intellectual is Mild-Impairment) and (Energy and Drive is Moderate-Impairment) and (Attention is Moderate-Impairment) and (Memory is Mild-Impairment) and (Psychomotor is Severe-Impairment) and (Emotional is Mild-Impairment) and (Perceptual is Mild-Impairment) and (Thought is Moderate-Impairment) and (Higher-level Cognitive is Mild-Impairment) and (Mental-language is Mild-Impairment) and (Calculation is Moderate-Impairment) and (Sequencing complex movements is Mild-Impairment) and (Experience of self and time is Mild-Impairment) ***then*** (Dementia Stage is Early-stage).

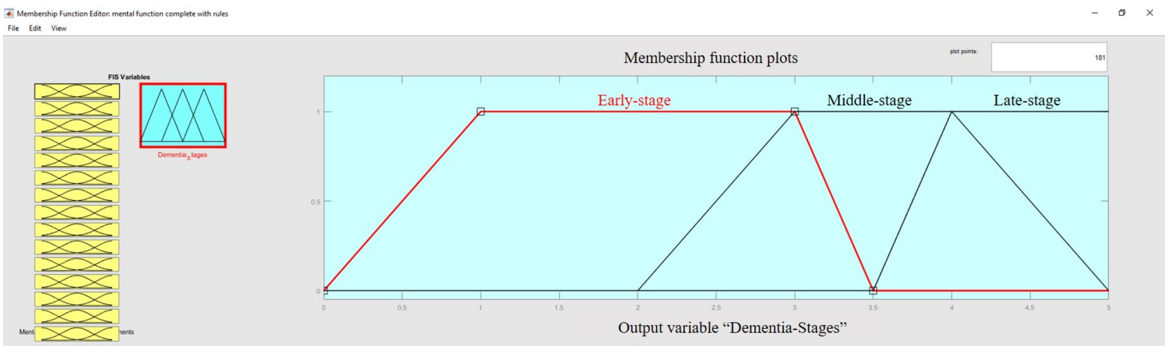


Fig. 5.8 Membership function of FIS output for *ICF* "mental functions"-Early stage.

ii) There is room for further development of the proposed concept in the light of the evaluation results and based on the combination of current new methodologies as a hybrid approach.

For instance, it might be possible to improve the performance of our DePicT Melanoma CLASS system through the use of convolutional neural networks (CNNs) instead of k-NN and SVMs. A current research trend involves the computerized analysis of suspicious skin lesions for malignancy using images captured by digital cameras. Analysis of such images is usually challenging owing to the presence of disturbing factors such as illumination variations and light reflections from the skin surface. One important stage in the diagnosis of melanoma is the segmentation of the lesion region from normal skin. A CNN can combine local and global contextual information to output a label for each pixel, producing a segmentation mask that correctly shows the overall lesion region. This mask can be further refined via post-processing. The experimental results produced using this method often outperform those of existing state-of-the-art algorithms in terms of segmentation accuracy, suggesting that this method can be useful in the development of further applications.

iii) There is room for further development of the proposed concept by using the current evaluation results and methodologies to extend the case study.

For instance, further study following the ontological approach would allow us to develop an ontology of our system for aspects of the MobiAssist project. The aim of MobiAssist is to increase the physical activity of dementia patients and their caregivers to enhance mental and physical capabilities and thereby reduce strain on caregivers. To this end, an ICT-based mobility-assistant system is being developed for patients suffering from dementia diseases and their relatives. The system applies measure relevant to biographical backgrounds, language, music, games, play, and emotions and is currently being evaluated in a caregiving setting. Along these lines, DePicT Dementia Onto-CLASS can be further developed based on the dementia-sport ontology containing the class of "Exercise," which includes exercises aimed at improving physical abilities and psychosocial health. The class has four subclasses "Balance," "Muscle strength," "Postural correction," and "Mobility." "Balance," in turn, covers exercises that can help to prevent falls and is divided into the two subclasses, "Balance exercises in sitting" and "Balance exercises in standing." The "Muscle strength" subclass includes exercises that help maintain healthy bone mass and prevent age-related muscle loss. The subclass "Postural correction" includes exercises for improving body, and finally, the "Mobility" subclass includes exercises that lead to the improvement of the ability to perform optimal movements. The classes of "APP," "Image," and "Video" are used to introduce related exercises within this format and can help patients, their relatives, and caregivers in efficient performance of these exercises.

iv) It is also possible to further adapt the proposed concept based on the current evaluation results and methodologies to other domains or fields.

Our system can be applied in a wide variety of fields—injection molding, for instance. Manufacturing processes have undergone steady technological growth that has made them more efficient, agile, and progressive on one hand and more complex on the other hand.

This growth has necessitated the application of a diversity of diagnostic tools to support and maintain production systems at a suitable level of capability. Effective fault detection and diagnosis methods can minimize the costs of reworking, plant time-outs, maintenance time, and improving reliability and safety. As an example of this, a prototype for fault detection, identification of failures, and reduction of a system downtime in injection molding production process has been proposed by us in [189]. The system contributes a prototype of a web-based fault detection system that employs a CBR approach to the detection of injection molding faults.This is implemented by a CBR system that defines relationships between injection molding features and fault occurrences. All process features used in the study were determined based on the troubleshooting guidelines of large manufacturers of injection molding machines (IMMs), which in future research will be replaced by the features of particular products in certain IMMs. The relationships between IMM features and injection molding faults are identified in such a manner that each process parameter reflects its importance and belongs to an IMM fault via a special fuzzy set. These sets can be used to further estimate case similarities during CBR analysis. In this process, CBR enables the system to sort the relevance of factors influencing the occurrence of faults and to determine appropriate solutions to problems. Thus, the system can learn from its previous problem-solving experience. This model of fault detection reduces the time needed to obtain solutions without a high degree of dependency on experts. The most similar case can be chosen for reuse of its solution and serves as an input to the adaptation phase. This process improves the IMM maintenance results obtained by developed prototypes in real manufacturing processes. The fault detection system also incorporates a self-learning capability that enables it to assess the causes of injection molding faults, with new fault cases added to the case base, or to adapting existing cases to maximize the overall performance of the system.

References

[1] Aamodt, A. (1991). *A knowledge-intensive, integrated approach to problem solving and sustained learning*. Phd thesis, University of Trondheim.

[2] Aamodt, A. (1995). Knowledge Acquisition and Learning by Experience – The Role of Case-Specific Knowledge Knowledge Acquisition and Learning by Experience - The Role of Case-Specific Knowledge. In G. Tecuci, Y. K. e. M. L. and Acquisition, K., editors, *Integrated Approaches, Academic Press*, volume 8, pages 197–245. Integrated Approaches, Academic Press.

[3] ADEAR (2010). Home Safety for People with Alzheimer's Disease. Technical Report 5179, The ADEAR Center is a service of the National Institute on Aging and National Institutes of Health.

[4] Adeyanju, I. A. (2011). *Case reuse in textual case-based reasoning*. Phd thesis, Robert Gordon University.

[5] Agnar, A. and Plaza, E. (1994). Case-Based reasoning: Foundational issues, methodological variations, and system approaches. *AI Communications*, 7(1):39–59.

[6] Aha, D. W., Breslow, L. A., and Maney, T. (1998). Supporting Conversational Case-Based Reasoning in an Integrated Reasoning Framework. In *Case-Based Reasoning Integrations. Papers from the {AAAI} Workshop*, pages 7–11.

[7] Aha, D. W., Mcsherry, D., and Yang, Q. (2005). Advances in conversational case-based reasoning. *The Knowledge Engineering Review*, 20(03):247.

[8] Ahmed, M. U., Begum, S., and Funk, P. (2012a). A hybrid case-based system in clinical diagnosis and treatment. In *Proceedings - IEEE-EMBS International Conference on Biomedical and Health Informatics: Global Grand Challenge of Health Informatics, BHI 2012*, pages 699–704.

[9] Ahmed, M. U., Begum, S., Funk, P., Xiong, N., and Schéele, B. V. (2008). Case-based Reasoning for Diagnosis of Stress using Enhanced Cosine and Fuzzy Similarity. *Transactions on Case-Based Reasoning for Multimedia Data*, 1(1):3–19.

[10] Ahmed, M. U., Begum, S., Funk, P., Xiong, N., and von Scheele, B. (2011). A multi-module case-based biofeedback system for stress treatment. *Artificial Intelligence in Medicine*, 51(2):107–115.

[11] Ahmed, M. U., Begum, S., Olsson, E., Xiong, N., and Funk, P. (2010). Case-based reasoning for medical and industrial decision support systems. *Studies in Computational Intelligence*, 305:7–52.

[12] Ahmed, M. U., Begum, S., and School, P. F. (2012b). System Overview on the Clinical Decision Support System for Stress Management. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, pages 111–116, Lyon, France.

[13] Ahmed, M. U., Islam, A. M., and Loutfi, A. (2012c). A Case-Based Patient Identification System using Pulse Oximeter and a Personalized Health Profile. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, pages 117–127, Lyon, France.

[14] Ahn, H. and Kim, K.-j. (2009). Global optimization of case-based reasoning for breast cytology diagnosis. *Expert Systems with Applications*, 36(1):724–734.

[15] AIM (2017). AIM at Melanoma.

[16] Alavi, M. and Leidner, D. E. (2001). Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *Management Information Systems Quarterly*, 25(1):107–136.

[17] Ali, A.-R. and Deserno, T. (2012). A Systematic Review of Automated Melanoma Detection in Dermatoscopic Images and its Ground Truth Data. *Proceedings of SPIE*, 8318.

[18] Althoff, K. D., Bergmann, R., Wess, S., Manago, M., Auriol, E., Larichev, O. I., Bolotov, A., Zhuravlev, Y. I., and Gurov, S. I. (1998). Case-based reasoning for medical decision support tasks: The Inreca approach. *Artificial Intelligence in Medicine*, 12(1):25–41.

[19] Althuizen, N. and Wierenga, B. (2014). Supporting Creative Problem Solving with a Case-Based Reasoning System. *Journal of Management Information Systems*, 31(1):309–340.

[20] Alzheimer's Association. Medication Safety and Alzheimer's.

[21] Alzheimer's Association. Respite Care.

[22] Alzheimer's Association (2017). Alzheimer's Association, What Is Alzheimer's?

[23] Amailef, K. and Lu, J. (2013). Ontology-supported case-based reasoning approach for intelligent m-Government emergency response services. *Decision Support Systems*, 55(1):79–97.

[24] American Cancer Society (2017). Cancer Facts and Figures 2017. *Genes and Development*, 21(20):2525–2538.

[25] Aquin, M. D., Lieber, J., and Napoli, A. (2006). Adaptation Knowledge Acquisition : a Case Study for Case-Based Decision Support in Oncology To cite this version : HAL Id : inria-00116888. *Computational Intelligence, Wiley*, 22(3/4):161–176.

[26] Arshadi, N. and Badie, K. (2000). A compositional approach to solution adaptation in case-based reasoning and its application to Tutoring Library. In *Proceedings of 8th German Workshop on Case-* ....

[27] Ashford, J. W., Rosen, a., and Adamson, M. (2011). *Handbook of Imaging the Alzheimer Brain*, volume volume 2.

[28] Aslan, B. and Geller, S. (2016). *Eine Android App auf Grundlage von Case Based Reasoning zur Früherkennung von Hautkrebs*. Bachelor thesis, University of Siegen.

[29] Bach, K. and Althoff, K.-D. (2012). Developing case-based reasoning applications using myCBR 3. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 7466 LNAI, pages 17–31.

[30] Badarunisa, M. B., Sebastian, D., Rangasayee, R. R., and Kala, B. (2015). ICF-Based Analysis of Communication Disorders in Dementia of Alzheimer's Type. *Dementia and Geriatric Cognitive Disorders Extra*, 5(3):459–469.

[31] Banerjee, S. and Chowdhury, A. R. (2015). Case based reasoning in the detection of retinal abnormalities using decision trees. In *Procedia Computer Science*, volume 46, pages 402–408.

[32] Bareiss, E. R., Porter, B. W., and Wier, C. C. (1988). Protos: an exemplar-based learning apprentice. *International Journal of Man-Machine Studies*, 29(5):549–561.

[33] Becker, C., Cameron, I. D., Klenk, J., Lindemann, U., Heinrich, S., König, H. H., and Rapp, K. (2011). Reduction of femoral fractures in long-term care facilities: The Bavarian fracture prevention study. *PLoS ONE*, 6(8).

[34] Begum, S., Ahmed, M. U., Funk, P., Xiong, N., and Von Scheele, B. (2009). A Case-based decision support system for individual stress diagnosis using fuzzy similarity matching. *Computational Intelligence*, 25(3):180–195.

[35] Begum, S. and Barua, M. U. A. S. (2012). Multi-Scale Entropy Analysis and Case-Based Reasoning to Classify Physiological Sensor Signals. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, pages 129–138, Lyon, France.

[36] Beißel, S. (2011). *Ontologiegestütztes Case-Based Reasoning*. Gabler Verlag, Springer Fachmedien Wiesbaden GmbH.

[37] Beyaz, Y. (2014). *Design und Implementierung eines Gesundheitswissensportals bezugnehmend auf die elektronische Gesundheitsakte*. Master thesis, University of Sigen.

[38] Bichindaritz, I. (2003). Solving Safety Implications in a Case Based Decision- Support System in Medicine.

[39] Bichindaritz, I., Kansu, E., and Sullivan, K. M. (1998). Case-based reasoning in care-partner: Gathering evidence for evidence-based medical practice. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 1488:334–345.

[40] Boisot, M. H. (1999). *Knowledge Assets: Securing Competitive Advantage in the Information Economy*. Oxford University Press.

[41] Borrajo, L., Seara Vieira, A., and Iglesias, E. (2015). Tcbr-hmm: An hmm-based text classifier with a cbr system. *Appl. Soft Comput.*, 26(C):463–473.

[42] Bos, L., Marsh, A., Carroll, D., Gupta, S., and Rees, M. (2008). Patient 2.0 Empowerment. In Hamid R. Arabnia, A. M. e., editor, *Proceedings of the 2008 International Conference on Semantic Web & Web Services*, pages 164–167. SWWS08.

[43] Bose, R. (2003). Knowledge management-enabled health care management systems: Capabilities, infrastructure, and decision-support. *Expert Systems with Applications*, 24(1):59–71.

[44] Bousbahi, F. and Chorfi, H. (2015). MOOC-Rec: A Case Based Recommender System for MOOCs. *Procedia - Social and Behavioral Sciences*, 195:1813–1822.

[45] Bridge, D. and Healy, P. (2012). The ghostwriter-2.0 case-based reasoning system for making content suggestions to the authors of product reviews. *Knowledge-Based Systems*, 29:93–103.

[46] Bridges, W. (2010). Managing Transitions William Bridges Brief summary of key points. Technical report.

[47] Brien, D., Glasgow, J., and Munoz, D. (2005). *The Application of a Case-Based Reasoning System to Attention-Deficit Hyperactivity Disorder*, pages 122–136. Springer Berlin Heidelberg, Chicago, IL, USA, August 23-26.

[48] Brown, A. (2011). An update on Google Health and Google PowerMeter.

[49] Brüninghaus, S. and Ashley, K. D. (2001). The role of information extraction for textual cbr. In *Proceedings of the 4th International Conference on Case-Based Reasoning: Case-Based Reasoning Research and Development*, ICCBR '01, pages 74–89, London, UK. Springer-Verlag.

[50] Brüninghaus, S. and Ashley, K. D. (2005). Reasoning with textual cases. In Muñoz-Ávila, H. and Ricci, F., editors, *Case-Based Reasoning Research and Development*, pages 137–151, Berlin, Heidelberg. Springer Berlin Heidelberg.

[51] Burke, R. (2007). Okundu-Hybrid Web Recommender Systems. In *The Adaptive Web*, volume 4321, pages 325–341.

[52] Burke, R. D., Hammond, K. J., Kulyukin, V. A., Lytinen, S. L., Tomuro, N., and Schoenberg, S. (1997). Question answering from frequently asked question files: Experiences with the faq finder system. Technical report, Chicago, IL, USA.

[53] Burrington-Brown, J., Fishel, J., Fox, L., Friedman, B., Giannangelo, K., Jacobs, E., Lang, D., Lemery, C., Malchetske, B., Morgan, J., Murphy, K., Okamoto, C., Peterson, R., Robin, D., Smith, C., Sweet, D., Thomas, M., Wolter, J., and Zallar, B. (2005). Defining the personal health record. AHIMA releases definition, attributes of consumer health record. *Journal of AHIMA*, 76(6):24–25.

[54] Byrne, K. and Orange, J. B. (2005). Conceptualizing communication enhancement in dementia for family caregivers using the WHO-ICF framework. *International Journal of Speech-Language Pathology*, 7(4):187–202.

[55] Carlucci, D. and Schiuma, G. (2004). Managing Knowledge Assets for NPD Performance Improvement: Results of an Action Research Project BT - Practical Aspects of Knowledge Management. In Karagiannis D., R. U. e. P. A. o. K. M., editor, *PAKM 2004. Lecture Notes in Computer Science, vol 3336.*, pages 271–281, 5th International Conference, PAKM 2004, Vienna, Austria, December 2-3. Springer Berlin Heidelberg.

[56] Carlucci, D. and Schiuma, G. (2012). Managing knowledge assets for business performance improvement. *Journal of Knowledge Management*, 16(4):515–522.

[57] Caron, F., Vanthienen, J., and Baesens, B. (2013). Comprehensive rule-based compliance checking and risk management with process mining. *Decision Support Systems*, 54(3):1357–1369.

[58] Chakraborty, S., Pal, C., Chatterjee, S., Chakraborty, B., and Ghoshal, N. (2015). Knowledge-based system architecture on CBR for detection of cholera disease. *Advances in Intelligent Systems and Computing*, 343:155–165.

[59] Chang, C.-L. (2005). Using case-based reasoning to diagnostic screening of children with developmental delay. *Expert Systems with Applications*, 28(2):237–247.

[60] Chattopadhyay, S., Banerjee, S., Rabhi, F. A., and Acharya, U. R. (2013). A Case-Based Reasoning system for complex medical diagnosis. *Expert Systems*, 30(1):12–20.

[61] Chawki, M. B., Nauer, E., Jay, N., and Lieber, J. (2017). *Tetra: A Case-Based Decision Support System for Assisting Nuclear Physicians with Image Interpretation*, pages 108–122. Springer International Publishing, Trondheim, Norway, June 26-28.

[62] Choudhury, N. and Begum, S. A. (2016). A Survey on Case-based Reasoning in Medicine. *(IJACSA) International Journal of Advanced Computer Science and Applications*, 7(8):136–144.

[63] Choudhury, N. and Begum, S. A. (2017). CASE-BASED REASONING : A SURVEY. *Indian Journal of Computer Science and Engineering (IJCSE)*, 8(3):333–340.

[64] Chuang, C.-L. (2011). Case-based reasoning support for liver disease diagnosis. *Artificial Intelligence in Medicine*, 53(1):15–23.

[65] Cohen, A. B., Nahed, B. V., and Sheth, K. N. (2013). Mobile medical applications in neurology. *Neurology: Clinical Practice*, 3(1):52 LP – 60.

[66] Cohen, P. R. (1989). Evaluation and Case-Based Reasoning. In Hammond, K., editor, *Proc. of the 2nd darpa Workshop on Case-Based Reasoning*, pages 168–172. Morgan Kaufmann.

[67] Cohen, P. R. and Howe, A. E. (1988). How Evaluation Guides AI Research. *AI Magazine*, 9(4):35–43.

[68] Coit, D. G., Thompson, J. A., Algazi, A., Andtbacka, R., Bichakjian, C. K., Carson, W. E., Daniels, G. A., DiMaio, D., Fields, R. C., Fleming, M. D., Gastman, B., Gonzalez, R., Guild, V., Johnson, D., Joseph, R. W., Lange, J. R., Martini, M. C., Materin, M. A., Olszanski, A. J., Ott, P., Gupta, A. P., Ross, M. I., Salama, A. K., Skitzki, J., Swetter, S. M., Tanabe, K. K., Torres-Roca, J. F., Trisal, V., Urist, M. M., McMillian, N., and

Engh, A. (2016). NCCN Guidelines Insights: Melanoma, Version 3.2016. *Journal of the National Comprehensive Cancer Network : JNCCN*, 14(8):945–58.

[69] Corchado, J. M., Bajo, J., and Abraham, A. (2008). GerAmi: Improving healthcare delivery in geriatric residences. *IEEE Intelligent Systems*, 23(2):19–25.

[70] Cordier, A., Fuchs, B., Lieber, J., Mille, A., and Others (2007). On-line domain knowledge management for case-based medical recommendation. In Editors), D. W. and (volume, D. K., editors, *5th workshop on CBR in the Health Sciences, a workshop of the seventh International Conference on Case-Based Reasoning (ICCBR-07)*, pages 285–294, Aug 2007, Belfast, United Kingdom. HAL Id: inria-00189782.

[71] Craw, S., Wiratunga, N., and Rowe, R. C. (2006). Learning adaptation knowledge to improve case-based reasoning. *Artificial Intelligence*, 170(16-17):1175–1192.

[72] Cunningham, C., Weber, R., Proctor, J. M., Fowler, C., and Murphy, M. (2004). Investigating graphs in textual case-based reasoning. In Funk, P. and González Calero, P. A., editors, *Advances in Case-Based Reasoning*, pages 573–586, Berlin, Heidelberg. Springer Berlin Heidelberg.

[73] Davenport, T. H., Prusak, L., and Prusak, L. (1998). *Working Knowledge: How Organizations Manage What They Know*. Harvard Business School Press, Boston, MA, USA.

[74] De Paz, J. F., Rodríguez, S., Bajo, J., and Corchado, J. M. (2009). Case-based reasoning as a decision support system for cancer diagnosis: A case study. *International Journal of Hybrid Intelligent Systems*, 6(2):97–110.

[75] Diaz, F., Fdez-Riverola, F., and Corchado, J. (2006). gene-CBR: A CASE-BASED REASONIG TOOL FOR CANCER DIAGNOSIS USING MICROARRAY DATA SETS. *Computational Intelligence*, 22(3-4):254–268.

[76] Dickson, G., Lindstrom, R., Black, C., and Gucht, D. V. D. (2012). Evidence-Informed Change Management in Canadian Healthcare Organizations. Technical Report June, Canadian Health Services Research Foundation Canadian Health Services Research Foundation (chsrf.ca), Ottawa, Ontario.

[77] Dobrev, A., Stroetmann, K. a., Stroetmann, V. N., Artmann, J., Jones, T., and Hammerschmidt, R. (2008). Report on The conceptual framework of interoperable electronic health record and ePrescribing systems. Technical Report April, empirica Communication and Technology Research, Oxfordstr. 2, 53111 Bonn, Germany.

[78] Douali, N., Papageorgiou, E. I., Roo, J. D., and Jaulent, M. C. (2011). Case Based Fuzzy Cognitive Maps (CBFCM): New method for medical reasoning: Comparison study between CBFCM/FCM. In *Fuzzy Systems (FUZZ), 2011 IEEE International Conference on*, pages 844–850.

[79] Douglas, S. (2004). Non-pharmacological interventions in dementia. *Advances in Psychiatric Treatment*, 10(3):171–177.

[80] Draper, B. (2004). *Dealing with Dementia: A Guide to Alzheimer's Disease and Other Dementias*. Allen & Unwin.

[81] E. Ekong, V., G. Inyang, U., and A. Onibere, E. (2012). Intelligent Decision Support System for Depression Diagnosis Based on Neuro-fuzzy-CBR Hybrid. *Modern Applied Science*, 6(7):79–88.

[82] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., and Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639):115–118.

[83] EUROPEAN COMMISSION (2012). EC 2012_Staff Working document_Vocational education and training for better skills, growth and jobs. Technical report, EUROPEAN COMMISSION, Strasbourg, 20.11.2012.

[84] European Committee for Standardization (2004). European Guide to good Practice in Knowledge Management-Part 4: Guidelines for Measuring KM. Technical report, EUROPEAN COMMITTEE FOR STANDARDIZATION, rue de Stassart, 36 B-1050 Brussels ©.

[85] Eysenbach, G. (2008). Medicine 2.0: Social Networking, Collaboration, Participation, Apomediation, and Openness. *J Med Internet Res*, 10(3):e22.

[86] Faran, D., Hauptman, A., and Raban, Y. (2006). Organizing the toolbox - Typology and alignment of KI solutions. In Jetter A., Schröder HH., Kraaijenbrink J., W. F. e. K. I., editor, *Knowledge Integration: The Practice of Knowledge Management in Small and Medium Enterprises*, pages 47–64. Physica-Verlag HD.

[87] Fellbaum, C. (1998). A semantic network of english: The mother of all wordnets. *Computers and the Humanities*, 32(2):209–220.

[88] Franceschini, F., Galetto, M., and Maisano, D. (2007). *Management by Measurement: Designing Key Indicators and Performance Measurement Systems*. Springer-Verlag Berlin Heidelberg, 1st edition.

[89] Frucci, M., Perner, P., and Sanniti di Baja, G. (2008). Case-based reasoning for image segmentation by watershed transformation. *Studies in Computational Intelligence*, 73:319–353.

[90] Galushka, M., Zheng, H., Patterson, D., and Bradley, L. (2005). Case-Based Tissue Classification for Monitoring Leg Ulcer Healing. In *18th IEEE Symposium on Computer-Based Medical Systems (CBMS'05)*, pages 353–358.

[91] Georgopoulos, V. C. and Stylios, C. D. (2008). Complementary case-based reasoning and competitive fuzzy cognitive maps for advanced medical decisions. *Soft Computing*, 12(2):191–199.

[92] Ghavifekr, S. and Hussin, S. (2011). Managing systemic change in a technology-based education system: A malaysian case study. *Procedia - Social and Behavioral Sciences*, 28:455–464.

[93] Gierl, L. and Stengel-Rutkowski, S. (1994). Integrating consultation and semi-automatic knowledge acquisition in a prototype-based architecture: Experiences with dysmorphic syndromes. *Artificial Intelligence in Medicine*, 6(1):29–49.

[94] Gierl L., Bull M., S. R. (1998). CBR in Medicine. In Lenz M., Burkhard HD., Bartsch-Spörl B., W. S. e., editor, *Case-Based Reasoning Technology, Lecture Notes in Computer Science, vol 1400.*, pages 273–279. Springer, Berlin, Heidelberg.

[95] Gitlin, L., Kales, H., and Lyketsos, C. (2012). Managing Behavioral Symptoms in Dementia Using Nonpharmacologic Approaches: An Overview. *JAMA: the journal of the . . .* , 308(19):2020–2029.

[96] Goel, A. K. and Diaz-Agudo, B. (2017). What's Hot in Case-Based Reasoning. In *Proceedings of the 31th Conference on Artificial Intelligence (AAAI 2017)*, pages 5067–5069, San Francisco, California, USA, February 4–9. Association for the Advancement of Artificial Intelligence.

[97] Golobardesa, E., Llorá, X., Salamóa, M., and Martí, J. (2002). Computer aided diagnosis with case-based reasoning and genetic algorithms. *Knowledge-Based Systems*, 15(1-2):45–52.

[98] Goodridge, W., Peter, H., and Abayomi, A. (1999). The Case-Based Neural Network Model and Its Use in Medical Expert Systems. In Horn W., Shahar Y., Lindberg G., Andreassen S., W. J. e. A. I. i. M., editor, *AIMDM 1999. Lecture Notes in Computer Science, vol 1620.*, pages 232–236. Springer-Verlag Berlin Heidelberg.

[99] Gronau, N. and Weber, E. (2004). Management of Knowledge Intensive Business Processes. In Desel J., Pernici B., W. M. e. B. P. M., editor, *BPM 2004. Lecture Notes in Computer Science, vol 3080*, pages 163–178, Potsdam, Germany, June 17-18. Springer, Berlin, Heidelberg.

[100] Gschwind, Y. J. and Pfenninger, B. (2016). *Training zur Sturzprävention*. bfu – Beratungsstelle für Unfallverhütung, 2. auflage edition.

[101] Gu, D., Li, J., Bichindaritz, I., Deng, S., and Liang, C. (2017). *The Mechanism of Influence of a Case-Based Health Knowledge System on Hospital Management Systems*, pages 139–153. Springer International Publishing, Trondheim, Norway, June 26-28.

[102] Gu, D. X., Liang, C. Y., Li, X. G., Yang, S. L., and Zhang, P. (2010). Intelligent technique for knowledge reuse of dental medical records based on case-based reasoning. *Journal of Medical Systems*, 34(2):213–222.

[103] Gu, M. and Aamodt, A. (2006). Evaluating CBR systems using different data sources: A case study. In Roth-Berghofer T.R., Göker M.H., G. H. e. A. i. C.-B. R., editor, *ECCBR 2006. Lecture Notes in Computer Science, vol 4106.*, pages 121–135. Springer, Berlin, Heidelberg.

[104] Haddad, M., Moertl, D., and Porenta, G. (1995). SCINA : A Case-Based Reasoning System for the Interpretation of Myocardial Perfusion Scintigrams. pages 761–764.

[105] Han, M. and Cao, Z. J. (2015). An improved case-based reasoning method and its application in endpoint prediction of basic oxygen furnace. *Neurocomputing*, 149(PC):1245–1252.

[106] Hansen, M. T., Nohria, N., and Tierney, T. (1999). What's your strategy for managing knowledge? *Harvard business review*, 77(2):106–116,187.

[107] Hardman, L. (2009). *Dementia (Diseases and Disorders).* Cengage Gale.

[108] Haughom, J. (2017). Five Deming Principles That Help Healthcare Process Improvement.

[109] He, W. (2014). A framework of combining case-based reasoning with a work breakdown structure for estimating the cost of online course production projects. *British Journal of Educational Technology*, 45(4):595–605.

[110] HealthVault (2017). healthvault.

[111] Helsper, J. and Jung, M. (2017). Projektgruppe „Wissensbasiertes System zur Unterstützung der medizinischen Ausbildung (MedAusbild)“ Sommersemester 2017. Technical report, Institute of KBS & KM, University of Siegen, Institute of KBS & KM, University of Siegen.

[112] Henriet, J., Leni, P. E., Laurent, R., and Salomon, M. (2014). Case-Based Reasoning adaptation of numerical representations of human organs by interpolation. *Expert Systems with Applications*, 41(2):260–266.

[113] Hiatt, J. (2006). *ADKAR : a model for change in business, government and our community*. Loveland, Colorado Prosci Learning Center Publications, first edit edition.

[114] Hiatt, J. and Creasey, T. (2012). *Change Management: The People Side of Change*. Prosci Learning Center Publications.

[115] Hilgers, D. (2008). *Performance Management.* Springer, Gabler Verlag.

[116] HIMSS (2017). Electronic Health Records.

[117] Hopper, T. (2007). The ICF and dementia. *Seminars in Speech and Language*, 28(4):273–282.

[118] Hörbst, A., Schabetsberger, T., and Ammenwerth, E. (2008). Die Elektronische Gesundheitsakte-Interesse und Akzeptanz der Tiroler Bürger. In *eHealth2008– Medical Informatics meets eHealth*, pages 47–53, Wien, 29.-30. Mai 2008. eHealth2008.

[119] Hsia, T.-l., Lin, L.-m., Wu, J.-h., and Tsai, H.-t. (2006). A Framework for Designing Nursing Knowledge Management Systems. *Interdisciplinary Journal of Information, Knowledge, and Management*, 1:138–143.

[120] Hsu, C. C. and Ho, C. S. (2004). A new hybrid case-based architecture for medical diagnosis. *Information Sciences*, 166(1-4):231–247.

[121] Hsu, C.-C. H. C.-C. and Ho, C.-S. H. C.-S. (1998). A hybrid case-based medical diagnosis system. *Proceedings Tenth IEEE International Conference on Tools with Artificial Intelligence (Cat. No.98CH36294).*

[122] Huang, M. J., Chen, M. Y., and Lee, S. C. (2007). Integrating data mining with case-based reasoning for chronic diseases prognosis and diagnosis. *Expert Systems with Applications*, 32(3):856–867.

[123] Huang, M.-L., Hung, Y.-H., Lee, W.-M., Li, R. K., and Wang, T.-H. (2012). Usage of Case-Based Reasoning, Neural Network and Adaptive Neuro-Fuzzy Inference System Classification Techniques in Breast Cancer Dataset Classification Diagnosis. *Journal of Medical Systems*, 36(2):407–414.

[124] Hughes, B., Joshi, I., and Wareham, J. (2008). Health 2.0 and Medicine 2.0: Tensions and Controversies in the Field. *J Med Internet Res*, 10(3):e23.

[125] IEEE Task Force on Process Mining (2011). Process Mining Manifesto. Technical report.

[126] Ienca, M., Fabrice, J., Elger, B., Caon, M., Pappagallo, A. S., Kressig, R. W., and Wangmo, T. (2017). Intelligent Assistive Technology for Alzheimer's Disease and Other Dementias: A Systematic Review. *Journal of Alzheimer's Disease*, 56(4):1301–1340.

[127] Jagannathan, R., Petrovic, S., McKenna, A., and Newton, L. (2010). A fuzzy non-linear similarity measure for case-based reasoning systems for radiotherapy treatment planning. In Papadopoulos H., Andreou A.S., B. M. e. A. I. A. and Innovations, editors, *Artificial Intelligence Applications and Innovations, AIAI 2010. IFIP Advances in Information and Communication Technology, vol 339*, pages 112–119. Springer, Berlin, Heidelberg.

[128] Jagannathan, R., Petrovic, S., McKenna, A., and Newton, L. (2012). A novel two-phase retrieval mechanism for a clinical case-based reasoning system for radiotherapy planning. *International Journal on Artificial Intelligence Tools*, 21(04):1240017.

[129] Jeng, B. C. and Liang, T. P. (1995). Fuzzy indexing and retrieval in case-based systems. *Expert Systems With Applications*, 8(1):135–142.

[130] Jetter, A., Kraaijenbrink, J., Schröder, H., and Wijnhoven, A. B. (2006). *Knowledge Integration: The Practice of Knowledge Management in Small and Medium Enterprises*. Physica-Verlag.

[131] Juarez, J., Garcia-Gonzalez, B., Palma, J., Antequera, M., Bego~NaMartinez, and Antunez, M. C. (2012). Supporting Frontotemporal Dementia Protocols by CBR Graph-Models. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, pages 87–96, Lyon, France.

[132] Kalz, M. and Specht, M. (2014). Assessing the crossdisciplinarity of technology-enhanced learning with science overlay maps and diversity measures. *British Journal of Educational Technology*, 45(3):415–427.

[133] Kavitha, J. C., Suruliandi, A., Nagarajan, D., and Nadu, T. (2017). Melanoma Detection in Dermoscopic Images using Global and Local Feature Extraction. *International Journal of Multimedia and Ubiquitous Engineering*, 12(5):19–28.

[134] Khelassi, A. and Mohammed Amine CHIKH (2012). Cognitive Amalgam with a Fuzzy sets and case based reasoning for accurate cardiac arrhythmias diagnosis. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, pages 69–79, Lyon, France.

[135] Khussainova, G., Petrovic, S., and Jagannathan, R. (2015). Retrieval with Clustering in a Case-Based Reasoning System for Radiotherapy Treatment Planning. *Journal of Physics: Conference Series*, 616(1).

[136] King, W. R., Marks, P. V., and McCoy, S. (2002). The most important issues in knowledge management. *Communications of the ACM*, 45(9):93–97.

[137] Klahold, A., Uhr, P., Ansari, F., and Fathi, M. (2014). Using word association to detect multitopic structures in text documents. *IEEE Intelligent Systems*, 29(5):40–46.

[138] Klingauf, K., Li, D., and Ortmann, J. (2017). Projektgruppe „Wissensbasiertes System zur Unterstützung der medizinischen Ausbildung (MedAusbild)“ Wintersemester 2016/7. Technical report, institute of KBS & KM, University of Siegen, institute of KBS & KM, University of Siegen.

[139] Koch, O. (2017). *Entwicklung einer Android E-Learning App die Pfleger und Angehörige von Demenzkranken Menschen unterstützt*. Bachelor thesis, University of Siegen.

[140] Kolodner, J. (1993). *Case-Based Reasoning*, volume 7.

[141] Koppar, A. R. and Sridhar, V. (2009). A workflow solution for electronic health records to improve healthcare delivery efficiency in rural India. In *Proceedings - International Conference on eHealth, Telemedicine, and Social Medicine, eTELEMED 2009*, pages 227–232. IEEE computer society.

[142] Koton, P. (1989). A medical reasoning program that improves with experience. *Computer Methods and Programs in Biomedicine*, 30(2-3):177–184.

[143] Kotter, J. P., Cohen, D. S., and Hoover, L. (2004). The heart of change: Real-life stories of how people change their organizations. *Performance Improvement*, 43(7):45–46.

[144] Kummervold, E. P., Chronaki, E. C., Lausen, B., Prokosch, H.-U., Rasmussen, J., Santana, S., Staniszewski, A., and Wangberg, C. S. (2008). eHealth Trends in Europe 2005-2007: A Population-Based Survey. *J Med Internet Res*, 10(4):e42.

[145] Kwiatkowska, M. and Atkins, S. (2004). Case Representation and Retrieval in the Diagnosis and Treatment of Obstructive Sleep Apnea : A Semio- fuzzy Approach. In *Proceedings European Case Based Reasoning Conference, ECCBR 04*, pages 1–10, Madrid, Spain, August 30 - September 2. ECCBR.

[146] Lamontagne, L. and Lapalme, G. (2004). Textual reuse for email response. In *Advances in Case-Based Reasoning*, pages 242–256.

[147] Larson, E. W. and Gray, C. F. (2014). *Project management : the managerial process*. McGraw Hill Higher Education, 6 edition.

[148] Lau, S. M. A. (2011). Hospital-Based Nurses' Perceptions of the Adoption of Web 2.0 Tools for Knowledge Sharing, Learning, Social Interaction and the Production of Collective Intelligence. *J Med Internet Res*, 13(4):e92.

[149] Leake, D. (2015). Problem Solving and Reasoning: Case-Based. *International Encyclopedia of the Social & Behavioral Sciences*, 19(2):56–60.

[150] Leake, D. B. (1996). *Case-Based Reasoning: Experiences, Lessons and Future Directions*. MIT Press, Cambridge, MA, USA, 1st edition.

[151] Leal, Y., Ruiz, M., Lorencio, C., Bondia, J., Mujica, L., and Vehi, J. (2013). Principal component analysis in combination with case-based reasoning for detecting therapeutically correct and incorrect measurements in continuous glucose monitoring systems. *Biomedical Signal Processing and Control*, 8(6):603–614.

[152] LeBozec, C., Jaulent, M. C., Zapletal, E., and Degoulet, P. (1998). Unified modeling language and design of a case-based retrieval system in medical imaging. *Proc AMIA Symp*, pages 887–91.

[153] Lee, T., Ng, V., Gallagher, R., Coldman, A., and McLean, D. (1997). Dullrazor®: A software approach to hair removal from images. *Computers in Biology and Medicine*, 27(6):533–543.

[154] Lenz, M., Burkhard, H.-D., and Brückner, S. (1996). Applying case retrieval nets to diagnostic tasks in technical domains. In *Proceedings of the Third European Workshop on Advances in Case-Based Reasoning*, EWCBR '96, pages 219–233, London, UK, UK. Springer-Verlag.

[155] Levine, R. (2010). *Defying Dementia: Understanding and Preventing Alzheimer's and Related Disorders*. Rowman & Littlefield Poblishers, 1 edition.

[156] Lewin, K. (1951). Field Theory in Social Science: Selected Theoretical Papers. Kurt Lewin , Dorwinc Artwright. *Social Service Review*, 25(3):409–410.

[157] Leyland, M., Hunter, D., and Dietrich, J. (2009). Integrating change management into clinical health information technology project practice. In *CONGRESS 2009 - World Congress on Privacy, Security, Trust and the Management of e-Business*, pages 89–99. IEEE computer society.

[158] Liao, Z., Mao, X., Hannam, P. M., and Zhao, T. (2012). Adaptation methodology of CBR for environmental emergency preparedness system based on an Improved Genetic Algorithm. *Expert Systems with Applications*, 39(8):7029–7040.

[159] Lieber, J. (2007). Application of the Revision Theory to Adaptation in Case-Based Reasoning: The Conservative Adaptation. In *Lecture Notes in Computer Science*, volume 4626, pages 239–253.

[160] Liebowitz, J. and Beckman, T. J. (1998). *Knowledge Organizations: What Every Manager Should Know*. CRC Press, Inc., Boca Raton, FL, USA, 1st edition.

[161] Lin, R.-H. (2009). An intelligent model for liver disease diagnosis. *Artificial Intelligence in Medicine*, 47(1):53–62.

[162] Lin, R. H. and Chuang, C. L. (2010). A hybrid diagnosis model for determining the types of the liver disease. *Computers in Biology and Medicine*, 40(7):665–670.

[163] Little, S., Salvetti, O., and Perner, P. (2008). Evaluating a case-based classifier for biomedical applications. In *Proceedings - IEEE Symposium on Computer-Based Medical Systems*, pages 584–586. IEEE.

[164] Loebbecke, C. and Crowston, K. (2012). Knowledge Portals: Components, Functionalities, and Deployment Challenges. In *International Conference on Information Systems (ICIS)*, number 1, pages 1–18, Orlando, FL (2012).

[165] López, B., Pous, C., Gay, P., Pla, A., Sanz, J., and Brunet, J. (2011). EXiT CBR: A framework for case-based medical diagnosis development and experimentation. *Artificial Intelligence in Medicine*, 51(2):81–91.

[166] Lu, J., Bai, D., Zhang, N., Yu, T., and Zhang, X. (2016). Fuzzy Case-Based Reasoning System. *Applied Sciences*, 6(7):189.

[167] Mace, N. L. and Peter V. Rabins (2012). *The 36-Hour Day: A Family Guide to Caring for People Who Have Alzheimer Disease, Related Dementias, and Memory Loss*. Grand Central Life & Style.

[168] Mace, N. L. and Rabins, P. V. (2012). *The 36-Hour Day: A Family Guide to Caring for People Who Have Alzheimer Disease, Related Dementias, and Memory Loss*. 5. auflage edition.

[169] Macura, R. and Macura, K. (1995). MacRad: radiology image resource with a case-based retrieval system. *Case-based reasoning research and development*, pages 43–54.

[170] Maier, R. (2007). *Knowledge Management Systems: Information and Communication Technologies for Knowledge Management*. Springer-Verlag Berlin Heidelberg, 3rd edition.

[171] Malara, A., Sgrò, G., Ceravolo, F., and Curinga, G. (2015). Profiles of Icf Disability in Alzheimer and Vascular Dementia. *Journal of Aging Research & Clinical Practice*, 62(October 2016).

[172] Malhotra, A., Younesi, E., Gündel, M., Müller, B., Heneka, M. T., and Hofmann-Apitius, M. (2014). ADO: A disease ontology representing the domain knowledge specific to Alzheimer's disease. *Alzheimer's and Dementia*, 10(2):238–246.

[173] Malhotra, Y. (2003). Measuring knowledge assets of a nation: Knowledge systems for development. In *United Nations Advisory Meeting of the Department of Economic and Social Affairs Division for Public Administration and Development Management*, pages 1–52.

[174] Marling, C., Bunescu, R., Shubrook, J., and Schwartz, F. (2012). System Overview: The 4 Diabetes Support System Cindy. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, pages 80–86, Lyon, France.

[175] Marling, C., Montani, S., Bichindaritz, I., and Funk, P. (2014). Synergistic case-based reasoning in medical domains. *Expert Systems with Applications*, 41(2):249–259.

[176] Marling, C., Shubrook, J., and Schwartz, F. (2008). Case-based decision support for patients with Type 1 diabetes on insulin pump therapy. In Althoff KD., Bergmann R., Minor M., H. A. e. A. i. C.-B. R., editor, *ECCBR 2008. Lecture Notes in Computer Science, vol 5239*, volume 5239, pages 325–339. Springer Berlin Heidelberg.

[177] Marling, C. and Whitehouse, P. (2001). Case-Based Reasoning in the Care of Alzheimer ' s Disease Patients. In Aha D.W., W. I. e. C.-B. R. R. and Development, editors, *ICCBR 2001. Lecture Notes in Computer Science, vol 2080*, pages 702–715, Vancouver, BC, Canada ,30 July - 2 August. Springer Berlin Heidelberg.

[178] Masood, A. and Al-Jumaily, A. A. (2013). Computer aided diagnostic support system for skin cancer: A review of techniques and algorithms.

[179] McDaid, D. and Park, A.-L. (2010). Online Health: Untangling the Web. Technical report, Bupa.

[180] McGinty, L. and Smyth, B. (2001). Collaborative case-based reasoning: Applications in personalised route planning. In Aha D.W., W. I. e. C.-B. R. R. and Development., editors, *ICCBR 2001. Lecture Notes in Computer Science, vol 2080.*, pages 362–376. Springer, Berlin, Heidelberg.

[181] McKinsey (2011). Are Physicians Willing to Change.

[182] Misra, S. (2015). New report finds more than 165,000 mobile health apps now available, takes close look at characteristics & use. Technical report, IMS Institute for Healthcare Informatics.

[183] Mizuno, Y., Fisher, A., and Hanin, I. (2002). Mapping the Progress of Alzheimer's and Parkinson's Disease. In Mizuno, Y., Fisher, A., and Hanin, I., editors, *International Conference on Progress in Alzheimer's and Parkinson's Diseases, Advances in Behavioral Biology*, page 566. Springer US.

[184] Montani, S., Leonardi, G., Bottrighi, A., Portinale, L., and Terenziani, P. (2012). Extending a time series retrieval tool to deal with sub-series matching: an application to the hemodialysis domain. In Montani, S., Marling, C., and Bichindaritz, I., editors, *CBR in the Health Sciences Workshop at the Twentieth International Conference on Case-Based Reasoning*, number ICCBR, pages 59–68, Lyon, France.

[185] Montani, S., Leonardi, G., Bottrighi, A., Portinale, L., and Terenziani, P. (2013). Supporting flexible, efficient, and user-interpretable retrieval of similar time series. *IEEE Transactions on Knowledge and Data Engineering*, 25(3):677–689.

[186] Montani, S. and Portinale, L. (2006). ACCOUNTING FOR THE TEMPORAL DIMENSION IN CASE-BASED RETRIEVAL: A FRAMEWORK FOR MEDICAL APPLICATIONS. *Computational Intelligence*, 22(3-4):208–223.

[187] Montero, M. A. and Prado, S. (2009). Electronic Health Record as a Knowledge Management Tool in the Scope of Health BT. In Procedures, R. D. e. K. M. f. H. C., editor, *K4HelP 2008. Lecture Notes in Computer Science, vol 5626*, pages 152–166. Springer Berlin Heidelberg.

[188] MRF (2017). Melanoma Research Foundation.

[189] Nasiri, S., Allayarov, I., and Fathi, M. (2017a). Developing a prototype of case-based system utilizing fuzzy sets to detect faults of injection molding process. In York Sure-Vetter, S. Z. and (Edt.), A. H., editors, *proceedings of WM 2017*, volume 1821, pages

92–96, Karlsruhe, Germany, April 5-7. Tagungsband der 9. Konferenz Professionelles Wissensmanagement (Professional Knowledge Management).

[190] Nasiri, S., Ansari, F., and Fathi, M. (2013a). Dynamics of knowledge assets and change management perspectives. In *IEEE International Conference on Electro/Information Technology (IEEE EIT)*, pages 1–6, Rapid City, SD, USA, 9-11 May. IEEE.

[191] Nasiri, S., Aslan, B., Geller, S., and Fathi, M. (2016). A Prototype of Case-based Skin Cancer Detector for Android Phones based on DePicT Concept: CBMelanom. In *2016 International Conference on Computational Science and Computational Intelligence*, pages 1126–1133.

[192] Nasiri, S., Dornhöfer, M., and Fathi, M. (2013b). Improving EHR and Patient Empowerment based on Dynamic Knowledge Assets. In (Ed.), M. H., editor, *Lecture Note in Informatics(LNI) – Proceedings, Geselschaft für Informatik(GI)*, pages 402–413, September 16-20, Koblenz, Germany. Köllen Druk+Verlag.

[193] Nasiri, S. and Fathi, M. (2017). Case Representation and Similarity Assessment in a Recommender System to Support Dementia Caregivers in Geriatric and Palliative Care. In Kofod-Petersen, A. A. S. R.-G., Anders, and (Editors), editors, *the Twenty-Fifth International Conference on Case-Based Reasoning (ICCBR 2017) Workshop Proceedings*, number June, pages 157–166, Trondheim, Norway.

[194] Nasiri, S., Jung, M., Helsper, J., and Fathi, M. (2018). Detect and predict melanoma utilizing tcbr and classification of skin lesions in a learning assistant system. In Rojas, I. and Ortuño, F., editors, *Bioinformatics and Biomedical Engineering*, pages 531–542, Cham. Springer International Publishing.

[195] Nasiri, S., Klingauf, K., Li, D., and Ortmann, J. (2017b). DePicT Dementia CLASS: Medical Learning Assistant System. In *The Twenty-Fifth International Conference on Case-Based Reasoning (ICCBR 2017) Workshop Proceedings*, page 293, Trondheim, Norway. Kofod-Petersen, Antonio A. Sanchez Ruiz-Granados and Anders (Editors).

[196] Nasiri, S., Sepehri, M., and Khobreh, M. (2011). Utilizing acquired healthcare knowledge, based on using electronic health records. In Holzinger, Andreas, Simonic, K.-M. E., editor, *7th Conference of the Workgroup Human-Computer Interaction and Usability Engineering of the Austrian Computer Society, USAB 2011, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinfor*, volume 7058 LNCS, pages 429–439, Graz, Austria, November 25-26. Springer Berlin Heidelberg.

[197] Nasiri, S., Zenkert, J., and Fathi, M. (2015). A medical case-based reasoning approach using image classification and text information for recommendation. In Rojas I., Joya G., C. A. e. A. i. C. I., editor, *IWANN 2015. Lecture Notes in Computer Science, vol 9095.*, volume 9095, pages 43–55, Palma de Mallorca, Spain, 10-12 June. Springer, Cham.

[198] Nasiri, S., Zenkert, J., and Fathi, M. (2017c). Improving CBR adaptation for recommendation of associated references in a knowledge-based learning assistant system. *Neurocomputing*, 250:5–17.

[199] Nicolas, R., Vernet, D., Golobardes, E., Fornells, A., Puig, S., and Malvehy, J. (2009). Improving the Combination of CBR Systems with Preprocessing Rules in Melanoma Domain. In *Workshop Proceedings of the 8th International Conference on Case-Based Reasoning*, pages 225–234.

[200] Nilsson, M. and Funk, P. (2004). A Case-Based Classification of Respiratory Sinus Arrhythmia. In Funk P., G. C. P. e. A. i. C.-B. R., editor, *ECCBR 2004. Lecture Notes in Computer Science, vol 3155*, pages 673–685, Madrid, Spain, August 30 - September 2. Springer Berlin Heidelberg.

[201] Nonaka, I. and Takeuchi, H. (1995). The Knowledge-Creating: How Japanese companies create the dynamics of innovation. *Oxford University Press*, 3(4-5):25–27.

[202] Novais, T., Dauphinot, V., Krolak-Salmon, P., and Mouchoux, C. (2017). How to explore the needs of informal caregivers of individuals with cognitive impairment in Alzheimer's disease or related diseases? A systematic review of quantitative and qualitative studies. *BMC Geriatrics*, 17(1).

[203] Obota, O. and E.Uzoka, F.-M. (2009). A framework for application of neuro-case-rule base hybridization in medical diagnosis. *Applied Soft Computing*, 9(1):245–253.

[204] Pal, K. S. and Shiu, C. K. S. (2004). *Foundations of Soft Case-Based Reasoning*, volume 7.

[205] Park, Y.-J., Kim, B.-C., and Chun, S.-H. (2006). New knowledge extraction technique using probability for case-based reasoning: application to medical diagnosis. *Expert Systems*, 23(1):2–20.

[206] Patterson, D., Rooney, N., Galushka, M., Dobrynin, V., and Smirnova, E. (2008). Sophia-tcbr: A knowledge discovery framework for textual case-based reasoning. *Knowledge-Based Systems*, 21(5):404–414.

[207] Perner, P. (1999). An architecture for a \uppercase{CBR} image segmentation system. *Journal of Engineering Applications of Artificial Intelligence*, 12(6):749–759.

[208] Perner, P. (2008). Introduction to case-based reasoning for signals and images. *Studies in Computational Intelligence*, 73:1–24.

[209] Perner, P. (2014). Mining sparse and big data by case-based reasoning. *Procedia Computer Science*, 35(C):19–33.

[210] Perner, P., Perner, H., Jänichen, S., and Bühring, A. (2004). Recognition of airborne fungi spores in digital microscopic images. In *Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04)*, volume 3, pages 566–569. IEEE computer society.

[211] Petrovic, S., Mishra, N., and Sundar, S. (2011). A novel case based reasoning approach to radiotherapy planning. *Expert Systems with Applications*, 38(9):10759–10769.

[212] Phuong, N. H., Tu, N. B., Ding, L., and Hirota, K. (2001). Case Based Reasoning Using Fuzzy Set Theory and the Importance of Features in Medicine. In *Ieee*, pages 872–876. IEEE.

[213] Pla, A., López, B., Gay, P., and Pous, C. (2013). EXiT*CBR.v2: Distributed case-based reasoning tool for medical prognosis. *Decision Support Systems*, 54(3):1499–1510.

[214] Polanyi, M. (1966). *The Tacit Dimension*. Peter Smith.

[215] Portinale, L. and Montani, S. (2008). A Fuzzy logic approach to case matching and retrieval suitable to SQL implementation. In *Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI*, volume 2, pages 241–245.

[216] Prestmo, T., Bach, K., Aamodt, A., and Mork, P. J. (2017). *Evolutionary Inspired Adaptation of Exercise Plans for Increasing Solution Variety*, pages 272–286. Springer International Publishing, Trondheim, Norway, June 26-28.

[217] Prosci (2017). Prosci Change Management Learning Center.

[218] Quellec, G., Lamard, M., Bekri, L., Cazuguel, G., Cochener, B., and Roux, C. (2007). Multimedia medical case retrieval using decision trees. In *Proceedings of the 29th Annual International Conference of the IEEE EMBS*, pages 4536–4539, Cité Internationale, Lyon, France, August 23-26. IEEE.

[219] Rashedi, E., Nezamabadi-Pour, H., and Saryazdi, S. (2014). Long term learning in image retrieval systems using case based reasoning. *Engineering Applications of Artificial Intelligence*, 35:26–37.

[220] Reategui, E. B., Campbell, J. A., and Leao, B. F. (1997). Combining a neural network with case-based reasoning in a diagnostic system. *Artificial Intelligence in Medicine*, 9(1):5–27.

[221] Rebuge, Á. J. d. S. (2012). *Business Process Analysis in Healthcare Environments*. Master thesis, Technical University of Lisbon.

[222] Recio-Garcia, J. A., Díaz-Agudo, B., Jorro-Aragoneses, J. L., and Kazemi, A. (2017). *Intelligent Control System for Back Pain Therapy*, pages 287–301. Springer International Publishing, Trondheim, Norway, June 26-28, 2017,.

[223] Richter, M. M.; Weber, R. O. (2013). *Case-Based Reasoning A Textbook*. Springer, Berlin, Heidelberg.

[224] Riesbeck, C. K. and Schank, R. C. (1989). *Inside Case-Based Reasoning*. L. Erlbaum Associates Inc., Hillsdale, NJ, USA.

[225] Robertson, H., Nicholas, N., Georgiou, A., Johnson, J., and Hayen, A. (2015). Dementia in Europe : A Spatial Dashboard System for Chronic Disease Management. (May):1–18.

[226] Rodríguez, Y., González, M., Aguirre, A., Espinosa, M., Grau, R., García, J. O., Rovira, L. E., and García, M. M. (2008). *Prediction of Pediatric Risk Using a Hybrid Model Based on Soft Computing Techniques*, pages 472–481. Springer Berlin Heidelberg, Atizapán de Zaragoza, Mexico, October 27-31.

[227] Roitman, H., Yogev, S., Tsimerman, Y., and Peres, Y. (2012). On the support of flexible patient privacy policies in social-medical discovery. In et al. (Eds.), J. M., editor, *Quality of Life through Quality of Information*, volume 180, pages 813–817. European Federation for Medical Informatics and IOS Press.

[228] Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. *CoRR*, abs/1505.0:234–241.

[229] Sabouri, P., GholamHosseini, H., Larsson, T., and Collins, J. (2014). A cascade classifier for diagnosis of melanoma in clinical images. In *Conference proceedings : Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, pages 6748–6751.

[230] Sahama, T., Liang, J., and Iannella, R. (2012). Impact of the social networking applications for health information management for patients and physicians. In *Studies in Health Technology and Informatics*, volume 180, pages 803–807.

[231] Sanghani, P. (2009). Knowledge Management Implementation : Holistic Framework Based on Indian Knowledge Management Implementation :. In /pacis200, editor, *Pacific Asia Conference on Information Systems (PACIS)*, number May. AIS Electronic Library (AISeL).

[232] Saraiva, R., Bezerra, J., Perkusich, M., Almeida, H., and Siebra, C. (2015). A Hybrid Approach Using Case-Based Reasoning and Rule-Based Reasoning to Support Cancer Diagnosis: A Pilot Study. *Studies in Health Technology and Informatics*, 216:862–866.

[233] Sarasohn-Kahn, J. (2013). Physicians like mobile health apps for patient health – eClinicalWorks on transformational path. Technical report, eClinicalWorks.

[234] Scherer, M. J., Federici, S., Tiberio, L., Pigliautile, M., Corradi, F., and Meloni, F. (2012). ICF Core Set for Matching Older Adults with Dementia and Technology. *Ageing International*, 37(4):414–440.

[235] Schiuma, G. (2009). The managerial foundations of knowledge assets dynamics. *Knowledge Management Research & Practice*, 7(4):290–299.

[236] Schmidt, R. and Gierl, L. (2001). Case-based reasoning for antibiotics therapy advice: An investigation of retrieval algorithms and prototypes. *Artificial Intelligence in Medicine*, 23(2):171–186.

[237] Schmidt, R., Montani, S., Bellazzi, R., Portinale, L., and Gierl, L. (2001). Cased-Based Reasoning for medical knowledge-based systems. *International Journal of Medical Informatics*, 64(2-3):355–367.

[238] Schmidt, R., Pollwein, B., and Gierl, L. (1999). Prognoses of multiparametric medical time courses applied to kidney function assessments. *International Journal of Medical Informatics*, 53:253–263.

[239] Schmidt, R., Vorobieva, O., and Gierl, L. (2003). Case-based Adaptation Problems in Medicine. In *Proceedings of WM2003*. WM2003.

[240] Schnell, M., Couffignal, S., Lieber, J., Saleh, S., and Jay, N. (2017). *Case-Based Interpretation of Best Medical Coding Practices—Application to Data Collection for Cancer Registries*, pages 345–359. Springer International Publishing, Trondheim, Norway, June 26-28.

[241] Sharaf-El-Deen, D. A., Moawad, I. F., and Khalifa, M. E. (2014). A new hybrid case-based reasoning approach for medical diagnosis systems. *Journal of Medical Systems*, 38(2).

[242] Shi, W. and Barnden, J. A. (2005). *Using Inductive Rules in Medical Case-Based Reasoning System*, pages 900–909. Springer Berlin Heidelberg, Monterrey, Mexico, November 14-18.

[243] Shimazu, H. (2002). ExpertClerk: A conversational case-based reasoning tool for developing salesclerk agents in e-commerce webshops. *Artificial Intelligence Review*, 18(3-4):223–244.

[244] Sizov, G. and Öztürk, P. (2013). Query-focused association rule mining for information retrieval. In *SCAI*.

[245] Sizov, G., Öztürk, P., and Aamodt, A. (2015). Evidence-driven retrieval in textual cbr: Bridging the gap between retrieval and reuse. In *ICCBR*.

[246] Sizov, G., Öztürk, P., and Marsi, E. (2016). Compositional adaptation of explanations in textual case-based reasoning. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 9969 LNAI, pages 387–401.

[247] Stang, A., Garbe, C., Autier, P., and Jöckel, K.-H. (2016). The many unanswered questions related to the German skin cancer screening programme. *European Journal of Cancer*, 64:83–88.

[248] Sumithra, R., Suhil, M., and Guru, D. S. (2015). Segmentation and classification of skin lesions for disease diagnosis. In *Procedia Computer Science*, volume 45, pages 76–85.

[249] Sunyaev, A., Leimeister, J. M., Schweiger, A., and Krcmar, H. (2007). Die Elektronische Gesundheitskarte und Sicherheitsaspekte: Ein Vorschlag zur Entwicklungsbegleitenden Sicherheitsevaluation aus Anwendersicht. In *INFORMATIK 2007: Informatik trifft Logistik. 37.*, number May 2014. Jahrestagung der Gesellschaft für Informatik e.V. (GI).

[250] Taylor, J. (2003). *Managing Information Technology Projects: Applying Project Management Strategies to Software, Hardware, and Integration Initiatives*. Amacom, New York, NY, USA, first edition.

[251] Teodorović, D., Šelmić, M., and Mijatović-Teodorović, L. (2013). Combining case-based reasoning with Bee Colony Optimization for dose planning in well differentiated thyroid cancer treatment. *Expert Systems with Applications*, 40(6):2147–2155.

[252] Thistlethwaite, J. E., Davies, D., Ekeocha, S., Kidd, J. M., MacDougall, C., Matthews, P., Purkis, J., and Clay, D. (2012). The effectiveness of case-based learning in health professional education. A BEME systematic review: BEME Guide No. 23. *Medical Teacher*, 34(6):e421–e444.

[253] Tonarelli, L. (2015). Smartphone apps are key for patient health.

[254] Töpel, T., Neumann, J., and Hofestädt, R. (2007). A medical case-based reasoning component for the rare metabolic diseases database RAMEDIS. In *Twentieth IEEE International Symposium on Computer-Based Medical Systems (CBMS'07)*, pages 7–11. IEEE computer society.

[255] Turkington, C. (2003). *The Encyclopedia of Alzheimer's Disease*. Facts on File.

[256] Tversky, A. (1977). Features of Similarity. *Readings in Cognitive Science: A Perspective from Psychology and Artificial Intelligence*, 84(4):290–302.

[257] Tyagi, A. and Singh, P. (2015). ACS: Asthma care services with the help of case base reasoning technique. In *Procedia Computer Science*, volume 48, pages 561–567.

[258] Uhr, P. (2014). *CIMAWA Entwicklung und Anwendung einer textbasierten Assoziations-Berechnungsmethode*. Phd thesis, University of Siegen.

[259] Uhr, P., Klahold, A., and Fathi, M. (2013). Imitation of the Human Ability of Word Association. *The International Journal of Soft Computing and Software Engineering [JSCSE]*, 3(3):248–254.

[260] Van Dam, K., Oreg, S., and Schyns, B. (2008). Daily work contexts and resistance to organisational change: The role of leader-member exchange, development climate, and change process characteristics. *Applied Psychology*, 57(2):313–334.

[261] Van den Branden, M., Wiratunga, N., Burton, D., and Craw, S. (2011). Integrating case-based reasoning with an electronic patient record system. *Artificial Intelligence in Medicine*, 51(2):117–123.

[262] van der Aalst, W. M. P. (2011). *Process Mining: Discovery, Conformance and Enhancement of Business Processes*. Springer Publishing Company, Incorporated, 1st edition.

[263] Vasudevau, C., Smith, S. M., and Ganesan, K. (1994). Fuzzy logic in case-based reasoning. In *NAFIPSIFISNASA 94 Proceedings of the First International Joint Conference of The North American Fuzzy Information Processing Society Biannual Conference The Industrial Fuzzy Control and Intellige*, pages 301–302.

[264] Vorobieva, O., Gierl, L., and Schmidt, R. (2003). Adaptation Methods in an Endocrine Therapy Support System. In *The Fifth International Conference on Case-Based Reasoning*, pages 80–88.

[265] Wang, C. S. and Li, Y. H. (2012). A recommender mechanism based on case-based reasoning. *Expert Systems with Applications*, 39(4):4335–4343.

[266] Watson, I. (1999). Case-based reasoning is a methodology not a technology. *Knowledge-Based Systems*, 12(5):303–308.

[267] Weber, B., Wild, W., and Breu, R. (2004). CBRFlow: Enabling Adaptive Workflow Management Through Conversational Case-Based Reasoning. In Funk P., G. C. P. e. A. i. C.-B. R., editor, *ECCBR 2004. Lecture Notes in Computer Science, vol 3155.*, volume 3155, pages 434–448. Springer, Berlin, Heidelberg.

[268] Weber, R. O., Ashley, K. D., and Brüninghaus, S. (2005). Textual case-based reasoning. *The Knowledge Engineering Review*, 20(03):255–260.

[269] Wettler, M. and Rapp, R. (1993). Computation of Word Associations Based on the Co-Occurrences of Words in Large Corpora. In *Proc. of the 1st Workshop on Very Large Corpora: Academic and Industrial Perspectives*, number project 536, pages 84–93.

[270] WHO (2001). The International Classification of Functioning, Disability and Health. Technical report, WHO Library Cataloguing-in-Publication Data, Geneva.

[271] WHO (2005). WHO Knowledge Management Strategy. Technical report, World Health Organization, Geneva.

[272] WHO (2017). WHO iSupport: E-programme for Carers of People Living with Dementia.

[273] Wijethilake, D., Vatsalan, D., Seneviratne, G., Chapman, K., Thilakaratne, K., Sudhahar, S., Arunathilake, S., and Wickramasinghe, Y. (2010). HealthChange: A change management model for an eHealth solution in developing countries. In (Eds), P. C. and Cunningham, M., editors, *ISTAfrica 2010*, pages 1–8. IIMC International Information Management Corporation.

[274] Wijnhoven, F. (2006). Knowledge Management : More than a Buzzword. In *Knowledge Integration*, pages 1–16. Physica-Verlag HD.

[275] Wilke, W. and Bergmann, R. (1998). Techniques and knowledge used for adaptation during case-based problem solving. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 1416, pages 497–506.

[276] Wilke, W., Vollrath, I., Althoff, K.-D., and Bergmann, R. (1997). A Framework for Learning Adaptation Knowledge Based on Knowledge Light Approaches. In *Proceedings of the Fifth German Workshop on Case-Based Reasoning*.

[277] Wille, M., Innerebner, V., and Mörth, M. (2007). Sturzprophylaxe im Seniorenalter. Technical report, am ISW Innsbruck.

[278] Wilson, D. C. and O'Sullivan, D. (2008). Medical imagery in case-based reasoning. In *Studies in Computational Intelligence*, volume 73, pages 389–418.

[279] Winblad, B., Amouyel, P., Andrieu, S., Ballard, C., Brayne, C., Brodaty, H., Cedazo-Minguez, A., Dubois, B., Edvardsson, D., Feldman, H., Fratiglioni, L., Frisoni, G. B., Gauthier, S., Georges, J., Graff, C., Iqbal, K., Jessen, F., Johansson, G., Jönsson, L., Kivipelto, M., Knapp, M., Mangialasche, F., Melis, R., Nordberg, A., Rikkert, M. O.,

Qiu, C., Sakmar, T. P., Scheltens, P., Schneider, L. S., Sperling, R., Tjernberg, L. O., Waldemar, G., Wimo, A., and Zetterberg, H. (2016). Defeating Alzheimer's disease and other dementias: a priority for European science and society. *The Lancet Neurology*, 15(5):455–532.

[280] Wiratunga, N., Koychev, I., and Massie, S. (2004). Feature selection and generalisation for retrieval of textual cases. In Funk, P. and González Calero, P. A., editors, *Advances in Case-Based Reasoning*, pages 806–820, Berlin, Heidelberg. Springer Berlin Heidelberg.

[281] WMC (2017). World Medical Card.

[282] World Health Organization (2012). Management of patient information. Technical report, WHO Library Cataloguing-in-Publication Data Management, Geneva.

[283] Yager, R. (1997). Case based reasoning, fuzzy systems modeling and solution composition. In Leake D.B., P. E. e., editor, *Lecture Notes in Computer Science (Lecture Notes in Artificial Intelligence), vol 1266.*, pages 633–642. Springer, Berlin, Heidelberg.

[284] Yan, A., Shao, H., and Wang, P. (2015). A soft-sensing method of dissolved oxygen concentration by group genetic case-based reasoning with integrating group decision making. *Neurocomputing*, 169:422–429.

[285] Yao, B. and Li, S. (2010). ANMM4CBR: a case-based reasoning method for gene expression data classification. *Algorithms for Molecular Biology*, 5(14):1–11.

[286] Yin, Z., Dong, Z., Lu, X., Yu, S., Chen, X., and Duan, H. (2015). A clinical decision support system for the diagnosis of probable migraine and probable tension-type headache based on case-based reasoning. *Journal of Headache and Pain*, 16(1):1–9.

[287] Zack, M. H. (1999). Developing a Knowledge Strategy. *California Management Review*, 41(3):125–145.

[288] Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3):338–353.

[289] Zahedi, G. (2017). *Die Entwicklung eines ontologischen CBR Empfehlungssystems für Demenzpatienten*. Master thesis, University of Siegen.

[290] Zekri, F., Bouaziz, R., and Turki, E. (2015). A fuzzy-based ontology for Alzheimer's disease decision support. In *IEEE International Conference on Fuzzy Systems*.

[291] Zhang, B., Li, X., and Wang, S. (2015). A novel case adaptation method based on an improved integrated genetic algorithm for power grid wind disaster emergencies. *Expert Systems with Applications*, 42(21):7812–7824.

Appendix A

Experimental survey results

This survey has been done in 2014 from 222 volunteers about their knowledge in EHRs, PHRs and user's communication in experience sharing and accessing information online [37]. The comparative results of this study from participants' point of view is illustrated in Fig. A.1-A.7.

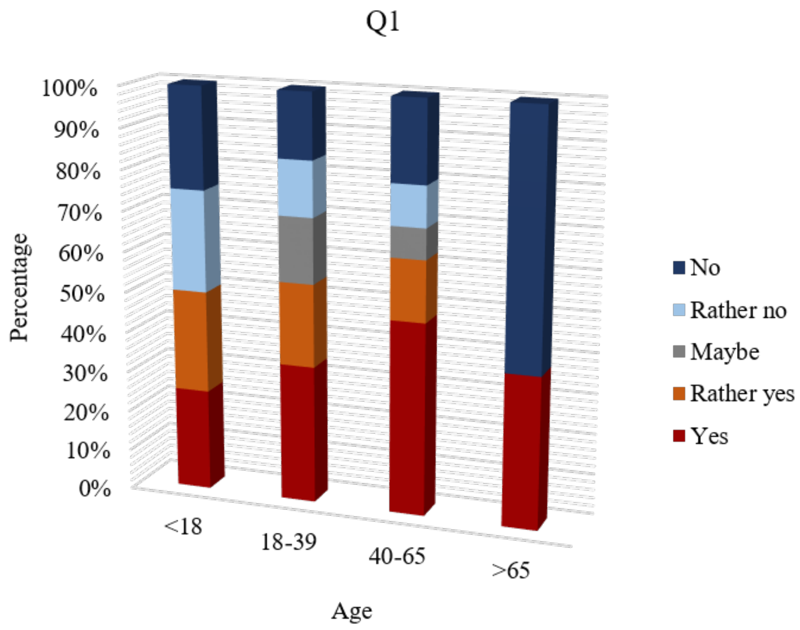


Fig. A.1 Q1 - Do you have any information about the EHR - a patient point of view.

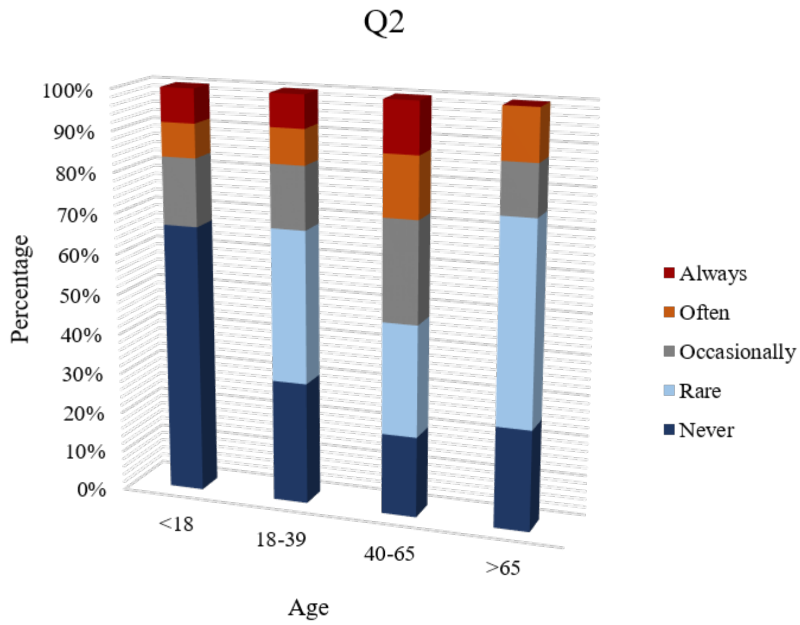


Fig. A.2 Q2 - How often do you collect your medical data.

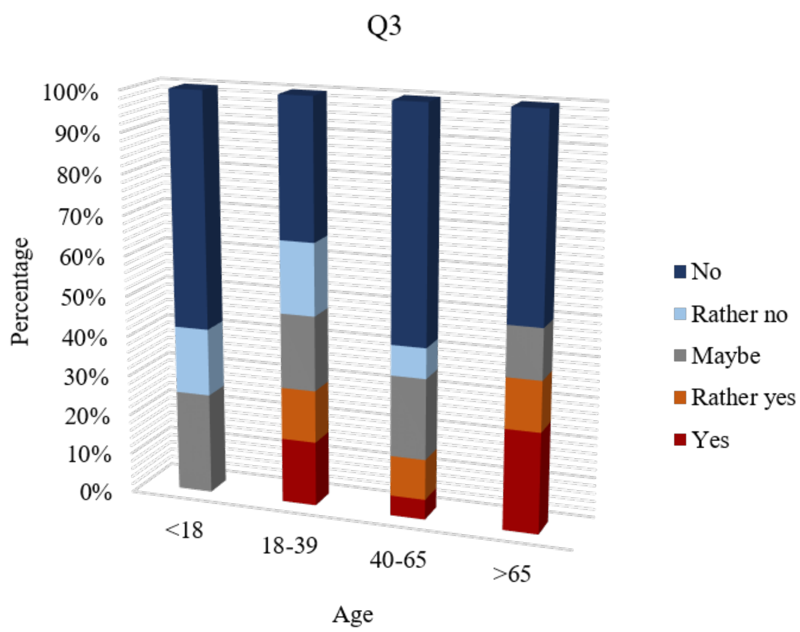


Fig. A.3 Q3 - Would you like to get your medical records online.

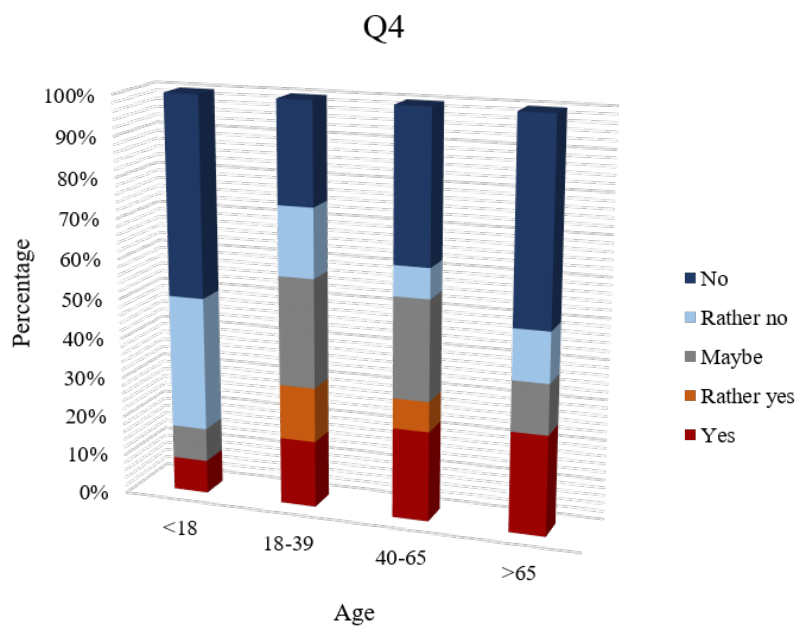


Fig. A.4 Q4 - Would you like to edit your medical records.

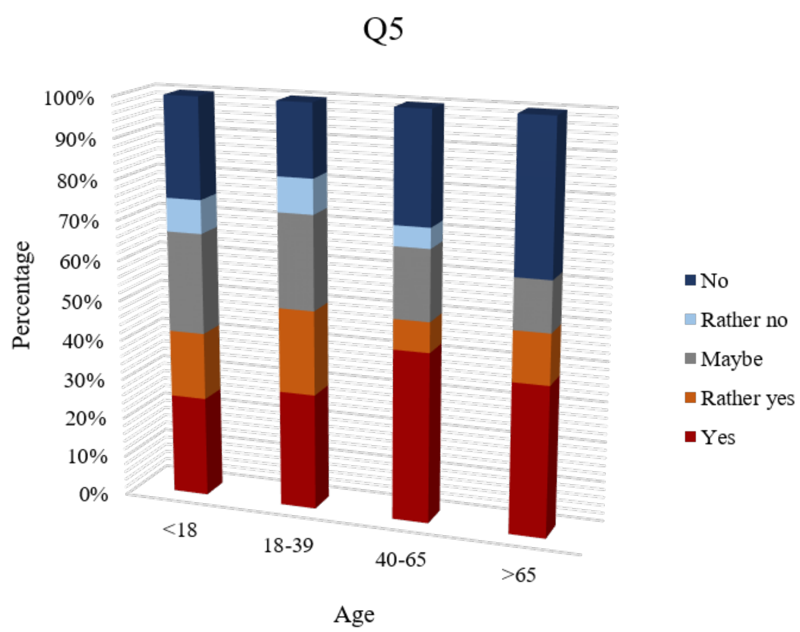


Fig. A.5 Q5 - Would you like your doctors to be able to access your electronic health/medical records.

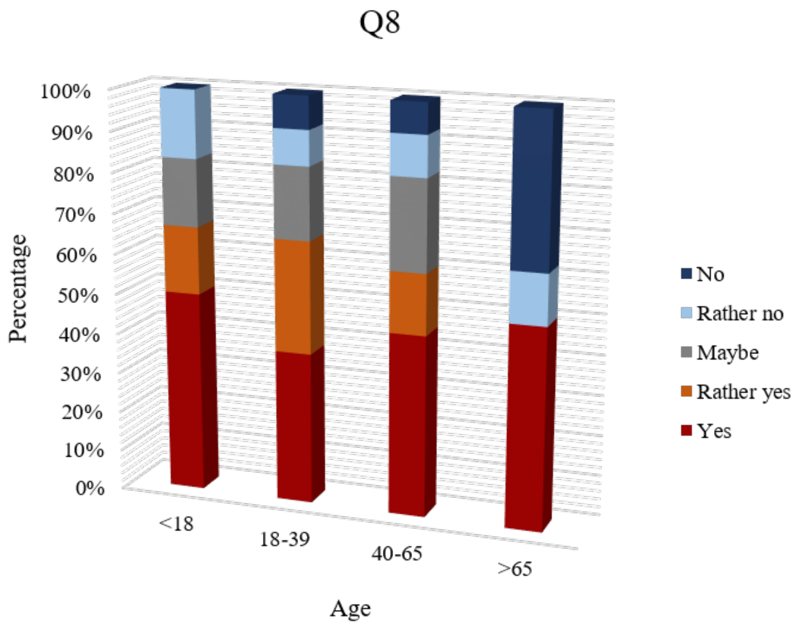


Fig. A.6 Q8 - Suppose you had a serious illness, would you like to exchange the records with people who have the same disease.

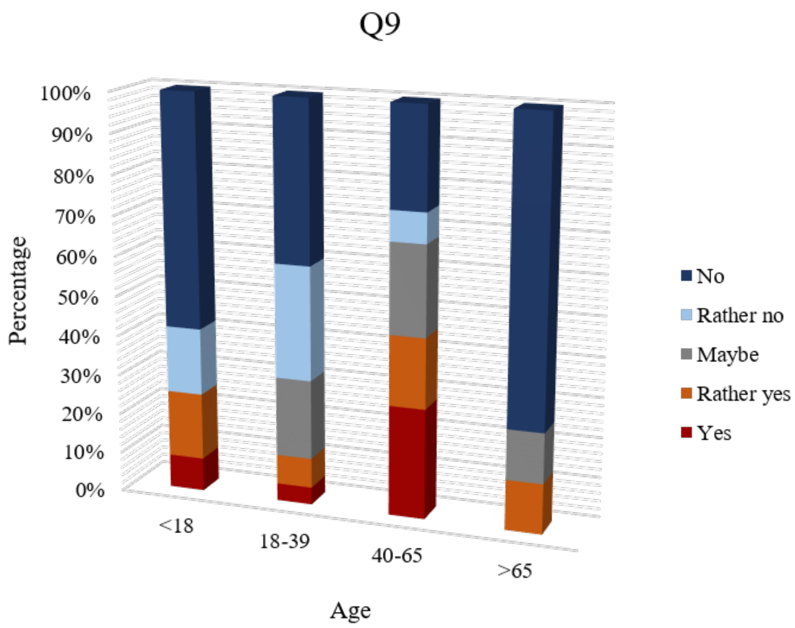


Fig. A.7 Q9- Do you inform sufficiently about the electronic health record from health insurance and the German Ministry of Health.

Appendix B

Medical CBR Systems from 1988 to the present

Some medical CBR systems are reviewed in this research and list in Table B.1, in chronological order which classify based on their objectives, CBR types and other AI techniques, application area, similarity and adaptation mechanism, and dataset.

Table B.1 Medical CBR systems

Obj.	Ref.	Sys.	CBR Type/Technique	App. Area	Sim./Adaptation	dataset
Classification and Diagnosis	[32]	Protos	CBR	Hearing disorders	Exemplar-based / –	200 sequential cases from Baylor College of Medicine
Diagnosis	[142]	CASEY	CBR/ Rule-based, domain theory and Model-based reasoning	Coronary disease	Adaptation with rules	45 patients with symptoms of heart failure covering about 15 different diseases
Diagnosis	[93]	GS.52	CBR	Dysmorphic syndromes	Prototype-based, Tversky and Rosch /Adaptation performed with the application of constraints (contradictions)	229 prototypes which have been collected since 1987 in the department of pediatrics genetics at the university of Munich
Classification	[169]	MacRad	CBR	Radiology Images	Template matching with backtracking/ –	300 cases with 3,000 images that present intracranial masses on skull X-rays, CTs, MRIs, and angiograms
Image Interpretation	[104]	SCINA	CBR/ Rule-based reasoning	Myocardial Perfusion Scintigrams	–/ Adaptation performed with Rule-base	A case library of I00 patients who had been submitted to coronary angiography and perfusion scintigraphy was compiled by a retrospective data base search
Diagnosis	[220]	–	CBR / Neural networks	Congenital heart diseases	Similarity between a case and a diagnosis descriptor/ –	two cardiological databases with a total of 214 CHD cases
Diagnosis	[121]	–	CBR/ Fuzzy logic, Neural networks, Induction, Knowledge-based technology	General	Adaptation performed with Rule-base	–
Knowledge-support assistance	[39]	CARE-PARTNER	CBR/ Rule-based reasoning, and Information retrieval	General	Retrieval and Adaptation performed with rules, cases and pathways	This system is applied to the long-term follow-up (LTFU) of patients having undergone a stem-cell transplant (SCT) at the Fred Hutchinson Cancer Research Center (FHCRC) in Seattle
Classification	[152]	IDEM	CBR / UML	Radiology and pathology Images	–	–
Classification	[94]	TeCoMED	CBR / Rule-based reasoning, Model-based reasoning	Epidemics	Compositional Adaptation	–

Obj.	Ref.	Sys.	CBR Type/Technique	App. Area	Sim./Adaptation	dataset
Classification	[207]	–	CBR/ Image processing, and Data mining	Medical image analysis	Image information and Tversky non-image information /–	The images of 30 patients which are labelled by University of Leipzig
Classification	[238]	COSYL	CBR	Kidney function	Prototype-based / –	100 data sets from the NIMON data base
Diagnosis	[98]	MED2000	CBR / Neural networks	Haematological diseases	CBNN /–	30 classical Haematological cases
Diagnosis	[212]	–	CBR / Fuzzy logic	Lung diseases	Similarity based on fuzzy sets /–	1026 patient records of 18 types of lung diseases and it applies successfully at the Vietnam National Institute of Tuberculosis and Lung diseases
Planning	[177]	Auguste	CBR/ Rule-based reasoning	Alzheimer's disease	Mini Mental Status Examination (MMSE) Scores and k-NN / –	Twenty-eight cases
Classification	[97]	CaB-CS	CBR / Genetic algorithm	Breast cancer	Minkowski and Clark/ –	breast cancer dataset from contains 216 images previously diagnosed by surgical biopsy
Planning	[264]	–	CBR / Rule-based reasoning	Endocrinology	–/ Task oriented adaptation model developed	–
Diagnosis	[120]	–	CBR/ Neural networks, Fuzzy theory, Induction, Utility theory, and Knowledge-based planning technology	Multiple diseases	Adaptation performed with knowledge-based planning	–
Classification	[200]	–	CBR/ Rule-based reasoning	Respiratory sinus arrhythmia	Similarity distance/–	100 pre-recorded data
Diagnosis	[145]	Somnus	CBR/ Fuzzy logic, and Semiotics	Obstructive sleep apnea	crisp values, fuzzy values, and general concepts / –	37 patient records from UCC Sleep Disorders Clinic
Classification, Knowledge acquisition/ management	[210]	–	CBR/ Image processing	Recognition of Airborne Fungi Spores	Cross correlation / –	Six fungal strains representing species with different spore types
Classification	[47]	–	CBR / Attention-deficit	hyperactivity disorder	–	The child cases consisted of 76 children diagnosed in the community with ADHD and 76 normal control children (6 to 16)
Diagnosis	[59]	–	CBR	Development delay in children	Kolodner similarity/ Adaptation performed with the help of human experts	210 cases of children with developmental delay in a selected screening center
Diagnosis	[242]	–	CBR / Induction	Multiple disorders	Manhattan distance for continuous or scaled parameters and Value Difference Metric / Inductive Adaptation with rules	Two case bases from sonography SonoConsult
Classification, planning, knowledge acquisition/ management	[186]	RHENE	CBR /Temporal Abstractions	Hemodialysis in NEphrological disorders	Temporal dimension in case-based retrieval / –	–
Diagnosis, classification, knowledge acquisition/ management	[25]	KASIMIR	CBR/ Fuzzy logic and Ergonomic	Breast cancer	–/ Adaptation guided retrieval	databases of semi-automatic AKA
Diagnosis, classification	[75]	geneCBR	CBR/ Fuzzy Logic	Cancer	Fuzzy patterns/ Adaptation performed with the help of human expert	Bone marrow (BM) samples from 43 adult patients
Diagnosis, classification	[205]	–	Statistical CBR / Probability	General	Distance threshold / –	five real-life medical data sets obtained from the UCI - dermatology, heart Pima Indian diabetes, Wisconsin breast cancer and BUPA liver disorder
Diagnosis, planning therapy information	[254]	–	CBR	Inborn metabolic disease	–	RAMEDIS database: 750 case reports that are characterized by altogether 4300 symptoms, 29000 laboratory values
Classification	[218]	–	CBR/ Decision trees	Diabetic retinopathy	Multimodal decision tree based indexing /–	63 patient files containing 1045 photograph
Diagnosis, Knowledge acquisition/ management	[70]	FRAKAS	CBR	Oncology	Conservative adaptation performed	–
Planning	[176]	–	CBR	Type 1 diabetes	–	20 patients with Type 1 diabetes: 50 cases of problems in blood glucose control
Classification	[163]	ProtoClass	CBR	General	–	IRIS Plant and EColi datasets
Diagnosis	[9]	–	Textual CBR/ Fuzzy logic	Stress	Fuzzy and Cosine similarity /–	39 cases classified by the domain expert

Obj.	Ref.	Sys.	CBR Type/Technique	App. Area	Sim./Adaptation	dataset
Prediction	[226]	SAPRIM	CBR/ Neural networks, Fuzzy Logic	Pediatric risk	–	–
Planning, Knowledge acquisition/ management	[69]	GerAmi	CBR and Variational calculus	Alzheimer's disease	–/ Adaptation performed	–
Diagnosis, classification	[74]	–	CBR, Neural networks, Statistics	Leukemia	Adaptation performed with Classification Tree	212 samples
Diagnosis	[203]	–	CBR/ Neural networks, Rule-based reasoning	Hepatitis	–/ Rules and NN	45 patients from three hospitals
Diagnosis	[161]	–	CBR /Classification and regression tree(CART)	Liver diseases	nearest neighbours / –	64 cases with different types of liver diseases
Diagnosis	[14]	GOCBR	CBR /Genetic algorithms	Breast Cancer	NN matching/–	Image database (212 with cancer, and 357 with fibrocystic disease) for classification algorithm testing, made publicly available by Dr. William H.Wolberg of the University of Wisconsin Hospitals
Diagnosis classification	[199]	–	CBR/ Rule-based reasoning	Melanoma	Rules/–	Dermatoscopy and the Reflectance Confocal Microscopy image data
Diagnosis	[34]	–	CBR and Fuzzy logic	Stress	Distance Function, matrix and fuzzy set /–	39 reference cases classified by the domain expert
Classification	[285]	ANMM4	CBR	Gene expression data	Additive Nonparametric Margin Maximum/–	Leukemia contains 47 cases of acute lymphoblastic leukemia (ALL) and 25 cases of acute myeloid leukemia (AML) with the expression levels of 7,129 genes. Colon contains expression levels of 40 tumor and 22 normal colon tissues. SRBCT contains gene-expression data from cDNA microarrays of 2308 genes. GCM (Global Cancer Map) consists of 198 human tumor samples covering 14 different cancer types. The gene number is 16,063
Knowledge management	[102]	CBR-DENT	CBR and Fuzzy Logic	Odontology	Eulerian-Lagrangian distance similarity algorithm /Rule base	Two hospitals, the People's Hospital and Boai Hospital of Preventing and Curing Dental Illness
Diagnosis	[162]	–	CBR, Analytic hierarchy process, Neural networks	Liver diseases	similarities of both qualitative and quantitative features/–	510 outpatient visitors to a medical center in Taiwan during the 1 year from March 2005 to February 2006 was collected as the cases in the dataset
Planning	[127]	–	CBR and Fuzzy logic	Brain cancer radiotherapy	Fuzzy non-linear Similarity /Adaptation suggested, but not performed	Brain cancer patient cases
Planning	[10]	–	CBR and Fuzzy logic	Stress	Distance function, similarity matrix and fuzzy similarity/ Calculation of average features of most similar cases	53 reference cases from 31 subjects
Diagnosis	[78]	–	Case-based Fuzzy cognitive maps	Urinary tract infection	–	71 patients with urinary tract infections
Diagnosis	[64]	–	CBR and Neural networks (Back propagation network)	Liver disease	Euclidian distance /–	166 outpatient visitors at a medical center in Taiwan from 2006 to 2008
Planning	[211]	–	CBR, fuzzy sets, Dempster–Shafer theory	Prostate Cancer	Dempster–Shafer/Repair mechanism for dose plan	72 anonymised patient records obtained from the Nottingham City Hospital
Classification	[261]	Excelicare CBR	CBR and Genetic Algorithm	Electronic patient record	k-NN, GroupSim/–	–
Diagnosis	[165]	eXiT*CBR	CBR	Breast cancer	Distance method / Classification matrix, confusion matrix	Breast cancer dataset consists of 871 cases, 628 corresponding to healthy women and 243 to women with breast cancer
Diagnosis	[8]	–	CBR, Fuzzy logic, Rule-based reasoning, textual information retrieval	Stress	Fuzzy similarity/–	12 women and 34 men between the ages 23 to 51
Classification, planning	[184]	–	CBR	Hemodialysis	–	–
Diagnosis	[134]	–	CBR, Rule-based reasoning, Distributed reasoning, Fuzzy logic	Cardiac arrhythmia	Fuzzy similarity/–	data set contains the parameters of 745 heartbeats
Planning	[174]	4DSS	CBR/ Rule-based reasoning	Type 1 diabetes	k-NN/Adaptation performed with expert	80 cases
Supporting protocol design	[131]	GRACE	CBR	Frontotemporal dementia	Graph-based and distance method/Adaptation performed with rule-base	8 cases contains 4 AD and 4 FD cases
Diagnosis, classification, planning	[12]	–	CBR, Fuzzy logic, Rule-based reasoning, textual information retrieval	Stress Management	Distance function, matrix and fuzzy similarity/–	68 cases

Obj.	Ref.	Sys.	CBR Type/Technique	App. Area	Sim./Adaptation	dataset
Patient identification	[13]	–	CBR	General	Euclidean distance /–	–
Classification	[35]	–	CBR and Fuzzy logic	Physiological sensor signals	Euclidian and Fuzzy similarity matching/–	19 cases where are classified as 'healthy' and 'stressed' by an expert
Diagnosis	[81]	–	CBR, Neural networks, and Fuzzy logic	Depression disorder	Fuzzy similarity/–	–
Classification, diagnosis	[123]	–	CBR, Neural networks, Adaptive Neuro-Fuzzy Inference System	Breast cancer	k-NN/–	Mammographic data set; BI-RADS was developed by the American College of Radiologists as a standard of comparison for rating mammograms and breast ultrasound images
Classification (retrieval)	[185]	–	CBR	Comparative genomics	Temporal Abstractions/–	10,388 hemodialysis cases collected at the Vigevano hospital, Italy
Diagnosis	[60]	–	CBR	Premenstrual syndrome	k-NN/Menu-driven approach	53 anonymous PMS cases
Diagnosis	[213]	eXiT*CBR.v2	CBR, Genetic algorithms, and Cooperative multi agent system technology	General	Agent weights/Adaptation performed	871 cases: 628 healthy women and 243 women with breast cancer
Planning	[151]	–	CBR and Principal component analysis	Continuous glucose monitoring	–	The data collected from 22 patients in an ICU
Planning	[251]	–	CBR and Bee colony optimization	Thyroid cancer	Similarity for attributes/–	120 examples of a physician's decisions. Patients used in this research are those who were treated in the University Clinical Center in Kragujevac, Serbia
Representations of human organs	[112]	EquiVox	CBR and Neural networks	Numerical representation of human organs	Adaptation performed with ANN	–
Diagnosis	[241]	–	CBR and Rule-based reasoning	Breast Cancer and Thyroid disease	Distance/ Adaptation performed with rules	The thyroid disease dataset constitutes 215 instance and the Mammographic mass dataset contains 595 instances
Diagnosis	[286]	–	CBR	Headache	k-NN/ –	The test dataset was composed of an additional 222 historical cases, 76.1% of which had been diagnosed with PM and 23.9% of which had been diagnosed with PTTH
Classification	[257]	–	CBR	Asthma	Numeric and symbolic/ –	–
Planning	[135]	–	CBR and Clustering	Radiotherapy (Brain Cancer)	Euclidean distance /–	10 clusters
Diagnosis	[232]	–	CBR and Rule-based reasoning	Four types of gastrointestinal cancer	k-NN/–	forty-eight cases from real patients: six cases of patients with anal cancer, six with esophageal cancer, fifteen with colorectal cancer, and twenty-one with stomach cancer
Diagnosis	[58]	CEDS	CBR	Cholera	–	
Diagnosis, recommendation	[197]	DePicT	CBR /text-mining	General	Tversky and word association strength/–	–
Diagnosis	[31]	–	CBR, Fuzzy clustering and Decision trees	Retinal Abnormalities	–	Images from the public databases were divided into two groups, one consisting the training set comprising of 10 images of each abnormality (60 images) and the other the test set (79 images) out of a total of 139 images
Recommendation	[191]	DePicT CBMelanom	CBR /myCBR	Melanoma	–	–
Diagnosis, recommendation	[198]	DePicT CLASS	TCBR /text-mining	General	word association strength /compositional adaptation	–
Diagnosis, image interpretation	[61]	Tetra	CBR/ontology	necrosis and ischemia	Ontological, frequency and probability of diagnoses/–	8000 images for the case base, 905 for testing-Centre Hospitalier R´egional Universitaire
Diagnosis, management	[101]	CBHKS	CBR	Hospital management	–	–
Diagnosis, recommendation	[216]	selfBACK	CBR/ GA	non-specific low back pain (LBP), Cold start problem	–/ adaptation performed with GA-generated solutions	9 cases from the selfBACK project
Diagnosis, recommendation	[222]	Kazemi Back System (KBS)	CBR	Back pain	k-NN/Expert	40 patients (14:female, 26:male)
Best practice interpretation	[240]	–	CBR	Cancer registries	distance function between patient records /–	–
Diagnosis, recommendation	[193]	DePicT Dementia CLASS	TCBR /text-mining	Dementia	word association strength/–	37 dementia related books

Appendix C

Reference books, papers and sample tests

Dementia:

1. Anthea Innes and Louise Mccabe, Evaluation in Dementia Care. Jessica Kingsley Publishers, ISBN 1-84310-429-6, 2007.

2. Barbara Messer, Pflegeplanung für Menschen mit Demenz: Einfach, echt und individuell planen und schreiben, Schlütersche, ISBN 9783842681194, 2010.

3. Bonnie Juettner, Dementia (Diseases and Disorders), Health Professions Press, ISBN 1-4205-0042-2, 2014.

4. Bruce L. Miller and Bradley F. Boeve, The Behavioral Neurology of Dementia, Cambridge University Press, ISBN 978-0-521-85395-8, 2009.

5. Danuta Lipinska, Person-Centred Counselling for People with Dementia, Jessica Kingsley Publishers, ISBN 978-1-84310-978-5, 2009.

6. Dawn Brooker, Person-Centred Dementia Care: Making Services Better, Jessica Kingsley Publishers, ISBN 9781846425882, 2006.

7. Ed Halliwell, Still going strong: A guide to living with Dementia, Mental Health Foundation, ISBN 978-1903645741, 2005.

8. Eileen Shamy, A Guide to the Spiritual Dimension of Care for People with Alzheimer's Disease and Related Dementia: More than Body, Brain and Breath, Jessica Kingsley Publishers, ISBN 9781846423888, 2003.

9. Erik D. Roberson, Alzheimer's Disease and Frontotemporal Dementia, Humana Press, Springer Science+Business Media, LLC, ISBN 978-1-60761-743-3, 2011.

10. Gabriela Stoppe, Competence Assessment in Dementia, Springer-Verlag Wien, ISBN 978-3-211-72368-5, 2008.

11. Gemma M. M. Jones, Bère L. Miesen, Care Giving in Dementia Research and Applications, Routledge, ISBN 978-1583911891, 2004.

12. Gudrun Schaade, Demenz-Therapeutische Behandlungsansätze für alle Stadien der Erkrankung, Springer-Verlag Berlin Heidelberg, ISBN 978-3-540-89541-1, 2009.

13. H. Elisabeth Philipp-Metzen, Die Enkelgeneration im ambulanten Pflegesetting bei Demenz, VS Verlag für Sozialwissenschaften, Springer Fachmedien Wiesbaden, ISBN 978-3-531-16118-1, 2008.

14. Helen Buell Whitworth, James Whitworth, A Caregiver's Guide to Lewy Body Dementia, Demos Health, 978-1932603934, 2010.

15. James Thorpe, Henry Edwards Huntington- A Biography, University of California Press, ISBN 9780520082540, 1994.

16. Johanna Radenbach, Aktiv trotz Demenz: Handbuch für die Aktivierung und Betreuung von Demenzerkrankten, Schlütersche, ISBN 978-3-89993-219-5, 2009.

17. John Keady, Charlotte Clarke and Sean Page, Partnerships in community mental health nursing and dementia care, Open University Press, ISBN 0-335-21581-5, 2007.

18. John O'Brien, David Ames, Ian McKeith and Edmond Chiu, Dementia with Lewis Body and Parkinson's Disease Dementia, CRC Press, ISBN 9781841843957, 2005.

19. Manfred Gerlach, Heinz Reichmann und Peter Riederer, Die ParkinsonKrankheit Grundlagen, Klinik, Therapie, Springer-Verlag Wien, ISBN 978-3-7091-3748-2, 2001.

20. Maurice D. Mulvenna, Chris D. Nugent, Supporting People with Dementia Using Pervasive Health Technologies, Springer London, ISBN 978-1-84882-550, 2010.

21. Nawab Qizilbash, Lon S. Schneider, Henry Brodaty, Evidence-based Dementia Practice, Blackwell Science Ltd, ISBN 0-632-05296-1, 2003.

22. P. Giannakopoulos, P. R. Hof, Dementia in Clinical Practice, Frontiers of Neurology and Neuroscience, Vol. 24, ISBN 978-3-8055-9015-0, 2009.

23. James N. Parker and Philip M. Parker, Huntington Disease: A Bibliography and Dictionary for Physicians, Patients, and Genome Researchers, ISBN 0-497-11235-3, 2007.

24. Robert A. and Levine M.D., Defying Dementia: Understanding and Preventing Alzheimer's and Related Disorders, Rowman & Littlefield Publishers, ISBN 978-1442204836, 2010.

25. Serge Gauthier, Philip Scheltens, Jeffrey L. Cummings, Alzheimer's and Related Disorders Annual, CRC Press, ISBN 9780203492857, 2004.

26. Robert Perry, Ian McKeith, Elaine Perry and Jeffrey L. Cummings, Dementia with Lewy Bodies: Clinical, Pathological, and Treatment Issues, Cambridge University Press, ISBN 978-0521561884, 1996.

27. Thomas J. Visser, Huntington's Disease: Etiology and Symptoms, Diagnosis and Treatment, Nova Science Publishers, ISBN 978-1-61728-451-9, 2010.

28. Philip M. Parker, Niemann-Pick Disease - A Bibliography and Dictionary for Physicians, Patients, and Genome Researchers, ICON Group International, ISBN 978-0497113803, 2007.

29. Peter A. Lichtenberg, Daniel. Murman and Alan M. Mellow, Handbook of Dementia: Psychological, Neurological, and Psychiatric Perspectives, John Wiley & Sons, ISBN 9780471690412, 2004.

30. Brian Draper, Dealing with Dementia, A Guide to Alzheimer's Disease and Other Dementias, Allen & Unwin, ISBN 978-1865088532, 2004.

31. Robert H. Paul, Vascular Dementia: Cerebrovascular Mechanisms and Clinical Management, Humana Press, ISBN 978-1-59259-824-3, 2005.

32. Sarah R. Jacobsen, Vascular Dementia: Risk Factors, Diagnosis and Treatment (Neuroscience Research Progress), Nova Biomedical, ISBN 978-1611223132, 2011.

33. Barbara Messer, Pflegeplanung für Menschen mit Demenz einfach, echt und individuell planen und schreiben, Schlütersche, ISBN 978-3899932201, 2009.

Melanoma:

34. Claus Garbe: Management des Melanoms. Springer-Verlag Berlin Heidelberg, ISBN 978-3-540-28988-3, 2006.

35. L. Held, T.K. Eigentler, C. Garbe, Der Onkologe, In: Springer Medizin, 15(8), pp 738–743, 2009.

36. Peter Altmeyer, Volker Paech, Enzyklopädie Dermatologie, Allergologie, Umweltmedizin, Springer-Verlag Berlin Heidelberg, ISBN 978-3-540-89542-8, 2011.

37. Léon C van Kempen, Margaret Redpath, Caroline Robert, Alan Spatz, Molecular pathology of cutaneous melanoma, In: Melanoma Management, 1(2):151–164, 2014.

38. Brunner, Georg: A nine-gene signature predicting outcome in cutaneous melanoma, Journal of Cancer Research and Clinical Oncology, 139(2):249–258, 2013.

39. Radhika Kainthla, Kevin B Kim, and Gerald S Falchook, Dabrafenib for treatment of BRAF-mutant melanoma. Journal of Pharmgenomics Pers Med, 7:21-29, 2014.

40. Benjamin Scheier, Rodabe Amaria, Karl Lewis, Rene Gonzalez: Novel therapies in melanoma, Journal of Immunotherapy, 3 (12):1461–1469, 2011.

41. L. Topalian et. al, Survival, Durable Tumor Remission, and Long-Term Safety in Patients with Advanced Melanoma Receiving Nivolumab, Journal of Clinical Oncology, 32(10):1020-1030, 2014.

42. Wiecker TS, Luther H, Buettner P, Bauer J, Garbe C, Moderate sun exposure and nevus counts in parents are associated with development of melanocytic nevi in childhood: a risk factor study in 1,812 kindergarten children, Journal of Cncer, 97(3):628-638, 2003.

43. Riemer M, UV Protection Law. Enhancing the protection of minors against health risks from solaria, Journal of Hautarzt, 57(12):1133-7, 2006.

44. Friedman RJ, Rigel DS, Kopf AW, Early detection of malignant melanoma: the role of physician examination and self-examination of the skin, Journal of Cancer for Clinicians, 35:130–151, 1985.

45. Rigel DS, Friedman RJ, Kopf AW, Polsky D., ABCDE – an evolving concept in the early detection of melanoma, Journal of Archives of Dermatology, 141(8):1032-4, 2005.

46. Grob JJ, Bonerandi JJ, The 'ugly duckling' sign: identification of the common characteristics of nevi in an individual as a basis for melanoma screening, Journal of Archives of Dermatology, 134(1):103-4, 1998.

47. Ernest, C., Melanoma: Biologically Targeted Therapeutics, Springer Science+Business Media New York, ISBN 978-1-59259-159-6, 2002.

Sample Tests:

1. alz A http://www.alz.org/de/10-symptome-alzheimer-demenz.asp
2. alz B https://www.alzheimer-forschung.de/alzheimer-krankheit/symptome.htm
3. alz C http://www.alzheimer.de/alzheimer/alzheimer/Symptome/Typische-Symptome.html
4. Vascular Dementia A http://www.netdoktor.de/krankheiten/demenz/vaskulaere-demenz/
5. Vascular Dementia B https://www.pflege.de/leben-im-alter/krankheiten/demenz/vaskulaere-demenz/
6. Vascular Dementia C http://gesundpedia.de/Vaskul%C3%A4re_Demenz
7. FTD A http://doczz.com.br/doc/943267/das-wichtigste-11–die-frontotemporale-demenz
8. FTD B https://www.deutsche-alzheimer.de/die-krankheit/frontotemporale-demenz.html
9. FTD C https://www.neuronation.de/demenz/die-pick-krankheit
10. Huntington A https://www.dhh-ev.de/Was-ist-Huntington
11. Huntington B http://www.apotheken-umschau.de/Morbus-Huntington
12. Huntington C http://www.onmeda.de/krankheiten/chorea_huntington-symptome-1576-4.html
13. Parkinson A http://www.parkinson-aktuell.de/was-ist-parkinson/symptome-fuer-parkinson
14. Parkinson B http://www.leben-mit-parkinson.de/parkinson/symptome/
15. Parkinson C http://www.vitanet.de/krankheiten-symptome/morbus-parkinson/symptome/erste-anzeichen

16. Lewy A https://www.deutsche-alzheimer.de/unser-ser-vice/foren/beitraege/umgang_und_tipps_zur_alltagbewaeltigung/onkel_hat_lewy_body_demenz.html?L=Referenten

17. Lewy B https://www.yumpu.com/de/document/view/1454706/die-lewy-korperchen-demenz-deutsche-alzheimer-gesellschaft-ev

18. Lewy C https://de.wikipedia.org/wiki/Lewy-K%C3%B6rper-Demenz#Diagnose

19. Meningit A http://www.apotheken-umschau.de/Gehirn/Gehirnhautentzuendung-Symptome-11502_3.html

20. Meningit B https://www.lifeline.de/krankheiten/meningitis-hirnhautentzuendung-id78979.html

21. Meningit C https://www.9monate.de/gesundheit-vorsorge/kinderkrankheiten/hirnhautentzuendung-meningitis-id94019.html

22. CJK A http://www.meine-gesundheit.de/creutzfeldt-jakob-krankheit

23. CJK B http://www.netdoktor.de/krankheiten/creutzfeldt-jakob-krankheit/

24. CJK C http://www.sprechzimmer.ch/sprechzimmer/Krankheitsbilder/Creutzfeldt_Jakob_Krankheit_CJK.php

Appendix D

ICF Code results for patients with Alzheimer's disease

ICF codes of dementia (Alzheimer's disease) in early, middle and late stages which is used in DePicT Dementia CLASS illustrated in Fig. D.1-D.4.

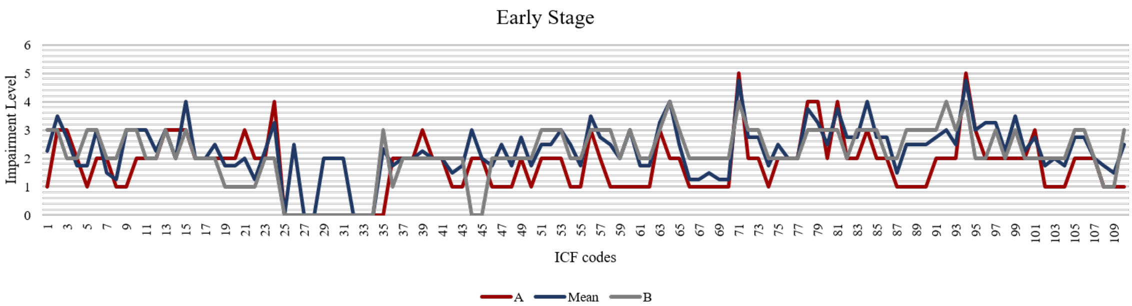


Fig. D.1 Impairment in *ICF* codes of Alzheimer patient in the early stage.

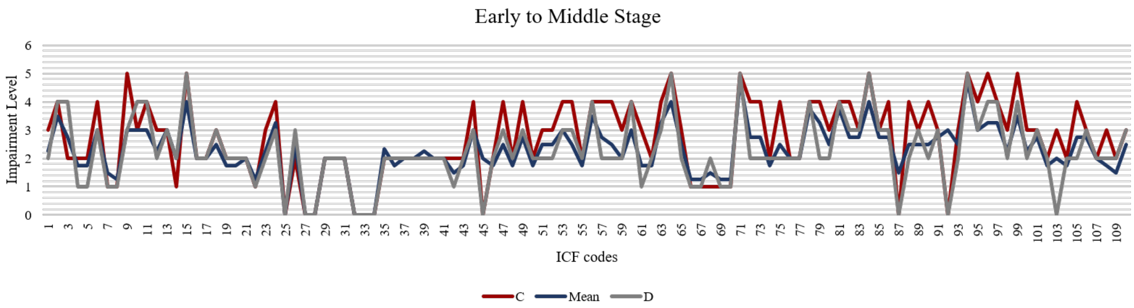


Fig. D.2 Impairment in *ICF* codes of Alzheimer patient in the early-to middle-stage.

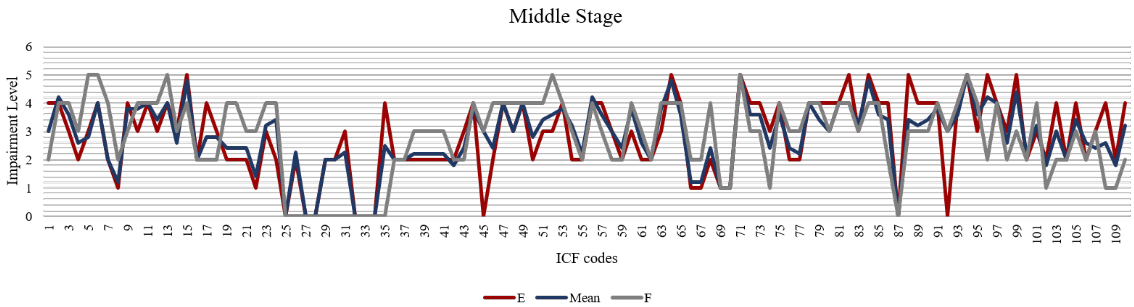


Fig. D.3 Impairment in *ICF* codes of Alzheimer patient in the middle stage.

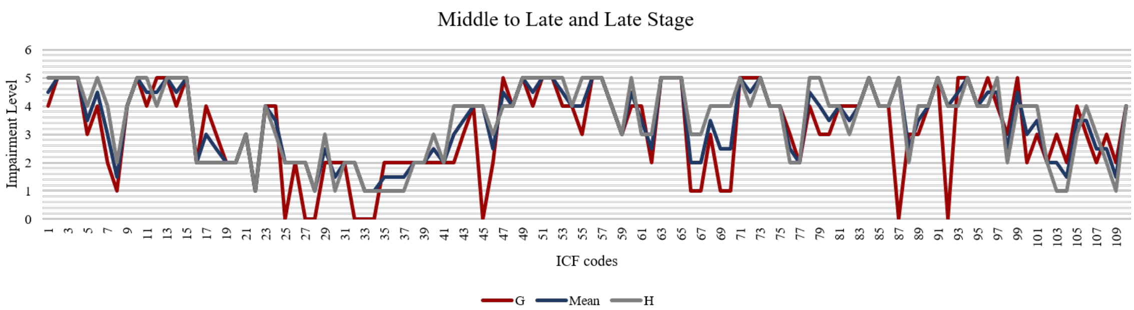


Fig. D.4 Impairment in *ICF* codes of Alzheimer patient in the middle-to-late and late stages.

Appendix E

Screenshots of the applications

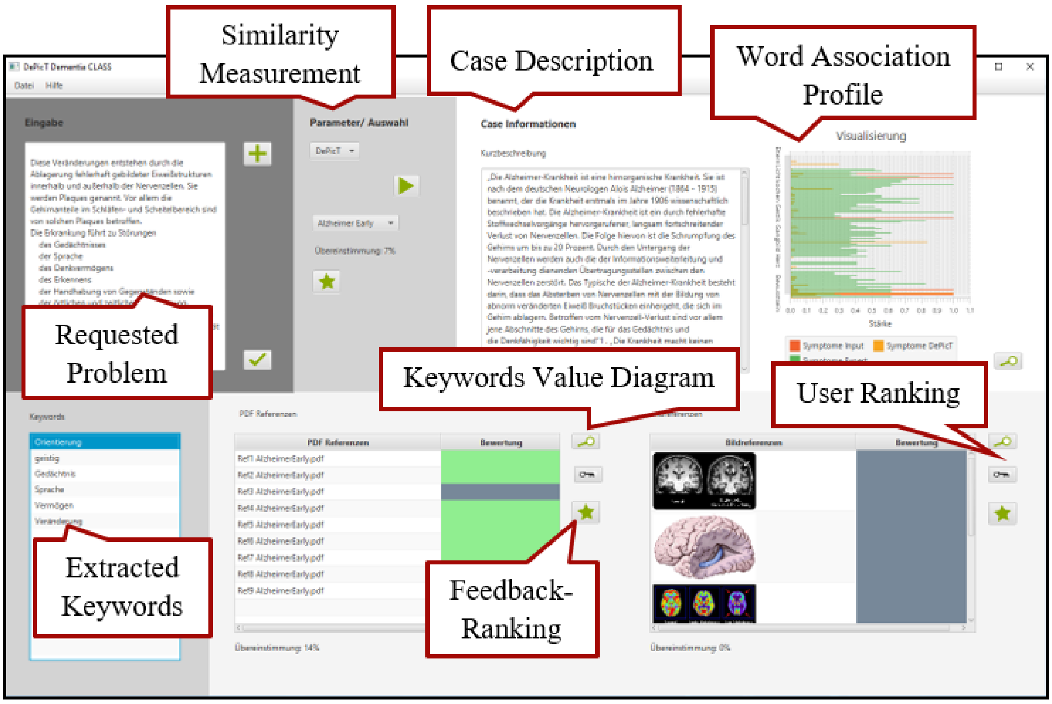


Fig. E.1 DePicT Dementia CLASS-Case retrieval: user view [195] [193].

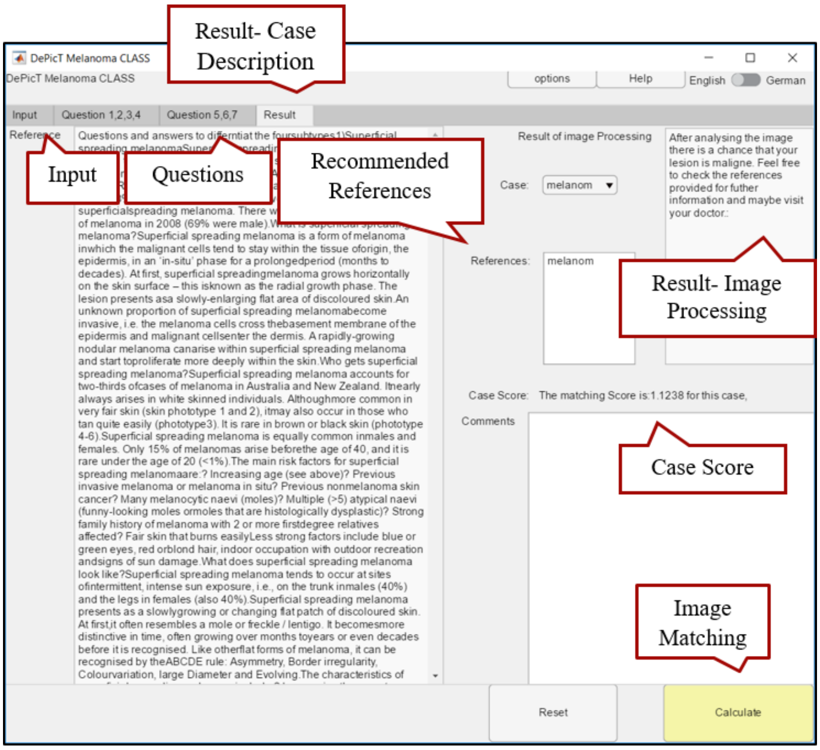
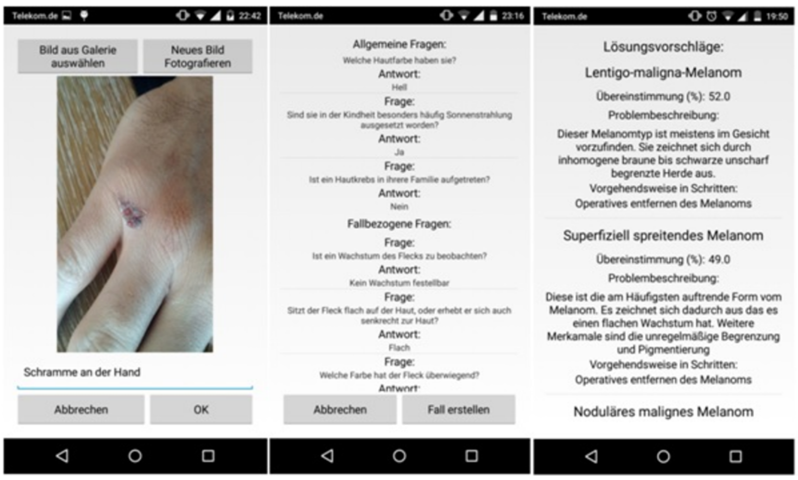


Fig. E.2 DePicT Melanoma CLASS-Result view [111][194].



a) b) c)

Fig. E.3 CBMelanom APP Screenshots [28][191]: a) Case creating by adding the new image from affected area, b) The question-dialog, c) Retrieval results and similarity degrees of the most similar cases.

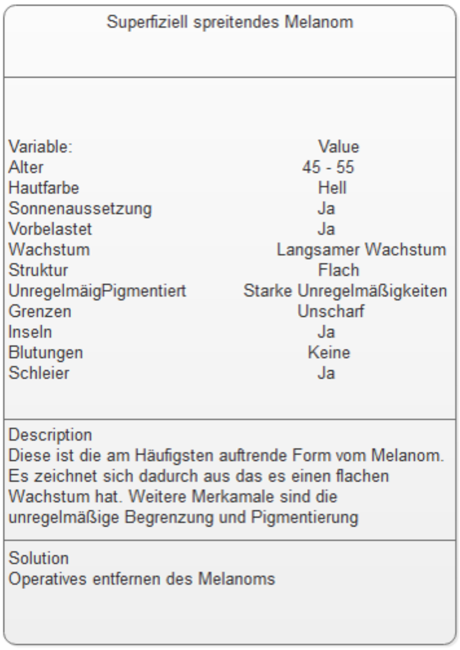


Fig. E.4 Case example of CBMelanom [28][191].

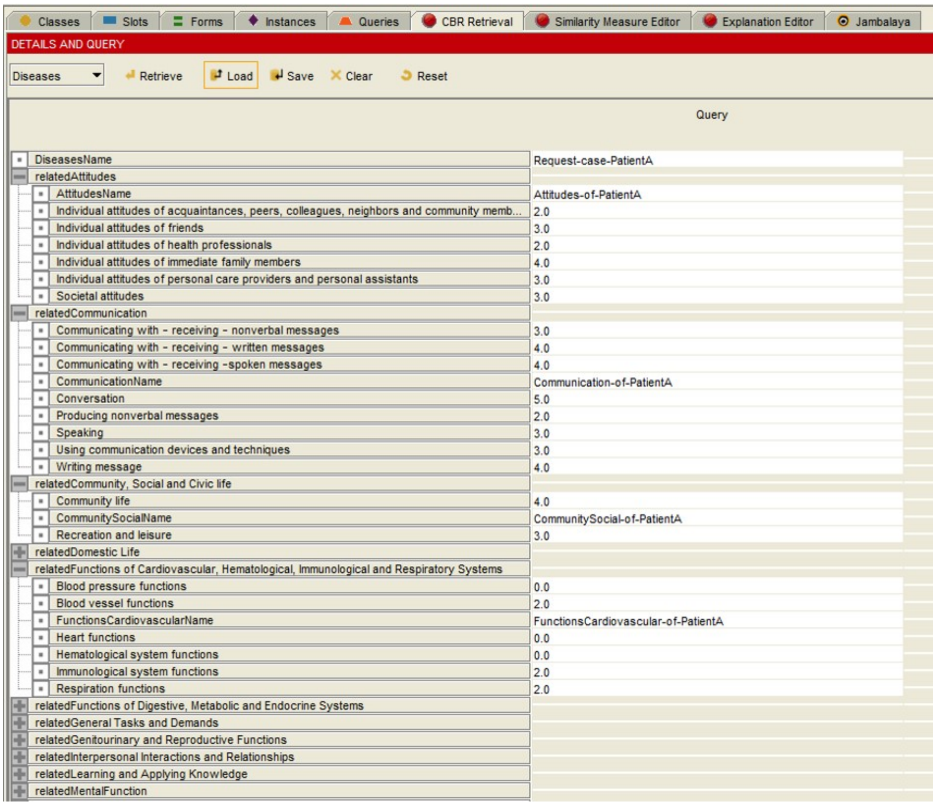


Fig. E.5 Case query of DePicT Dementia Onto-CLASS.

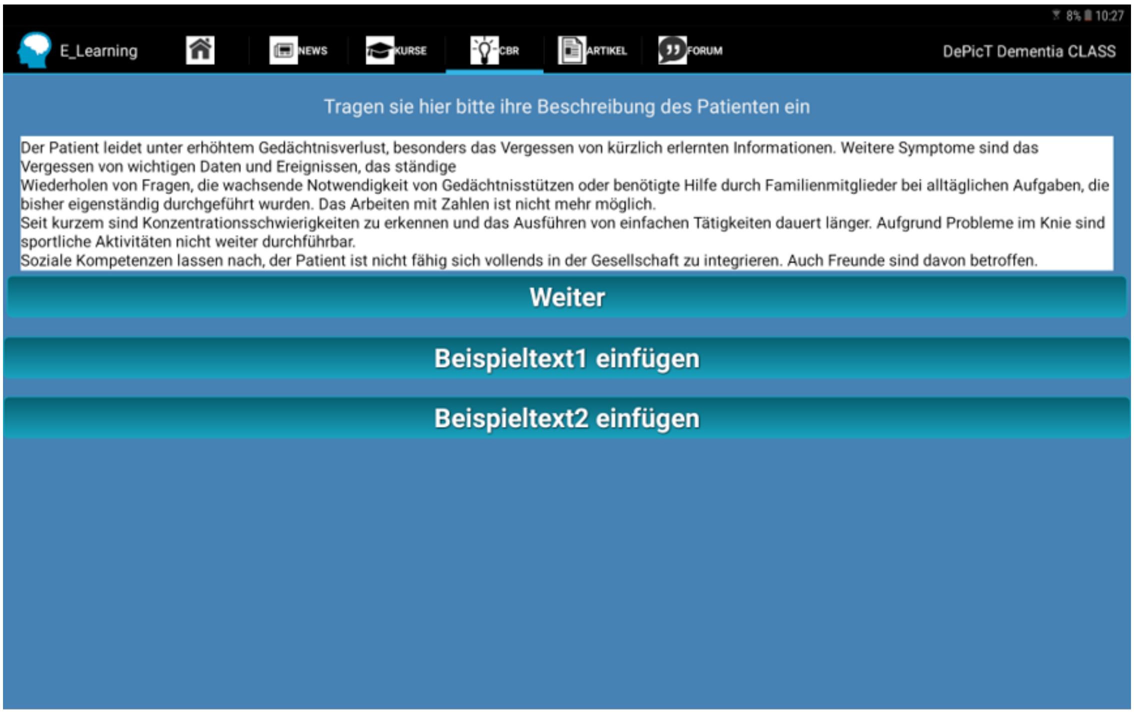


Fig. E.6 DePicT Dementia CLASS APP -User view: inserting input and selecting similarity measure.

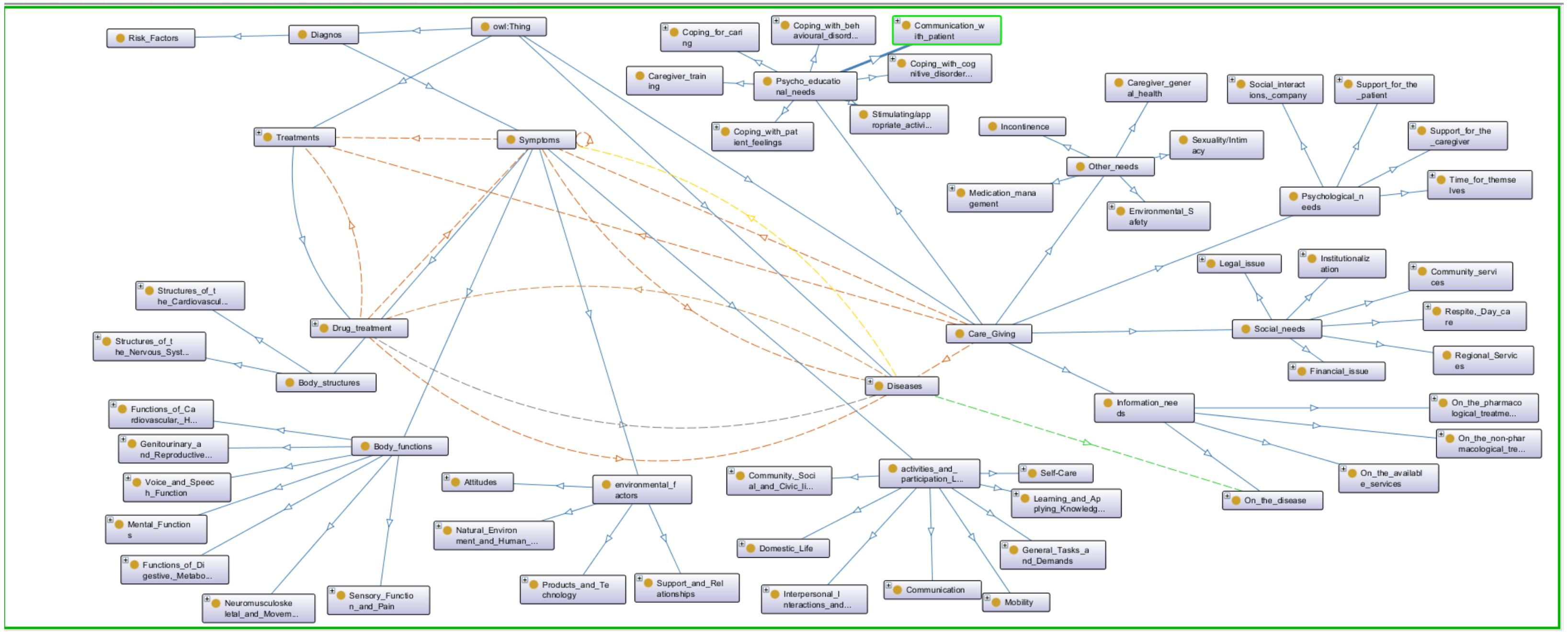


Fig. E.7 DePicT Dementia Onto-CLASS – OntoGraf.

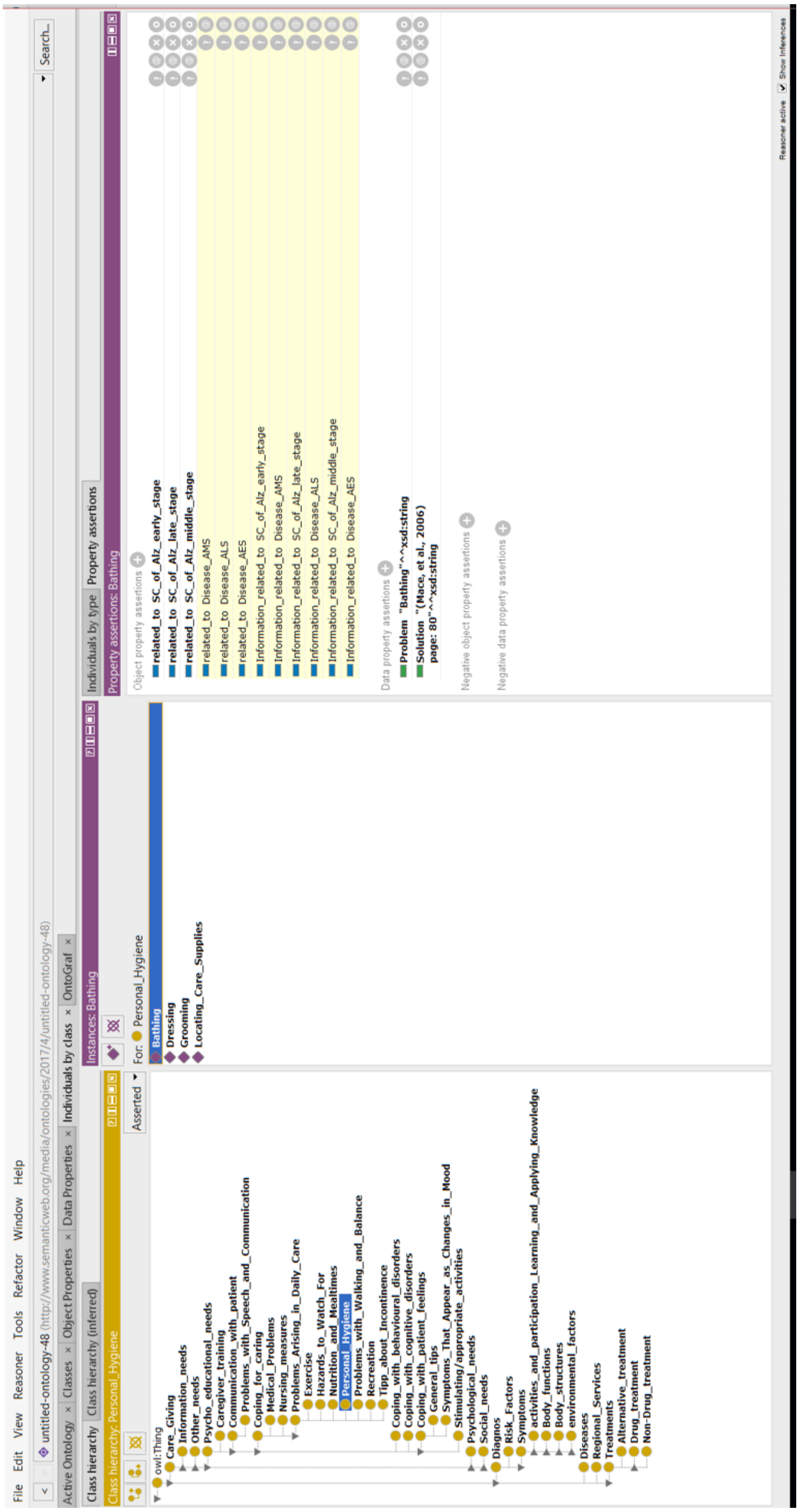


Fig. E.8 DePicT Dementia Onto-CLASS – Reasoning sample.