

ADDIS ABABA UNIVERSITY
COLLEGE OF GRADUATE STUDIES
SCHOOL OF INFORMATION SCIENCE

APPLICATION OF CASE-BASED REASONING FOR
ANXIETY DISORDER DIAGNOSIS

GETACHEW WASSIE

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DISORDER DIAGNOSIS

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Names and Signature of Members of the Examining Board

_____	_____
Chair person, Examining Board	Signature
_____	_____
Advisor	Signature
_____	_____
Examiner	Signature

DEDICATION

I would like to dedicate this thesis to my Dad and Mom.

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First and foremost I would like to thank God and Holy Mother who made all things possible, and granted me success in my thesis work and entire journey.

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LIST OF ACRONYMS

AI – Artificial Intelligence

AMDDKBS – Anxiety Mental Disorder Diagnosis Knowledge-Based System

APA – American Psychiatric Association

CBR – Case-Based Reasoning

CBRSADD – Case-Based Reasoning System for Anxiety Disorder Diagnosis

CBRSADD- Case-based Reasoning System for Anxiety Disorder Diagnosis

CSV – Comma Separated Value

DSM – IV – Diagnostic and Statistical Manual 4th edition

DSM-V - Diagnostic and Statistical Manual 5th edition

GUI: Graphic User Interface

jCOLIBRI – java Cases and Ontology Libraries Integration for Building Reasoning
Infrastructure

SF- Similarity Function

SSRIs - Selective Serotonin Reuptake Inhibitors

TCAs - Tetracyclic Antidepressants

WFMH – World Federation for Mental Health

WHO – World Health Organization

WHO-AIMS - World Health Organization Assessment Instrument for Mental Health Systems

ABSTRACT

Medical domains have been an application domain of choice for Artificial Intelligence since its founding years in expert systems. The reason for this application is the knowledge complexity presented by the domain, as well as the leading industry market share of healthcare. The success of Artificial Intelligence in different healthcare applications resulted in the emergence of case-based reasoning. The main focus of this research is on application of case-based reasoning in the domain of mental health, specifically the application on a case-based reasoning system for anxiety disorder diagnosis. The main goal of this research is developing a prototype case-based reasoning system that can give decision support for anxiety disorder diagnosticians at a different level of expertise. Overcoming the limitations of a rule-based knowledge base system such as incremental learning and specific knowledge acquisition are the instigation of this research. To achieve the goal of this research the literature has been thoroughly reviewed from both Artificial Intelligence sub-field of case-based reasoning and mental health more specifically anxiety disorder diagnosis literature. For the implementation of the prototype, successfully solved cases are acquired from Amanuel Mental Specialized Hospital. In addition, the main parameters are identified in consultation with anxiety disorder experts. Then, the implementation of the prototype using jCOLIBRI case-based reasoning framework is realized. Finally, testing of the prototype case-based reasoning system is done to evaluate the performance of the system. The testing of the prototype is performed from two sides. The first one is testing in terms of precision and recall and registered 71% and 82% respectively. In addition to this, the average solution similarity using methods Leave One Out evaluator and Hold Out evaluation achieved performance of 73% and 75.5% respectively. The second one is the performance of the system is evaluated by the potential users' of the system and achieved 83.2% performance.

CHAPTER ONE

INTRODUCTION

1.1. Background

The application of Artificial Intelligence (AI) in the field of Medical Science can be classified into two: identification and treatment of physical diseases (cardiology, internal medicine, orthopedics) and mental disorders (psychology, psychiatry) (Schwartz et al., 1997).

There are many kinds of physical diseases and mental disorders throughout the world that affect human beings in different aspects. Mental disorder is one of those diseases that affect the mental health of individuals at different economic, educational and age levels. It is one of the most non-communicable diseases in the world, and it is one of the great invisible problems of developing societies (Paris et al., 2006). Currently, mental disorder becomes a major public health problem, and it makes a considerable independent contribution to the burden of disease worldwide (Tefera et al, 2004; WFMH, 2010). However, the provision of mental healthcare is one of the most under resourced and neglected health services (WHO-AIMS, 2009).

Mental disorder refers to problems within the brain and mind that cause severe and unusual changes or problems with feelings, behaviors and senses, thoughts, understanding of events and the ability to communicate with other people (Korhonen & Marja, 2006). Additionally, mentally sick people are liable for other diseases like HIV, TB, diabetes, cardiovascular diseases, cancer, respiratory diseases (WFMH, 2010). Due to this, people with these disorders are often subjected to social isolation, poor quality of life, low achievement or success and increased mortality. Mental disorders touch the lives of everybody at different age levels, economic level and educational status. Mental disorders affect the social relationships, education, work efficiency, quality of life, and productivity of individuals.

Mental health professionals classify mental disorders into different categories based upon their similarity in their symptoms and syndromes. According to APA (2000) classification, there are sixteen mental disorder categories. Some of these are anxiety disorders, mood disorders,

psychotic disorders, personality disorders, substance-induced disorders, adjustment disorders and somatoform disorders.

Among these, anxiety disorders are the major neurological disorders that prevalently occurred generally throughout the world, particularly, in developing countries like Ethiopia (Ashenafi et al, 2001; Derek, 2008). As Ashenafi et al. (2001), Atalay et al. (2006), Derek (2008) and Menelik (2008) stated these disorders are occurring in all ages of people in Ethiopia. So, this research focuses on anxiety disorder diagnosis using case-based reasoning (CBR) technique.

Nowadays, there is an increasing appreciation of the role that computers are playing to improve the overall health delivery system. Specifically, knowledge-based systems play a great role in Medicine (Kalogeropoulos et al, 2002). There are a number of intelligent systems developed by different researchers for decision support system for health professionals.

Since the time when the implementation of MYCIN (Shortliffe, 1976) many of the early AI systems attempted to apply rule-based systems in developing computer-based diagnosis systems. Conversely, for a broad and complex medical domain, the effort of applying a rule-based system has encountered several problems (Ahmed et al., 2008). Some of the preliminary criteria for implementing a rule-based system are that the problem domain should be well understood, constant over time and the domain theory should be strong (Ahmed et al., 2008). For example, in psychophysiology, the diagnosis of stress is so difficult that even an experienced clinician might have difficulty in expressing his knowledge explicitly (Ahmed et al., 2008). As Ahmed et al. (2008) indicate that large individual variations and the absence of general rules make it difficult to diagnose stress and predict the risk of stress-related health problems. On the other hand, CBR works well in such domains where the domain knowledge is not clear enough i.e. weak domain theory (Ahmed et al., 2008). In rule-based systems, given the specific characteristics of physical diseases, specialized systems were widely used for this field, since the clinical symptoms indices are easily expressed in numeric values (clinical exams, temperature, blood pressure, heartbeat), making the sanity standard's deviation measurable (Schwartz et al., 1997). Besides, the combination of the symptoms and their respective values, according to rules progressively more defined, is decisive in establishing the final diagnosis, which cannot rescind the physician's direct appreciation and observation (Schwartz et al., 1997).

Several systems were developed employing different techniques, in the attempt to improve the quick and safe establishment of a diagnosis (Rich & Knight, 1994; Turner, 1992): MYCIN, INTERNIST-1 /CADUCEUS, MDX, CASEY, MEDIC. The common features to all these systems are the manipulation of measurable symptoms and the existence, even if implicit, of a rule-based module. Nevertheless, on the mental health field, similar systems haven't been applied, basically for two reasons (Schwartz et al., 1997). The first reason occurs in designing a diagnostic system, because the difficulty in establishing precise values of symptoms; almost all symptoms in this medical field are merely observable, not measurable (e.g., fear, anxiety, aggressiveness, cruelty, shrinking from contact) (Schwartz et al., 1997). This means that the perception of these symptoms itself implies a subjective attitude of the observer (in this case, the psychologist or psychiatrist). The professionals in this area choose to register only the existence or absence of a certain symptom in a patient, at times assigning fuzzy values (severe or medium perceivable sign) (Schwartz et al., 1997). The second reason arises from the fact that the same symptom can appear in different contexts leading to different diagnosis.

In Ethiopia, Seblewongel (2011) developed a prototype knowledge base system using rule-based technique called Anxiety Mental Disorder Diagnosis Knowledge-Based System (AMDDKBS). To enhance the performance of AMDDKBS, Seblewongel (2011) recommended that hybrid strategy approaches should be investigated, which combines CBR that helps the system to learn from documented experiences.

1.2. Statement of the Problem and its Justification

It is obvious that provision of healthcare services is a major challenge for most developing countries. Some of these challenges are lack of highly qualified medical human resources, financial as well as the ability to manage and transform scarce resources to meet healthcare needs (WHO-AIMS, 2009). Studies indicate that mental disorder is a serious health problem in developing countries (Ashenafi et al, 2001; Derek, 2008). Ethiopia is one of the developing countries, which is exposed to mental disorder problems (WHO, 2005; Abebaw et al, 2007). Mental health is the basic and serious health problem in the country (Dereje & Atalay, 1999;

Tefera et al, 2008; Yeup et al, 2008). Among the different mental health problems the one that is the most prevalent in Ethiopia is anxiety disorder which mostly attacks the youngsters and the most productive portion of the population.

Financial resources for mental healthcare in Ethiopia are extremely inadequate (WHO, 2006). In the country, mental health often receives low priority and gets limited resources (WHO, 2006). Financial resources, which are allocated for mental healthcare, are very few. Mental health spending in the country is less than 1% of the total health budget (WHO-AIMS, 2009). As a result, mental health services in Ethiopia holdup behind other health services (WFMH, 2010). In Ethiopia, Amanuel Mental Specialized Hospital is the only specialized hospital for inpatient and outpatient services for all mental illness and related problems (WHO, 2006). Almost all mental health professionals are residing in this hospital (WHO, 2006). Some other hospitals like St.Paulos Hospital and Zewuditu Hospital are giving some outpatient services but in most of such kinds of hospitals, experts work as part-time workers (WHO, 2005).

Shortage of psychologists and psychiatrists, their unfair distribution and lack of knowledge among primary healthcare workers are the main challenges that become an obstacle to address mental health services satisfactorily throughout the country (WHO, 2006; WHO-AIMS, 2009). In the majority of primary healthcare institutions, there are no highly qualified mental health professionals. Primary healthcare workers do not have good and enough knowledge for diagnosing mental disorders. Due to this, in most of the primary healthcare sectors mental disorder patients may not get the appropriate treatment. This is because of the lack of knowledge among primary healthcare workers and general practitioners. Not all clinicians are competent diagnosticians of mental disorders (WHO, 2006; WHO-AIMS, 2009). So, mental disorder patients are exposed to misdiagnose by primary healthcare workers and non-mental health workers. Additionally, as WHO (2006) and Yeshashwork (2010) indicated that there is no awareness about mental disorder within the community

To tackle the above mentioned problems, Seblewongel (2011) developed a knowledge-based system using rule-based system for anxiety disorder diagnosis and she achieved 85% accuracy using predictive validation technique even though the system has its own limitations.

Different researchers developed several systems employing diverse techniques, in the attempt to improve a quick and safe establishment of a diagnosis (Rich & Knight, 1994; Turner, 1992). But, the common features to all the systems are the manipulation of measurable symptoms and the existence, even if implicit, of a rule-based module. Nevertheless, in the mental health field, similar systems haven't been applied, mainly for two reasons: difficulty in establishing symptoms and their values and strong interaction among the symptoms, and the second reason arises from the fact that the same symptom can appear in different contexts leading to different diagnosis (Schwartz et al., 1997). On the other hand, CBR works well in such domains where the domain knowledge is not clear enough i.e. weak domain theory (Ahmed et al., 2008). Almost all mental illness are not measurable but they are observable (fear, anxiety, aggressiveness, cruelty, shrinking from contact). So, Seblewongel (2011) in her research recommended that CBR approach should be investigated to enhance the performance of AMDDKBS. But, Seblewongel's work has different limitations such as knowledge acquisition and self-learning capability.

Furthermore, CBR systems can learn automatically which is very important as the medical domain is evolving with time (Ahmed et al., 2008). Ahmed et al. (2008) presented that rule-based systems cannot learn automatically as new rules are usually inserted manually. In addition, CBR minimizes the task of knowledge acquisition and can solve problems using specific knowledge. Therefore, this study attempts to develop a prototype CBR system that can use previous patient history of Amanuel Mental Specialized Hospital anxiety disorder patients to diagnose new patients.

To the best of the researchers' knowledge, there is no research that applies CBR for anxiety disorder diagnosis. So, in this study an attempt has been made to apply CBR for anxiety disorder diagnosis.

To this end, this study will explore and answer the following research questions.

1. Can CBR overcome the problems of rule-based reasoning, especially the learning component and knowledge acquisition?
2. How much is the prototype accepted by the domain experts during evaluation of the system?

1.3. Objective of the Study

The research has both general and specific objectives as stated below.

1.3.1. General Objective

The main objective of this study is to design and develop a prototype CBR system for diagnosing patients with anxiety disorder in order to provide advice to domain experts and enhance services given to patients.

1.3.2. Specific Objectives

The following are the specific objectives that will be achieved in the course of the study along with the general objective.

- To review different global and local researches that can help for the successful completion of the study.
- To acquire anxiety disorder knowledge from experts and documents and model the acquired knowledge using appropriate modeling technique.
- To build a prototype CBR system for anxiety disorder diagnosis.
- To test the performance and user acceptance of the prototype.
- To recommend further research based on the conclusion drawn at the end of the study.

1.4. Scope of the Study

Due to different factors such as limitation of time and resources, the scope of the study is restricted only at Amanuel Mental Specialized Hospital. The other reason for limiting the research area at this hospital is, since there is no knowledge source other than this hospital in Ethiopia. Almost all mental health professionals are working in this hospital. For prototype development only anxiety disorder symptoms are used. During testing and evaluation of the prototype, only Amanuel Mental Specialized Hospital anxiety disorder case team members are involved.

The extent to which the prototype is used by the anxiety disorder experts is that the experts are not recommended to use the retrieved solutions automatically; instead they have to adapt the

retrieved solution in a way that fit to the new problem at hand. Patients may use the prototype for self-help and treatment strategy but, they are not allowed to prescribe medications using the system.

1.5. Significance of the Study

From this study, primary healthcare workers and mental health professionals, specifically the inexperienced mental health professionals are the immediate beneficiaries to enhance their day to day activities. The prototype has great significance to teach primary healthcare workers, general reactionaries and psychiatry nurses in order to have well understanding about anxiety disorders. As a result, those health workers can use the system in diagnosing anxiety disorder in primary healthcare sectors where highly qualified mental health professionals are unavailable. The developed prototype CBR system is used to give advising services for diagnosing patients with anxiety disorder. The CBR system is developed using the knowledge of multiple mental health domain experts and documentary sources which is used as organizational memory. Therefore, it gives better advisory services where highly qualified mental health professionals are not found.

1.6. Methodology

To realize the main goal of this study, different methods and techniques are used.

1.6.1. Literature Review

For the successful completion of this study, different global and local researches have been thoroughly reviewed starting from the beginning of the study until its completion. Journal articles, proceedings, conference papers, manuals, reports and books are reviewed for achieving the research objective.

1.6.2. Method of Data Collection

In this study to acquire the needed knowledge, primarily documented anxiety disorders patient diagnosis history is used from Amanuel Mental Specialzed Hospital. In addition, knowledge is gathered from mental health professionals, psychiatrists and psychologists at Amanuel Mental Specialized Hospital by using interviewing. To elicit knowledge from domain experts, both structured and unstructured interview have been used. Structured interview is used for questions

that have predefined answers (both closed questions and listing of items). Whereas unstructured interview is used when a question needs explanation and even the interviewee can add his/her own questions that are expected to be important to the research. All the acquired knowledge is verified in consultation with the domain experts.

The main data source for this study is previously solved anxiety disorder patient cases of Amanuel Mental Specialized Hospital. The cases are available in hardcopy form. These cases are entered in to a computer through the assistance of a professional psychiatry nurse.

1.6.3. Sampling Technique and Sample Size

Purposive sampling technique is used to collect previous anxiety disorder patient cases archived in Amanuel Mental Specialized Hospital, because there is no knowledge source other than this hospital in Ethiopia. Even the domain experts are selected purposefully based on the profession or expertise, educational qualification, experience and their respective position in anxiety disorder diagnosis. Three experts are consulted in the course of the study and one psychiatry nurse is involved in the registration of the patient cases from the card. 50 patient cases are used for prototype development and experimentation. There is no standard number of cases to be used for CBR system development. For example, Ethiopia (2002), Yemisrach (2009), Alemu (2010) and Henok (2011) used cases 39, 40, 51 and 45 respectively for building and testing their prototype. The main reason for taking only 50 anxiety disorder cases is all the records are available on paper in free text format. Even, the cases are mixed with other patient cases. Consequently, extracting the features and identifying the anxiety patient records needs professional knowledge and sufficient time. Therefore, these factors limit the number of records to be used in this research.

1.6.4. Case Representation, Indexing, Selection and Retrieval

For this research, the acquired cases are represented using one of the different case representation methods that are appropriate for the researcher. Among the different case representation methods, feature-value case representation method is used. Other case representation methods like relational database case representation, predicate based representation and soft computing case representation methods have their own advantages and disadvantages. But, for this study feature-value representation method is appropriate. The reason

for representing cases using feature-value representation is that this approach supports nearest neighbor retrieval algorithm and it represents cases in an easy way (Salem et al., 2005; Bergmann et al., 2005). In addition to representation of cases, case indexing is another important issue in CBR systems to facilitate the retrieval of cases.

Cases are selected and retrieved in a ranked order based on their similarity for the given new case query. There are different case retrieval algorithms that different CBR systems used as discussed in section 2.3 of this research. For this research nearest neighbor retrieval algorithm is used to measure the similarity of input case with cases in the case base.

1.6.5. Implementation Tool

Nowadays, there are two important CBR implementation frameworks available for free for teaching and academic research. These are myCBR which is developed by German Research Center for Artificial Intelligence and jCOLIBRI which is developed by Group of Artificial Intelligence Applications (GAIA). Both tools have their own capabilities and limitations. For example, the main limitations of myCBR are:

- Does not support full CBR cycles (only Retrieval and Retain are supported).
- Does not work with external database.
- Applicable for simple CBR applications.

For this research jCOLIBRI CBR Framework is selected based on the following unique capabilities.

- jCOLIBRI supports the full CBR cycles (Retrieval, Reuse, Revise and Retain as discussed in section 2.3 of this research)
- Suitable for developing large scale applications.
- jCOLIBRI is extensible, reusable, different types of users and different purposes (development, research and/or teaching), compatible with commercial applications and, supporting different types of CBR systems, since it is just a .jar file suitable for web applications.
- jCOLIBRI works well in external database.

1.6.6. Testing Procedure

Once the CBR prototype is developed, it is been tested its functionality and user acceptance of the system. The actual users (domain experts) tested the prototype using representative test cases. Then the performance of the system was evaluated by taking the following parameters into consideration: The users' feedback, regarding:

- The relevance of the information retrieved (how similar the cases stored in the case base to the case at hand).
- The relevance of the fields (attributes) in the case structure.
- The ease of use of the system, in terms of the entry and output forms layout and level of detail.

Cases average similarity is used to evaluate the performance of the CBR prototype system. The methods used to test the average solution similarity are Leave One Out evaluator and Hold Out evaluator. Leave One Out evaluation method uses all the cases as queries. It executes so many cycles as cases in the case base. In each cycle one case is used as a query. Hold Out evaluator evaluation method splits the case base in two sets: one used for testing where each case is used as a query, and another that acts as a normal case base. This process is performed several times. In addition to this, the standard measures of relevance in the information retrieval (precision and recall) have been used to evaluate the performance of the prototype.

1.7. Organization of the Thesis

This section of the research summarizes the overall contents of the thesis.

Chapter 1: Introduction - In this chapter the researcher tries to discuss the background of the study, a statement of the problem with its justification, objective of the study, the scope of the study, the significance of the study and the methodologies used to conduct the research.

Chapter 2: Literature Review - This chapter mainly focuses on the review of literature. In this section, the conceptual discussion of CBR mainly focuses on the definition of CBR, CBR life cycles, CBR techniques, CBR tools, CBR performance evaluation methods and application of the CBR system in the medical domain specifically in mental health.

Chapter 3: Knowledge Acquisition and Modeling - This chapter presents the knowledge acquisition process, identification of major parameters, conceptual discussion of the acquired knowledge and conceptual modeling of the acquired knowledge.

Chapter 4: Design and Implementation - In this chapter the design and implementation of the prototype are realized. The architecture of the new prototype CBR system for anxiety diagnosis is developed. The implementation tool used is jCOLIBRI version 1.1.

Chapter 5: Testing and Performance Evaluation of the Prototype – In this chapter the performance of the prototype is evaluated both the performance of the system and the acceptance of the system by the users. In addition, the functionality of all the CBR cycles is tested.

Chapter 6: Conclusion and Recommendation - The last chapter of this thesis. In this chapter the main findings are summarized and based on the findings, recommendations are proposed for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

The aspiration for computer systems being able to support human experts during complex problem-solving task is a usual topic of AI research. In order to enable a computer system to give rational support when solving problems in a complex application domain, it is essential to provide it with specific knowledge within that domain. A number of methodologies to realize such knowledge knowledge-based systems have been developed, such as, rule-based approach. In recent years, CBR has become a very popular technique for developing knowledge-based systems that can give rational support using specific knowledge. In some real-world application domains, it has even emerged to one of the commercially most successful approaches compared to other techniques developed in AI research such as rule-based systems. Using CBR, different applications have been developed yet, to solve problems in different domains. CBR is useful for a wide variety of problem-solving tasks, including classification, planning, diagnosis, design and decision support (Kolodner, 1992; Lenz, et al, 1998).

The previous chapter to this study discussed the problem that has to be investigated by this study, and the methodology used for the successful completion of the study. This chapter provides a conceptual discussion of CBR, application of CBR in the medical domain more specifically in mental health and gives a highlight about related researches to the study.

2.2. Case-based Reasoning

CBR is a set of new theory and research method developed by the domain of AI in 1977 by Schank and Abelson (Schank & Abelson, 1977). The field of CBR, which has a relatively young history, arose out of the research in cognitive science (Richterandv & Aamodt, 2005; Pal & Shiu, 2004). CBR (Kolodner 1993; Aamodt & Plaza, 1994) is an AI technique to support the capability of reasoning and learning in advanced decision support systems. Specifically, it is a reasoning paradigm that exploits the specific knowledge collected on previously encountered and solved situations, which are known as cases. According to Kolodner (1993), CBR means

reasoning from experiences or old cases in an effort to solve problems, critique solutions, and explaining inconsistent situations. Instead of modeling a complete domain theory, for example, by using rules, CBR exploits single situation-specific knowledge chunks called cases, which are easier available than generalized knowledge about the domain. In the traditional sense of problem-solving, a case represents a particular problem with a corresponding solution.

CBR is a problem-solving approach that makes use of previous, similar situations and reuses information and knowledge about such situations (Kolodner, 1993). Basically, CBR technology is a reasoning procedure or framework instead of a specific algorithm (Watson, 1999). It uses different technologies and algorithms to solve problems. Hence, as long as the practical measure proposed meets the requirements of CBR, it is a CBR solution.

CBR is a problem solving paradigm that in many respects is fundamentally different from other major AI approaches (Aamodt & Plaza, 1994). CBR, instead of relying solely on general knowledge about a problem domain, or making associations along generalized relationships between problem descriptors and conclusions, it can utilize the specific knowledge of previously experienced, concrete problem situations. A new problem is solved by finding a similar past case, and reusing it in the new problem situation. A second important difference is that CBR has also been an approach to be incremental, sustained learning, since a new experience is retained each time a problem has been solved, making it immediately available for future problems. The CBR field grew rapidly over the last few years, as seen by its increased share of papers at major conferences, available commercial tools, and successful applications in daily use.

A case-based reasoner will be presented with a problem, either by a user or by a program or system (Pal & Shiu, 2004). The case-based reasoner then searches its memory of past cases (called the case base) and attempts to find a case that has the same problem specification as the case under analysis. If the reasoner cannot find an identical case in its case base, it will attempt to find a case or multiple cases that most closely match the current case.

In situations where a previous identical case is retrieved, assuming that its solution was successful, it can be offered as a solution to the current problem. In the more likely situation that the case retrieved is not identical to the current case, an adaptation phase occurs. During adaptation, differences between the current and retrieved cases are first identified and then the

solution associated with the case retrieved is modified, taking these differences into account. The solution returned in response to the current problem specification may then be tried with the appropriate domain setting.

The structure of a CBR system is usually devised in a manner that reflects separate stages. However, at the highest level of abstraction, a CBR system can be viewed as a black box that incorporates the reasoning mechanism and the following external facets (Pal & Shiu, 2004):

- The input specification or problem situation
- The output that defines a suggested solution to the problem
- The memory of past cases, the case base, that are referenced by the reasoning mechanism

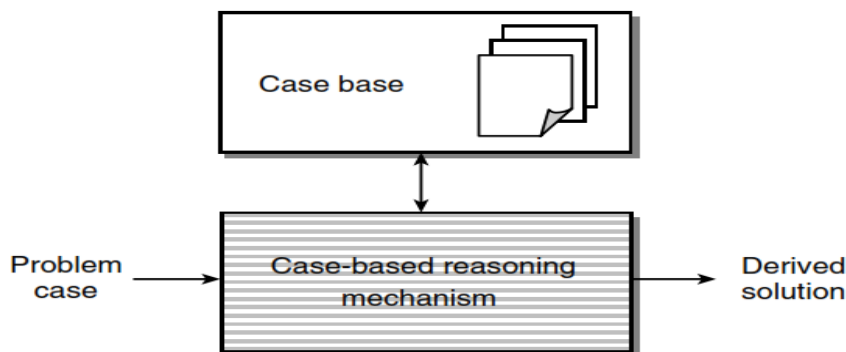


Figure 2.1: CBR System (Pal & Shiu, 2004)

In most CBR systems, the CBR mechanism, alternatively referred to as the problem solver or reasoner, has an internal structure divided into two major parts: the case retriever and the case reasoner (Pal & Shiu, 2004). The case retriever's task is to find the appropriate cases in the case base, while the case reasoner uses the cases retrieved to find a solution to the problem description given. This reasoning process generally involves both determining the differences between the cases retrieved and the current case, and modifying the solution to reflect these differences appropriately. The reasoning process may or may not involve retrieving additional cases or portions of cases from the case base.

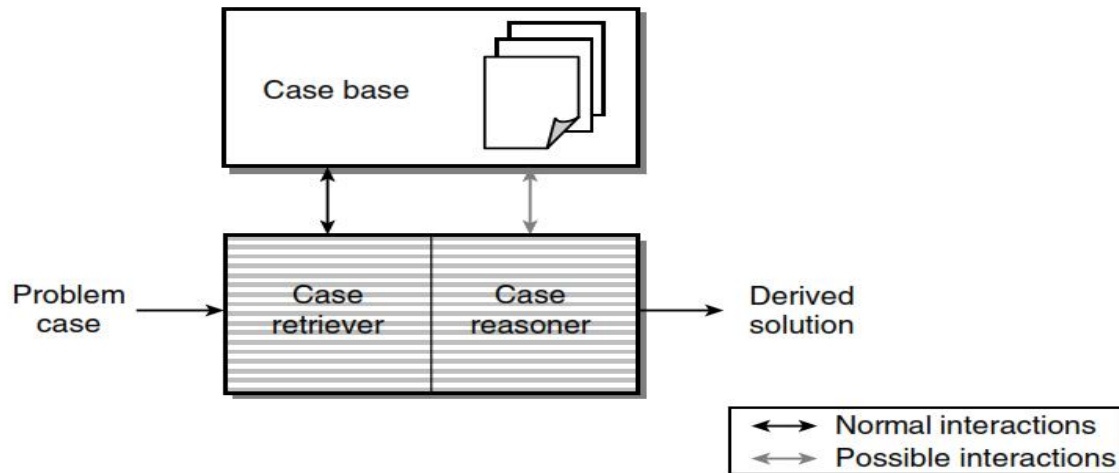


Figure 2.2: The Major Components of the CBR System (Pal & Shiu, 2004)

2.2.1. CBR System versus Rule-Based System

The approach of CBR can be contrasted with that used in other knowledge-based systems, such as rule-based or combined frame-rule-based systems. In rule-based systems, one has a rule-base consisting of a set of production rules of the form: IF X, THEN Y, where X is a condition and Y is an action. If the condition X holds true, the action Y is carried out. Condition X can be a composite condition consisting of, say, a conjunction of premises X1; X2; ...; Xn. In addition, a rule-based system has an inference engine that compares the data it holds in working memory with the condition parts of rules to determine which rules to fire.

The use of production rules for solving problems demands rule-based reasoning. Rule-based reasoning is the process of drawing conclusions by linking together generalized rules, starting from scratch (Leake, 1996). According to Kolodner (1993), although some rules are very specific, the goal of rule-based reasoning is to formulate rules that are generally applicable. An important advantage of rules, in general, is the economy of storage they allow (Kolodner, 1993). Conversely, the following are some disadvantages of rule-based reasoning (Eshach & Bitterman, 2003):

- **The problem of applicability.** In rule-based reasoning, bringing some general piece of knowledge to solve a specific problem situation is too difficult. When rules are expressed

too abstractly, the terms tend to be unintelligible to the novice and tend to mean a variety of specific things to the expert.

- **Ill-defined domains or domains which have weak domain theory.** In domains that are not completely understood, the rules do not encompass all the situations they are asked to cover or are assumed to cover, may admit tacit exceptions, or can be contradicted and negated by other rules.
- **The limitation of mental capacity.** Rule-based reasoning requires that the problem solver takes into account all the domain rules. However, in many real-life situations the problem solver is not capable of doing that, under the pressure of time, as the number of rules required for solving a problem may be unmanageably large (Leake, 1993).

Subsequently, these shortcomings in rule-based reasoning based knowledge base has given rise to the idea of development of CBR (Alterman, 1989) based knowledge base.

CBR systems are an alternative, in many situations, to rule-based systems. In many domains and processes, referring to cases as a means of reasoning can be an advantage due to the nature of this type of problem solving (Pal & Shiu, 2004). One of the most time consuming aspects when developing a rule-based system is the knowledge acquisition task. Acquiring domain-specific information and converting it into some formal representation can be a huge task and in some situations, especially those with less well understood domains, formalization of the knowledge cannot be done at all. Case-based systems usually require significantly less knowledge acquisition, since it involves collecting a set of past experiences without the added necessity of extracting a formal domain model from these cases. In many domains there are insufficient cases to extract a domain model, and this is another benefit of CBR. A CBR system can be created with a small or limited amount of experience and then developed incrementally, adding more cases to the case base as they become available.

According to Prentzas and Hatzilygeroudis (2007) and Pal and Shiu (2004) the major advantages of CBR from various points of view discussed as follows.

- **Reducing the knowledge acquisition task.** By eliminating the need to extract of a model or a set of rules, as is necessary in model/rule-based systems, the knowledge acquisition tasks of CBR consist primarily of the collection of relevant existing experiences/cases

and their representation and storage. Usually cases are available in different application domains.

- **Avoiding repeating mistakes made in the past.** In systems that record failures as well as successes, and perhaps the reason for those failures, information about what caused failures in the past can be used to predict potential failures in the future.
- **Providing flexibility in knowledge modeling.** Due to their rigidity in problem formulation and modeling, model-based systems sometimes cannot solve a problem that is on the boundary of their knowledge or scope or when there is missing or incomplete data. In contrast, case-based systems use past experience as the domain knowledge and can often provide a reasonable solution, through appropriate adaptation, for these types of problems.
- **Reasoning in domains that have not been fully understood, defined, or modeled.** In a situation where insufficient knowledge exists to build a causal model of a domain or to derive a set of heuristics for it, a case-based reasoner can still be developed using only a small set of cases from the domain. The underlying theory of domain knowledge does not have to be quantified or understood entirely for a case-based reasoner to function.
- **Making predictions about the probable success of a given solution.** When information is stored regarding the level of success of past solutions, the case-based reasoner may be able to predict the success of the solution suggested for a current problem. This is done by referring to the stored solutions, the level of success of these solutions, and the differences between the previous and current contexts of applying these solutions.
- **Learning over time.** As CBR systems are used, they encounter more problem situations and create more solutions. If solution cases are tested subsequently in the real-world and a level of success is determined for those solutions, these cases can be added to the case base and used to help in solving future problems. As cases are added, a CBR system should be able to reason in a wider variety of situations and with a higher degree of refinement and success.
- **Reasoning in a domain with a small body of knowledge.** While in a problem domain for which only a few cases are available, a case-based reasoner can start with these few known cases and build its knowledge incrementally as cases are added. The addition of

new cases will cause the system to expand in directions that are determined by the cases encountered in its problem-solving endeavors.

- **Reasoning with incomplete or imprecise data and concepts.** As cases are retrieved, they may not be identical to the current case. Nevertheless, when they are within some defined measure of similarity to the present case, any incompleteness and imprecision can be dealt with by a case-based reasoner. Although these factors may cause a slight degradation in performance, due to the increased disparity between the current and retrieved cases, reasoning can continue.
- **Providing a means of explanation.** CBR systems can supply a previous case and its (successful) solution to help convince a user of, or to justify, a proposed solution to the current problem. In most domains there will be occasions when a user wishes to be reassured about the quality of the solution provided by a system. By explaining how a previous case was successful in a situation, using the similarities between the cases and the reasoning involved in adaptation, a CBR system can explain its solution to a user. Even for a hybrid system, one that may be using multiple methods to find a solution, this proposed explanation mechanism can augment the causal (or other) explanation given to a user.
- **Extending too many different purposes.** The number of ways in which a CBR system can be implemented is almost unlimited. It can be used for many purposes, such as creating a plan, making a diagnosis, and arguing a point of view. Therefore, the data dealt with by a CBR system are able to take many forms, and the retrieval and adaptation methods will also vary. Whenever stored past cases are being retrieved and adapted, CBR is said to be taking place.
- **Extending to a broad range of domains.** CBR can be applied to extremely diverse application domains. This is due to the seemingly limitless number of ways of representing, indexing, retrieving, and adapting cases.
- **Reflecting human reasoning.** As there are many situations where we, as humans, use a form of CBR, it is not difficult to convince implementers, users, and managers of the validity of the paradigm. Similarly, humans can understand a CBR system's reasoning and explanations and are able to be convinced of the validity of the solutions they receive from a system. If a human user is wary of the validity of an earlier solution, they are less

likely to use this solution. The more critical the domain, the lower the chance that a past solution will be used and the greater the required level of a user's understanding and credulity.

2.3. CBR Cycle

At the heart of the system, CBR has been formalized for purposes of computer reasoning as a four-step process which are mostly called 4REs (Retrieval, Reuse, Revise and Retain) (Aamodt & Plaza, 1994).

2.3.1. Retrieval

In CBR, retrieval is remembering previous cases stored in the case base to solve new problems at hand. The first step which is the most important step in CBR cycle is retrieval of previous cases that can be used to solve the target situation (new problem). Given a target problem, retrieve cases from memory those are relevant to solving it. A case consists of a problem description, its solution, and typically annotations about how the solution was derived (Aamodt & Plaza, 1994). Since retrieval is the first step in CBR, it affects the whole CBR system because others cycles are based on it. The selection of corresponding useful cases is then left to the CBR system which retrieves cases to be used for solving the problem by employing so called similarity measures. To retrieve relevant cases to the target problem, appropriate similarity measurement should be used (Mantaras et al, 2005).

The first step is the retrieval of one or several cases considered to be useful to support solving the current problem. The hope is to retrieve one or several cases that contain solutions that can be easily reused in the current problem-solving context (Mantaras et al, 2005). Because it is usually very unlikely that the case base already contains a problem description that matches the new problem exactly, a method to estimate the utility of available cases is required. According to the basic CBR assumption (similar problems have similar solutions) and here the concept of similarity is used. This means, the task of the retrieval phase is to select cases whose problem descriptions are similar to the current problem's description. The underlying assumption is that these cases contain solutions being very similar to the searched, but still unknown solution of the current problem (Aamodt & Plaza, 1994; Mantaras et al, 2005).

To realize this retrieval task, CBR systems employ special similarity measures that allow the computation of the similarity between two problem descriptions. Because the interpretation of this similarity strongly depends on the particular domain, similarity measures are part of the general knowledge of the system.

Different researchers describe the main tasks during retrieval of cases. For example - Aamodt and Plaza (1994) grouped case retrieval subtasks into three:

- **Identify features.** Involves indexing the problem with the most descriptive feature in order to match it with indexed matched cases. In other words, it identifies its descriptive properties and takes out the properties which don't describe the problem strongly.
- **Initially match.** Finding previous cases that match with the problem at hand and it retrieves a set of plausible candidates. That means it involves searching and similarity assessment to produce similar cases.
- **Select.** Selecting the best-matched case from the set of similar cases. It is based on the similarity assessment result that best matched case or set of cases is selected as output of the retrieval process.

The other prominent author in CBR Kolodner (1992) subdivides the retrieving process into:

- **Recall previous cases.** The main goal of this step is to retrieve "good" cases that have the potential to make relevant predictions about the new case.
- **Select the best subset.** The objective of this step is to select the best cases from the result of the first step. Sometimes it is appropriate to choose one best case; sometimes a small set is needed.

The quality of the retrieval process depends on its descriptive feature identifying algorithm, searching algorithm and similarity assessment method. In CBR there are different case retrieval algorithms but the two most frequently used are nearest neighbor and induction case retrieval algorithms (Singh et al, 2007; Watson & Marir, 1994). These algorithms can be used alone or in combination with each other.

Nearest Neighbor Retrieval Algorithm

Nearest-neighbor retrieval technique is to measure similarity between the source case and the case which we are searching (Lang & Lau, 2002). The nearest neighbor algorithm

measures the similarity of stored cases with a new input case, based on matching a weighted sum of features (Kyung-Ho & Dongkon, 1999; Watson & Marir, 1994; Singh et al, 2007). When a new case doesn't exactly match with old cases then this algorithm will return nearest match from CBR library. It is suitable when there are attributes that have numeric (continuous) value (Fag & Songdong, 2007). But the retrieval time of this algorithm increases linearly as the case in the case base increases.

The algorithm for nearest neighbor is as follows (Salem et al, 2005):

For each feature in the input case
Find the corresponding feature in the stored case base
Compare the two values to each other and compute the degree of match
Multiply by a coefficient representing the importance of the feature to the match
Add the results to drive an average match score
This number represents the degree of match of the old case to the input.

The nearest neighbor algorithm can be represented in the following equation (Watson & Marir, 1994).

$$NN(I, R) = \frac{\sum_{i=0}^n w_i \times \text{sim}(f_i^I, f_i^R)}{\sum_{i=0}^n w_i}$$

Where:

w is the importance weighing of an attribute,

I is the target case,

R is source case

i is individual attributes from 1 to n ,

sim is the local similarity function, and

f_i^I and f_i^R are the values for attribute i in the input case (I) and case in the case base (R) respectively

n is the number of attributes in the case base.

Induction Retrieval

Depending on the size of the case base, the information amount contained in single cases, and the complexity of the used similarity measure, the retrieval step is often a challenging task with respect to computation time. In order to manage this complexity, a large number of different retrieval strategies have been developed (Wess et al, 1993; Schaaf, 1996; Schumacher & Bergmann, 2000).

In inductive retrieval, use past cases to extract rules or construct decision (Lang & Lau, 2002). This technique finds target case-based on index source case. Cases are divided into a decision tree structure. Inductive retrieval used to retrieve set of matched cases and then nearest-neighbor retrieval rank these cases according to their similarity with target case.

2.3.2. Reuse

After selecting one or several similar cases, the reuse step tries to apply the contained solution information to solve the new problem. Often a direct reuse of a retrieved solution is impossible due to differences between the current and the old problem situation. Then the retrieved solutions have to be modified in order to fit the new situation. How this adaptation is performed strongly depends on the particular application scenario (Wilke & Bergmann, 1998).

In general, adaptation methods require additional general knowledge about the application domain. Because this leads to additional knowledge acquisition effort, many CBR systems used today do not perform case adaptation automatically, but leave this task to the user. Then, of course, the quality of the retrieval step influences the problem-solving capabilities of the entire CBR system primarily. Even if automatic adaptation is provided, the qualities of the retrieval result will strongly influence the efficiency of the system due to its impact on the required adaptation effort.

After adapting the retrieved case automatically or manually to fit the current situation, a solved case is obtained containing a suggested solution for the current problem.

2.3.3. Revise

Depending on the employed adaptation procedure, the correctness of the suggested solution often cannot be guaranteed immediately. Then it becomes necessary to revise the solved case. How such a revision is performed, strongly depends on the particular application scenario. For example, it might be possible to apply the suggested solution in the real-world to see whether it works or not. However, often a direct application of an uncertain solution is impossible due to the corresponding risks (e.g. medical diagnosis systems). Then the revision has to be performed manually by a human domain expert or by alternative methods such as computer simulation. Usually, the focus of the revise phase lays on the detection of errors or inconsistencies in the suggested solution and the initiation of further problem-solving attempts (Aamodt & Palaza, 1994).

2.3.4. Retain

If the solved case has passed the revise step successfully, a tested/repaired case will be available representing a new experience that might be used to solve similar problems in the future. The task of the CBR cycle's last step is to retain this new case knowledge for future usage. Therefore, the new case may be added to the case base. In most cases, a general storage of all generated cases is not always useful. In order to enable better control of the retain process, various approaches for selecting cases to be retained have been developed (Aha, 1991; Smyth & Keane, 1995b; Leake & Wilson, 2000; Ferrario & Smyth, 2000; Reinartz et al, 2000). These approaches often imply a reorganization of the entire case base when adding a new case, for example, by removing other cases.

Generally, the capability to acquire new case knowledge during a CBR system's lifetime principally adds these systems to the class of learning systems. Conversely, many CBR systems developed so far do not exploit this concept of the CBR cycle at all. This holds true especially for the commercially employed systems. Further, the original idea of the CBR cycle focuses on learning case knowledge.

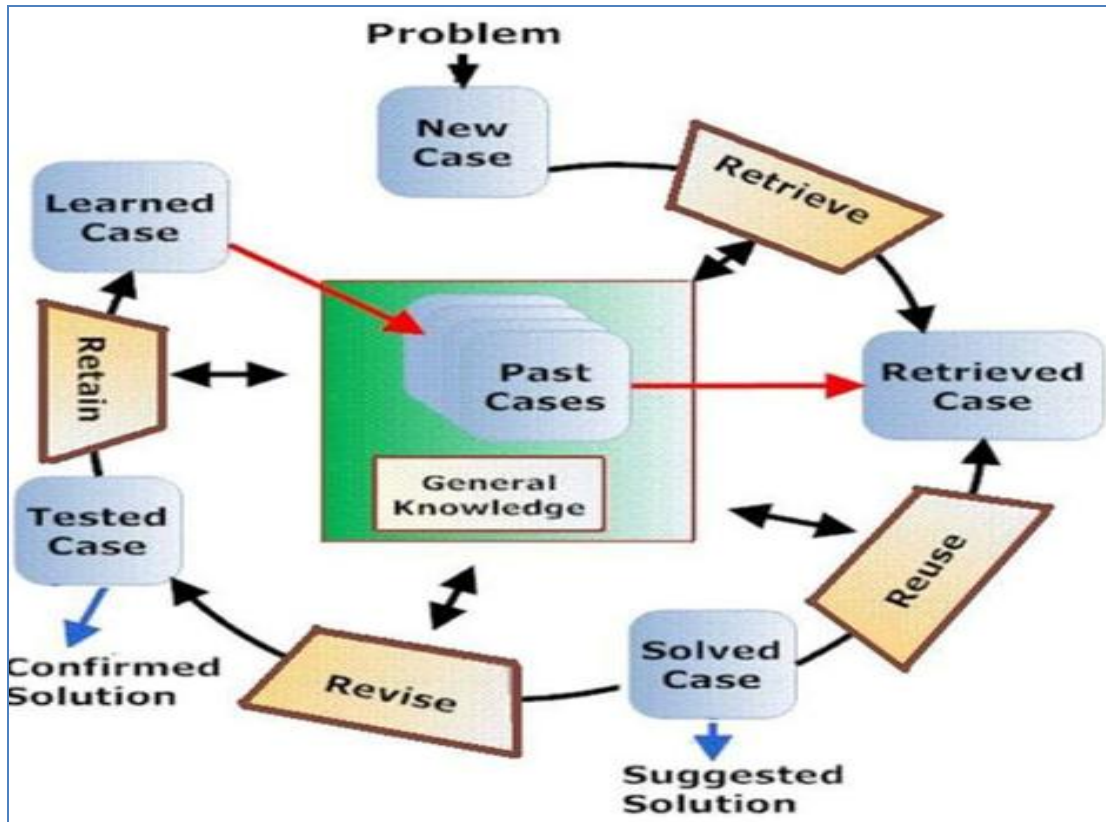


Figure 2.3: CBR Life Cycle Introduced by Aamodt and Plaza (1994)

2.4. CBR Techniques

CBR has different techniques (Aamodt & Plaza, 1994). Among these: Case Representation, Indexing, Storage, Retrieval and Adaptation are the commonly used techniques in any CBR research. Now, these techniques will be discussed briefly in the following subsections.

2.4.1. Case Representation

Case is a specific piece of knowledge representing an experience (Aamodt & Plaza, 1994). It contains the information which is content of case and situation where that information or experience can be used. Different type of data can be stored in a case. CBR community has a lack of consensus what information should be stored in a case. But, case should represent two things. The first one is functionality of information and the easiest way in which information is obtained in the case. Whenever we want to choose representation format of a case, we have to keep in mind following factors (Pal & Shiu, 2004).

- Language or shell in which we have to implement the CBR system. Selection of shell may reduce number of formats for case representation.
- Indexing and search mechanism. Format of case should be selected according to search mechanism. Case format should be able to interact with mechanism easily.
- Type or structure associated with content.

Cases also have to be structured for efficient case retrieval. There are two types of structures. Structure types are Common Structure and Hierarchical Structure. A memory model for the chosen form of case representation depends on following factors:

- The representation used in the case base.
- Number of features that are used to match cases during search.
- Number and complexity of cases.

Case is a combination of two components. Components are a description of a problem and its solution. Problem description consists of a set of attributes and values. Based on the description attributes values solutions are predicted.

2.4.2. Indexing

Index is a computational data structure can be held in memory and also can search quickly (Aamodt & Plaza, 1994). For example, databases use index to speed up retrieval of data. Information in a case can be two types:

1. Indexed information use for retrieval.
2. Unneeded information that may provide information to user but not used in retrieval.

Let us take the example of medical systems, where patient's age, sex, height and weight can be used as index features. That information is helpful for future retrieval. The patient's photograph can be included as an unneeded feature which can't be used in the retrieval. Picture should be helpful for doctor for remind patient. Index should have following features (Aamodt & Plaza, 1994; Pal & Shiu, 2004):

- Be predictive.
- Should show the purpose for which case will be used.
- It should be easy to recognize it in the future.

- It must address the future use of the case base.

Indices can be selected in both ways: manually and automatically. If you choose index manually then you have to decide a purpose of case. Automated indexing has many methods including:

- In different-based indexing, index has to differentiate a case from another case.
- In the inductive learning method, features are identified which latterly uses as an index.
- Appropriate set of indices produce by similarity and explanation-based method for those cases which have same information.

2.4.3. Storage

One important aspect of the efficient CBR system is case storage (Aamodt & Plaza, 1994). It represents a logical view what is stored in case. For efficient retrieval, case base should be organized in a manageable way. These methods referred as a case-memory model. Two best models are Schank's and Kolodner's dynamic-memory model. 2nd is category-exemplar model of Porter and Bareiss.

2.4.4. Retrieval

Case retrieval is a process of finding cases which are closest to current case (Pal & Shiu, 2004). For efficient case retrieval, there should be selection criteria which will judge a case. CBR major research area is retrieval. There are four retrieval techniques in which all of them are discussed in the CBR cycle section.

2.4.5. Case Adaptation

It is a technique to alter retrieved case for reproducing new solution for new problem (Lang & Lau, 2002). It may be the most important step which adds intelligence. Case adaptation improves overall problem solving ability of CBR. These three techniques are used mostly in CBR systems (Lang & Lau, 2002).

Structural Adaptation

In structural adaptation, formulas and rules are directly applied to the stored solution in CBR library. When case applies to these rules and formulas, the CBR system adapts this case and match with new problems.

Derivational Adaptation

It is a technique to reuse the rules and formulas to produce a new solution to a current problem. Solutions which are retrieved must be stored as additional case in the CBR library so it reproduces new solution to the new case.

Null Adaptation

It uses no adaptation at all. It just applies whatever solution is retrieved to the current problem without adapting it. Null adaptation is useful for problems which involve complex reasoning.

2.5. CBR Tools

There are different types of tools that can be used for developing a CBR system. Most of these tools are commercial and few of them are non-commercial. The following CBR tools are indicated on the paper of Ashraf and Iqbal (2006) and Watson and Marir (1994).

ReCall

This CBR tool is written in C++ language. It provides both nearest neighbor and inductive retrieval algorithm. It can run on windows and UNIX workstations under Motif, Sun, HP series 700 and DEC Alpha, designed in open architecture that allows the user to add CBR functionality in the application.

ReMind

It is produced by Cognitive Systems Inc. It is basically developed for Macintosh, but after some time, it is also developed for Windows and UNIX. ReMind offer template, nearest neighbor, inductive and knowledge-based retrieval. Its limitation is retrieving speed. Nearest neighbor is

very slow, on the other hand inductive retrieval is very fast. When it creates inductive index, then it becomes slow (Watson & Marir, 1994). It will be able to access data in ODBC-compliant databases and very influential tool.

ART*Enterprise

It is the product of Inference Corporation's (Watson & Marir, 1994). In 1980, ART was advertised as an AI-based tool. Inference dropped the label of AI and now ART*Enterprise marker as an integrated and object-oriented development tool.

ART* Enterprise has many features (Watson & Marir, 1994). It offers cross-platform support for all operating system. It provides excellent environment to integrate CBR with others application. Since the whole package is very powerful, ART*Enterprise is ideal tool for embedded CBR functionality within a corporate wide information system. Its package includes graphic user interface (GUI) builder.

CasePower

Inductive Solutions Inc. developed CasePower tool. That tool builds its cases in matrix environment provided by Microsoft Excel. Rows and columns of spread sheet are used to define cases and their attributes. It uses nearest neighbor retrieval and reduces the search time by calculating the index in advance. If new case is retained, then entire set of case indices must be recalculated (Watson & Marir, 1994).

CBR-Express

This CBR tool primarily designed for help desk applications by Inference Corporation. It provides a comfortable user interface and fast retrieval speed. It has simple case structure and nearest neighbor retrieval algorithm of cases. The key features of CBR-Express are to handle free-form text and enable customers to describe their problem in own words. The use of trigrams means that CBR-Express is reluctant of spelling mistakes and typing errors such as letter transpositions. It stores cases in relational database. CBR-Express is network ready and cases can be shared between organization's networks.

Kate

This tool is developed by AcknoSoft (Watson & Marir, 1994) that can run on MS Windows, Mac, or SUN. Kate is made up of Kate-induction, Kate-CBR, Kate-Editor and Kate-Runtime, this tool support both kind of Nearest Neighbor and Inductive retrieval algorithm. Kate-Induction is an ID3-based induction system that supports object-oriented representation of cases. Cases can be imported from many databases and spread sheets. Induction algorithm can make use of background knowledge. In induction algorithm, retrieval using trees is extremely fast. Kate-CBR uses nearest-neighbor approach. It supports same case objects hierarchies as Kate-Induction. Two techniques can be combined in a single application. Users can customize similarity assessments.

CaseAdvisor

It is marketed by Sentenia Software at Frazier University in Canada (Watson & Marir, 1994). It is also developed by Inference's CBR product. This software has three parts (Watson & Marir, 1994). These are CaseAdvisor Authoring, CaseAdvisor Resolution and CaseAdvisor WebServer

Eclipse – The Easy Reasoner

It is a product of Haley Enterprises. Eclipse is implemented in C by NASA. In late 1980, the former chief scientist of Inference developed a new language like Eclipse. Eclipse is available for Dos, Windows and UNIX platforms. It supports nearest neighbor and inductive retrieval (Watson & Marir, 1994).

Esteem

It is from Esteem Software (Watson & Marir, 1994). It is developed in Intellicorp's Kappa-PC. Esteem uses kappa's inference engine for developers to create adaptation rules. It supports application which has multiple case-bases and nested cases. This means that one can reference another case-base through an attribute slot in a case.

Casuel

European INRECA project developed Casuel (Watson & Marir, 1994). It is a common case representation language. Basically, it is interface between all INRECA component systems. Casuel is a flexible, object-oriented and frame like language.

Caspian

It is a CBR tool developed at the University of Aberystwyth in Wales (Watson & Marir, 1994). It can run on Ms-DOS and Macintosh. It has simple command line interface which can be integrated with a GUI front end if required. It performs simple nearest-neighbor match and uses rules for case adaptation.

jCOLIBRI

jCOLIBRI is a technological evolution of COLIBRI and it is an object-oriented framework in Java which is designed for building CBR systems. It is a java-based and uses JavaBeans technology for case representation and automatically generation of user interface. This framework is developed by the GAIA artificial intelligence group in Complutense University in Madrid. The framework is built in two hierarchical levels- upper and lower. The lower level consists of library of classes (Software modules) for full 4REs CBR cycle, also for definition of cases, attributes and connectors for access to outer databases. The upper level is “black box” – graphical interface, which allows non-complicated user CBR application generation based on lower level’s modules.

jCOLIBRI supports full CBR cycle. At the retrieve stage the nearest N cases are retrieved. At reuse stage several methods for adaptation are available (direct proportion and also in ontology). At revise stage methods for revision of cases are realized, as well methods for new indices generation and methods for decision making (preference elicitation). At retain stage there are methods for query retaining to the case base for future use. iCOLIBRI allows retrieval from clustered and indexed case bases and submits program interfaces (connectors) to access text and XML files, as well standard and descriptive logic databases. These interfaces can be used for diagnostic systems database access. There are lots of CBR applications, developed on jCOLIBRI based: additional shells (abstract levels) for distributed CBR systems, statistical CBR systems,

multi-agent supervisor systems for text file classification, and lots of CBR recommender systems.

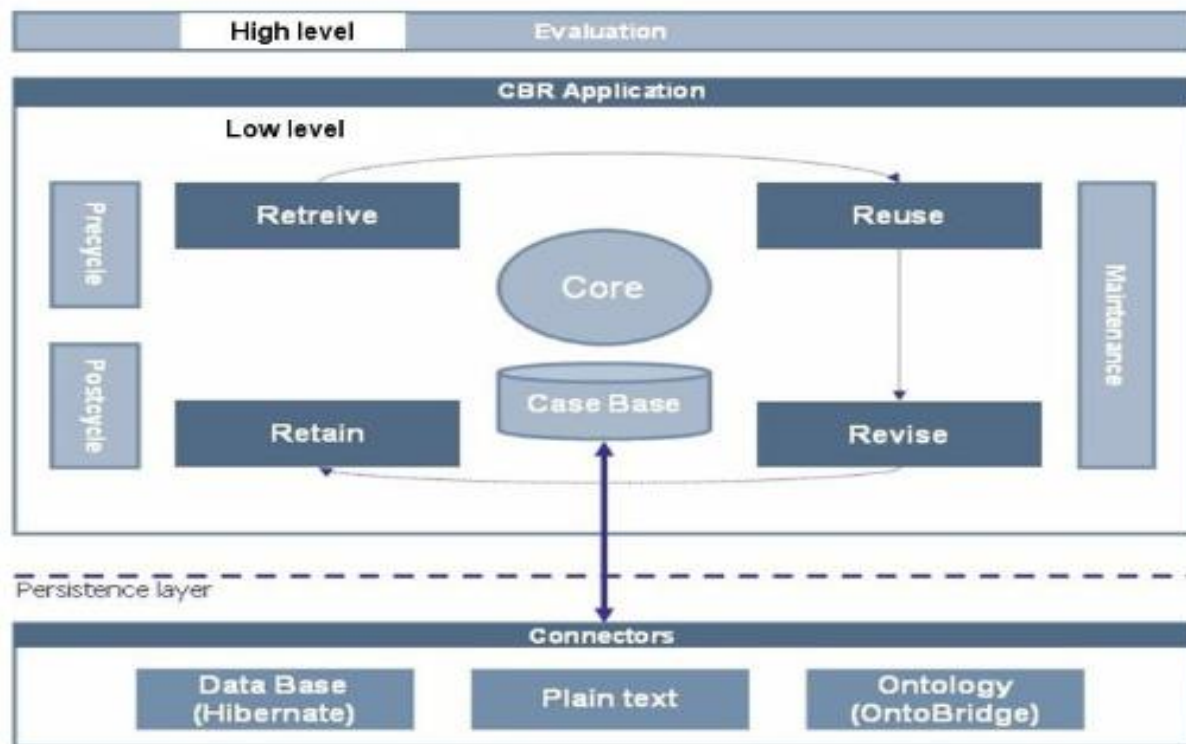


Figure 2.4: Software Architecture of jCOLIBRI (Atanasov & Antonov, 2012)

myCBR

myCBR is one of the most popular CBR software platforms. It is a framework with certain capabilities and limitations. The most popular version of myCBR is a plug-in of open source ontology editor Protégé (Stahl & Roth-Berghofe, 2008), but there are available some web-based versions and integration into other software. myCBR is developed by the German Research Center for Artificial Intelligence (Stahl & Roth-Berghofe, 2008). The platform has open source code written in Java and is accessible to all users. It can be easily modified by the users depending on the purpose. The purpose of myCBR is to minimize the efforts to create CBR applications. For this normal use, without modifying the source code, no programming skills are required, but expertise in a specific CBR-developed applications. Its programming code is well documented. .

The framework myCBR supports description of cases with various attributes: numeric, character, string, logical and class type. The templates of the cases are generated as classes or subclasses with a number of attributes, called slots.

The CBR cases are objects of the class described by its attributes. Each attribute can participate in the class with its value and a weight that determines the significance of the attribute in relation to others. Attributes a weight of zero (0) is not considered when searching the case base database.

Usually, case decisions have attributes with zero weight. In myCBR are given the opportunity to edit the similarity functions (SF) on class level class (global SF) and on an attribute level (local SF). At the class level the SF are weighed sum, Euclidean difference, maximum or minimum. On attribute level the SF can modified through the GUI and the can be symmetrical, asymmetrical, step-type or smooth step-type, linear or polynomial (Atanassov & Antonov, 2012).

In myCBR the case and their attributes created manually or automatically. The automatic generation of attributes (slots) is done during the import procedure of the Comma Separated Value (CSV) file. Then to each column name of the CSV file is assigned an attribute with the same name to each row of the file the new case (instance of the class) is created in the case base database. With regard to maintenance the CBR 4REs cycle phases, myCBR supports only Retrieve and Retain. During the retrieve phase all precedents extracted. They are presented sorted by degree of similarity based on the chosen global SF. The query to the case base database could be done on the basis of all or part of the attributes, describing the case (Atanassov & Antonov, 2012).

On retain phase myCBR allows to save the query as a new case, also to use an old case as a basis for a new query. myCBR is entirely based on GUI, proving a ready-windows templates and forms for defining classes, attributes SFs, queries to the case base database, visualization of found results and more.

myCBR does not work with external database (Atanassov & Antonov, 2012). It stores the cases in the text file or in an XML file. That's way it cannot support the case indexation and cluterization. The case cannot be graphically represented in the GUI, but it is possible to present the distribution of the values of a selected attribute for all cases in the database. No interfaces to

external systems and database are available in myCBR. It is valid regarding the interfaces to real-time or diagnosis systems.

2.6. CBR System Performance Evaluation Methods

Evaluation of knowledge base system includes both system performance (statistical analysis) and user acceptance (Buchanan & Forsythe, 1991). The statistical analysis for CBR can be conducted for both retrieval and reuse process. The first task of CBR is to retrieve cases that are relevant to the new case (Aamodt & Plaza, 1994). As retrieval task of the CBR aims to retrieve cases relevant cases from the case base, precision and recall are useful measures of retrieval performance in CBR (McSherry, 2001). Recall is defined as the ratio of the number of relevant cases returned to the total number of relevant cases for the new case in case base (Junker et al, 1999; McSherry, 2001). Whereas precision is the ratio of the number of relevant cases returned to the total number of cases for a give new case (Junker et al, 1999; McSherry, 2001).

$$Recall = \frac{\text{Number of relevant cases retrieved}}{\text{Total number of relevant cases}}$$

$$Precision = \frac{\text{Number of relevant cases retrieved}}{\text{Total number of cases retrieved}}$$

Only system performance evaluation based on statistical analysis does not assure the applicability of the system in the real life. Even though system that achieves better system performance statistically, it may not be comfortable to the user in solving the particular problem (Buchanan & Forsythe, 1991). As a result of this user acceptance is conducted to assess the applicability of the system for the real life.

2.7. Applications of CBR in Medicine

Many researchers are working on medical CBR with many diverse applications, ranging from psychiatry and epidemiology to clinical diagnosis. Most of them aim for a successful implementation of CBR methods to enhance the work of health experts, and to improve the efficiency and quality of healthcare. Early CBR in medical publications appeared in the late 1980's (Kolodner & Kolodner, 1987; Koton, 1988; Turner, 1988; Bareiss & Porter, 1987). The applications of CBR in medicine focus mainly on diagnosis, classification, planning and tutoring. Many systems have been applied; some of these applications are discussed in the next.

Two milestone papers exemplify CBR coupled with evidence-based decision-making and CBR in a clinical setting (Holt et al, 2006). In the first paper, Bichindaritz et al (1998) applied CBR to provide evidence-based medical decision-support over the Internet. They integrated automatic processing of medical practice guidelines and clinical pathways with CBR. It was called Care Partner and it used cases and prototypical cases to represent the variety and complexity of knowledge. This knowledge system was interactive and allowed physicians to select and organize diagnoses, treatment, follow-up actions and make recommendations according to the latest validated medical expertise. In the second paper, Schmidt and Gierl (2001) successfully implemented CBR in the complex domain of intensive care medicine for antibiotic therapy decision support, where physicians are accountable for their decisions.

Task type	Citation	System Name	Application Domain
Diagnosis and decision support systems	(Kolodner & Kolodne, 1987)	<i>SHRINK</i>	Psychiatry
	(Koton, 1988)	<i>CASEY</i>	Heart Failure
	(Turner, 1988)	<i>MEDIC</i>	Dyspnoea
	(Lopez & Plaza, 1993)	<i>BOLERO</i>	Pneumonia
	(Bradburn & Zeleznikow, 1993)	<i>FLORENCE</i>	Healthcare Planning
	(Bichindaritz, 1995)	<i>MNAOMIA</i>	Psychiatry
	(Haddad <i>et al.</i> , 1997)	<i>SCINA</i>	Detection of Coronary Heart Diseases
	(Bichindaritz <i>et al.</i> , 1998)	<i>CAREP-ARTNER</i>	Stem Cell Transplantation
	(Marling & Whitehouse, 2001)	<i>AUGUSTE</i>	Alzheimer's disease
Classification Systems	(Bareiss & Porter, 1987)	<i>PROTOS</i>	Audiological
	(Macura <i>et al.</i> , 1994)	<i>MACRAD</i>	Image Analysis
	(Grimnes & Aamodt, 1996)	<i>IMAGECREEK</i>	Image Analysis
	(Bichindaritz & Potter, 1994; Bichindaritz & Potter, 2004)	<i>PHYSYST</i>	Phylogenetic Classification

	(Perner, 1999)	<i>CTS</i>	Image Analysis
Planning Systems	(Bichindaritz & Seroussi, 1992)	<i>ALEXIA</i>	Hypertension
	(Berger, 1994)	<i>ROENTGEN</i>	Radiation Therapy
	(Petot <i>et al.</i> , 1999)	<i>CAMP</i>	Daily Menu Planning
	(Montani <i>et al.</i> , 2000)	<i>T-IDDM</i>	Diabetes treatment
Tutoring Systems	(Gierl, 1993)	<i>ICONS</i>	Antibiotics therapy for intensive care
	(Fenstermacher, 1996)	<i>CADI</i>	Cardiac auscultation

Table 2.1: Medical CBR Systems adapted from Holt et al (2006)

Researchers who have contributed substantially to CBR in medicine include Gierl, Schmidt, and their colleagues, who focused on a range of applications including children dysmorphic syndromes, antibiotics therapy advising for intensive care, and monitoring emerging diseases (Gierl, 1993; Schmidt & Gierl, 2001). Notable is their *ICONS* system (Gierl, 1993), first applied to the determination of antibiotic therapy treatment for intensive care, and then to the prognosis of kidney function defects. For this latter application, *ICONS* learned prototypes associated with graded levels of severity through temporal abstraction (Gierl, 1993) and matched new cases with these prototypes to predict the severity of a renal disease.

Bichindaritz, Sullivan, Seroussi, Kansu, Potter, and their colleagues focused on hypertension diagnosis and therapy, psychiatric diagnosis, treatment and follow-up, stem cell transplantation long-term follow-up decision support, as well as phylogenetic classification (Bichindaritz & Seroussi, 1992; Bichindaritz & Potter, 1994; Bichindaritz, 1995; Bichindaritz *et al.*, 1998; Bichindaritz & Potter, 2004). In *ALEXIA* (Bichindaritz & Seroussi, 1992), CBR used a deep pathophysiological model of hypertension to assess the similarity between cases favoring the most important attributes in the model. *MNAOMIA* (Bichindaritz, 1995) is a CBR system that can adapt to the medical task at hand, namely diagnosis, treatment planning, and clinical research assistance. Later refined in *CARE-PARTNER* (Bichindaritz *et al.*, 1998), this CBR system proposed a cooperation framework between cases and clinical practice guidelines in the domain of stem-cell post-transplant care.

Portinale, Bellazzi, Montani, Stefanelli, and their colleagues focused on diabetic patients' management, therapy and haemodialysis treatment (Montani *et al.*, 2000; Schmidt *et al.*, 2001). Their system highlighted the importance of temporal abstraction to facilitate similarity assessment between cases, and thus retrieval (Montani *et al.*, 2000).

Marling, Petot, Sterling, Whitehouse, and their colleagues (Petot *et al.*, 1999; Marling and Whitehouse, 2001), focused on designing individualized therapy plans (i.e., for nutrition menus, patient care for Alzheimer's, and cardiac and pulmonary disease). In particular, *AUGUSTE* (Marling & Whitehouse, 2001) demonstrated the utility of CBR for supporting treatment planning in a medical domain lacking a strong domain theory. Perner (1999) focused on biomedical image interpretation, segmentation and similarity analysis for computed tomographies and microscopic images.

2.8. Related Works

In the domain of law, Ethiopia (2002) and Yemisrach (2009) investigated the application of CBR system. Ethiopia (2002) developed a prototype CBR system form Amharic legal precedent retrieval using CBR-Works CBR framework and Yemisrach (2009) developed child criminal law CBR system using jCOLIBRI CBR framework. Ethiopia used 39 precedent cases to build and test the prototype. Using recall and precision performance measurements, she achieved 95.05% average recall and 82% average precision. Ethiopia recommended that adding high number of cases in the case base will increase the performance of the system. In the same domain, Yemisrach (2009) used 40 children criminal cases for building and testing children criminal cases prototype. She tested the prototype by setting 80% threshold level and five test cases. Using the five test cases and 80% threshold level, she achieved 87.5% precision and 41.01% recall. Feature selection from free text and identifying the optimal attribute are the major challenges in her work. Therefore, she recommended natural language processing for automatic feature selection and machine learning algorithms to select optimal attributes should be investigated.

In the domain of health, Alemu (2010) and Henok (2011) developed a prototype knowledge based system using CBR techniques. Alemu (2010) developed a CBR system for adverse drug reaction antiretroviral drug cases consultancy service. For building and testing the prototype

Alemu (2010) used 51 typical adverse drug reactions cases. Using 10 test cases, he achieved average recall and precision 72% and 63% respectively. Alemu (2010) faces different challenges such as extracting features from free text, weighting importance of the extracted features and the adaptation system to be used. To overcome these problems, he proposed investigating natural language processing to extract features, using machine learning algorithms for feature weighting and investigating different adaptation techniques. Likewise, Henok (2011) developed a prototype knowledge based system using CBR technique for hypertension management. He used 45 hypertension patient cases for building and testing the prototype. Using 7 test cases from the case base he registered 86.1% average recall and 60% average precision. The challenges that Henok faces and the recommendations proposed are almost similar to Alemu (2010) except Henok proposed a hybrid knowledge based system using rule-based and CBR systems to increase the performance of the prototype.

Generally, the common features of all the systems are the case representation method and the retrieval algorithm the researchers used are similar. All the researchers used nearest neighbor retrieval algorithm, feature-value case representation method and the standard measures of performance in information retrieval to evaluate the effectiveness of their system (Ethiopia, 2002; Yemisrach; 2009; Alemu; 2010; Henok, 2011). But, Henok (2011) is unique from others by using accuracy performance evaluation to evaluate the reuse capability of his system.

CHAPTER THREE

KNOWLEDGE ACQUISITION AND MODELING

3.1. Knowledge Acquisition

In knowledge engineering, there are two most important steps that are significant during the development of knowledge-based systems that every knowledge engineer should consider. The first one is acquiring the required knowledge from experts and relevant documents and the second one is representing the acquired knowledge with the appropriate knowledge representation method. Knowledge acquisition is the process of extracting and organizing knowledge from human experts and other sources such as books, databases, the internet, research papers, documents, one's own experience and transferring to the knowledge base (Abbas et al, 2008). It is the general term used for the process of developing a computational problem solving model such as developing a program to be used in some consultative or advisory role (Birmingham & Klinker, 2009). Knowledge acquisition is the most significant step in the development of knowledge base system, but at the same time it is the most difficult task that needs great care, patience and attention.

Therefore, the main objective of this chapter is to collect anxiety disorder patient cases and model how anxiety disorder patients are treated. The main features regarding to anxiety disorder diagnosis and the fundamental concepts are identified about the diagnosis procedures that help to develop the proposed prototype CBR system. Generally, this chapter covers the knowledge (cases) acquisition phase and the conceptualization process. The basic attributes and concepts, which are crucial in the diagnosis process, are identified. For the purpose of this study, this proposed CBR system is named as Case-Based Reasoning System for Anxiety Disorder Diagnosis (CBRSADD).

3.1.1. The Knowledge and Case Acquisition Process

The process of knowledge and case acquisition of this research encompasses some basic activities such as gathering the needed knowledge, analyzing that knowledge, identifying

important concepts and parameters (symptoms) and finally modeling them in using decision tree structure.

In this study to acquire the needed cases, both secondary and primary sources of knowledge are used. Primary knowledge is gathered from various experts in the domain area from Amanuel Mental Specialized Hospital by using structured and unstructured interviews (interview questions used are presented in Appendix I). During the preliminary investigation, psychiatrist doctors, trainee psychiatrists, psychiatric nurses, and psychologists are included to explore the dimensions of anxiety disorder problems. During this time, the researcher is trying to conduct informal kinds of interviews with these experts. All the experts replied almost similar information about anxiety disorder and they said they used Diagnostic and Statistical Manual for mental disorder 4th edition (DSM-IV) as a guideline for diagnosing mental disorders in which anxiety disorder is a part. Due to this the researcher selects only three experts from anxiety case team.

These experts selected purposefully for extensive discussion using structured and unstructured interviews to understand the domain knowledge and to verify the cases acquired from the previous patient history. These experts are practically participating throughout the research work, and they are consulted to confirm the correctness of the acquired knowledge. In addition, secondary source of knowledge has been gathered from the internet, mental disorder diagnosis guidelines (especially, DSM-IV), manuals, research papers and journal articles. But, the primary data source is patient history of Amanuel Mental Specialized Hospital anxiety disorder patients.

The results of the discussion with the experts indicate that almost all mental professionals in Ethiopia use international guidelines for mental health diagnosis. As the experts explained, Ethiopia does not have its own guideline(s) used for mental disorder diagnosis in general and anxiety disorder diagnosis in particular. Instead, mental health professionals in Ethiopia use international guidelines for diagnosing mental disorder related problems. Currently, almost in all situations the two major international guidelines used are international classification of diseases 10th edition (ICD – 10) which is prepared by WHO and DSM - IV which is developed by APA. Principally, DSM - IV has been used practically in Ethiopia.

Major disorders and their symptoms and signs identified from both from the domain experts and documentary sources along with its proposed solution, and refined through consultations with the experts. These identified anxiety disorders include phobic (agoraphobia, specific phobia and social phobia), panic disorder, generalized anxiety disorder, obsessive – compulsive disorder and reactions to severe stress disorders (post –traumatic stress disorder and acute stress order).

3.1.2. Anxiety Disorders

Anxiety is a universal experience and, as such, is a part of the human condition. It is a complex experience, with psychological, physiological, behavioral and cognitive manifestations. It is a universal part of the human condition, but becomes abnormal when its intensity and duration grow excessively, or when it occurs without recognizable threat (Noyes & Hoehn-Saric, 1998). It serves as a biological warning system that is activated by danger. It may also occur following a loss or may arise from intra-psychic conflict, as in the conflict between inner drives and external demands or between conflicting value systems. Anxiety is a distressing emotion usually associated with bodily discomfort. In contrast to depression, which is a reaction to loss and is oriented toward the past, anxiety is a reaction to threat and is directed toward the future. The threat may involve danger, lack of support or what is unknown. Normal anxiety prepares the individual for a protective response. Low levels of anxiety are helpful in coping with adversity, but high levels cause impairment and can even be disorganizing. Anxiety becomes abnormal when its intensity and duration is disproportionate to the potential for harm, when it occurs in situations known to be harmless, or occurs without any recognizable threat.

Anxiety is a natural response and a necessary warning adaptation in humans. Anxiety becomes a pathological disorder when it is excessive and uncontrollable, requires no specific external stimulus, and manifests with a wide range of physical and affective symptoms as well as changes in behavior and cognition.

During the knowledge acquisition process, the most widely occurring and principal anxiety disorder groups are identified. These include phobic disorders (agoraphobia, social phobia and specific phobia), disorders due to severe stress (post – traumatic stress disorder and acute stress disorder), obsessive – compulsive disorder, generalized anxiety disorder and panic disorder.

As indicated in the following figure (Figure 3.1), the diagnosis of anxiety disorders includes five sub diagnoses. These are obsessive – compulsive disorder diagnosis, phobic diagnosis, panic disorder diagnosis, generalized anxiety disorder diagnosis and reaction to severe stress disorder diagnosis. Again, phobic diagnosis and reactions to severe stress diagnosis has three and two sub diagnosis respectively. The following figure shows these disorders.

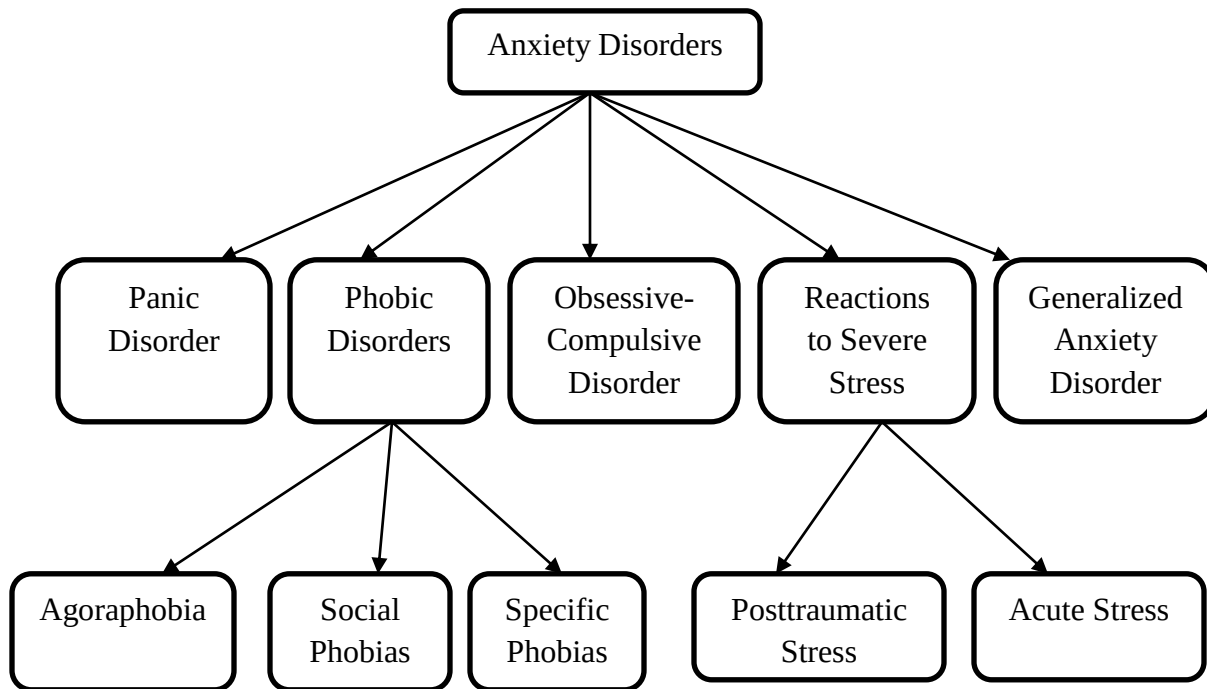


Figure 3.1: Different Types of Anxiety Disorders

3.1.2.1. Panic Disorder

Panic disorder is an anxiety disorder characterized by the spontaneous unexpected occurrence of panic attacks. The attacks are relatively short-lived (usually less than an hour) periods of intense anxiety or fear, which is accompanied by somatic symptoms such as palpitation and tachyon (Paris et al, 2006). Panic disorder is a serious health problem, but in many cases it can be successfully treated (APA, 2000).

The main symptom of panic disorder is the occurrence of panic attacks. A panic attack is a period of intense fear or discomfort, developing suddenly and peaking within 10 minutes. Panic

attacks are characterized by a short period of intense of impending doom, derealization, and increase heartbeat with accompanying physical symptoms, such as chest pain, dizziness and shortness of breath.

3.1.2.2. Phobic Disorders

Phobic disorders are disorders, which result in due to fear of some situations or objects. Phobia is an irrational fear of an object, place, activity or situation (Paris et al, 2006). The most commonly occurring phobic disorders are agoraphobia, social phobia and specific phobia.

Agoraphobia: is a condition where the sufferer becomes anxious in environment that are unfamiliar or where he/she perceives that they have little control. Triggers for this anxiety may include crowds and wide open spaces or travelling, even short distances (APA, 2000). Agoraphobia consists of multiple and varied fears and avoidance behavior that center around three main themes:

- Fear of leaving home
- Fear of being alone and
- Fear of being away from home in situations where one can feel trapped, or embarrassed

Specific Phobia: is characterized by clinically significant anxiety provoked by exposure to a specific feared object or situation, often leading to avoidance behavior (APA, 2000). Specific phobia is a disorder, which is characterized by marked and persistent fear that is excessive or unreasonable, cued by the presence or anticipation of a specific object or situation. Associate to this fear, patients with specific phobia show symptoms like heart pounding and sweating

Social Phobia: is characterized by clinically significant anxiety provoked by exposure to certain types of social or performance situations, often leading to avoidance behavior (APA, 2000). Social phobia occurred mostly in social related situations (Paris et al, 2006).

3.1.2.3. Obsessive – Compulsive Disorder

Obsessive - compulsive disorder is a mental disorder, most commonly characterized by intrusive and repetitive thoughts resulting in compulsive behaviors and mental acts that the person feels driven to perform aimed at reducing anxiety by preventing some dreaded event or by resolving a more nebulous sense of tension (Bandelow et al, 2008). Intrusive thoughts are unwelcome,

involuntary thoughts, images or unpleasant ideas. In severe cases, it affects a person's ability to function in everyday activities. The disorder often has a serious impact on the sufferer's and their family's quality of life. In addition the psychological self-awareness of the irrationality of the disorder can be painful (APA, 2000). Obsessions recurrent and persistent thoughts, impulses or images that are experienced as intrusive and causing marked anxiety. The thoughts, impulses or images are not simply excessive worries about real-life problems. The persons attempt to ignore or suppress such thoughts, impulses or images or to neutralize them with some other thought or action.

Similarly, compulsion can be defined as repetitive behaviors such as praying, counting, checking repeatedly that the person feels driven to perform in response to an obsession. The behaviors or mental acts are aimed at reducing distress or preventing some dreaded events or situations. However, these behaviors or mental acts either are not connected in a realistic way with what they are designed to neutralize or prevent.

3.1.2.4. Generalized Anxiety Disorder

Generalized anxiety disorder is an anxiety disorder that is characterized by excessive, uncontrollable and often irrational worry (APA, 2000). This excessive worry often interferes with daily functioning. Generalized anxiety disorder brings catastrophes and anticipates disaster on everyday matters such as such issues, money, death, family and friend related problems, or work difficulties (APA, 2000).

Generalized anxiety disorder often exhibits a variety of symptoms and physical signs including fatigue, headaches, muscle tension, difficulty swallowing, trembling or twitching, sweating and hot flashes. As experts said, these symptoms must be consistent and on-going persisting at least for 6 months for a formal diagnosis of generalized anxiety disorder to be introduced.

3.1.2.5. Reaction to Severe Stress Disorders

Reactions to stress disorders are developed due to the presence of severe stressor events in the later life of a patient (APA, 2000). These include post-traumatic stress disorder and acute stress disorder.

Post-traumatic stress disorder and acute stress disorder are anxiety disorders that can be developed after exposure to one or more traumatic events that threatened or caused grave physical harm. It is a severe and ongoing emotional reaction to an extreme psychological trauma. This stressor may involve someone's actual death, a threat to the actual patient's or someone else's life, serious physical injury, an unwanted sexual act, a threat to the physical or psychological integrity or overwhelming psychological defenses (Bendelow et al, 2008). Post-traumatic disorder and acute stress disorder are conditions where a person begins to experience anxiety symptoms and begins to relive certain events from one's past (Paris et al, 2006). It can also involve a person trying to avoid certain stimuli that can relate to a particular event. The diagnosis of both of them is similar. The difference lies in the duration of the traumatic events. The diagnosis of acute traumatic stress disorder can be given only with the first month following a traumatic event whereas if post-traumatic symptoms were to persist beyond a month, the clinician would assess for the presence of post-traumatic stress disorder.

All the symptoms of post-traumatic stress disorder and acute stress disorder are categorized into three clusters as intrusive (re-experiencing) symptoms, avoidance symptoms and arousal symptoms.

As experts said, for the diagnosis of post-traumatic stress disorder and acute disorder a person must have experienced a traumatic event where he/she experienced, witnessed or was confronted with an event where there was the threat of or actual death or serious injury. The event may also have involved a threat to the person's physical well-being or the physical well-being of another person.

All the basic identified concepts, symptoms, syndromes and parameters of each anxiety disorder are modeled in figure 3.2.

3.2. Conceptual Modeling

Once the required knowledge is acquired from anxiety disorder patient cases, anxiety disorders experts and other relevant documents, the next step is modeling the knowledge. The knowledge modeling step involves organizing and structuring of the knowledge gathered during knowledge acquisition. This activity provides an implementation independent specification of the

knowledge to be represented in the knowledge base. Knowledge modeling is the concept of representing information and the logic for the purpose of capturing, sharing and processing knowledge to simulate intelligence (Makhfi, 2011). Here, the basic concepts that tell the main activities and decisions are made to solve cases in the domain are modeled.

Conceptual modeling is a crucial step in the knowledge acquisition process so as to understand well the problem domain and to prepare the knowledge representation phase. There are different conceptual modeling techniques and for this study decision tree structure is used to model how anxiety disorder diagnosis is performed.

3.2.1. Anxiety Disorder Diagnosis Process and Decision Tree Structure

Logical View

A mental health diagnosis involves many steps beginning with asking questions about the patient's signs and symptoms, medical history, and performing physical examination along with the different risk factors (APA, 2000; Paris et al., 2006). Even though there are no laboratory tests to diagnose specifically mental illness, the physician may use various tests to make sure that the absence and presence of symptoms and not caused by different risk factors. According to experts' response during interviewing, the main information for the physician is the dialogue between the patient, patient families and by observing the attitudes, behaviors, and social interaction of the patient during diagnosis of anxiety patient. The physician then determines if the person's symptoms and degree of disorder direct to a diagnosis of a specific disorder.

Anxiety disorder diagnosis is dominated by gathering sufficient information from the patient or from his/her family members and by observing the activities of the patient (APA, 2000). During the diagnosis procedure, the critical step is getting a patient history to understand well the dimensions of the patient problems. After that, asking a patient or anybody who is with the patient why he/she is coming to the hospital and what was happening in the life of the patient. During this time, an expert (mostly a psychiatrist or psychologist) extracts important symptoms and syndromes from the sessions and identifies the mental disorder category or group of the patient (Bendelow et al., 2008). After identifying the disorder group, the expert continues with detailed diagnosis of the group of disorders. Then, the expert will probably refer to the DSM – IV criteria to compare the patient symptoms to those in the DSM. Finally, the psychiatrist

estimates the probable presence of a disorder and recommends appropriate treatment either psychotherapy or pharmacotherapy or otherwise refers to the patient to clinical psychologists accordingly.

Anxiety disorders are medical conditions and require a diagnosis to be made by a qualified medical professional (Noyes & Hoehn-Saric, 1998; APA, 2000; Paris et al., 2006). Usually, unlike physical diseases, there are no blood tests or other laboratory tests, there are no x-rays or brain scans, which will definitely determine if someone has an anxiety disorder or not. Instead simply checking the absence and presence of symptoms along with observation of the patients' behavior is important in the diagnosis of anxiety disorder.

As with many mental disorder problems, the diagnosis of anxiety disorder is based on the symptoms of the patient. In the initial evaluation stage of the diagnosis, a psychiatrist will ask questions about the medical history of the patient. He/she will ask questions about physical and emotional illness and disorders the patient has had in the past (Bendelow et al., 2008). In addition, the doctor will assess:

- What symptoms the patient is experiencing, both physically and mentally
- How often the patient experiences symptoms of anxiety
- How long has been having symptoms
- How the symptoms interfere with the patient's daily life

Here is a simple sample dialogue between a patient and a doctor (Abdrabou & Salem, 2010).

Initial situation: One day, a woman felt fear of going to the market because she fears that she may get sudden attack there.

Doctor and patient dialogue: Have you had increased heart bit (palpitation)? Yes

Have you had excessive sweating? No

Have you had feeling sense of being lost? Yes

Have you had fear of having sudden attack? Yes

How you had fear of being alone outside home? Yes

Decision 1: The complaint may have the disorder agoraphobia

Decision 2: The second decision made by the doctor is cognitive behavior therapy and relaxation techniques.

The following are the major symptoms and signs of different anxiety disorders (APA, 2000; Noyes & Hoehn-Saric, 1998).

Major Symptoms of Panic

- Trembling
- Palpitation/ hear pounding
- Chest pain
- Nausea/ vomiting
- Unrealistic intense fear
- Breathlessness / difficulty of breathing
- Derealization (feeling of unreality)/ depersonalization
- Fear of sudden attack
- Excessive sweating

Major Symptoms of Agoraphobia

- Fear of being alone in public places/ e.g. Restaurants
- Fear of being alone at home/outside home
- Feeling sense of being lost
- Fear of having sudden attack
- Anticipatory anxiety

Major Symptoms of Social Phobia

- Marked and persistent fear of social settings
- Blushing
- Fear of being watched
- Difficulty of being assertive
- Fear judging by others

Major symptoms of Specific Phobia

- Fear of specific object

- Marked and persistent worry
- Limited fear
- Palpitation/Heart pounding

Major Symptoms of Obsessive-Compulsive Disorder

- Recurrent and persistent disturbing thoughts, images or impulses
- Excessive repetitive behaviors and/or mental acts
- Frequent thoughts of violence
- Fear of being poisoned/contaminated

Major Symptoms of Generalized Anxiety Disorder

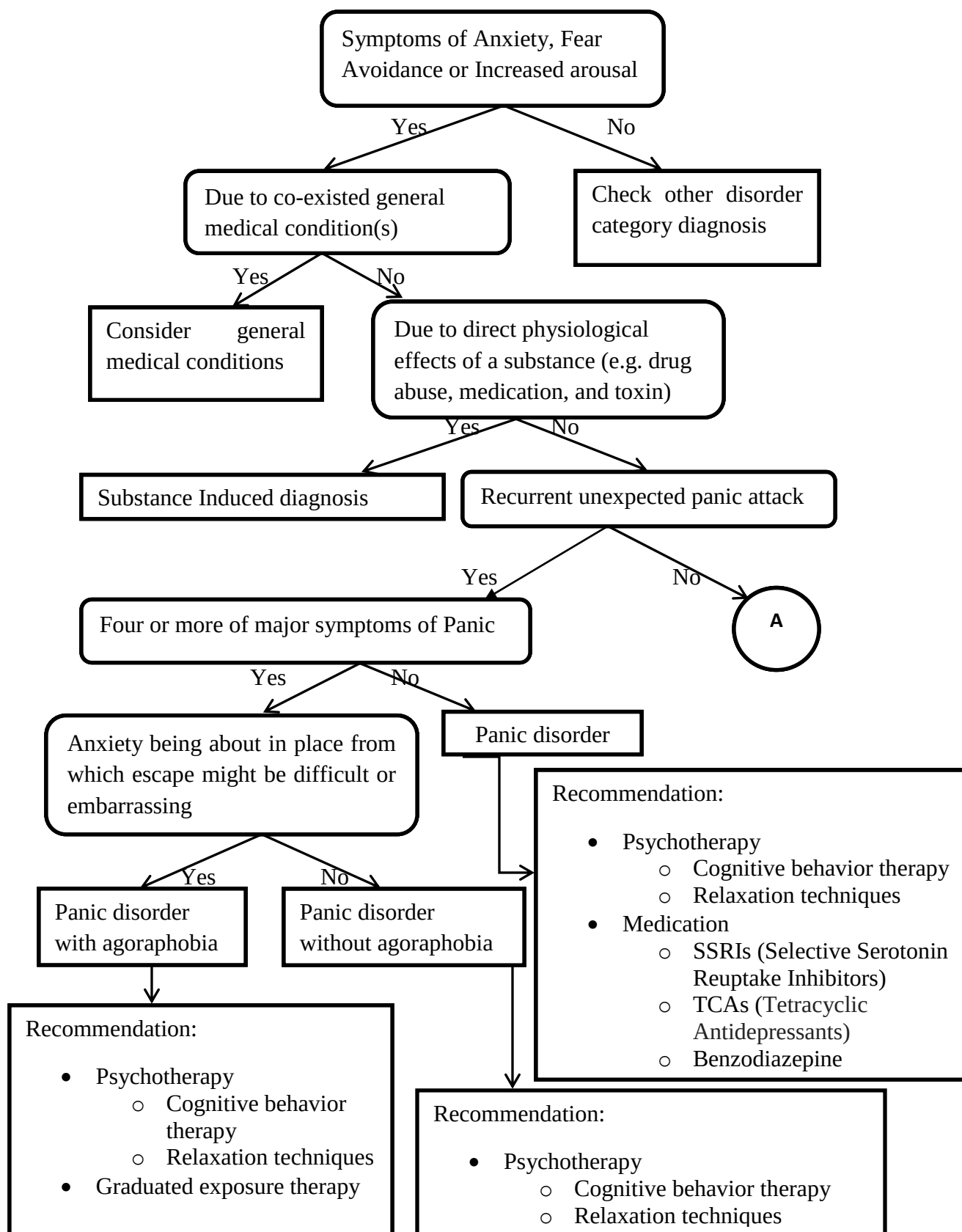
- Difficult concentrating
- Being easily fatigued
- Muscle tension
- Sleep disturbance
- Irritability

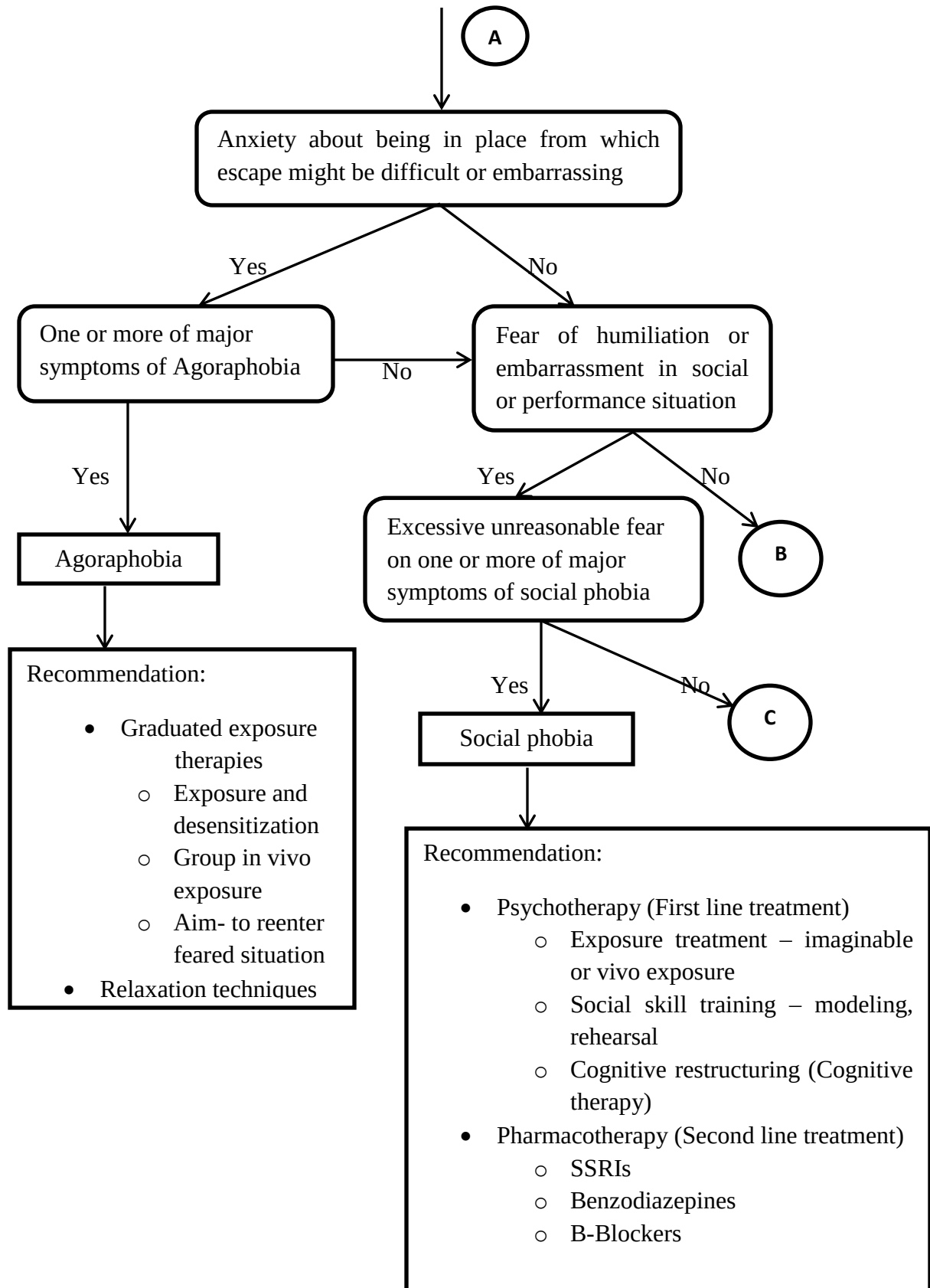
Major Symptoms of Severe Stressor Disorders

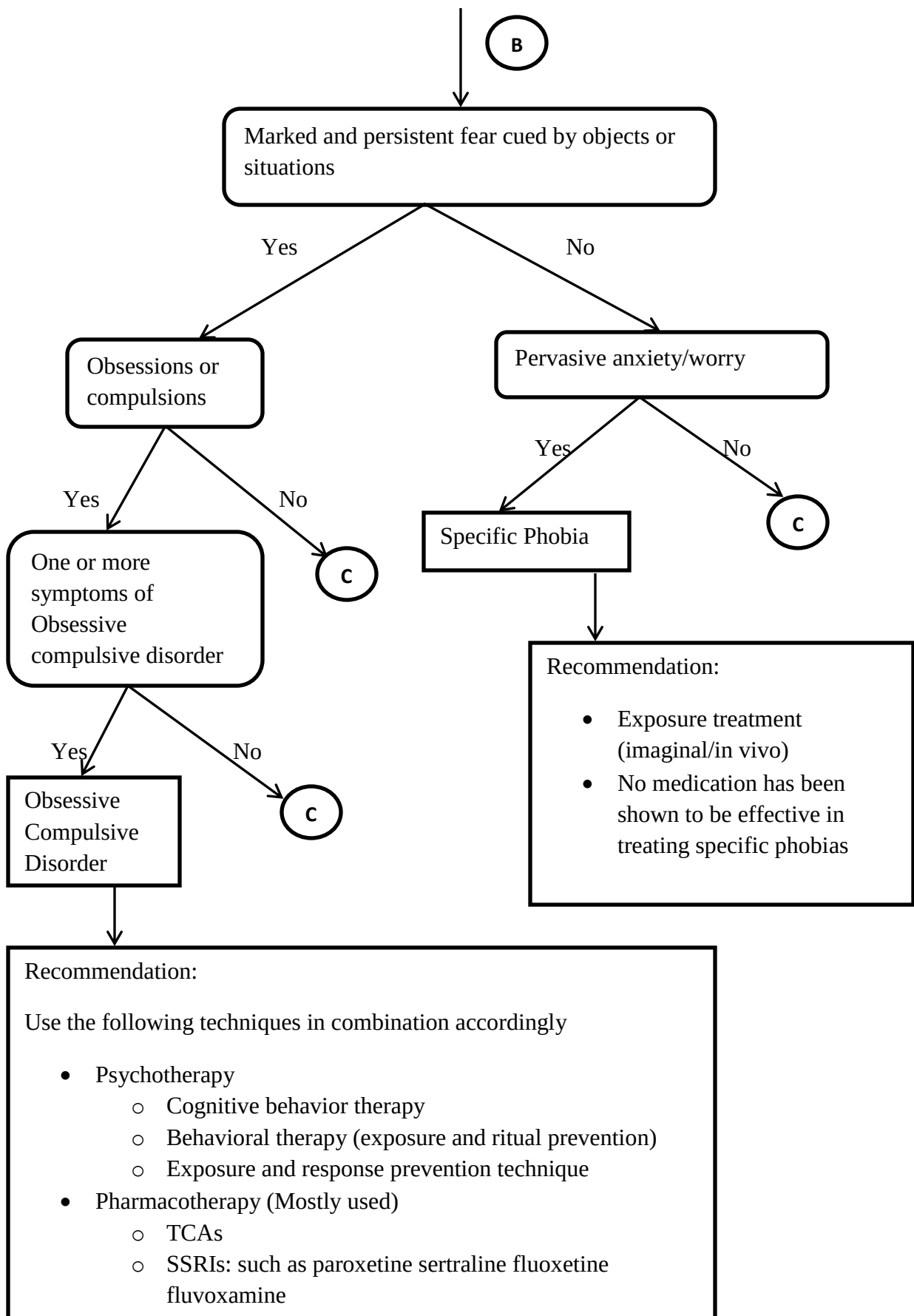
- Re-experiencing of the traumatic events
- Flashbacks
- Nightmares
- Avoiding things that remind the trauma
- Intense physical reactions to reminders of the event
- Increased arousal of traumatic events

In addition to the above major symptoms, age and gender are taken into consideration during anxiety disorder diagnosis and treatment. Narrow et al. (2007) their book entitled with “Gender and Age Consideration in Psychiatric Diagnosis” are the main research agenda for DSM-V.

The following decision tree shows the different levels of decisions that anxiety disorder clinicians use during anxiety diagnosis and treatment.







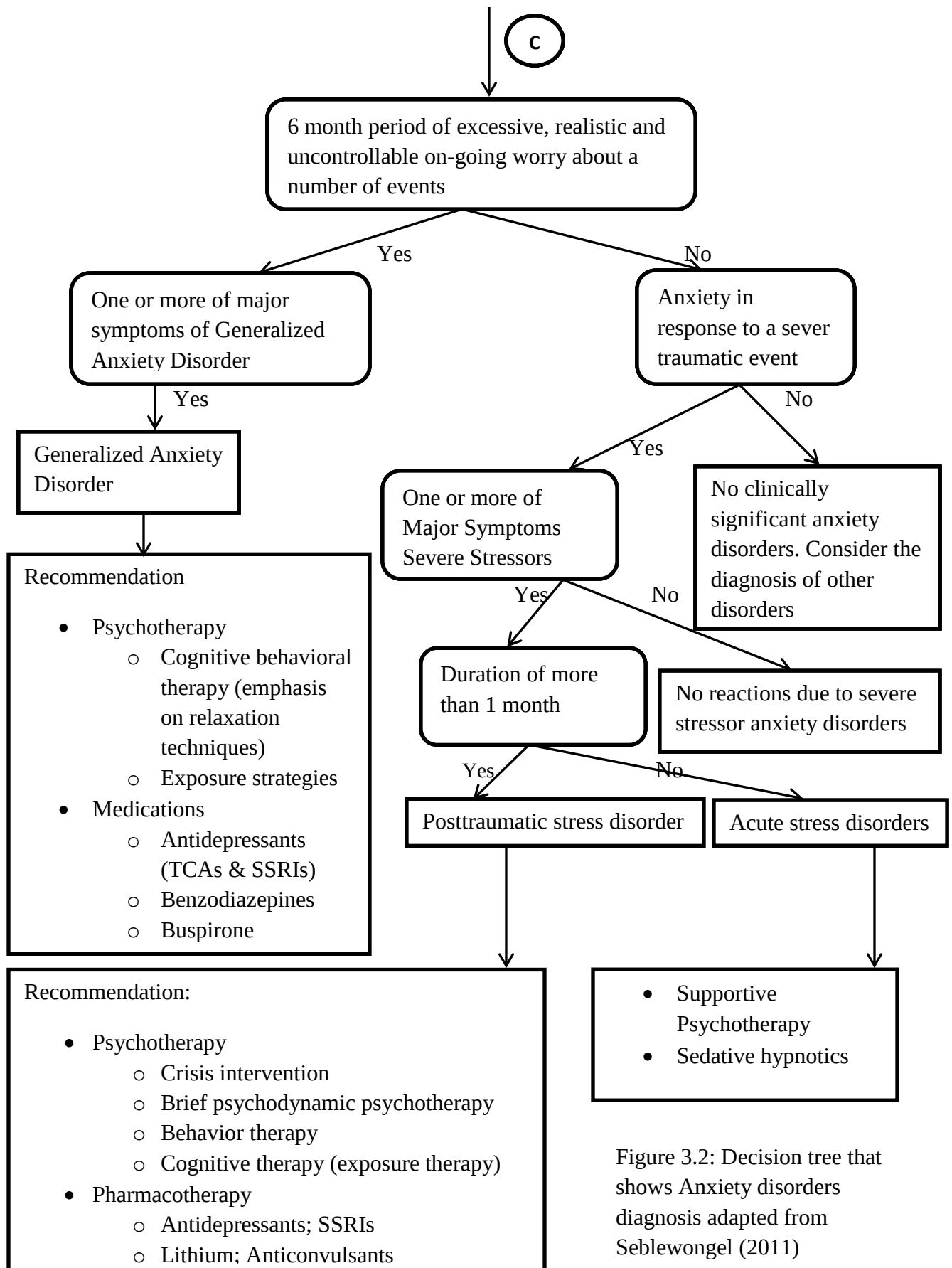


Figure 3.2: Decision tree that shows Anxiety disorders diagnosis adapted from Seblewongel (2011)

3.3. Anxiety Disorder Diagnosis Case Structure

Anxiety disorder diagnosis case structure has two important parts. The first one is the problem descriptions or situation and the second one is the solution.

Problem Description/Situation: It is the part of the case structure that is consisted of attributes which describes the problem to be solved.

Solution: This part of the case structure provides the recommended diagnosis and treatment given to patients based on the problem descriptions.

Therefore, the researcher identified the different description and solution attributes with the help of anxiety disorder expert and DSM – IV manual. But, there were different challenges during identification and representation of case structure.

The first challenge is that the attributes (the symptoms in this case) used to diagnose anxiety disorder are too many. Due to the time limitation and scarcity of resources, the researcher selects those symptoms that are most frequently recorded in the patient history. The other challenge is some attributes are difficult for representation. For example the duration of the symptom is difficult for representation because the duration of different symptoms is recorded in in different units of measurement such as seconds, days, weeks, months. Since it is so difficult to represent the duration of symptoms, it is not included in the case structure even though it is important in the decision making. Culture is also its own contribution to anxiety disorder diagnosis, but it is difficult to represent in this case structure (APA, 2000; Narrow et al., 2007).

Finally, after the case structure is constructed, the cases that build the case base are collected from the anxiety disorder patients' card history. This stage is another big challenge for the researcher because the patients' history is recorded on paper. Since converting cases from paper to computer understandable format is a hard work for the researcher, one professional psychiatry nurse is participated during the conversion.

Attribute Name	Parameter
Age	Description
Gender	Description
Trembling/Shaking	Description
Palpitation/ Heart pounding	Description
Chest pain	Description
Nausea	Description
Fear	Description
Breathlessness	Description
Derealization/Depersonalization	Description
Sweating	Description
Blushing	Description
Thoughts of violence	Description
Easily Fatigue	Description
Muscle Tension	Description
Sleep Disturbance/Sleeplessness	Description
Irritability	Description
Trauma	Description
Flashbacks	Description
Nightmares	Description
Loss of Interest	Description
Vertigo/Dizziness	Description
Loss of Weight	Description
Headache	Description
Forgetfulness	Description
Restlessness	Description
Class	Solution
Recommended Treatment	Solution

Table 3. 1: Shows the Case Structure for Anxiety Disorder Diagnosis

Short descriptions of attributes that are used for building the case structure are presented as follows (Noyes & Hoehn-Saric, 1998; APA, 2000; Paris et al, 2006; Narrow et al., 2007).

Age: is the age of the patient.

Gender: is the term used to refer to a person's self-representation as male or female, or the psychosocial expression of living as a man or a woman. The values of this attribute are male and female.

Trembling/Shaking: arms, hands, feet, fingers, toes, legs, any part of the body, and even the entire body may feel shaky and like it is trembling or vibrating during panic attack. This attribute is used to check the presence and absence of trembling.

Palpitations/Heart Pounding: it is an awareness of the beating of the heart brought about by change in the heart's rhythm or rate during panic attack. This attribute is used to check the presence and absence of trembling.

Chest Pain: any discomfort around the chest.

Nausea: is stomach discomfort and vomiting due to different psychological effects.

Fear: is an intense aversion to or apprehension of a person, place, activity, event, or object that causes emotional distress and often avoidance behavior. The values of this attribute are any situation and object.

Breathlessness: is shortness of breath due to panic attack.

Derealization/Depersonalization: is a feeling of unreality or altered reality, to which panic attack patients are subjected.

Sweating: sweating not to by heat but, by panic attack.

Blushing: a sudden and brief redness of the face and neck due to emotion commonly happens when panic attacks are related to social or performance anxiety.

Thoughts of Violence: hurting others or trying to injure himself or herself.

Easily Fatigue: feeling of exhaustiveness due to different psychological effects.

Muscle Tension: associated with muscle aches or soreness.

Sleep Disturbance/Sleeplessness: lack of sleeping at night due to different factors.

Irritability: Irritability is a kind of signal, that an unpleasant or potentially threatening situation cannot be avoided or solved in an appropriate way.

Trauma: re-experiencing previous physical injuries and harms. The harms will leads to intensive fear of the situation.

Flashbacks: Flashbacks are considered one of the re-experiencing symptoms of posttraumatic stress disorder. As the name implies, in a flashback, a person may feel or act as though a traumatic event is happening again.

Nightmare: it is a type of sleep disruption, or parasomnia, characterized by frightening psychological content. Nightmares provoke a feeling of imminent physical danger with a sensation of being trapped or suffocated.

Loss of Interest: is the decrease in interest or pleasure to perform ones' day to day activities.

Vertigo/Dizziness: feeling of losing control or faintness

Loss of Weight: the decrease in weight.

Headache: it is also called brain ache and occurred due to different factors such drug abuse, loud sound and addiction.

Forgetfulness: individual's behavior accompanied by an inability to recall important personal information that is too extensive to be explained.

Restlessness: mostly occurred in generalized and panic disorders and the patient feeling keyed up or on edge.

Class: all the above attributes are description attribute whereas this attribute is a solution attribute and recommends the type of disorder to the user based on the similarity of input case and the old case in the case base.

Recommended Treatment: it also a solution and provides a recommendation of treatment based on the similarity of cases.

CHAPTER FOUR

DESIGN AND IMPLEMENTATION OF THE PROTOTYPE

4.1. Introduction

The design and implementation part of this section involves the actual development of a scaled down workable CBR system for anxiety disorders diagnosis. Therefore, having all the necessary cases and the knowledge from the domain expert and different relevant documents, the next task is coding the knowledge into computer using appropriate and efficient knowledge representation methods. For this research, jCOLIBRI 1.1 CBR frame work is used to develop the prototype.

The retrieval algorithm used in this research is nearest neighbor retrieval algorithm. This is because jCOLIBRI uses this algorithm for retrieval task. Nearest neighbor retrieval algorithm is also suitable when there are attributes which have numeric (continuous) value (Fang & Songdong, 2007).

4.2. Designing the Architecture of CBR SADD

The architecture of the CBR SADD system shown in figure 4.1 depicts how the prototype works during anxiety disorder diagnosis. As the new query (problem) is entered, the prototype of the system matches the new case to the solved case in the case base of the system by using similarity measurement. If relevant cases are found within the case base, then the prototype rank the relevant retrieved cases based on their global similarity. Next, the prototype proposes a solution. The proposed solution can be derived directly from a retrieved case that matches exactly or partially to the problem of the new case. But, using the proposed solutions directly may have a risk. Therefore, the user of the system should have made an adaptation by altering the differences between the proposed case and the new case. In addition to adaptation, case inconsistencies are revised if the retrieved case is not the same as the new case. Finally, the revised solution is retained in the case base for future problem solving.

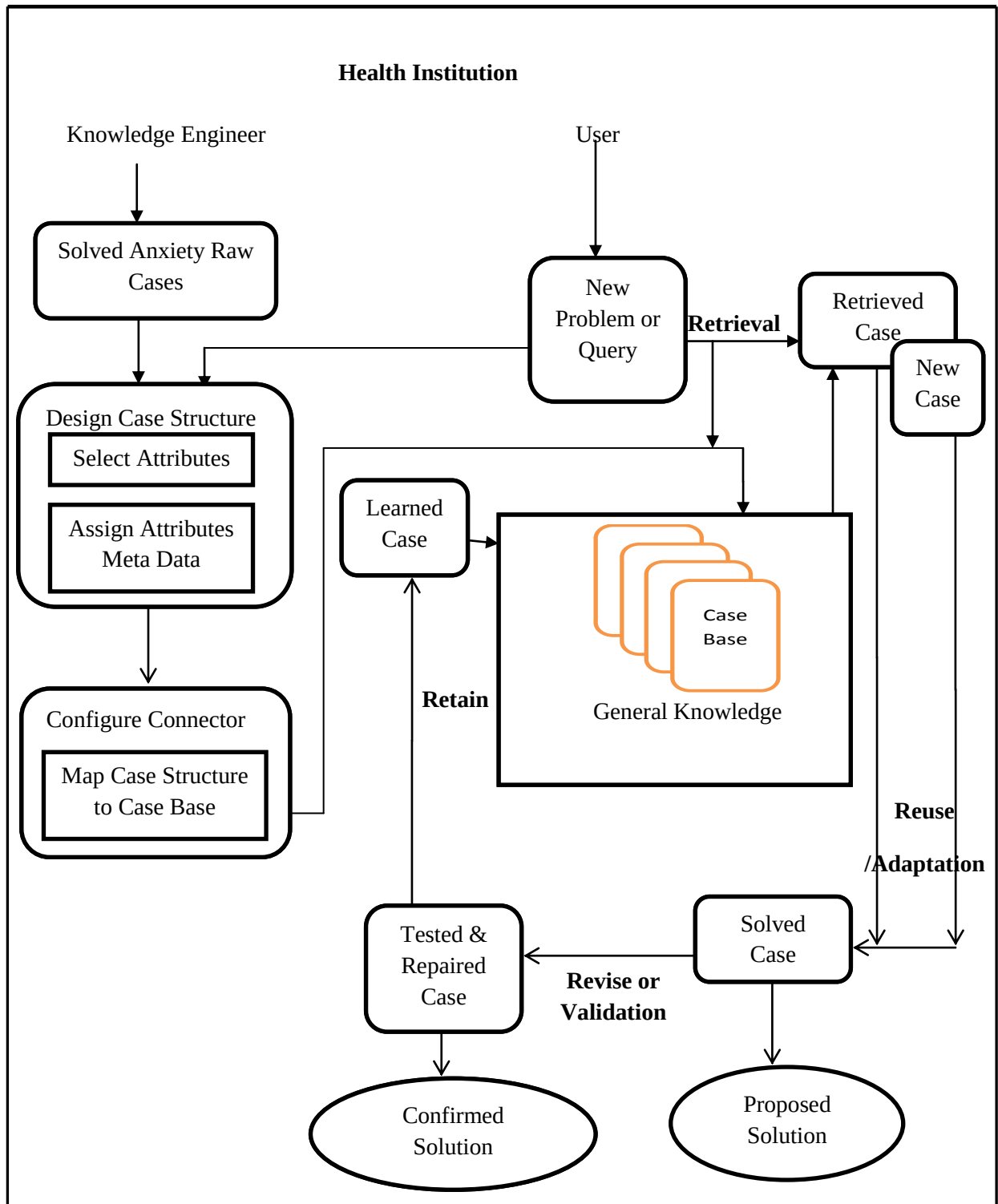


Figure 4.1: CBR SADD Architecture

4.3. Case-based Reasoning System for Anxiety Disorder Diagnosis

The development of a reasonably simple CBR application already involves a number of steps, such as collecting cases and background knowledge, modeling a suitable case representation, defining an accurate similarity measure, implementing retrieval functionality, and implementing user interfaces (Stahl & Roth-Berghofe, 2008). In this study, the researcher uses the main feature of jCOLIBRI to deliver the actual prototype. As Recio-Garcia and Daz-Agudo (2004) and Recio-Garcia, Díaz-Agudo and González-Calero (2008) presented jCOLIBRI has been constructed as a core module to offer the basic functionality for developing CBR application. Implementing a CBR application from scratch remains a time consuming software engineering process and requires a lot of specific experience beyond pure programming skills (Stahl & Roth-Berghofe, 2008). Therefore, using jCOLIBRI CBR framework minimizes the effort to develop an application by using other programming languages.

To run jCOLIBRI for the first time, click on the JColibri.bat file and it becomes ready for usage as shown in the following figure 4.2.



Figure 4.2: Depicts the Main Window of jCOLIBRI

Developing a CBR system is a complex task where many decisions must be made. In this study, the development of the CBR system for anxiety disorder diagnosis is divided into the following subsections which enable to achieve the objectives of the research.

4.3.1. Building the Case Base

During setting up the objectives of this study, one of the objectives is collecting anxiety patient cases in order to build a case base and represent the cases using the appropriate case representation method. So, the researcher collects anxiety patient cases from Amanuel Mental Specialized Hospital. The acquired cases are used to build anxiety disorder diagnosis CBR system that is used to assist by offering decision support to psychiatrists, psychologists, psychiatric nurses and other first line health professionals. All the acquired cases are stored as plaintext file in a feature-value representation format.

The case base is presented as a plaintext comprising of n columns representing case attributes ($A_1, A_2, A_3, \dots, A_n$) and each m rows representing individual cases C ($\{C_1, C_2, C_3, \dots, C_m\}$) each attribute has a sequence of possible k values associated to each column attribute $A=\{V_1, V_2, V_3, \dots, V_k\}$. The reason for representing cases using feature-value representation is that this approach supports nearest neighbor retrieval algorithm and it represents cases in an easy way (Salem et al., 2005; Bergmann et al., 2005).

4.3.2. Case Representation

The case representation is made in a way that easily fit to jCOLIBRI. Designing of such a case structure helps easily define the features available in the case and to measure the similarity between existing and new cases. Hence, the overall application of this research is to retrieve similar cases from the case base that can guide future reasoning, problem solving and also transforming a solution retrieved in a solution appropriate to the current problems. The collections of cases are represented in the feature-value representation to make efficient retrieval process. This is done through case indexing process. Indexing refers to assigning indices to cases for retrieval and comparison of a query to the case base (Luzelschwah, 2007).

4.3.3. Managing/Defining the Case Structure in jCOLIBRI

The acquired cases are saved in plaintext file format. Case attributes are Age, Gender, Trembling/Shaking, Palpitation/Heart pounding, Chest pain, Nausea, Fear, Breathlessness, Derealization, Sweating, Blushing, Thoughts of violence, Being easily fatigued, Muscle tension, Sleep disturbance/Sleeplessness, Irritability, Trauma, Flashbacks, Nightmares, Loss of Interest, Vertigo/Dizziness, Loss of weight, Headache, Forgetfulness, Restlessness, Class and Recommended Treatment are the important attributes chosen from all attributes. These attributes have significant impact on anxiety patient diagnosis.

Most of the case attributes have Boolean data type and a few attributes have string data type. Only age has integer data type. The reason for the use of Boolean data type for most of the attributes is, during the diagnosis of anxiety disorder the physician simply checks the absence and presence of the symptoms with respect to the significance of the attribute for her/his decision. Even the local similarity of all attributes which Boolean data type is equal and only age has interval. Global similarity of solution attributes is average.

Local similarity functions are used to compare simple attribute values. In this research, the following local similarity functions are used.

Equal: If you select equal local similarity for each attribute. Then your input and value of case base must be match. If value matches exactly then it will get result otherwise match failure.

Interval: When you select similarity interval and adjust interval value. Then, jCOLIBRI match value keeping in mind that interval. Exact value match is not compulsory in that type.

Global Similarity is linked with compound attributes and used to get similarity of collected attributes in unique similarity value. Global similarity used in this research is average similarity.

Average: It is a type of global similarity that considers the average of all attribute local similarity values. The algorithm works as follows (Watson & Marir, 1994; Salem et al., 2005; Henok, 2011).

Step 1: Find the local similarity of step for all attributes of the case which make up the case base

Step 2: Multiply the result of the local similarity of attributes with their corresponding attribute weight (importance value)

Step 3: Add the value of all attribute results of step 2

Step 4: Add all weights of attributes that represent the importance value of the attributes and multiply by the number of attributes

Step 5: Divide the result of step 3 by the result of step 4 and the result of this step is the global similarity that represents the degree of match of the old case with the new input case

4.3.3.1. Description of CBR SADD Case Attributes

Defining case structure in jCOLIBRI are done by using simple manage case structure window. It is very easy to define case structure with jCOLIBRI. Because it is simple to add attributes in description of case structure and set properties of attributes or metadata of attributes. Metadata of attributes are weight of attribute, data type of attribute and similarity function. During configuration of case structures, jCOLIBRI creates codes automatically and saved in xml file format. Most significant attributes are set by declaring higher weight as compared to other weights. Like in this CBR SADD application Trembling/Shaking, Palpitation/Heart pounding, Chest pain, Nausea, Fear, Breathlessness, Derealization, Sweating, Blushing, Thoughts of violence, Being easily fatigue, Muscle tension, Sleep disturbance/Sleeplessness, Irritability, Trauma, Flashbacks, Nightmares, Loss of interest, Vertigo/Dizziness, Headache, Loss of weight, Restlessness, Forgetfulness, Class and Recommended Treatment have more weights than other attributes such as Age and Gender.

CBR SADD prototype case base has 25 description attributes and 2 solution attributes. Solution attribute is used after finding best selected cases and show the type of the anxiety disorder and the recommended treatments given to the patient.

The following table 4.1 shows the description of case attributes regarding name, data type, weights, local and global similarity.

Significant Attributes			
Attribute Name	Data Type	Weight	Local Similarity
Trembling/Shaking	Boolean	0.9	Equal
Palpitation/ Heart pounding	Boolean	0.9	Equal
Chest pain	Boolean	0.8	Equal
Nausea	Boolean	0.7	Equal
Fear	String	1.0	Equal
Breathlessness	Boolean	0.8	Equal
Derealization/Depersonalization	Boolean	0.8	Equal
Sweating	Boolean	0.9	Equal
Blushing	Boolean	0.8	Equal
Thoughts of violence	Boolean	0.8	Equal
Easily Fatigue	Boolean	0.6	Equal
Muscle Tension	Boolean	0.6	Equal
Sleep Disturbance/Sleeplessness	Boolean	0.9	Equal
Irritability	Boolean	0.8	Equal
Trauma	String	0.7	Equal
Flashbacks	Boolean	0.8	Equal
Nightmares	Boolean	0.8	Equal
Loss of Interest	Boolean	0.5	Equal
Vertigo/Dizziness	Boolean	0.6	Equal
Loss of Weight	Boolean	0.7	Equal
Headache	Boolean	0.8	Equal
Forgetfulness	Boolean	0.5	Equal
Restlessness	Boolean	0.8	Equal
Other Attributes			
Age	Integer	0.5	Interval
Gender	String	0.5	Equal

Table: 4.1: Depicts Case Description

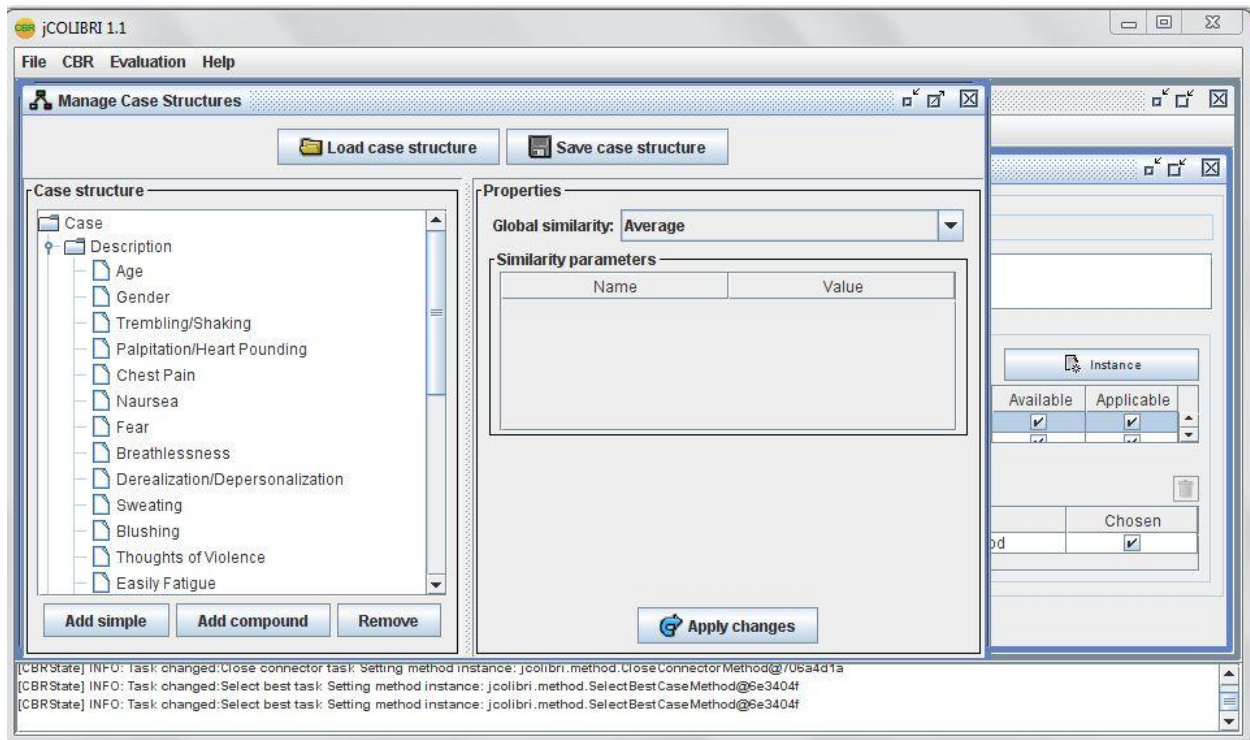


Figure 4.3: Configurations of Case Structure and Similarities

4.3.4. Managing Connectors

Once case structures are configured in jCOLIBRI, CBR systems must access the stored cases in an efficient way. jCOLIBRI splits the problem of case base management in two separate although related concerns: persistency mechanisms through connectors and in-memory organization.

Cases are often derived from legacy databases, thereby converting existing organizational resources into exploitable knowledge. To take advantage of these previously existing resources, facilitate intelligent access to existing information, and incorporate it as seed knowledge in the CBR system (the case base), jCOLIBRI offers a set of connectors to manage persistence of cases.

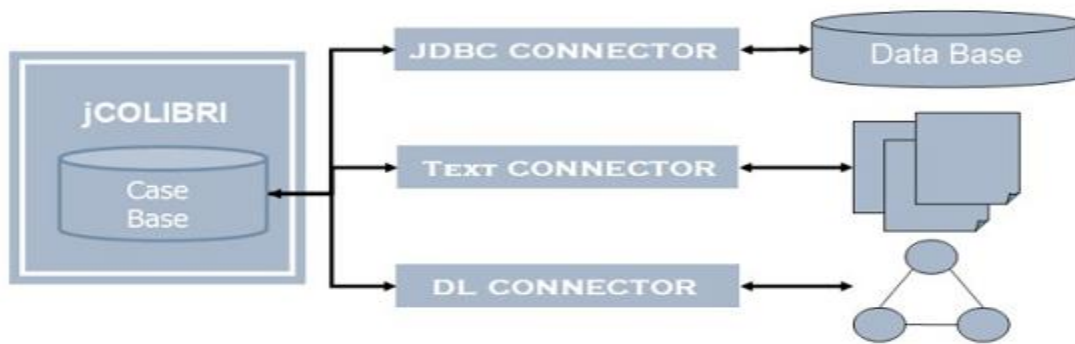


Figure 4.4: jCOLIBRI Connector Schema

Connectors are objects that know how to access and retrieve cases from the storage media and return those cases to the CBR system in a uniform way. Therefore connectors provide an abstraction mechanism that allows users to load cases from different storage sources in a transparent way. As shown in figure 4.4, jCOLIBRI includes connectors that work with plain text files, relational databases and Description Logics systems.

For the implementation CBR SADD prototype, the researcher used plaintext connector because anxiety disorder cases are stored in plaintext file format. Plaintext file case base connector is used for persistence of cases. In this connector, the researcher has to specify the path of case structure and also path of text file. All the attributes of a case should be mapped. This is connector's responsibility to retrieve data from case base and return it back to GUI. Like that of case structure, connector is also saved in xml format.

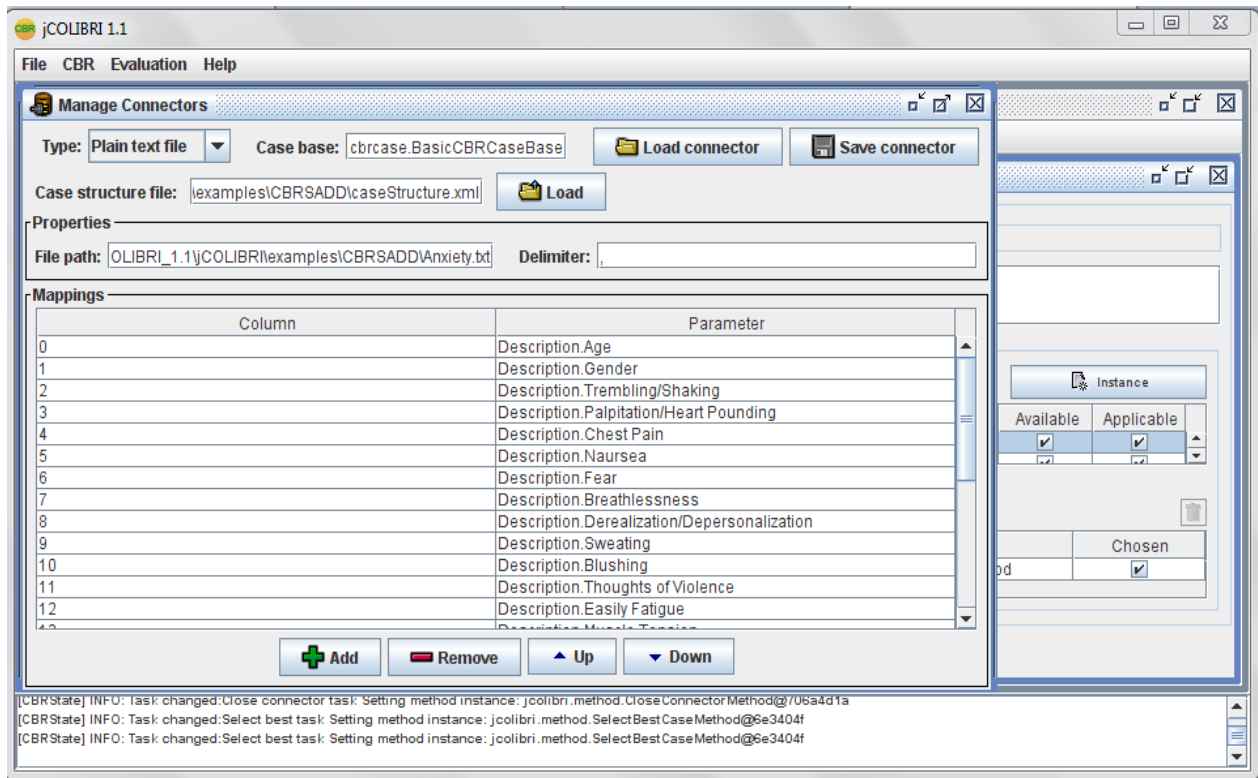


Figure 4.5: Managing Connector Configuration

4.3.5. Manage Tasks and Methods

4.3.5.1. Managing Tasks

For the development of CBRSADD prototype, the researcher used core package tasks. Core tasks which are used in CBRSADD prototype development are PreCycle, main CBR cycle and PostCycle.

PreCycle task executes before the main CBR cycle. Its task is to get all the cases in case base. Therefore, it is necessary to define path of connector in its subtask. There is only one subtask called obtain case task and it is used retrieve data from case base before the execution of the main CBR cycle.

Main CBR cycle is the main task of CBR cycle and it also has sub tasks. The developer has to give path of case structure in it. It knows number of case attributes that are available. It is called obtain query task. In addition to obtain query task, there are other significant tasks under the main CBR cycle. These are retrieve tasks, reuse tasks, revise task and retain tasks.

Retrieve tasks used to retrieve case(s) from the stored case base. Retrieve tasks also decomposed in to different subtasks. The subtasks include select working cases task, compute similarity task and select the best case. Select working case task selects cases from case base and stores them into current context. Compute similarity task compute similarity of the stored cases with the case entered by the user using the query window. Select best case shows the best matched of case(s) after computing the similarity of stored cases against the new case. It means that the number of best matched case(s) is shown to the user depending on the method used and the threshold.

Reuse tasks enable to reuse previously stored cases. It has three subtasks. These subtasks are: prepare cases for adaptation task, atomic reuse task reuse task. Prepare cases for adaptation task select cases from case base and stores them into context. Here also specifying the path of case structure in this method is needed. Atomic reuse task should be resolved by reuse resolution method.

Revise task is the evaluation stage about the selected solution in reuse phase. After selecting the most similar cases from the retrieved results, the solution for the problem should be confirmed and validated before the solution is stored for future use.

Retain tasks also used to CBR case retention on a persistence layer. It has also its own subtasks like select cases to store task and store cases task. Select cases to store task give authentication to the user for storing case. The store cases task enables to store case(s) into the case base.

The last task in managing tasks in jCOLIBRI is PostCycle. PostCycle task have only one sub task called close connectors task which is usually executed after the main CBR cycle. Its main task is to close a connection between case base and GUI.

Case Similarity, Matching and Ranking

The primarily goal of CBR system is to retrieve best similar cases by using some similarity assessment of heuristic functions. The similarity function involves in computing the similarity between the stored cases in the case base and the query, and selects nearest similar cases to the query. Therefore, jCOLIBRI uses the nearest neighbor algorithm as a cases retrieval technique. Nearest neighbor algorithm used to measure the similarity between the stored and the new queries, and return the search results within their ranked order. For each attribute in the query

and case, local similarity function measures the similarity between two simple attribute values. Based on the matching weighted sum features from those simple attributes, the similarity score between the queries and stored cases for each simple attribute is assigned.

Finally, the average score (global similarity) of each attribute between the case and the query are computed and the result is assigned to the object (the similarity between the stored case and the query). The maximum degree of similarity among the retrieved cases is displayed according to their ranked order.

4.3.5.2. Managing Methods

The method library stores classes that actually resolve the task. These classes can resolve the CBR cycle using in programming or using GUI. All tasks that are mentioned above should have their own methods to be assigned in order to achieve the tasks goal. The following are lists of methods which are used to solve tasks for this CBR SADD application.

LoadCaseBaseMethod: This method returns the whole available cases from the case base to designer. This method use connector to retrieve case base.

ConfigurQueryMethod: This method resolves obtain query task. By receiving case structure as input parameters, it displays a GUI window so that user can enter query to retrieve cases from the case base.

SelectAllMethod: This method allows displaying all the available cases from the case base to the result window.

SelectSomeMethod: This method resolves to select best task by choosing the 'n' most high similarity value from the returned cases. It requests the number of cases to give as input get best match with the requested input.

NumeriSimilarityComputationalMethod: this is used to calculate similarity between the query and cases that are stored in the case base.

NumericProportionMethod: it is the sub method of reuse task which involve in computing numeric proportion between the description attributes and solution attributes.

ManualRevisionMethod: Manual revision method permits users to modify cases in the query window as they need.

RetainChooserMethod: This method allows the user to choose the method. Chosen method will store case base. User can choose that he/she want this method to store in case base.

In general, these are some of the methods discussed and used for this research. But, there are many other methods available in jCOLIBRI method library. It is the task of the knowledge engineer to choose the most appropriate method during designing CBR application. Figure 4.6 shows the configuration of tasks and methods. In the configuration window depicted in figure 4.6 the left side shows the tasks and subtask and the right side shows the methods.

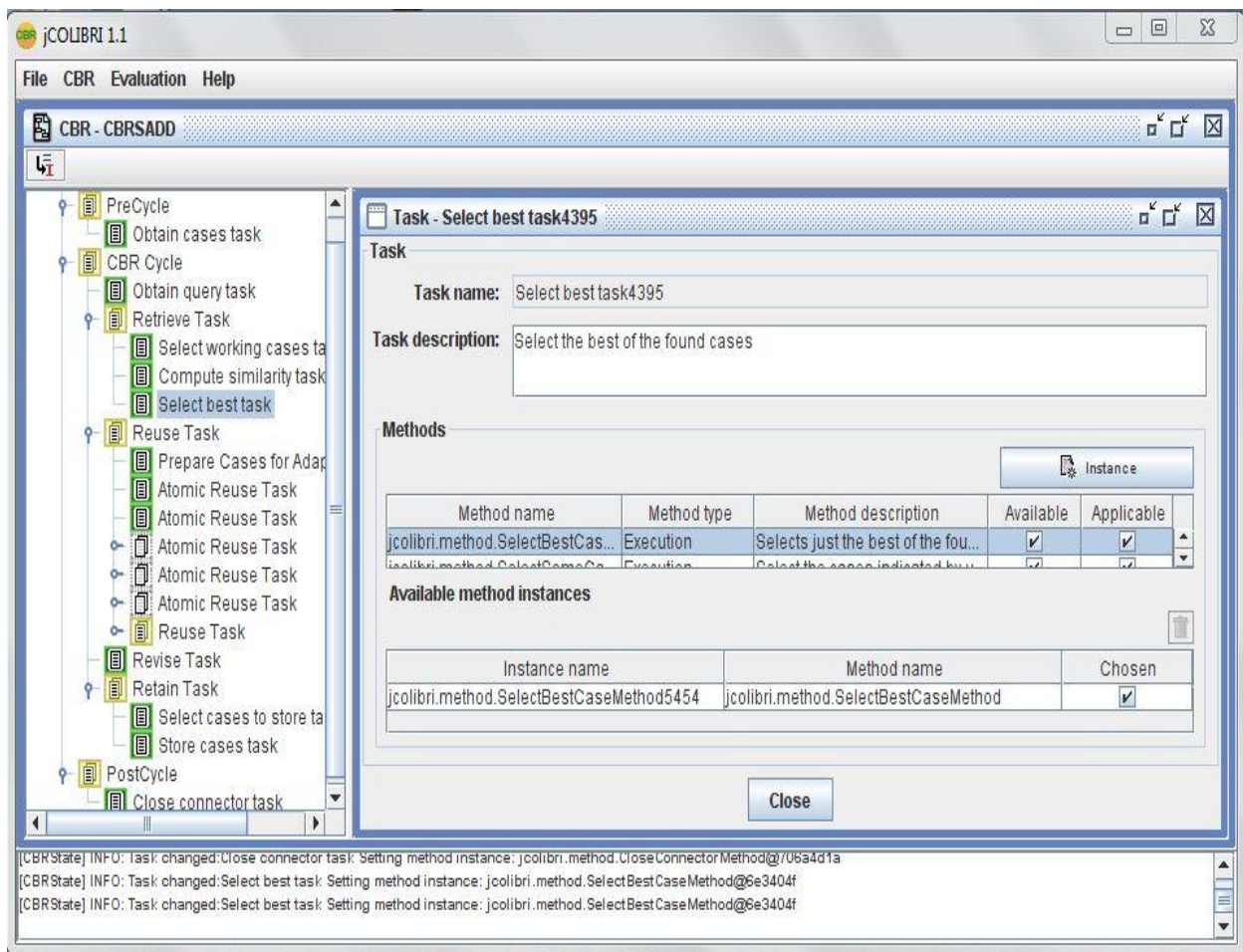


Figure 4.6: Tasks and Methods Configuration

Query

Requested parameters

Age	0	<input type="range" value="1.0"/>
Gender		<input type="range" value="1.0"/>
Trembling/Shaking	☐ false	<input type="range" value="1.0"/>
Palpitation/Heart Pounding	☐ false	<input type="range" value="1.0"/>
Chest Pain	☐ false	<input type="range" value="1.0"/>
Nausea	☐ false	<input type="range" value="1.0"/>
Fear		<input type="range" value="1.0"/>
Breathlessness	☐ false	<input type="range" value="1.0"/>
Derealization/Depersonalization	☐ false	<input type="range" value="1.0"/>
Sweating	☐ false	<input type="range" value="1.0"/>
Blushing	☐ false	<input type="range" value="1.0"/>
Thoughts of Violence	☐ false	<input type="range" value="1.0"/>
Easily Fatigue	☐ false	<input type="range" value="1.0"/>
Muscle Tension	☐ false	<input type="range" value="1.0"/>
Sleep Disturbance/ Sleeplessness	☐ false	<input type="range" value="1.0"/>
Irritability	☐ false	<input type="range" value="1.0"/>
Truama		<input type="range" value="1.0"/>
Flashbacks	☐ false	<input type="range" value="1.0"/>

Ok Cancel

Figure 4.7: Window for Case Entry into the Case Base

CHAPTER FIVE

TESTING AND PERFORMANCE EVALUATION OF THE PROTOTYPE

5.1. Experimental Setting

To develop any CBR application, the main building blocks are the previously solved anxiety disorder cases which are stored in the case base. Among the main objectives of this research, one of the objectives is building the case base which is the crucial step for the development of the CBR system. Therefore, to realize this objective, cases are collected from Amanuel Mental Specialized Hospital anxiety patients' records to build the case base. For this research a total of 50 cases are used to build the case base and to test the prototype. The evaluation part is basically focused on the performance of the prototype in terms of precision and recall. The average similarity of cases is also evaluated using Leave One Out evaluator and Hold Out evaluator. In addition the performance of the developed system is evaluated by the potential system users.

5.2. Testing the CBR Cycles and Evaluating the Performance of the CBRSADD

Now, this is the time to test the functionality of CBR cycles and the soundness of the prototype using selected test cases to check its validity and performance to domain experts. The effectiveness of the prototype is measured with recall and precision using test cases. In addition, the average similarity cases are tested using Leave One Out evaluator and Hold Out evaluator. In addition the performance of the system is evaluated from the users' side called user acceptance testing. In this user acceptance testing, potential users' of the system rate the applicability of the system in their day to day activities.

5.2.1. Evaluation of the Retrieval and Reuse Process by Using Statistical Analysis

Retrieval of previously stored cases to solve new problems is the first step in any CBR application. Retrieval of similar cases to the new case from previously solved cases is followed by the reuse of similar solutions. In this research retrieval of cases is performed using the nearest

neighbor retrieval algorithm because the implementation tool jCOLIBRI uses this algorithm. During retrieval, similar cases are retrieved to the new case with appropriate ranking. After that the user of the system can use the solution of the retrieved cases in a way that can fit to the problem at hand.

Therefore, retrieval and reuse of cases is successfully implemented in the CBRsADD application as shown in figure 5.1.

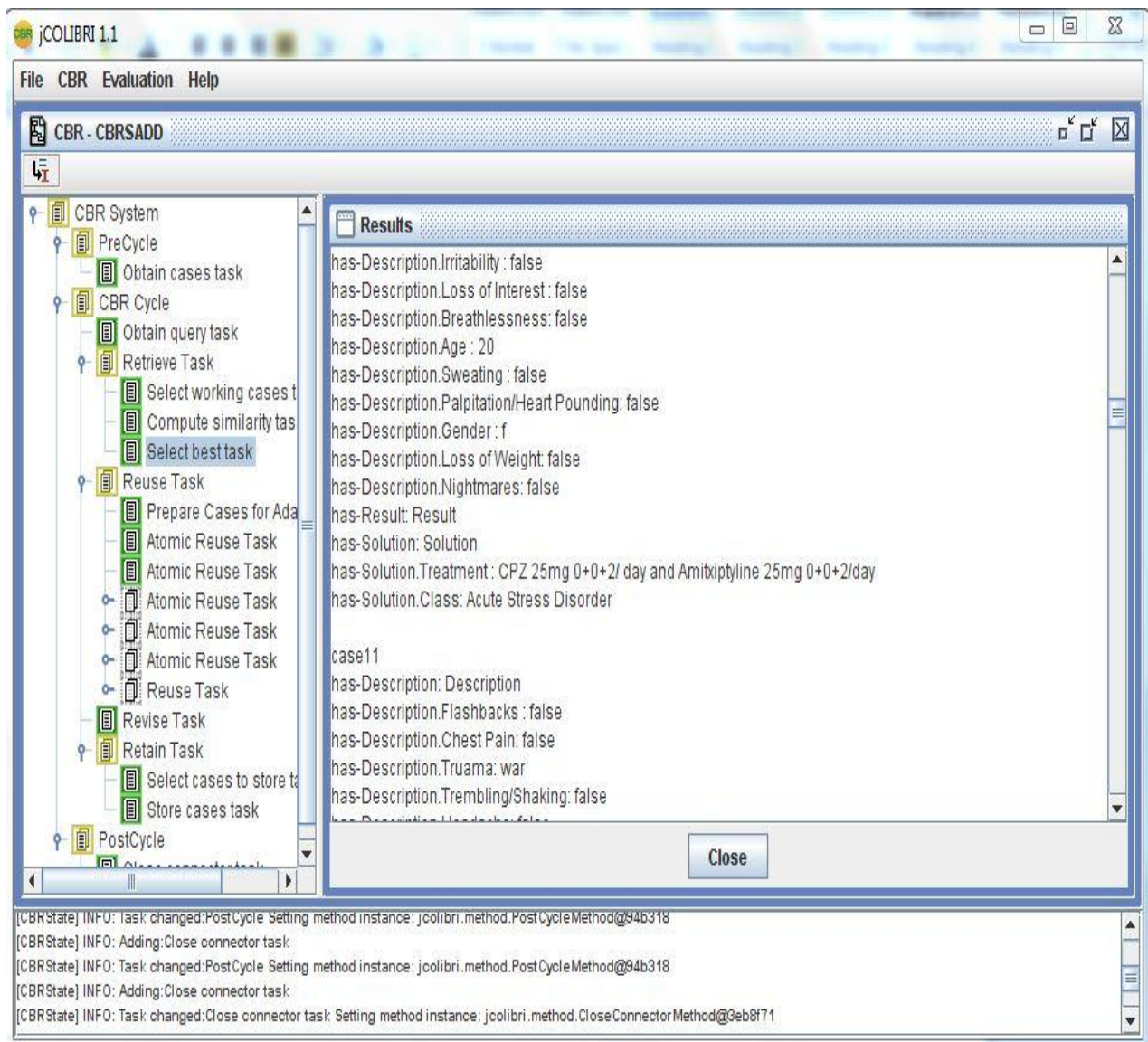


Figure 5.1: Shows Retrieval of Cases

The statistical analysis evaluation uses 50 anxiety cases that have been collected from Amanuel Mental Specialized Hospital. In this research, the effectiveness of the retrieval process of the CBR SADD is measured by using recall and precision. According to McSherry (2001) precision and recall are the commonly used measures of performance of the retrieval process in CBR. Recall is the ability of the retrieval system to retrieve all relevant cases to a given new problem (query) from the case base. On the other hand, precision is the proportion of retrieved cases that are relevant to a given query.

To conduct the evaluation, for each test case the relevant anxiety cases from the case base should be identified. For identification of relevant cases, test cases are given to the domain expert in order to assign possible relevant cases from the case base to each of the test cases. The domain expert uses the value of Class and Recommended Treatment (Solution) attributes of the anxiety case as the main concept to assign the relevant case to the test cases. After the identification of the relevant cases to the test cases by the domain expert, precision and recall are calculated.

Test Case	Relevant cases from the case base
case17	case34, case39, case29, case21, case28, case35, case48
case19	case26, case28, case39, case17, case21, case29
case20	case28, case26, case19, case1, case11, case39, case17
case21	case29, case48, case34, case35, case39
case22	case3, case9, case20, case5, case32
case23	case11, case40
case25	case15, case17, case19, case21, case23, case25

Table 5.1: Relevant Cases Assigned by the Domain Expert for Sample Test Cases

Once the relevant cases are identified and assigned to the test cases the next step is calculating the recall and precision value of the retrieval performance of the CBR system with a threshold interval.

As Henok (2011) indicated in his research, there is no standard threshold for the degree of similarity that has been used for retrieving relevant cases in CBR. Different CBR researchers use

different case similarity threshold. Henok (2011) used a threshold level of [1.0, 0.8) i.e. this means cases with global similarity score greater than 80% are retrieved. In this research, the threshold is set by the researcher. The threshold level of this research is selected by testing into two threshold groups. In the first test [1.0, 0.7) threshold is used and achieves a lower precision but a better recall. In the second test [1.0, 0.8) threshold is used and achieves a higher precision and with little reduction in recall. For this research, [1.0, 0.8) threshold is used.

Test Cases	Recall	Precision
Case17	0.86	0.67
Case19	0.67	0.57
Case20	1.0	0.78
Case21	0.60	0.75
Case22	0.80	0.67
Case23	1.0	0.67
Case25	0.83	0.83
Average	0.82	0.71

Table 5.2: Depicts Performance Measurement of CBRsADD using Precision and Recall

As shown in table 5.2 both recall and precision results are above average which is a hopeful result. The average recall and precision results 82% and 71% respectively which is also a promising result.

As seen in the table 5.2, for every test case more than average is registered both recall and precision. But, in medical domain achieving more than average recall and precision is not adequate. 100% or nearer to 100% recall and precision is expected. In terms of recall this research achieved a very good result. But, precision is somewhat lower compared to the average recall. This is because of the tradeoff between precision and recall.

5.2.2. Testing Average Case Similarity

Average similarity of cases is performed using the method `LeaveOneOutEvaluator` and `HoldOutEvaluator`. `LeaveOneOutEvaluator` evaluation method takes all the cases as queries. It executes so many cycles as cases in the case base. In each cycle one case is used as a query. Hence, using this method the average similarity of cases in the case base is around 73% as depicted in the figure 5.2 below.



Figure 5.2: Evaluation of Average Similarity of CBR SADD Application using `LeaveOneOutEvaluator`

Average similarity of cases using `HoldOutEvaluator` achieved a better result compared to `LeaveOneOutEvaluator`. This method splits the case base in two sets: one used for testing where each case is used as a query, and another that acts as a normal case base. This process is performed several times. In this experiment 8 test cases are used from the case base and achieved average similarity of around 75.5% as shown in the figure 5.3 below.



Figure 5.3: Evaluation of Average Similarity of CBR SADD Application using `HoldOutEvaluator`

5.2.3. Comparison of the Performance of CBR SADD with Previous CBR Systems

As indicated in table 5.3, Alemu (2010) and Henok (2011) achieved a lower precision compared to this work. But, Henok (2011) registered an interesting performance in the recall. The recall of this prototype is also almost nearer to Henoks' recall performance. In terms of precision, this work is better than the two CBR systems done by Alemu and Henok but still needs improvement.

In this research, the average similarity of cases is evaluated using Leave One Out evaluator and Hold Out evaluator methods which is not done by the two previous researchers. The results of this evaluation as indicated in table 5.3 tell that, there is a high variability of cases in the case base. If the numbers of cases are growing the heterogeneity of cases will be decreased and the average similarity of cases in the case base is increased. In addition to this, the high number of attribute may be the cause for lower average similarity and precision of the prototype. In this research the total numbers of attributes are 25 which is almost two fold of both Alemus' and Henoks' attributes.

Domain and Researcher	Tool	Retrieval Task		Average Similarity of cases	
		Recall	Precision	Leave One Out Evaluator Method	Hold Out Evaluator Method
AIDS Alemu (2010)	jCOLIBRI	72%	63%	Not Evaluated	Not Evaluated
Hypertension Henok (2011)	Python	86.1%	60%	Not Evaluated	Not Evaluated
Mental Health	jCOLIBRI	82%	71%	73%	75.5%

Table 5.3: Comparison of CBR SADD with the Previous CBR Systems

This work is different from Seblewongels' (2011) research in different aspects. Most of the problems of Seblewongels' research were overcome by this research. The main differences of this research from Seblewongels' (2011) work are summarized as follows.

- This research overcame the main limitation of Seblewongels' work i.e. learning the knowledge base over time impossible in rule-based prototype developed by Seblewongel (2011). But, this problem is overwhelmed by CBR in this research. As CBR systems are used, they encounter more problem situations and create more solutions. If solution cases are tested subsequently in the real-world and a level of success is determined for those solutions, these cases can be added to the case base and used to help in solving future problems. As cases are added, a CBR system should be able to reason in a wider variety of situations and with a higher degree of refinement and success.
- The prototype developed by this research can reason with small body of knowledge. While in a problem domain for which only a few cases are available, a case-based reasoner can start with these few known cases and build its knowledge incrementally as cases are added. The addition of new cases will cause the system to expand in directions that are determined by the cases encountered in its problem-solving endeavors. This is also another limitation of Seblewonges' work.
- The prototype developed in this research has the capability of reasoning with incomplete or imprecise data and concepts. In Seblewongels' prototype reasoning with incomplete knowledge is impossible. As cases are retrieved, they may not be identical to the current case. Nevertheless, when they are within some defined measure of similarity to the present case, any incompleteness and imprecision can be dealt with by a case-based reasoner. Although these factors may cause a slight degradation in performance, due to the increased disparity between the current and retrieved cases, reasoning can continue.
- This CBR SADD has the capability of reflecting human reasoning. As there are many situations where we, as humans, use a form of CBR, it is not difficult to convince implementers, users, and managers of the validity of the paradigm. Similarly, humans can understand a CBR system's reasoning and explanations and are able to be convinced of the validity of the solutions they receive from a system. If a human user is wary of the validity of an earlier solution, they are less likely to use this solution. The more critical

the domain, the lower the chance that a past solution will be used and the greater the required level of a user's understanding and credulity.

- CBR SADD have the ability of avoiding repeating mistakes made in the past. In systems that record failures as well as successes, and perhaps the reason for those failures, information about what caused failures in the past can be used to predict potential failures in the future. The reason for the failure of Seblewongels' prototype to avoid mistakes is it has no learning module.
- CBR SADD has the capability of providing flexibility in knowledge modeling. Due to their rigidity in problem formulation and modeling, rule-based systems sometimes cannot solve a problem that is on the boundary of their knowledge or scope or when there is missing or incomplete data. In contrast, case-based systems use past experience as the domain knowledge and can often provide a reasonable solution, through appropriate adaptation, for these types of problems.
- CBR SADD can solve specific problems but, rule-based systems cannot solve problems that need specific knowledge.

In general rule-based systems have a number of limitations. For applying rule-based reasoning in medical domain, preliminary criteria are the problem domain should be well understood, constant overtime and the domain theory should be strong. But, in the case of mental health applying rule-based systems is too difficult because of large individual variations, cultural differences, most of the symptoms of mental patient are not measurable, and the assessment and treatments are changing overtime.

5.2.4. Case Revision and Solution Adaptation Testing

In medical diagnosis adaptation is a commonly required task. Since this research main goal is developing anxiety disorder diagnosis system, adaptation is necessary. The purpose testing adaptation of solutions is to evaluate the systems' capability to reuse cases from the case base. Initially the system load case bases at the PreCycle stage and then selects working cases from the case base and stores the cases in to current context at the retrieval stage. The next stage is reusing the cases that are loaded in the working memory. If there is no difference between a current case and the retrieved similar cases, null adaptation of solution can be possible. When the previous

solution is not fully reasonable in the current problem, only few modifications are required to fit the current situation. This issue is a serious issue especially in medical diagnosis because of the corresponding risks. Therefore, the adaptation stage requires domain expert knowledge about how differences in problems of previous case and the current situation are occurred. So, it is up to the domain experts to reuse the retrieved cases to solve the new case rather than the system by itself derives solution. Hence, the adaptation stage of CBR SADD is left to the users of the system by comparing specified parameters of the retrieved and current case to modify the solution in a way that can fit to the problem at hand.

In general, the adaptation process of CBR SADD is successful as the case features of the previous and new case have similar or less inconsistency attribute values. On the other hand, no adaptation process can be performed as the attribute values of the previous and new cases have more dissimilar or totally different from the previous cases. However, often a direct application of an uncertain solution is impossible due to the corresponding risks, especially in medical diagnosis systems. Therefore, the adaptation has to be performed manually by a human domain expert as shown in the figure 5.4 below.

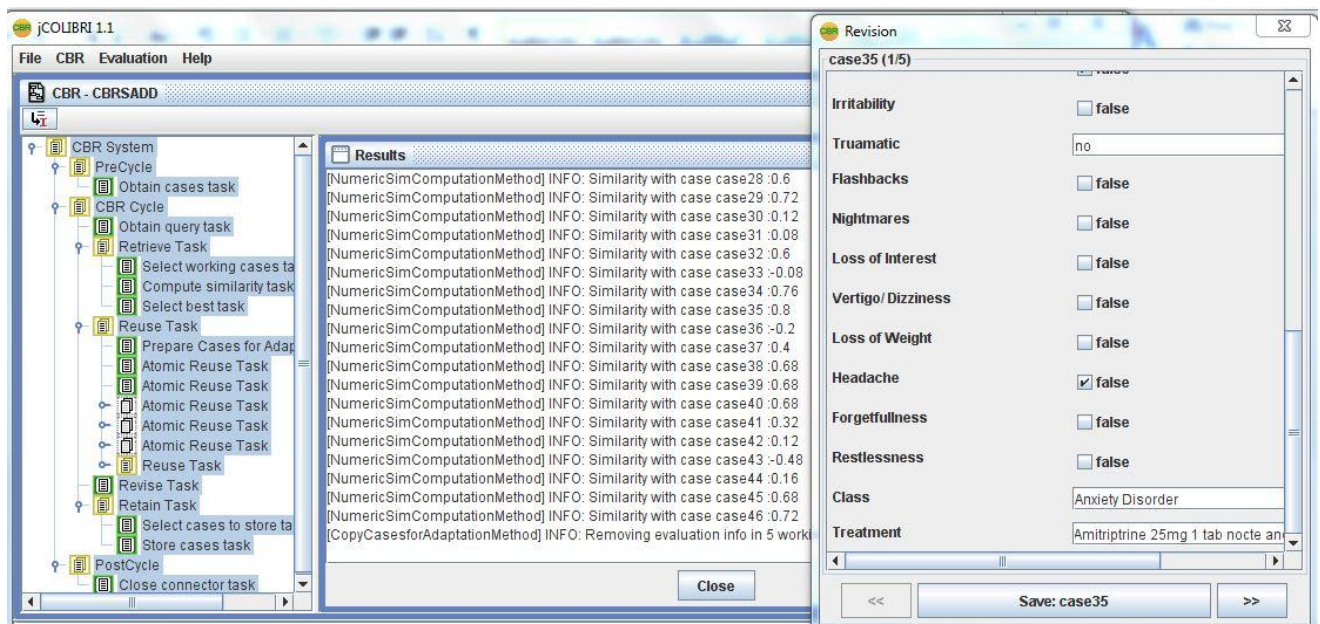


Figure 5.4: Depicts Revision Interface

5.2.5. Testing Case Retaining

Case retaining is the last cycle in CBR SADD which is an important step in storing new cases which will use for future diagnosis. Especially, in anxiety disorder diagnosis, retaining cases over time is important because mostly the treatments are psychotherapy which is mostly using psychiatrists and psychologists tacit knowledge and personal experience.

Medical CBR systems should be designed as life-long learning application. CBR systems in medicine should not be designed only to reuse past episodes with little modification instead retaining new cases for solving similar problems for the future is necessary because medicine is a rapidly changing field from time to time, and medical practice guidelines are regularly updated. Medications change, and new treatments emerge constantly. For example the main focus of this research, mental disorder diagnosis manual DSM is revised and updated four times. At this time there are many additions of anxiety disorder symptoms, risk factors and treatments even changes in the classification of diseases. Therefore, the recommendations for diagnosis, assessment and treatment that were good at diagnosis and treatments some years ago may today be obsolete in part. In this research, retaining cases after revision is possible by assigning case index manually as shown in figure 5.3.

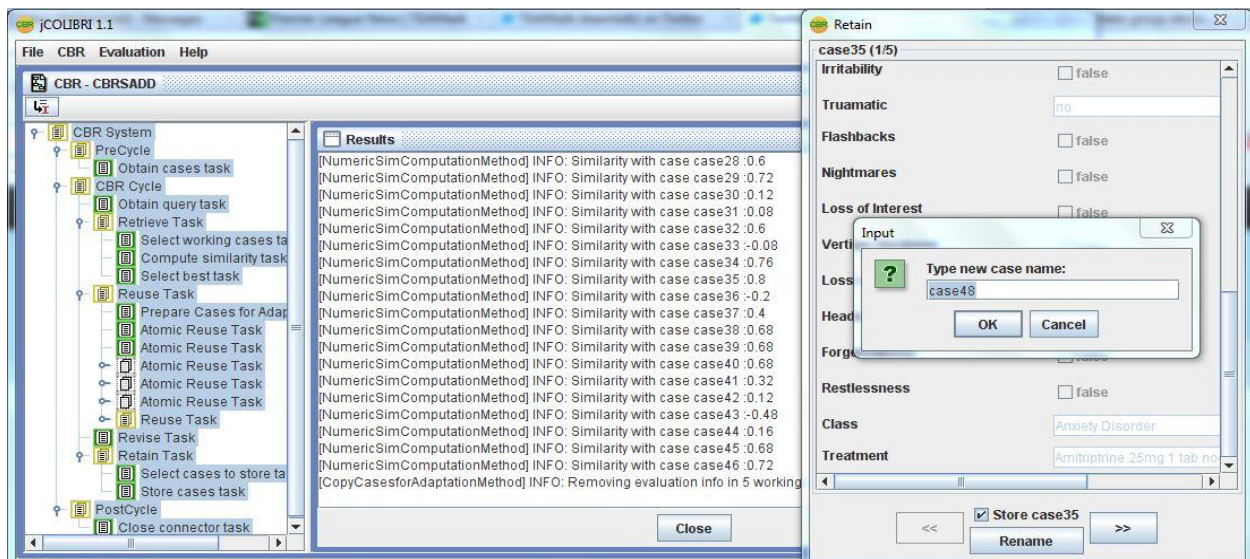


Figure 5.5: Case Retaining Dialog Box

5.3. User Acceptance Testing

User acceptance testing is performed in a real situation at Amanuel Mental Specialized Hospital specifically with anxiety case team members. During testing the users' acceptance, the applicability of the prototype is evaluated by potential users of the system. The anxiety case team consisted of three psychiatry doctors and three psychiatry nurses. Three psychiatry doctors those who participated in this research work from the beginning to the end by providing the necessary expertise knowledge evaluated the prototype and provide the necessary feedback. The three psychiatry nurses also evaluating the system by appraising the applicability of the system in providing decision support in anxiety disorder diagnosis.

During testing experts are requested to rank each parameter from to excellent by assigning value for poor=1, fair=2, good=3, very good=4, excellent= 5.

Evaluation Parameters	Performance Value					
	1	2	3	4	5	Average
Adequacy and clarity of decision support				4	2	4.3
Relevancy of the retrieved cases in the decision making				4	2	4.3
Fitness of the final solution to the problem at hand				5	1	4.7
Ease of use				6		4
Relevance of the attributes in representing the anxiety case			1	3	2	4.7
Is the system efficient in time			3	2	1	3.7
Is the system has adequate resource		2	2	2		3
Is the user interface interactive			1	4	1	4
Rate the significance of the system in the domain area				2	4	4.7
	Total Average					4.16

Table 5.4: Depicts User Acceptance Testing

As depicted in table 5.4, 67% of the respondents' rate adequacy and decision support as very good and the remaining 33% of the respondents rate as excellent. Similarly, relevance of the

retrieved cases in to support users decision making rated very good by 67% of the respondents whereas the remaining 33% of the respondents rate it as excellent. In the case of fitness of the final retrieved solution to the new problem at hand around 83% of the respondents rate the prototype is very good whereas only 17% of the respondents rate as excellent. All the respondents' rate ease of use of the system is 100% very good. 17% of the respondents rate the relevance of attributes in representing anxiety case rate as very good whereas 50% rate as good and the remaining 33.3% of the respondents' rate as excellent. Lower rating is assigned to the prototype efficiency in terms of time and the resource it has. Only 17% of the respondents' rate the system as excellent in terms efficiency in time. Around 33.3% of the respondents' rates the available resources are fair and in the same way 33.3% and 33.3% of the respondents' rate the resources available are good and very good respectively. The user interface of the prototype is also rated by respondents it is very good around 67% and the remaining 17% is assigned good and 17% excellent. To this end 67% of the respondents rate the applicability of the prototype in their domain excellent and the remaining 37% of the respondents very good. Finally, based on the evaluation of all the respondents the average performance of the prototype is 83.2%, which is above very good. This performance result shows the prototype has a promising applicability in diagnosing anxiety disorder diagnosis.

In general, the significance of CBR in anxiety disorder diagnosis has achieved an encouraging result. In addition, relevance and clarity of retrieved cases also rated by the respondents with a highest rating value. Domain experts assign a lower value compared to others is the resources available in the case base. Since the prototype learns over time, the resources will grow quickly. One interesting feedback provided by the domain experts is adding explanation facilities are in the system is very important. According to the domain experts, explanation facility is important in the adaptation of the retrieved solution. If users of the system get a more explanation about the retrieved solution and the problems itself, they can easily decide whether to use or not use the retrieved solution. According to the experts if the recommended treatment is a pharmacotherapy, the user should get more explanation about the medication recommended such as adverse effect and instruction of the dose.

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

Nowadays, the application of AI in medical domain attracts many researchers especially applying the sub field of CBR for medical diagnosis. The main focus of this research is diagnosing one of the mental diseases called anxiety disorder diagnosis using CBR approach. Therefore, this chapter concludes the overall findings of this research and based on the findings recommends other problems to be investigated by other researchers.

6.1. Conclusion

The study was conducted having the main goal of developing a prototype CBR system for anxiety disorder diagnosis that can assist the domain experts in diagnosing anxiety disorder patients. The reason for applying CBR in anxiety disorder diagnosis is, since applying rule-based reasoning for mental health is so difficult because the domain theory so weak and the symptoms of the patient is not measurable and quantifiable.

So, the development of the prototype is already realized with a number of constraints. During the prototype development, real-world patient cases are used from Amanuel Mental Specialized Hospital. For collecting the necessary cases and the implicit knowledge, different methods and techniques are used such as interviewing, document analysis and archived cases. Based on the guidance and consultation of anxiety disorder diagnosis experts major parameters are identified. The main parameters identified are major symptoms of anxiety disorder including age and gender as a support parameters. These parameters are used to create the appropriate case structure.

Rule-based knowledge-based systems are not efficient in medical domain especially in diagnosing mental health patients. The main reason for the failure of rule-based systems in mental health domain is the interrelatedness of symptoms, mostly the use of tacit knowledge for treating patients, difficulty to measure and quantify symptoms, and the treatment nature is changing and updated from time to time. The main problems of rule-based reasoning stated in

this research work is handling specific knowledge is impossible, learning the knowledge base over time is impossible, and rule-based systems face difficulty in knowledge acquisition. To overcome these shortcomings, CBR is a promising technique based on the assumption that similar problems are similar solutions.

Using the prominent CBR cycles (Retrieval, Reuse, Revise and Retain), CBR solve problems by reusing documented experiences. As the cases are retrieved, it does not retrieve only the cases that match with the new case exactly, but all other similar cases are retrieved based on their ranked order.

After developing CBR SADD, the experiments show that most of the problems of rule-based reasoning system are handled especially the learning component and specific knowledge acquisition. In CBR SADD, the first task is retrieval of cases by entering a new problem description (case) by using the query window. Then, similarity computation is performed and retrieves most similar cases. After retrieval of similar cases, reusing the previously solved cases from the case base is performed and followed by manual revision of cases to fit the problem at hand by anxiety disorder diagnosis experts. The last task is storing the revised case in the case base for future use.

When measuring the performance of the system, promising results are found. The standard measures of information retrieval (recall and precision) are used to measure the retrieval performance of CBR SADD. Using these evaluation methods, the system achieved 82% recall and 71% precision which is a hopeful result to apply CBR in the anxiety disorder diagnosis. The average solution similarity of CBR SADD application is tested using methods Leave One Out evaluator and Hold Out evaluator and achieved performance of 73% and 75.5% respectively. In addition the performance of the system is evaluated by the potential users' of the system and achieved 83.2% performance.

6.2. Recommendations

The main goal of this research is to develop a prototype CBR application for anxiety disorder diagnosis. At the beginning of this research, the researcher set up different specific objectives in harmony with the overall general objective of this study. To this end, almost all objectives are achieved successfully with some challenges and constraints. Therefore, there are a number of problems to be investigated by future researchers in applying CBR in mental health.

- The retrieval algorithm used for retrieval of cases for CBR SADD application is nearest neighbor retrieval algorithm. Since the case base of the system increases through incremental learning, the retrieval time increases linearly. Therefore, the retrieval performance will decrease from time to time. To overcome this problem investigating case maintenance techniques essential.
- In mental health concept interrelationships are mostly occurred in most situations. For example, a case base may have a previously solved specific phobia patient case that fears cars. When a new patient comes and query the case base with fear of automobiles, it may see the previously solved case as different from the current. Hence, to handle such types of problems, ontology based retrieval should be investigated.
- CBR SADD has no explanation facility. But, rule-based reasoning has explanation facility and CBR has the capability to incremental learning and specific knowledge acquisition. By combining these interesting capabilities of rule-based reasoning system and CBR system, a hybrid explanation-driven CBR system will improve the performance of CBR SADD.

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APPENDIX I

Interview Questions

The main objective of this interview questions is to elicit knowledge from anxiety disorder experts that will help for the development of a case-based reasoning system for anxiety disorder diagnosis. The interviewer records the respondents' response using pen, pencil and paper. I thank you in advance for your willingness and valuable time.

1. What is anxiety disorder?
2. What are the main anxiety disorder diagnosis procedures that you follow and which one is the crucial for your decision making process?
3. How do you identify the major symptoms of each anxiety disorder?
4. Do anxiety disorders have stages? If it has, what are they and by what measurement they are differentiated?
5. What attributes are considered by the clinician in order to identify whether the complaint has the disease or not?
6. If the complaint is anxiety patient, what things are considered by the clinician in order to manage the disease?
7. What are the main risk factors for anxiety disorders?
8. What are the main decisions that the clinicians make in anxiety disorder treatment?
9. Which attributes are the most important attribute in diagnosing the disease that the clinician should focus?
10. What are the main symptoms for anxiety disorder and which one of them are relatively common to most of the patients?
11. Do you have a standard guideline that you use for the diagnosis of anxiety disorder patients?
12. If your answer is yes for question number 12, when and in which case you use the guideline?
13. What are the major challenges during anxiety disorder diagnosis? And how can you manage the challenges you face?

Prototype Evaluation form for the Domain Expert

This is an evaluation form to be filled by anxiety disorder diagnosis experts in order to evaluate the applicability of the case-based reasoning system in anxiety disorder diagnosis. I thank you in advance for your willingness and valuable time.

Description of the parameter values are as follows.

Performance Value	1	2	3	4	5
Description	Poor	Fair	Good	Very good	Excellent

Instruction: Please, tick on the appropriate value for the corresponding parameter of the case-based reasoning system in anxiety disorder diagnosis.

Parameter	Performance Value				
	1	2	3	4	5
Adequacy and clarity of decision support					
Relevancy of the retrieved cases in the decision making process					
Fitness of the final solution to the problem at hand					
Ease of use					
Relevance of the attributes in representing the anxiety case					
Is the system efficient in time					
Is the system has adequate of resource					
Is the user interface interactive					
Rate the significance of the system in the domain area					

Declaration

I declare that the thesis is my original work and has not been presented for a degree in any other University.

Getachew Wassie

June 2012

This thesis has been submitted for examination with my approval as a University advisor.

Ato Getachew Jemaneh