

Research for Context-respectful Counseling Agent

文脈尊重型カウンセリング・エージェントの研究

DISSERTATION

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ABSTRACT

Counseling for information technology (IT) personnel lies at the intersection between the software development ecosystem where IT employees collaborate professionally and the social ecosystem where they communicate with each other to share the success or handle the failure of software development. Today, counseling has become a major issue in the IT industry, since the success rate of IT system development projects is as low as 30 %, and more than 60 % of IT professionals suffer from anxiety or other emotional problems. However, counselors supporting them lack in number overwhelmingly. To cope with this, a context-respectful counseling agent CRECA is proposed. This paper describes a conversational agent/ counseling agent CA aiming to replace human counselors assisting IT personnel in software development ecosystems toward future deployment to social ecosystems.

Utilizing IT domain knowledge, the proposed agent automatically adapts the vocabulary used in its responses according to the context and to the current phase of the conversation. Using context-respectful reflection support knowledge, the agent generates its response consisting of (1) chatterbot-like mirroring/paraphrasing for context sharing, (2) context-respectful mechanism of prompts for “context narrowing/digging” to help a client solve problems, and become aware of their solutions via deep reflections of IT personnel undergoing counseling.

Knowledge focusing on a single domain, such as IT counseling domain, and context-based/context-respectful reflection allow my counseling agent to work properly without having to acquire and manage a huge amount of knowledge.

More specifically, I extended context-respectful responses by adding summary functions in the context-respectful reasoning process, and to improve my validation ensuring greater number as well as higher diversity of participants, including IT professionals. For adding summary functions, an emotion focused context-respectful counseling agent (CRECA-E) is also proposed as an extended CRECA. It focuses on emotional words in clients’ utterances. To support clients’ reflection toward self-awareness of solutions, it replies with two sentences before and after clients’ emotional changes. While there is no such emotional change, it paraphrases a single sentence which clients have just said, though “context respectful” prompts such as “Say more” follows.

The experimental evaluation showed the promising result of the context-respectful method. Such as experimental results for CRECA show that clients interact with

CRECA on average two times longer than they do with ELIZA-style CA(ELIZA); also, a questionnaire-based validation has shown the average value of questionnaire's result was on the "agree" side for my agent, but on the "disagree" side for ELIZA.

Therefore, the user acceptance level of the proposed agent is much higher than that of conventional chatterbots. In addition, experimental results for CRECA-E show that CRECA-E on each average value of interact times, a questionnaire's result on trust and on self-awareness are CRECA-E > CRECA > ELIZA. Therefore, the client acceptance level of CRECA-E is much higher than that of CRECA, and that of CRECA is much higher than that of conventional chatterbots.

Knowledge focusing on a single domain, such as IT counseling domain, and context-based/context-respectful reflection allow the proposed counseling agent to work properly without having to acquire and manage a huge amount of knowledge.

To support a great number of IT related persons exposed in distressing situations, context-respectful counseling agent virtualized on the Web was evaluated. Python was used for implementing this agent.

Keywords: Counseling agent · Conversational agent · Digital ecosystem · Ontology
Context-respectfulness · Reflection · Self-awareness · Summarization · CRECA

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CHAPTER 1

INTRODUCTION

In the Information Technology (IT) field, most people are involved in development projects of software systems that have never been developed before. Throughout the years, the success rate of IT development projects has remained as low as 30% (Yaguchi R, Yoshida Y, 2008). In Japan, according to the Japanese Ministry of Health, Labor and Welfare, IT workers suffering from anxiety problems as well as lamenting psychological discomfort and lack of the effectiveness have reached 60% (MHLW, 2008). Let me give some concrete examples of the problems that affect IT workers in different positions. High-level/Top-level managers mostly face strategy problems. They need to make big decisions such as setting the goal of their business, or finding a way to increase its revenue or profit (Shinozaki T, 2008). Problems for less than middle management and other IT employees are more related to the risk of performing poorly in tasks they are in charge of, and to the corresponding impact on their careers (Shinozaki T, 2008).

Research by Kosh M. S. and Kerzner H. (1948) has identified risk factors that make some jobs especially stressful and demanding. They include “responsibility without authority”, “the pressure of strict deadlines”, “role ambiguity and conflict with other people”, etc. Especially, IT jobs have an additional stress factor, since workers have more problems in keeping up with the rapid pace of technology evolution or with sudden changes in development methodologies. In (Jaaksi A, 2007), for instance, A. Jaaksi reported on Nokia’s adoption of open source, noting that even experienced programmers found it stressful to master the content of rapidly evolving open source libraries.

While these risk factors are well known within the IT social ecosystem, the number of counselors available for discussing them is very limited. Even the author of this dissertation, who has more than 10 years of experiences as a counselor with 30 years as a successful project manager of large scale IT projects, can consult with no more than 20 to 30 people a month. Counseling is a laborious and time-consuming work. Inexperienced counselors hurt distressed persons (henceforth “clients”) or are not trusted by them. Thus the number of senior counselors who can save such clients is very limited to

around 1000 (Tokyo Branch of Japan Association of Industrial Counselors, 2014). Since this is just around 0.1% of distressed 60 % of 2 million IT persons in Japan (Statistics Bureau of MIC, 2012), distressed people have difficulties in spelling out their problems. Indeed, it would take several years to carry out traditional one-on-one counseling even at a small workplace of several hundred people. Thus, I came up with the idea of a software agent as a core component of software development ecosystems that can replace experts in the preliminary stages of counseling IT related persons or even IT professionals.

By the way, the term digital ecosystem has a broad meaning. This includes a human (or “social”) ecosystem and a software development ecosystem. The former consists of human actors, the relations among them, the activities they carry out, and their outcome (Bosch J, 2009). The “software development ecosystem” is a virtual working space where a group of IT professionals cooperate and interact by means of tools that enable, support and automate the activities carried out by the actors (IT related persons). Software development ecosystems take various forms, e.g., (1) software ecosystems of external developers contributing to the platform of a company or, (2) so called, social ecosystems where users either actively or passively contribute knowledge, content, goods and services, connections or behavior to the community. The emergence of a global (as opposed to company-wide) software development ecosystem is one of the most exciting developments for software companies (Bosch J, Bosch-Sijtsema P, 2010).

Although social and software development ecosystems can be viewed as distinct, in practice there is often a very strong overlapping between the two. IT professionals collaborate within the software development ecosystem, but interact with each other within a larger social ecosystem where they carry out activities like finding help and support to their problems. In this social ecosystem, each actor relies on relations with other professionals or to counselors, e.g., to handle and share success or failure. I envision counseling for IT personnel right at the software development ecosystems and towards the social ecosystem.

The idea of human-computer interaction based on agents capable of handling natural language is quite old; it began to emerge more than fifty years ago, with the Turing test (Turing A M, 1950). However, few would dispute that modern research on conversational agents started in the Sixties with ELIZA (Weizenbaum J, 1976); Weizenbaum J, 1966). An early variant of ELIZA, called DOCTOR, mimicked the behavior of a psychoanalyst by replying to users with keywords taken from their initial input (a technique called mirroring), and many users felt as if the DOCTOR was really listening to them. In

today's digital ecosystems this issue, at the conceptual and practical level, has become topical. Today, many implementations of conversational agents are available and several annual competitions like the Loebner Prize or the Chatterbox Challenge try to assess how well software agents can simulate human verbal interaction. As I shall see in the next Chapter, significant progress has been done in this field; however, most researchers concede that areas remain where conversational agents cannot yet help humans in solving real problems (Floridi L, Taddeo M, Turilli M, 2009). Indeed, it is difficult to provide a conversational agent with a sufficient amount of domain knowledge to make it a worthwhile advisor for a human user on a professional problem. Supporting the user with "learning by teaching" method (Biswas G et al., 2009) proposed. or automatically generated suggestions/prompts (a technique often called *scaffolding* (Van de Pol J, Volman M, Beishuizen J, 2010) can work well when problems are clear and solutions are known to teachers; there is no guarantee that these method can work to handle ill-specified problems whose solutions are known to neither teachers nor counselors.

Rather than by conversational techniques, my research was originated by direct observation of the interactions between counselors and their clients for acquiring the real expert's knowledge. In order to find solutions to such ill-specified problems of persons related to IT or software ecosystems, counselors and clients need to build up mutual trust (Asay T, Lambert M, 1999). This is because clients do neither speak freely nor show their true feelings without it, and still worse, they usually stop counseling dialogue in case of no mutual trust. Thus, by listening to clients for sharing their suffering situation/context, the counselor helps them to correctly represent their problem by promoting their reflection (Schon D, 1983) through context-respectful or problem digging prompts within their situation/context without hurting their mind, and leads them toward a solution. In my approach, clients find solutions by themselves and within themselves, with the help of a counseling agent capable of creating context-respectful (here, context-sharing and context-respectful) natural language responses in a restricted semantic or ontological domain of IT counseling.

From the syntactic point of view, my counseling agent (named context-respectful counseling agent; CRECA) does not use "why" and "how" scaffolding, but utilizes a combination of ELIZA-like mirroring (inspired by the Rogerian person-centered therapy (Rogers C R, 1966) and context-respectful reflection support prompts such as "please be more specific" or "please tell me more in detail".

A major feature of my technique is context-awareness. Besides the context-respectful approach mentioned above, I use an ontology-based modular vocabulary ra-

ther than the simple keywords used by the original ELIZA and its successors. This makes my agent's responses more situation-aware or context-aware, namely more context-sharing and more context-respectful, which help continue counseling dialogue without discouraging or spiritually hurting clients. As for implementation, my agent exploits 1) a context-respectful reasoning mechanism to reason based on dynamically changing situations and goals (Gonzalez A et al., 2010 ; Hung V, Gonzalez A, DeMara R, 2009), as well as 2) domain-specific counseling knowledge for IT workers.

Currently, several counseling systems have been newly introduced. The first example called "Counseling Dialog System with 5W1H extraction" (Han S et al., 2013) handles clients' emotion. This proposes counseling support techniques to interact with clients by paraphrasing, asking open questions, and reflecting their feeling. Four types of emotions (Happy, Sad, Angry, Afraid) are detected and so called 5W1H (When, Where, Who, What, Why, How) type open questions are followed. Open questions generated by 5W1H trigger to teach clients what to do. However, such questions as well as the rough emotional category destroy the context of the counseling and the dialogue stops frequently.

The second example is a dialogue system for career counseling proposed (Srivathsan G et al., 2011). The system is equipped with all the necessary domain specific information and knowledge (expertise) about various vocations and has the capability to infer the optimal solution. As ALICE-bot (Deryugina O V, 2010 ; ALICE) and LSA-bot (De Pietro O, De Rose M, Frontera G, 2005) etc. do, this system can offer various information to help clients solve their problems. However, it is useful only when the problem is clarified as a concrete job selection. Further, demanded information becomes wide spread. The amount of information as well as domain knowledge to select the information explosively increases in real problems. This causes significant cost/performance problems in practical counseling systems. Such problems do not occur in case of counseling agents using Rogerian client-centered active listening (Rogers C R, 1966; Raskin N, Rogers C R, Witty M, 2008), which are limited to paraphrases including those of multiple sentences that support clients to solve problems by their self-awareness without providing a lot of information.

For such client-centered counseling, human counselors need to firstly build up mutual trust with clients (Asay T, Lambert M, 1999) in order to help clients find solutions for real problems such as IT persons' sufferings. Indeed, if there is no mutual trust, clients spell out neither their true feelings nor their suffering situations, which is indispensable for clarifying or digging their problems. Only due to the mutual trust and continui-

ty to sincerely listen to clients (Rogers C R, 1966) the counselor can help them to correctly represent/verbalize their problems and promote their reflection to lead them toward self-awareness of the problem solutions.

Owing to these, clients' problems are clarified and narrowed down towards their self-awareness of solutions. However, my agent (CRECA) considers neither contents of previous dialogues nor dynamic emotional changes of context or situation. This technique is not sufficient for clients to find the important emotional fact lying in their problems towards their solution by themselves. As is described just below, the emotions of clients up to their current or latest utterance must be considered; especially, their emotional change has to be conveyed to them. Such dynamic emotion or emotional changes should be handled by counseling agents.

Human activity and thought are triggered and accompanied by emotion. Clients' situation and thought are expressed by their emotion or emotional word. Even a slight change of emotional words often effects human activity and thought. However, a computer does not have emotion. It only acts according to a program. A program does not accompany emotions that can be generated by status or situation of a human physical body (M. Okada, H. Mishima, M. Sasaki, 2001; Pardeck J (1987). Though a program can generate emotional words, they are inherently different from those triggering and accompanying human activities and thought. A program cannot recognize or understand human emotions, not to mention of client's suffering emotions, their situations, or their emotional contexts. Even human beings cannot completely understand emotions of other persons. Human counselors paraphrase clients' utterances. Still more, counselors summarize the contents or contexts of the multiple sentences in a counseling dialogue, focusing on emotional changes or dynamic emotion combined with chronologically ordered events. Thus, counselors can reply with such summary and paraphrases to act as if they understood the clients empathically. This is very effective for the counseling since clients continue trusting on counselors to keep the conversation and the reflection on themselves towards self-awareness of problem solutions. The dynamic emotion appears in a series of dialogue sentences as the change of emotional words which expresses clients' emotion. People recognize such dynamic emotion or emotional changes, if it is just summarized or paraphrased by others and reflect on themselves. Therefore, it is effective for the counseling to generate the response sentence by such summarization that extracts just the sentences or words expressing clients' emotional changes in a series of clients' utterances.

Thus, Emotion focused context-respectful counseling agent (CRECA-E) is proposed as an extended CRECA, which detects the change of emotional words (phrases) from the input sentences of clients. When a change in the emotional words occurs in clients' utterances, the agent summarizes them as reply sentences. For clients to deepen their reflection more easily and reach self-awareness more certainly, this summarization has the following effects: If clients accept the summary or the content of this reply sentence, they recognize their emotion or its change. Otherwise, clients recognize or reconfirm their true emotion or problem due to their own correction of the agent's reply sentence.

This agent helps suffering clients to understand the overview of their problems, to refine/clarify them, and then to acquire self-awareness of the solutions. Namely, this agent not only performs paraphrasing accompanied by context-preservation type prompting but also summarizes by focusing emotions along with a chronological sequence of events in the dialogue in order to promote the clients' reflection and the digging their problem towards the solution by self-awareness. In other words, the proposed emotion focusing context-respectful counseling agent (CRECA-E) focuses on clients' emotional words in dialogue sentences for counseling. Namely, to support clients' reflection toward their awareness of solutions, it replies with two sentences before and after their emotional changes. Only if there is no such emotional change, it paraphrases a single sentence which clients said or input immediately before, though "context respectful" prompts such as "Say more" are followed.

Owing to this reply with clients' emotional change as well as paraphrases followed by context-respectful prompts, the counseling agent behaves as if it empathizes with clients, and continues conversation without losing their trust. People recognize their dynamic emotion or emotional changes if it is summarized or paraphrased by trustful others. Thus, clients can reflect on themselves and verbalize/clarify their problems more and more. This leads to their self-awareness of the possible solution.

Further, it is required that a great number of people or clients have counseling concurrently as well as responsively. Assuming http server takes 3 milliseconds for the connection (Zembutsu M, 2011), 1000 clients can just connect to a Web server at once with 3 seconds of the maximum delay. However, context-respectful Counselling Agents (CRECAs: CRECA and CRECA-E) have at least for a few logging file accesses which take around 10 milliseconds usually. Thus, only 100 clients can do conversations to CRECAs on a Web server at once within 3 seconds of the maximum delay. Assuming 1000 clients are expected to do conversation, more than 10 computers are necessary to ensure the interactive responsiveness such as seconds. Still more, "https" that takes 10

times more of processing time compared with “http” is desirable since the counseling is very personal and its content should be hidden to others. In this case, still 10 times more scale-out (parallelism by cloud computers) is necessary. Therefore, my counseling agent is implemented as scalable Web applications on Django in ubiquitous (seeming to appear everywhere at the same time) as well as cloud computing environments. Thus, the agent is virtualized not only as a human-like counselor who pretends to keep empathy with clients through context respectful responses, but also as a distributed system in ubiquitous environments such as cloud computing to keep its responsive performance even if it is used by a great number of clients at the same time. Indeed, context-respectful (so-called “active listening”) counseling agents can be realized as scalable Web applications. They exploit “active listening” power (Shinozaki T, 2008). They do not need a huge amount of information to provide for clients as solutions or support. They provide only context-respectful information, namely at most slightly modified sentences or words listened from clients. Data access is independent among clients since agents use only clients’ utterances or their logs in each dialogue. Thus, the Web applications for such agents are scalable. They are virtualized and/or incarnated to act as if human counselors are virtually distributed or ubiquitous in a cloud computing environment. Owing to this, a great number of clients can have aforementioned context-respectful counseling concurrently as well as responsively.

Meanwhile, there are various types of clients. In my proposed system, among context-respectful counseling agents, clients can select their preferable agent or even try another agent when unsatisfied. Currently three types of counseling agents (CA1, CA2, CA3) can be selected, each has the following features: CA1(CRECA) ; paraphrasing for a single sentence + context-preserving prompt, CA2(CRECA-E) ; emotion focused summarization, namely paraphrasing for multiple sentences + context-preserving prompt, CA3(ELIZA-like CA) ; replying randomly but limitedly somewhat context-breaking responses to continue longer conversation (e.g., wide variety of prompts such as “How about your mother?”).

The remainder of the dissertation is organized as follows: Chapter 2 briefly reviews the state of the art related to counseling agents comparing with an overview on the concept of my counseling agent. Chapter 3 proposes a method to create my counseling agents. Chapter 4 discusses the implementation of the proposed agent system that can be virtualized and/or scalable on the Web. Chapter 5 evaluates the effects of context-respectful features and the scalability on the cloud computing environment. Finally, Chapter 6 draws the conclusions and outlines my future work.

The results of this research were presented at the Springer Journals: Computing(Shinozaki T, Yamamoto Y, Tsuruta S, 2015) and ,World Wide Web (Yamamoto Y, Shinozaki T , Ikegami Y, Tsuruta S, (Accepted in 2015)).

Parts of the work described here have been also presented at the following International Conferences:SITIS2012 (Shinozaki T, Yamamoto Y, Tsuruta S, 2012), Promac2012(Shinozaki T, Okada M, 2012)SITIS2013 (Shinozaki T, Ikegami Y, Bissay E, Tsuruta S, 2013) ,SMC2014 (Shinozaki T, Yamamoto Y, Tsuruta S, Damiani E, 2014) .

CHAPTER 2

RELATED WORK

2.1. Counseling

In the U. S., there are two major psychological counseling (known as psychotherapy) approaches: person-/client-centered therapy (Raskin N, Rogers C, Witty M, 2008) and cognitive behavior therapy (Faculty of Health Sciences of Simon Fraser University, 2007).

The client-centered therapy was presented by Rogers. Its hypothesis states that a congruent therapist, who provides unconditional positive regard and empathic understanding, will stimulate psychotherapeutic personality change in a vulnerable, incongruent client, if the client perceives these attitudes (Raskin N, Rogers C R, Witty M, 2008; Rogers C R, 1957). The therapy helps a client to clarify his problems and acquire self-awareness for solving the problems through counselor's sincere listening to him. Counselors receive, empathize with, and self-disclose to the client by replying with the client's keywords positively and responding sympathetically. To help a client in finding solutions to his problems, human counselors need to firstly build up mutual trust with the client and keep the trust (Asay T P, Lambert M J, 1999). I call this "context respectfulness" which is considered essential in the agent proposed here in this dissertation, since humans neither speak nor show their true feelings/facts without it.

Meanwhile, the cognitive behavior therapy can be considered as one kind of symptomatic treatment; a counselor and a client create and go through a concrete problem solution and its process according to the situation of the client. Yet, always creating and undergoing such individualized solution requires an enormous amount of knowledge information. Thus, the therapy is quite unsuitable to realize on computers especially for the view point of software development eco.

2.2. Conversational Agent technique

Related works on agent techniques are described here as the outline is shown in TABLE 1.

2.2.1 Conversational Agent

The first conversational agent was, as I mentioned in the previous chapter, probably ELIZA, developed in the Sixties by Joseph Weizenbaum (1976). An early variant of ELIZA, called DOCTOR, was introduced to simulate the interactions typical of client-centered psychotherapy. Such therapy, originally introduced by Rogers (Rogers C R, 1966), requires the counselor to utter only non-committal short sentences, in order to leave as much room as possible to the client's self-clarifications of her problems. Client-centered counselors empathize with clients by repeating the client's own words and responding sympathetically. Since DOCTOR just reproduced ("mirrored") the facts or emotions that appeared in client's input, it did not need to store a huge amount of domain knowledge. However, being entirely stateless and lacking the notion of context, DOCTOR could not lead clients' reflections towards specific goals. Successors of ELIZA, like PARRY (Parkinson R, Colby M, Faught W, 1976), Racter (Thomas E, Chamberlain W, 1984) and the more recent Loebner Prize winners Albert One, A.L.I.C.E., Ultra Hal and Elbot (Deryugina O V, 2010) go under the collective name of *chatterbots*¹. A chatterbot is nothing but a text-based conversation agent that can interact

TABLE 1. The Synthesis table of related works on agent techniques.

Techniques	Name/System	paper	Approach	Effects/defects
Conversational techniques	ELIZA	Hung V et al. (2009)]	paraphrasing	dialogue continue, not digged
	ALICE, CCS*	Artificial Intelligence Foundation(ALICE)	information offer	Contexts are not kept
	LSA-Bot	De Pietro O et al. (2005)	AIML knowledge on the Web	knowledge explosion, unscalable
	CDS**	Han S et al. (2013)	5W1H, four types of emotion	
Education/ learning	scaffolding	Van de Pol J et al. (2010)	instructional scaffolding offer	for clear/simple problems, most solutions known by teachers
	contingency	Kopp S et al. (2005), Sammut C (2001)	limited situational knowledge	
Summarization	abstractive	Gupta V et al. (2010)	searching new concepts	to re-tell shorter
	extractive	Takada T (2013)	word frequency/position	to select important sentences for efficient read/understanding
		Kennedy A et al. (2012)	emotional words	

CCS: Career Counseling System, CDS: Counseling Dialog System

¹ It is interesting to remark that only in the year 2000s, within the Loebner competition, conversational agents' performance managed to get back to the PARRY levels of nearly thirty years before, in spite of all the theoretical activity carried out since then.

with human users through some interface, such as an instant message service.

Basically, a chatterbot consists in a *parser* module that analyzes the user input, a *transformer* to generate the chatterbot's output based on the user's previous input(s) and some *domain knowledge* to guide the transformation. Some chatterbots, like the counseling agent described in this dissertation, are designed for specific purposes, while others can converse with human users on a wide range of topics (Deryugina O V, 2010).

While most of today's chatterbots rely on natural language processing techniques, the e-learning community has contributed some relevant approaches. G. Biswas et al. proposed the "learning-by-teaching" method (Biswas G et al., 2009). In this method, users firstly teach an agent called BETTY'S BRAIN about some problem by showing the agent how to solve it. Then, BETTY asks human learners questions starting with "why", "how" etc. about the problem solution enabling them to identify the knowledge they lack to handle the problem more effectively. However, BETTY does not hold the users' trust nor shares their emotional words. Therefore, it is hard for human users to become aware of their own psychological or professional problems by interacting with BETTY (Ball G, Breese J, 2000).

Related to the "learning-by-teaching" of BETTY'S BRAIN, the e-learning research community has introduced the notion of *scaffolding* (van de Pol J, Volman M, Beishuizen J, 2010). According to this notion, users are initially exposed to automatically generated suggestions (the "scaffolding"), regardless of their relevance to the problem at hand; as the users' problem awareness increases, scaffoldings are gradually removed and users are left to autonomously consider solutions.

Scaffolding techniques are known to work well when problems are clear and well defined (van de Pol J, Volman M, Beishuizen J, 2010). However, many counseling problems are unclearly defined and their solutions are unknown even to counselors, at least initially.

Therefore, it is important for counselors and clients to share experience and emotions and, at the same time, build up mutual trust, clarifying the client's problems together, and then trying to solve them. Thus, it is important to remark that even after client's problems are getting clarified and their solutions are getting closer, the mutual trust build-up process should not stop or at least, mutual trust must be continuously maintained. However, scaffoldings in learning chatterbots become less and less ("fade out", in its terminology) as learning goals are getting closer. Further, as mentioned above, scaffoldings and the like, often ask questions such as "why" or "how", which

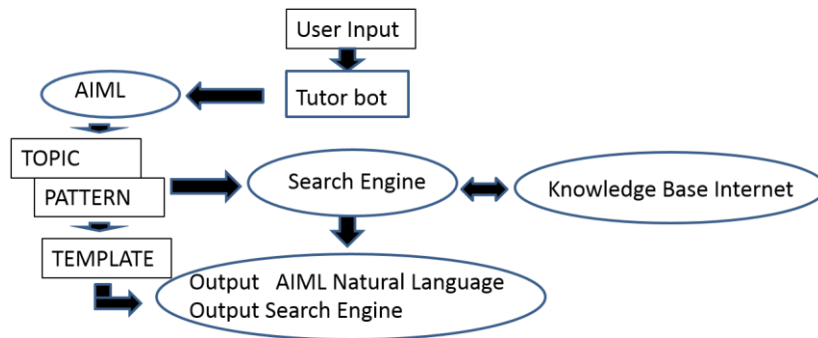


Fig. 1. Example of architecture of a conversational agent. Source: (De Pietro et al. 2005) expose users to an irrelevant and non-contextual conversation. This also has the risk of losing their motivation to continue the counseling.

Fig. 1 shows a conventional architecture of a conversational agent (De Pietro O, De Rose M, Frontera G, 2005). The user inputs a sentence that a conversational agent converts to an abstract language so called Artificial Intelligence Markup Language (AIML) (De Pietro O, De Rose M, Frontera G, 2005). This translation is used to analyze the content of the sentence and to make requests via a search engine in a knowledge base. The response in natural language is generated through an abstract language, also AIML, and will be presented to the user.

It is easy to see that the architecture of Fig. 1 is very rudimentary and rigid, particularly ill fitted to the context of a counseling system that requires keeping users' motivation alive. A major drawback is the absence of provisions for selecting the portion of domain knowledge that is relevant to the specific conversation. Due to the lack of such knowledge and selection or filtering, users are likely to be exposed to irrelevant or non-contextual comments, with the risk of losing their motivation to continue interaction with the agent. This phenomenon is also typical of the scaffolding approach: since scaffoldings are too specifically related or limited to clearly definable problems, they may suffer from non-related or non-contextual responses with little sharing of emotion or context for my counseling with unclear problems whose solutions can be known by neither counselors nor teachers.

Indeed, domain knowledge acquisition and selection are two major problems that prevented successful specialization of conversational agents to specific domains. Only in recent years there have been some cases of agents that became practical applications (Kopp S et al., 2005). While little analysis has been done to determine the differing needs, expectations, and behavior of human users in these environments, some

experimental results suggest the idea that humans expect more than the conversational agents can actually deliver (Robinson S et al., 2008). I argue that the problem lies in the dynamic nature of domain knowledge, often called knowledge *contingency*. Some conversational techniques try and cope with contingency by limiting the domain knowledge taken into account to generate responses to the current *situation* or *dynamic context* (Sammut C, 2001). They are in very simple domain such as teaching events in a museum, where the solution or goal is known by teachers. Therefore, they need a huge amount of domain knowledge if problems increase. They can neither consult nor cope with situations/contexts/problems, if the corresponding rules or procedures towards the solution to each problem are not incorporated as the domain knowledge. Usually in conversational techniques, contexts are pre-set at design time (Justine C, Stone M, Yan H, 2000).

In this dissertation, I select contexts based/ respectful on a preliminary conversation about the client's occupation and problem category as well as on his/her emotional state and events in his/her experiences and accomplishments. My contexts are then used for selecting chunks of knowledge to guide the transformation of user input into responses.

It is important to remark that even the best dialogue will not be effective without two pre-conditions: i) clients must seriously hope to obtain solutions to their problems, and ii) clients and counselors alike must have trust in each other (Rogers C R, 1966; Asay T P, Lambert M J, 1999). Also, counselor's utterances should not include trash information or sentences deviated from client's problem or their suffering situation, outside the counseling dialogue's context. Such sentences may hurt the client's feelings or discourage clients to continue counseling dialogue.

2.2.2 More Recent Researches

More recent researches of counseling systems are as follows: The first one is the counseling dialogue system which uses questions starting with 5W1H (who, what, when, where, why, how) (Han S et al., 2013). The system interacts with users through recognizing what the users say, predicting the context, and following the users' feelings. Namely, three counseling techniques such as paraphrasing, asking open questions which a question that cannot be answered with a yes or no but requires a developed answer, and reflecting user feelings were used for the purpose. In this approach, 5W1H information and four basic emotions (happy, afraid, sad, and angry) are extracted from

user utterances. System utterances are generated using the 5W1H information and the basic emotions. Asking 5W1H questions is generally effective to clarify the problem about the person's behavior.

This 5W1H type of questions can obtain formal ideas about clients' troubles if they answer for such questions. However, in IT counseling, clients' problems are vague as well as complicate. Therefore, computer systems cannot give the solutions due to knowledge explosion/acquisition problems. They can only support clients to reflect through conversation toward self-awareness of their problem solution.

Still more, clients do not usually feel 5W1H type questions to be worthy of answering, but feel strong stress to answer them. Thus the conversation stops before clients are self-aware of problem solutions. For example, when clients want to consult with something about their career problem, they mostly feel questions such as "where you are troubled" or "why you are troubled" are not important to them. The trust for agents is lost when they do such inappropriate or rather unrelated questions which are not context-respectful, namely, which do not respect clients' suffering situation or emotional context. Accordingly, clients stop the conversation before their reflection becomes deep.

My agent focuses on clients' emotion and responds context-respectfully using the summary of their emotional changes towards decreasing the discomfort namely towards awareness of solution. This enables a promotion of clients' reflection as described later in detail.

The other is a dialogue system for career counseling (Srivathsan G et al., 2011). It aims at a question and answer based AI application to provide students with career counseling. This paper says "With the aid of an Intelligent Expert System, the software is equipped with all the necessary domain specific information about various vocations and also the capability to draw apt inferences based on heuristic and judgmental knowledge, while providing the human psychologist touch. The interaction with the user is facilitated through aptitude and attitude tests taken by the user and also the Dialog Management System having Natural Language Interface. This system is a kind of learning agents and recursively incorporates new features based on relevant feedback given by the user."

Career focused counseling deals with a wide range of consultations from general career development to vocational guidance and job hunting (Savickas M, 2011; Brown D, 2002). When the target is clear such as the consultation for vocational guidance or job hunting, this kind of system is useful also as an information provider since dialogue with

clients offers such job selection information concretely. However, if the problem of the client is unclear as well as client's motivation for solving the problem is low, the therapist must help the client to have his reflection.

In many kinds of counseling, as above mentioned, counseling supports thinks like asking 5W1H questions or providing job information, which are very important as an element of consultation services.

However, to realize computer-based counseling designed for humans, a human emotion focusing function must be implemented. The most important factor, especially in the counseling for the clients who suffer from unclear mental problems is to build up clients' trust in his/her counseling agent (Asay T P, Lambert M J, 1999).

My proposed counseling agent creates response sentences by paraphrasing words/sentences in clients' input, with a method which has been focusing on emotional sentences/words in clients' input, and on the change in client's emotional utterances. This will not hurt the client's emotion through respecting or making much of emotional contexts or clients' suffering situations, since this neither asks often unrelated 5W1H questionnaire nor informs about various unnecessary knowledge compulsorily. My agent firstly builds up mutual trust with clients through sharing experiences and keep it by emotion focused paraphrasing and context-respectful prompts to clarify clients' problems, reflect themselves and lead them to self-awareness.

My agent replies with a paraphrased response, recognizing/using words especially emotional words in client's input. What is distinct about my agent is that it never asks 5W1H questions and never forces the client to provide his information but only responds by paraphrasing and summarizing. Also, it promotes s to detail or substantiate the problem so that the ongoing context may not be hurt. Accordingly, my agent can help the client to clarify his problem unknown even by counselors and find his solution by himself with his reflection emotion focusing and context-respectfully promoted.

2.2.3 Text Summarization

Ordinarily, text summarization methods can be classified into two types: extractive summarization and abstractive summarization (Gupta V, Lehal G S, 2010). Extractive summarization selects important sentences, paragraphs, etc. from the original document and recomposes them in a shorter form. The importance of the sentences is determined

by statistical and linguistic features of sentences. An abstractive summarization aims at understanding the original text and re-telling it by fewer words. For text understanding, linguistic methods are used and for re-telling it shorter, new concepts and expressions are searched, which describe it shorter, but keeps the most important information of the original text.

There are several works for extractive summarization. The majority of those works mainly has focused on superficial text features (e.g., word frequency, position of word), aiming only to reduce reading or searching time (Takada K, 2013). Kennedy et al. (2012) proposed summarization method focusing just on emotions. In a summarization for the client centered counseling, considering client's emotions and putting client's episodes in the chronological order is required. Client's problems usually involve emotions. Furthermore, providing the overview of the past events (so-called contexts) leading to certain emotion is effective for giving the client the objective perspective. Such context-respectful response leads to further continuation of conversation and deeper self-awareness. However, those conventional works do not consider both emotion and time series at once. Thus, those conventional works are not effective for my counseling purpose.

Meanwhile, many solutions of text summarization have been applied by intelligent tutoring systems for learning support (Guangbing Y et al., 2011). In my counseling agent function, those solutions will be discussed when summarize emotions and events are summarized in the total session of a counseling dialogue.

2.3. Web Scalability

My agent consults with each client independently. Further, it does not provide information but repeat/paraphrase clients' utterances prompting just sentences as "Say more". Therefore, knowledge/information or data access is very limited as well as has little storage conflict in my context-respectful agent. Thus, the agent has little problems in terms of cost and performance to scale out (Yamamoto G, 2013) when it is realized on the large-scale Web such as cloud computing systems. Therefore, even a great number of clients can consult the agent concurrently as well as responsively. Further, various types of clients such as students, works, haycaps, etc. can enjoy the counseling due to the above multiple kinds of context-respectful agents which can act as human counselors through compensating each other. The context-respectful counseling agent does not require a search for a vast amount of information or knowledge. Therefore, context-

respectfulness significantly decreases the cost of counseling agent's virtualization on the large scale Web such as cloud computing environments.

When compared with complex graph structures like WordNet (George A, Miller, 1995), the hierarchically shallow modularity by combining multilayered declarative knowledge in the higher level and entirely procedural knowledge in the lowest level is practically an important feature of my knowledge layer. This is because such well-balanced shallow modularity guarantees fast response as well as easy understandability leading to higher dependability, scalability, etc.

CHAPTER 3

PROPOSED METHOD

3.1. Context-respectful Counseling Agent (CRECA)

Context-respectful counseling agent (CRECA) has been designed to support actors (IT related persons) as one of important core components in a software development ecosystem, where psychological discomfort and on-the-job stress are documented phenomena. On the other hand, it can also be a part of a wider social ecosystem, relieving the spirits and improving the psychological fitness of IT professional even outside the working environment. In the software development ecosystem, interacting with CRECA can be seen as a sort of mental workouts, with the aim of improving psychological well-being and impact on a range of cognitive abilities not related to professional training.

Meanwhile, CRECA lies at an intermediate position between domain-specific learning/tutoring agents like BETTY'S BRAIN (Ball G, Breese J, 2000) and rather psychological or experimental but general conversational agents (chatterbots) with little or no domain expertise such as Cleverbot (Deryugina O V, 2010). CRECA works in two phases: (1) a problem-discovery phase to build up client's trust in CRECA and clarify the client's true problem by sharing client's suffering situation/context, and (2) a problem-solving phase to dig down the problem, leading the client towards problem solving.

In the problem-discovery phase, CRECA generates its responses using the domain specific knowledge such as IT worker counseling knowledge. In the problem-solving phase, through a context-respectful prompt generated by limited number of domain knowledge such as "Say more in detail", the problem/context is dug without discouraging clients for deepening reflection towards solution awareness. Fig. 2 shows the counseling protocol of CRECA.

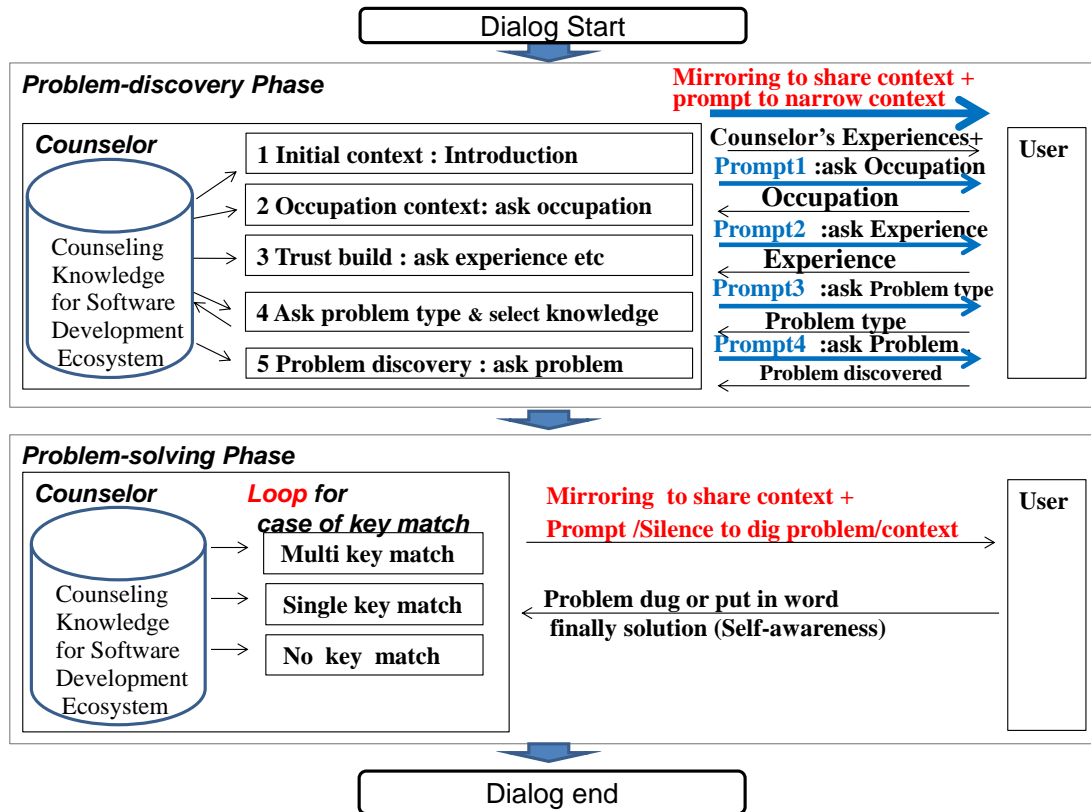


Fig. 2. Counseling protocol of proposed agent.

3.1.1 The Problem-discovery Phase

Then, the client's occupation is asked by CRECA's prompt to narrow down his/her field. For instance, if the client is an IT professional, his/her counseling is contextually processed as an IT worker by selecting domain knowledge chunks for counseling IT workers, based on contexts e.g., occupation such as IT workers. Next, the experience and accomplishments of the client are asked by prompts and shared as dialogue contexts among the client and CRECA. Then, the problem the client is suffering from is asked by CRECA's prompt, put into words through clients' reflection, and clarified using a set of CRECA's prompts pre-defined by using the counseling knowledge for narrowing the context. This phase matches the client's problem to a context (for instance job hunting, fitness, etc. for a student, and career development, interpersonal relationship for an IT worker) (upper part of Fig. 2). Thanks to this preliminary phase (problem discovery phase), sharing experiences/contexts with clients can be realized and narrowed/focused with limited amount of domain knowledge.

3.1.2 The Problem-solving Phase

The *problem-solving phase* (Fig. 2) consists of 1) rewording the client’s input using context-dependent keywords for sharing the detailed context/problem and 2) context-respectful prompting or waiting silently for digging the problem/context while maintaining client’s trust in CRECA with no deviation from context. Context-dependent keywords, called “CxKey” as acronym and abbreviated as key, are slot/attribute values filled in context objects. CxKey or key is a dialogue context or dialogue topic which is obtained by filling the slots (attributes) of context objects using the results of ontology mapping of keywords. Though details are described in the next chapter, this enables semantic matching by a domain oriented ontology dictionary, which leads to stronger context awareness from natural language text input by clients and a deep context share among clients and CRECA. Rewording in the problem-solving phase relies on 3 types of matching operations carried out on user input, as the following 1)-3). Here, keywords such as anxious, worried, afraid ... are emotion type keywords. Other keywords/phrases under the label “Event expression” in TABLE 6 are event type ones.

1) *Multiple (key) matching:*

This operation is done when multiple keys are matched, for catching emotional empathy together with events related to it. What the client has said is rephrased with multiple keys included in it and the context/problem is strongly shared or dug deeply by rewording/mirroring with several keys. Then, to further deepen client’s reflection, the agent outputs a prompt such as “please tell me more in details” or simply waits for client’s responses.

2) *Single (key) matching:*

This operation is done when only a single key is matched, for catching either emotional empathy alone or an event alone. What the client has said is rephrased with the matched key, and the context/problem is shared or dug by mirroring/rewording with the single key. Then, to deepen reflection, the agent outputs a prompt such as “tell me more concretely” or simply waits for client’s responses.

3) *No (key) matching:*

In case of no matching, CRECA resorts to Cleverbot-style mirroring followed by a prompt selected randomly to continue conversation. However, CRECA limits the prompts neither to break nor deviate from the context, like “Say more”, in-

stead of conventional one such as “Say about other persons” used traditionally by chatterbots from ELIZA through Cleverbot.

3.2. Emotion-focused Context-respectful Counseling Agent (CRECA-E)

3.2.1 CRECA with Summarization

To enhance the context-respectful counseling agent, the emotion-focused context-respectful counseling agent (CRECA-E) is proposed as an extended CRECA. This agent uses not only paraphrasing followed by context preserving prompts, but also the summary focusing on changes of clients’ emotional words or their history towards decreasing the discomfort or awareness of solution.

To reflect on clients-selves for solving their problems, the proposed agent engages a dialogue session just like human counselors. This agent partly relies on ELIZA-style mirroring but it focuses on clients’ emotional words in dialogue sentences for counseling. Namely, to support clients’ reflection toward their awareness of solutions, it responds by two sentences each before and after a change of their emotional words. Only if there is no such emotional change, the agent paraphrases a single sentence which clients said or input immediately before, though “context-respectful” prompts such as “Say more in detail” follow.

Owing to the responding sentences to clients’ emotional change as well as paraphrases followed by context-respectful prompts, the counseling agent behaves as if it empathizes with clients, and continues conversation without losing their trust. People accept their saying if or even if it is repeated by trustful others. Thus, clients can reflect on themselves and verbalize/clarify their problems more and more. This leads to their self-awareness of the best possible solution.

The human activity is triggered and accompanied by emotion. On the other hand, the computer acts as programmed and is not accompanied by emotion; even human beings cannot completely understand emotions of other persons. The human counselor paraphrases by using the sentences of the client. In addition, focusing on emotions, the counselor summarizes the change of clients’ emotion to lead them from discomfort to

comfort in their emotion. Thus, the counselor can pretend to understand the clients wholly and reply sympathetically towards promoting their reflection and their awareness of solution namely emotional comfort.

Therefore, my agent continues detecting the emotion words from the input sentences of the client. When the change in his emotions is recognized, the agent replies with a summary sentence. This summarized sentence has two aspects, namely(1) the agent confirms whether the content of this sentence is acceptable for the client and (2) the client then realizes the change of his emotions again by this sentence, continuing his reflection and reach to self-awareness.

As a conceptual feature of my proposed agent, extracting emotions or changes in emotions from conversational texts, the emotion focused counseling agent conveys them to the client with summary. In other words, the agent makes response sentences to the client summarizing the emotional change contained in the dialogue. The agent continues the conversation with the client context-respectfully or without disturbing the context by the response of this summarization of multiple sentences in conjunction with the response by the paraphrasing each single sentence having no emotional word. This interaction promotes the self-reflection of the client, and it leads the client to deepen self-reflection, and then reach self-awareness. In other words, it behaves like a counselor who is sharing the client sufferings. This agent continues to talk of counseling while maintaining the trust of the client.

My extended agent (CRECA-E) summarizes, as a unique point of its concept, the content of the dialogues which contain emotions of the client. In client-centered counseling, summarization considering emotion and their chronological order is required, because the problem often involves current emotion. Specifically, the agent recognizes emotion words in the conversations from the client, and then it gives summaries using the change in the emotions discovered among several dialogues. Also using a single paraphrased sentence with the summarizations, the dialogues can proceed context-respectfully (without ruining the context of the current dialogue). As a result, the reflection of the client is promoted and deepened, which enables him to discern himself and then finally have self-awareness. In other words, CRECA-E acts like a counselor who shares the distresses of the client, and carries on conversations with the client while maintaining his trust.

My previous counseling agent (CRECA) leads the client deepen his reflection by paraphrasing. In addition, the agent supports problem digging for making context static or

unchangeable. This considers the solution with neither the previous dialogue sentences nor dynamic change of contexts.

My extended counseling agent (CRECA-E) incorporates a function to summarize multiple sentences including previous sentences in dialogue to confirm somewhat complex/dynamic context or its change, aiming at condensing and catching up client's internal flame. By using summarizations at appropriate timing, the counselor can check out perceptions with client to see how accurate the listening has been. This skill helps the client in seeing his own personal distortions. And by condensing what has been said, the counselor offers the client a chance to review his own thinking. This approach makes the dialogue not to deviate from the context even when the client's emotion has changed. This keeps client's trust in CRECA-E and makes dialogue continue longer. For counseling to take effect, basically clients should be anxious to obtain solutions of their problems, but the following conditions are still required (Asay T P, Lambert M J, 1999; Rogers C R, 1966): 1) mutual trust between clients and counselors has been built up while identifying the framework of clients' problems, and 2) the trust should be kept

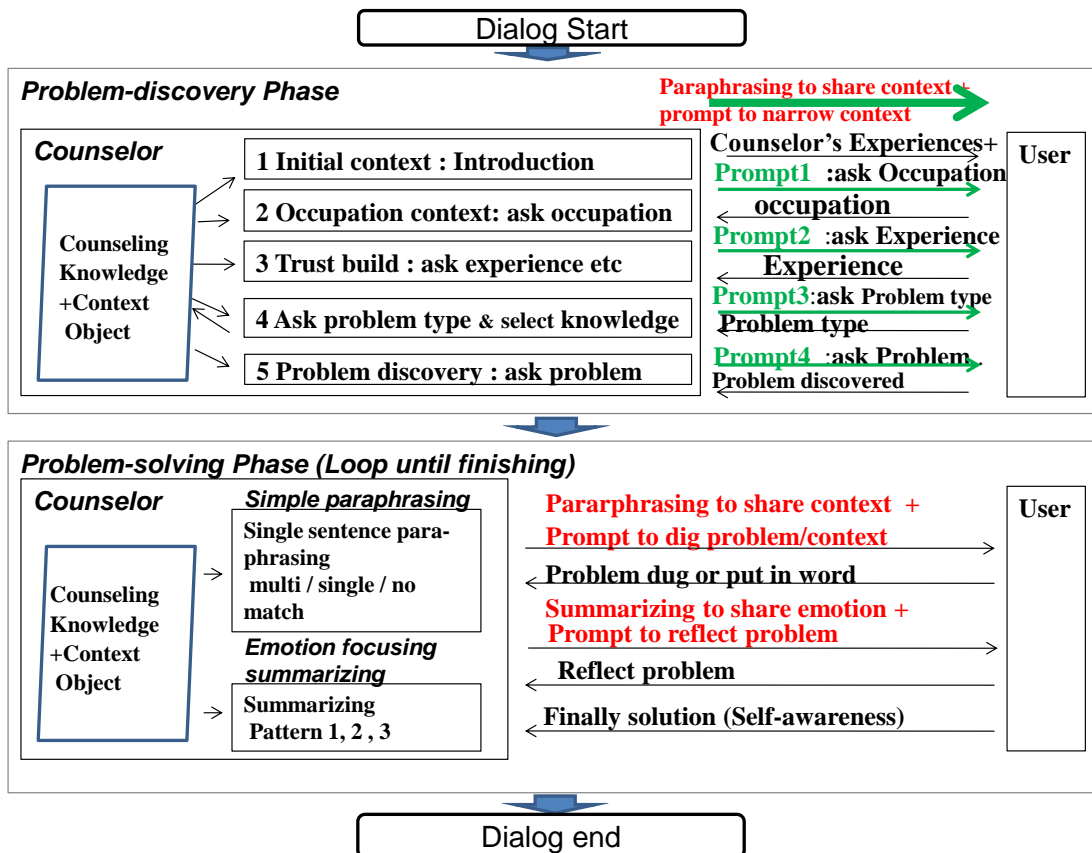


Fig. 3. Counseling procedure of emotion-focused counseling agent.

while clarifying and narrowing the problem until clients are aware of the solution. Thus, as shown in Fig. 3, the dialogue sessions could be divided into two phases: the *problem-discovery* phase and the *problem-solving* phase.

The *problem-discovery* phase aims at building up clients' trust in CRECA-E and clarifying the clients' problem framework. In this phase, the following steps are performed. First, there is an initial greeting. Secondly, the client's occupation is asked. Finally, career related experiences with clients are shared. Through this phase, CRECA-E narrows the range of considering context in the next phase.

The *problem-solving* phase aims at further narrowing down the client's problem framework (c.f., if the client is a worker, career development, interpersonal relationship at workplace, and so on) and at self-reflecting about the client's problem more deeply. In this phase, simple paraphrasing and emotion focusing summarization are proceeded. Simple paraphrasing in the problem-solving phase relies on 3 types of matching operations carried out on user input, as shown in 1) - 3) at the tail of the subsection 3.1.2. Emotion focusing summarization in the problem-solving phase is described in the next section 3.3.

3.2.2 Enhancement of Summarization Function

Client-centered or Active-listening type human counselors (Rogers C R, 1957 ; Shinozaki T, 2008), gives client a summary in the following situations (Ivey A E, Packard N G, Ivey M B, 2006); Japan Industry counselor Association, 2002):

- (a) At the beginning a conversation it summarizes the content of the last (previous) story (in case the counseling is continuing and not the first time);

"Last time we talked about ---."

- (b) Clarify what is happening in counseling, particularly when the conversation is particularly complex:

"You said---, see where we are to this point?/ and now you are saying---, aren't you?"

- (c) During a conversation it provides a smooth (contextual) flow from topic to topic;

"You 've been saying ---. Now you are saying ----- aren't you?"

- (d) Over the entire period of a conversation it brings together, what has been happening or stated in the conversation;

"Today we talk about ----./ You said ---, and now you are saying ----, aren't you?"

(e) Over several conversations, it brings the the thread of topics or contexts together;

“Last time you said ---- and today you say -----.”

CRECA-E’s summarization procedure is given as follows: (1) Summarization is not executed at the timing (a) and (e), since a continuation of the counseling session is not assumed. (2) since it is difficult to judge accurately the situation of timing b), we treat the timing b) as well as the timing c) because we think timing c) produces a similar effect as timing b). (3) Summarization at the timing (c) is expected when the topic has changed. Since it is difficult to catch transition of topic, CRECA-E’s summarization targets transitions of emotion. (4) The timing (d) surely comes when the conversation ends. To sum up, CRECA-E’s summarization is executed only at the timing (c) and (d). Albeit (c) and (d) provides the same sort of summarization, they are triggered in different situations. When clients seemed to change their emotion, (c) is triggered. In this situation, CRECA-E wants to confirm whether this is really intended. When a certain number of interactions continued without a summarization for several minutes, especially at the end of counseling, (d) is triggered to summarize or clarify clients’ sayings or minds.

Since it is impossible to exactly guess clients’ mind from their sentences, CRECA-E gives summary to ask whether it is consistent with clients’ thought. If the summary is inconsistent, clients will correct it. Thus, the summary needs neither to include all the episodes nor to be consistent. In the client centered counseling, summarization requires considering client's emotions and putting client's episodes in the chronological order. Client’s problems involve emotions. Providing the overview of the past events (namely contexts) leading to certain emotion is effective for giving clients the objective perspective. Such context respectful responses keep clients’ trust and lead to further continuation of conversation and deeper reflection.

3.3. Virtualization on the Large-scale Web-based Context-respectful Counseling Agents

There are situations or cases, in which clients feel bored with the strictly context respectful/preserving responses even including the summary. To cope with this, a function for longer conversation is added as context respectful ones in that it still fundamentally

use only the information listened from clients and does never use the external information such as one on the Web. This function can randomly select a little wider range of prompts that are a subset of ELIZA-like ones such as “really?” or “How about your mother?”. In some situations, some clients feel such responses are not context-preserving or context-respectful and stop conversation or to extend their topics towards more general ones. However, this also stops the context-respectful but monotonic responses and randomly causes longer conversation toward more reflection and self-awareness. For example, if the response is “really?”, clients may feel that they are not trusted and stop the conversation built on the trust or empathetic relation. If the response is “How about your mother?”, the topics will extend to more general ones such as his/her family and the clients own problems may not be narrowed or clarified directly though the agents obtain the related information and clients obtains the related awareness. However, this can be compensated if clients restart the agent without this function.

To combining these functions or methods described above, currently three types of counseling agents (CA1 - CA3) are supported. They have the following features: (CA1=CRECA) paraphrasing for a single sentence + context-preserving prompt, (CA2=CRECA-E) paraphrasing part enhancement to include the emotion focused summarization, namely paraphrasing for a single sentence as well as multiple sentences, (CA3=ELIZA-like CA) prompting part enhancement to include the somewhat ELIZA-like CA function to continue longer conversation, which are limited but, in some cases it contains context-breaking prompts such as “Really?” as mentioned above. Meanwhile, there are various types of clients. In my proposed system, among context respectful counseling agents, clients can select their preferable agent or try another agent when unsatisfied.

3.4. Expected Effects and Limitation

To promote client’s self-reflection for clarifying their problem toward self-awareness of solutions, CRECA-E has the following features: 1) trust build-up by introducing experiences of counselors as well as clients, 2) ELIZA-like CA mirroring (paraphrasing), 3) emotion focused summarization. Figure 4-6 show examples of resultant scenario dialogue.

First, in the *problem-discovery* phase, experiences and accomplishments of the counselor are introduced as the preparation for experience sharing.

Client : I am a third-year undergraduate.
CRECA : You are a third-year undergraduate.
 What did you experience and what were your noteworthy accomplishment in your high school days.

Client : I devoted myself to club activities in high school.

Client : I was finally able to participate in a prefectural tournament in the last summer in high school.
CRECA: You were finally able to participate in the prefectural tournament in the last summer in high school.

Fig.4. An example of a dialogue to organize the client's accomplishment according to his own experience.

Fig. 4 shows an example of a dialogue² where mutual trust is built up and the client's experiments and accomplishments are organized for reflection promotion in the specified context; the client reflects his own experience and then organizes his accomplishments by himself. Questions undertaken in such a process are given to the client according to several patterns prepared for students and workers respectively.

At the end of *problem-discovery* phase, the problem that the client is suffering from is put into words, and then categorized according to defined 5 or 6 groups, i.e., problems that likely to happen at campus or workplace: for example, career improvement, interpersonal relationship, school environment. Consequently, the appropriate context in *problem-solving* phase is set, as shown in Fig. 5.

My agent (CRECA/CRECA-E) consults with each client independently. Further, it

CRECA: If you are suffering from problems or if there is any bothering your mind, please do not hesitate to tell me.
Client : I am worried if I have steadily learned IT skills.
CRECA: You are worried if you have steadily learned IT skills. Then which one is your suffering related to: further career, interpersonal relationship, school environment, learning or self-anxiety?
Client : My suffering is related to future career.
CRECA: Your suffering is related to career improvement.
Client : Yes,-----

Fig. 5. An example of a dialogue to clarify the problem of the client.

² The actual conversation used my Japanese language module. Here, I provide an English translation for the sake of understandability.

CRECA : You have a problem concerning your future career. Now, clear your mind about the problem and talk to me about it.

Client : I wish to be a SE, but I am worried if I can get a job.
CRECA : You wish to be a SE, but you are worried if you can get a job. *Please tell me more.*
Client : I am afraid if I can get a good job because of my age and skills.
CRECA : **You said "I wish to be a SE, but I am worried if I can get a job". And now you are saying "I am afraid if I can get a good job because of my age and skills." aren't you.?**
Client : I feel uneasy if I can find a job related to IT in the near future because I am a slow learner of IT
 Note 1) Sentences in bold is the summarization output.

Fig. 6. Example of summarizing dialogues.

does not provide information but repeats / paraphrases clients' utterances and prompts just sentences such as "*Please tell me more*" as shown in Fig.6. Therefore, the knowledge / information or data access is very limited as well as the storage conflict in my context respectful agent. Thus, the agent has almost no problem with the computational costs and performance to scale out (Okada M, Mishima H, Sasaki M, 2001), when it is realized on the large-scale Web such as cloud computing systems. Therefore, even a great number of clients can consult with the agent concurrently as well as responsively. Further, various types of clients such as students, workers, handicaps, senior person, etc. can enjoy the counseling due to the above mentioned multiple kinds of context respectful agents, which can act like human counselors through compensating each other. For example, the agent simulates the male's words or the female's words³, pronounces the response sentence, output response characters very slowly, etc..

In the *problem-solving* phase, when the dialogues on specified problems of the client go on, related keywords are matched singularly or multiple, and responses to deepen client's reflection are continued and the client's reflection can be intensified by responding appropriately to him.

Through the above-mentioned method the system is utilizing only several hundreds of rules and enables context related recognizing/sharing work experience to be used for knowledge-selection, etc. and discovering client's main problem.

³ In Japanese natural conversation, this issue walks similar issues are addressed in different crays depluming on who addresses it, a male or female.

In addition, a summarization is performed by using the content of two or more sentences immediately before deepening the client's reflection more and more, as shown in Fig. 6.

If there is no emotional word detected, CRECA-E replies with paraphrases followed by context-respectful prompts to dig/narrow problems. Moreover, when any term for paraphrasing is not confirmed within the specified framework of client's problems, the issues such as explosive increase on knowledge acquisition or search cost can be solved by randomly selected responses as used in ELIZA. It is important to notice that CRECA/ CRECA-E is especially destined for IT workers and IT students for now. I made such a reduction in order to reduce the volume of the necessary knowledge. In future works it may be extended to other counselling applications.

3.5 Comparison with other works

Though my agent CRECA (CRECA-E also include in this section) exploits ELIZA's mirroring responses, they are followed by context preserving responses, which lead clients to deepen their reflection without transition to unrelated topics. CRECA further differs from ELIZA in selecting the response generation patterns by identifying the context from user inputs. The current context is identified and considered for response generation by using an appropriately grained context-based mechanism (Gonzalez A J, et al., 2010), which utilizes counseling expert knowledge though such counseling domain knowledge is just limited to problem decomposition to sub-problems. Additionally, my response generation patterns use several or multiple keyword matching type response constructions besides ELIZA-like single keyword matching (Weizenbaum J, 1966). By means of such context identification and response generation patterns, CRECA gives context respectful responses without a huge amount of domain knowledge that causes knowledge acquisition bottleneck and a storage problem.

My summarization is an abstractive summarization that aims at re-telling the original text by fewer words. Emotion-aware summarization by Kennedy et al. (2012) uses emotional words for an extractive summarization, namely for selecting important sentences. My summarization detects the change of emotional words as transition of client's mind and responds its confirming prompt for client's reflection. This makes CRECA more "context respectful" which respects the client's distressing emotional situation or context and promotes client's reflection. Namely, since conventional works

do not consider emotional transition, they are not effective for deep reflection toward self-awareness of solutions.

Compared with conventional related works such as summarized in TABLE 1, CRECA has the following advantages and disadvantages.

Advantage: Different from learning systems using scaffolding (Van de Pol J, Volman M, Beishuizen J, 2010) and contingency (Kopp S, et al., 2005); Sammut C, 2001) techniques, counselors need not know solutions, and CRECA can save persons suffering from vague and complex psychological problems. Different from systems such as ALICE etc. (The Artificial Intelligence Foundation(ALICE); Srivathsan G et al., 2011; De Pietro O, De Rose M, Frontera G, 2005) offering external information or solutions from Web or huge data bases, problems can be avoided about the explosion of information and knowledge to provide and/or select for clients.

Disadvantage: Neither solution nor external information is provided. Clients have to reflect on their sayings and find solutions by themselves. Deep reflection ability is necessary especially for difficult or very complicated problems.

CHAPTER 4

DESIGN AND IMPLEMENTATION OF CRECA

4.1. Conceptual Architecture

Let us start by discussing the conceptual architecture of my counseling agent CRECA/ CRWCA-S as shown in Fig. 7. Rather than translating user input into an abstract language like AIML (Wallace R S, 2003), I rely on language-specific dialogue processing modules for English and Japanese, connected to a local dictionary called an ontology dictionary as shown in Fig. 3. The natural language processing module extracts terms and their structure using an ontology dictionary, and then it saves them in *context objects*. Responses are created by using the information stored in context objects to select the relevant part (*i.e.*, the right prompts) from the counseling knowledge database (DB). In other words, the context (object) is a set of attribute-value tuples used to select a counseling agent's response or a counseling domain knowledge chunk that will drive the transformation of the user's inputs into such responses. The input-to-response transformation is represented as the counseling domain knowledge and enacted within a specific context (object) extracted by natural language processing that refers an ontology dictionary as shown in Fig. 7. This way, the same user input can generate different responses based on the active context.

To sum up, the conceptual architecture of my system CRECA (CRECA-E also included in this chapter) (Fig. 7) is composed of two major parts: a front-end component for processing natural language dialogues, and a back-end facility for context-respectful reasoning. The front-end module handles the user input in a language-dependent way; for the Japanese language, I use *MeCab* (Kudo T, Yamamoto K, Matsumoto Y, 2004), a fast and customizable Japanese morphological analyzer. A major feature of my CRECA's front-end module is using its local ontology-based vocabulary to detect the current context or dialogue's topics or to become aware of the client's situation, which

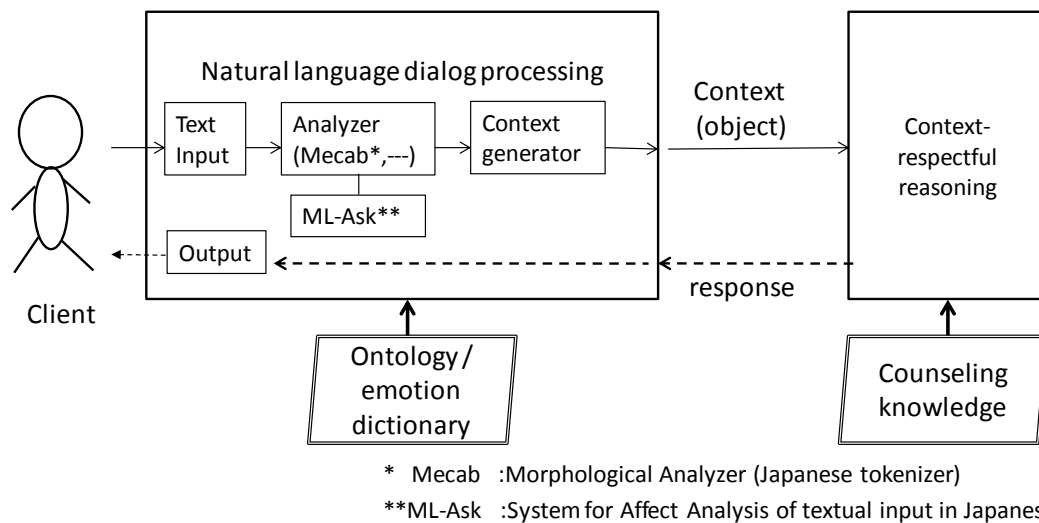


Fig. 7. Overall system architecture of CRECA.

the client is interested in, suffered from and/or wishes sharing with. The context or dialogue topic is obtained and sent to the back-end reasoning module by filling the slots (attributes, properties) of context objects using the results of ontology mapping of keywords. Here, the slot (attribute) name of context objects is predetermined as IT counseling (lexical) knowledge as described later in the section 4.3. The keywords are extracted from client's text input. This usage differs from conventional chatterbots (Dernoncourt F, 2012) using it for correcting user input orthographically in serious games necessary for fighting or winning rather than sharing or empathy. This detection generates a context object that is passed to the back-end reasoning facility. Based on user input and on the current context object, my context-respectful reasoning module in the CRECA can compute a correct dialogue follow-up (CRECA's response in dialogue) and communicate it to the front-end. In turn, the front-end displays this output (response) to the user.

4.2. Software Architecture

CRECA's software architecture has two major modules: the natural language dialogue processing module and the context-respectful reasoning module. The module structure is shown in Fig. 8.

A detailed explanation of each component module is provided here.

4.2.1 Natural language dialogue processing module

The natural language dialogue processing module consists of: a) an initialization and termination module that functions as an interface between humans and the CRECA, b) a dialogue text analysis module and c) a dialogue text input /output module.

- Initialization and Termination module: when the CRECA is launched, this component initializes the context objects and generates the dialogue-starting messages. At the end of the interaction, it saves all relevant information (including the conversation log) and generates the dialogue-end messages.
- Dialogue text analysis (context-aware) module: The dialogue texts are tokenized. In case of Japanese texts, *MeCab*, a Japanese morphological analyzer, is used. Then, context analysis is done. Namely, by using the ontology, a new context object is set or generated according to the user input, the current state of the old context object and the ontology dictionary.
- Dialogue text input /output module: The user input texts are read. Created responses are output.

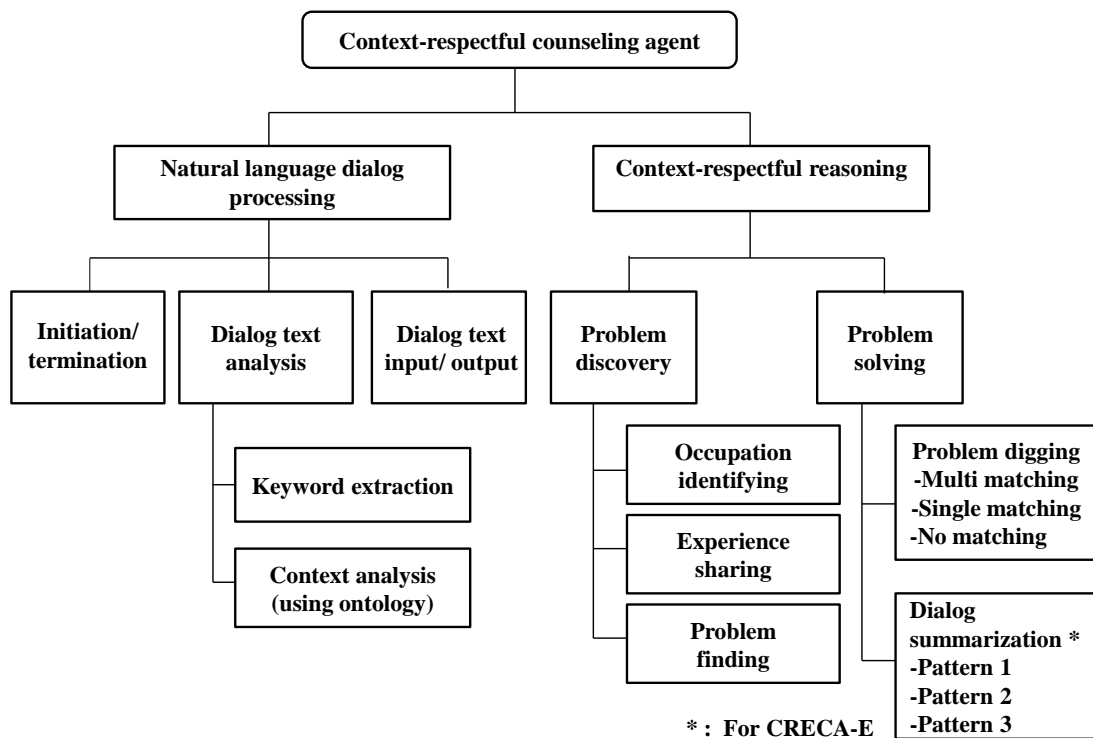


Fig. 8. Software architecture of context respectful counseling agent.

4.2.2 Context-respectful reasoning module

The context-respectful reasoning module uses the counseling knowledge DB to create responses, according to the current context. The counseling knowledge DB contains prompts to solicit the client's accomplishment, to narrow down (dialogue) context, or to dig problems / (dialogue) contexts, and to enable mirroring / rewording responses using the current context (object).

4.3. Knowledge Layer

The knowledge layer underlying CRECA is based on the following idea. By using ad-hoc, special purpose knowledge repositories it is possible to cover a large spectrum of natural language questions and find satisfactory answers through relatively shallow (but computationally efficient) keyword matching. This is opposed to huge general-purpose Web-based knowledge frameworks like WordNet and Open Mind, used for storytelling agents in (Tarau P, Figa E, 2004).

The knowledge layer for context-respectful counseling consists of the context-aware knowledge and the context-respectful reasoning knowledge. The context-aware knowledge includes the ontology dictionary and a context template. TABLE 2 shows

TABLE 2. Ontology knowledge layer for IT counseling example.

Occupation	Problem Type	Problem
IT worker	career	desired occupation
		vocational aptitude
		salary
		future job
		workplace's internal factors
		organizational position
		human relations
		organization's structure
		individual characteristics
		BSc / BA student
job fitness		
disagreement		
...		
school environment		
interpersonal relationship		
		self-anxiety

the structure of the ontology knowledge layer.

4.3.1 Context-respectful reasoning knowledge for counseling

The context-respectful reasoning knowledge to perform rudimentary-level counseling for IT personnel is hierarchically organized by multi-layered declarative knowledge called “context” such as Major Context (MC) and Minor Context (sub-context, ...) and procedural knowledge called Action Agent (AA) as shown in Fig. 9.

This kind of hierarchically shallow modularity by combining multilayered declarative knowledge in the higher level and entirely procedural knowledge in the lowest level is practically an important feature of my knowledge layer as compared to complex graph structures like WordNet (Miller G A, 1995). This is because such well-balanced shallow modularity guarantees fast response as well as easy understandability leading to higher dependability, scalability, etc. To realize such kind of modularity, the context-respectful reasoning knowledge contains context related information for grouping knowledge database as each of knowledge chunks by the above mentioned declarative knowledge called “context” and for transiting to other groups when the context changed.

Major contexts include 1) a problem discovery major context to identify the client’s

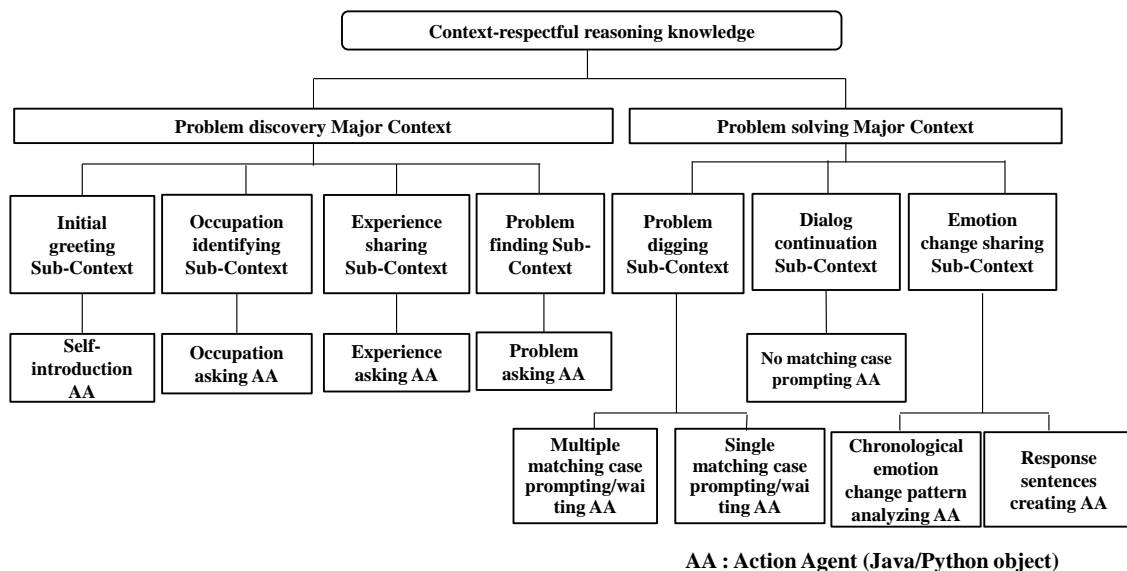


Fig. 9. Architecture of context-respectful reasoning knowledge.

TABLE 3. Ontology to identify occupation.

Occupation	Related keywords
BSc student	Science (math, physics, ...), engineering (computer, civil, ...), institute of technology (MIT, Caltech, ...), ...
BA student	Economics, management, law, ...
IT worker	System development, SE, CE, ...

problems and 2) a problem solving major context to lead clients to self-awareness of the solution.

A. Problem discovery Major Context

It is the context where 1) the client's occupation is identified, 2) the client's experiences and accomplishments are shared for build-up client's trust in CRECA, and 3) the client's problem is discovered. The Major Context has the following sub-contexts.

➤ Initial greeting Sub-Context

For the first step towards client's trust in CRECA, this context contains the knowledge needed to introduce counselor's experience and accomplishment as the initial greeting.

➤ Occupation identifying Sub-context

This context contains the knowledge needed to identify the type of the client's occupation by keywords and results of their translation using ontology dictionaries (TABLE 3). After the occupation of the client is answered by clients and identified by CRECA, a transition to the client's trust in CRECA sub-context is made.

➤ Experience Sharing Sub-Context

For client's trust in CRECA, this context contains the knowledge (TABLE 4) needed to ask work experience and accomplishment of the client according to an identified occupation. When a "No additional learning" message from the client arrives, CRECA transits to the problem finding sub-context.

➤ Problem finding Sub-Context

This context contains the knowledge needed to identify a client's problem type

TABLE 4. Knowledge to ask experiences based on occupation context.

Occupation	Knowledge to ask experiences
BSc student /	At high school: experience, achievement/learning
BA student	At university: purpose to enter university, experience, achievement/learning
IT Worker	Reason to work at the company, work experience and achievement, ...

TABLE 5. Ontology to find problem type (student's example).

Problem type (Problem Category)	Related keywords
Career improvement	Future career, career, future work/ job, work/ job, fitness, ...
School environment	School attendance hour, campus environment, meal, laboratory, club activity ...
Interpersonal relationship	Human relationship, friend, teacher, classmate, circle member, ...
Self-anxiety	Part-time job, ambition tiredness, love, ...
Learning	Learning, Learning courses, Acquisition unit, ...
...	

from keywords in the user input and their translation using ontology-like dictionaries. This context can select it out of 6 problem types, based on related keywords of the ontology dictionary (TABLE 5). For example, this context estimates that a client's problem type is career improvement from keywords such as "future job". After a client's problem is identified, CRECA transits to the Problem solving Major Context.

B. Problem solving Major Context

This context looks into the identified major problem of a client and leads the client to the self-awareness needed for solving them.

➤ Problem digging Sub-Context

This context contains the knowledge needed to map the client's problem to one of the 5-10 problems contained in problem types. TABLE 6 contains problems, their sub-levels, and the emotional expression ontology.

This context can support multiple matching reasoning AA (Action Agents) and single key matching prompt AA. The former is an auxiliary agent that, when the user input matches more than one term in a sub problem, acquires the corresponding context and creates responses based on the multiple keyword matching list. The latter is an auxiliary agent that applies single-keyword verification when a single term of the user input matches a term contained in a sub problem. When no keyword is matched, it transits to a dialogue-promoting sub-context.

➤ Dialogue continuation Sub-Context

This context contains the knowledge needed to create dialogue-promoting responses for when no keyword match is available. Responses are created by mirroring sentences that the client has just input or by randomly selecting a pattern from the pre-determined response patterns.

➤ Emotion change sharing Sub-Context

This context contains the knowledge that is needed to create summarization responses when emotion words change in dialogue. This context consists of chronological emotion change patterns analyzing AA and Response sentence creating AA. The former is an auxiliary agent that detects emotion word change chronologically and also detects summarize pattern 1, 2 or 3. The latter is an auxiliary agent that creates response dialogue depends on pattern.

Declarative context knowledge such as major contexts and sub contexts includes two types of rules such as transition rules and action rules (execution rules).

- 1) Transition rules trigger a transition from the current to the next context. For example, when a (context) object extracted from “no additional learning” message is received in the Experience Sharing Sub-Context in CRECA, CRECA transits to the problem finding sub-context of Fig. 9.
- 2) Action rules activate lower level contexts or calls out procedures (functions) within the context or lowest-level procedural knowledge chunks called AA (Action Agent).

4.3.2 Context-aware knowledge

The context aware knowledge of CRECA is composed of a context template and an ontology dictionary. It is used for the awareness of the context from natural language texts input by clients. Input texts are tokenized by *MeCab* etc. and keywords are extracted. By using ontology dictionary, keywords are translated to dialogue topics. The context template is instantiated and its slots are filled with keywords or dialogue topics to generate context objects. Context objects are used by context-respectful reasoning for counseling.

There are 3 kinds of ontology-like dictionaries as follows.

A. *Occupation Type*

It is an ontology-like dictionary used for extracting the type of the client’s occupation according to the occupational terminology (TABLE 3 as shown above). My occupational categories (Employment Security Bureau, Ministry of Health, Labor and Welfare, 2011) for IT workers consider unique job titles used in companies besides 11 kinds of

TABLE 6 Ontology to identify problem (student's career example).

Problem (ProblemType Context template name⇒CA's recognition)	Related phrases	
	Event expression(desires/facts/situations)	Emotional expression
Job hunting	wish to be a (SE, PM,...) ,cannot enter (company's name)	An*, W**, Af***
Job fitness	(what job, SE, PM, ...) suits me, (which company, company's name, ...) is good for me, ...	An , W, Af, ...
Disagreement	don't want to work, ...	An , W, Af, ...
...	...	

*: Anxious; **: Worried; ***: Afraid

occupations taken from the document Skill Standards for IT professionals (ITSS)⁴ (Information-technology Promotion Agency (IPA), 2008) by IPA which standardize IT related occupations based on skills

B. Problem Type

This ontology is used to translate the related keyword extracted from input texts and to identify the type of problems which clients are suffering from. An example of CRECA is shown in TABLE 5 as shown above.

C. Problem

This ontology-like dictionary is provided corresponding to each problem type context as shown in TABLE 6 as shown above. The Context Analysis module in Fig. 8 selects the ontology-like dictionary that fits to the previously shared problem type context. Using the context-dependently selected dictionary, the module translates the related keywords and/or phrases to narrow down the problem type and to find the client's problem.

The context template consists of attribute-value pairs, as shown in TABLE 7. This knowledge is instantiated by filling its slot to generate context objects. Context objects are sent to and used in context-respectful reasoning module as shown in Fig. 8.

The slots are filled with the results of the context analysis. Namely, they are filled with the keyword or its translation result by the ontology-like dictionary mentioned above. Keywords are extracted by a token analyzer from natural language texts which clients input.

⁴ Job categories explained in ITSS Career Framework: marketing, sales, consultant, IT architect, project management, IT specialist, software development, customer service, IT service management, education

TABLE 7. Context template and range of attribute value.

Attribute	Attribute value (range)
Occupation	IT workers, BSc/BA students
Problem type	<i>BSc/BA students</i> ; career, school environment, interpersonal relationship, self-anxiety, ...
	<i>IT workers</i> ; career, workplace's internal factors, organizational position, human relation, individual characteristics, ...
Problem	<i>Career (BSc/BA students)</i> ; job hunting, job fitness, disagreement, skills, ...
	<i>Career (IT workers)</i> ; desired occupation, vocational aptitude, salary, future job, ...
Emotional expression	anxious, worried, afraid, ...

Also, TABLE 7 shows the structure of a context template and the ranges of each attribute value that can be filled in.

4.3.3 Processing flow

Fig. 10 shows the complete processing flow of CRECA’s context-respectful reasoning based on the knowledge layer described so far. As discussed above, the flow includes the following two phases: the problem-discovery phase and the problem-solving phase.

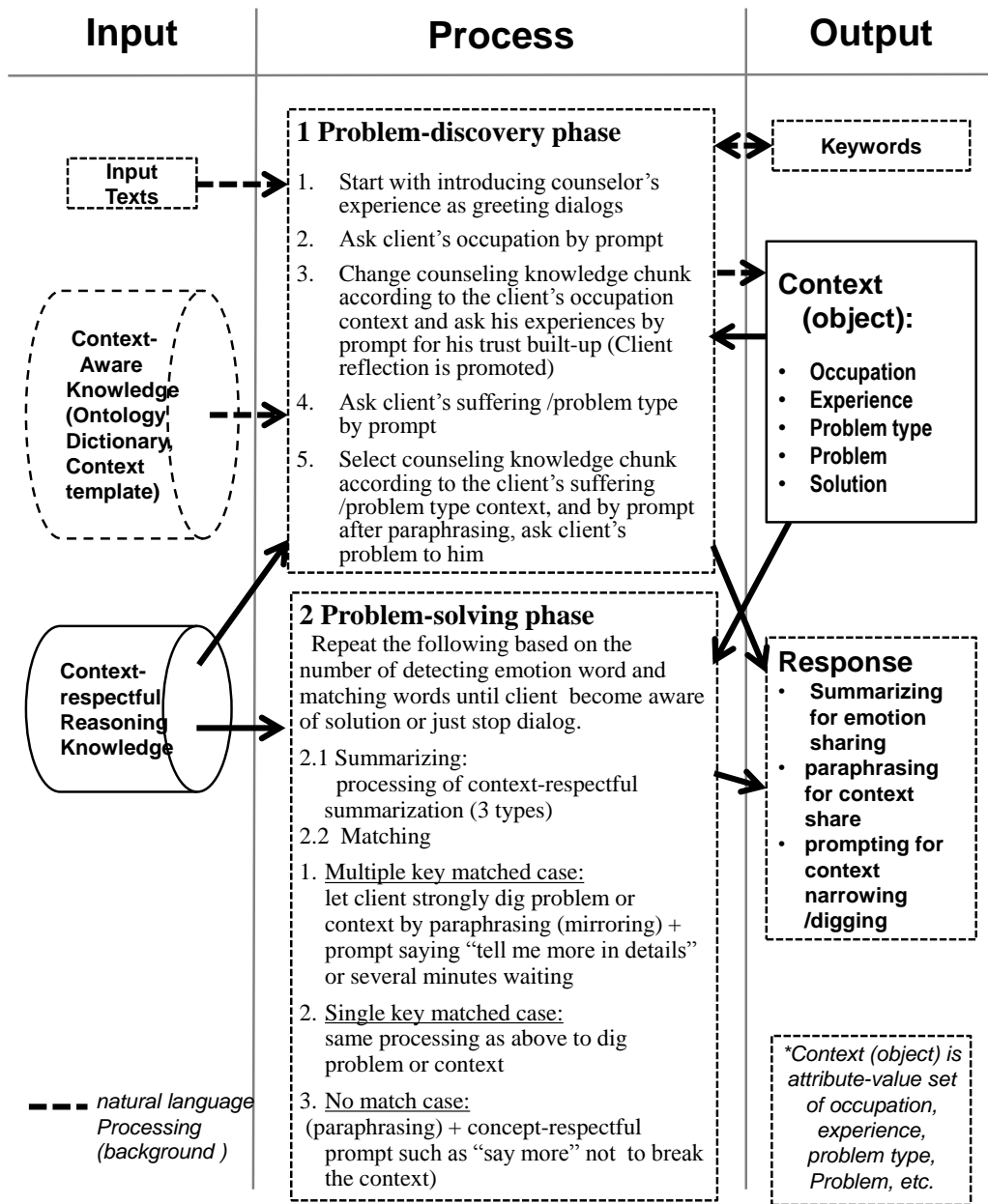


Fig. 10 Processing flow of proposed agent.

4.4. Implementation of Dialogue Summarization Module

The agent summarizes the contents of the dialogue by focusing or recognizing emotional word. In other words, the agent creates response sentences to the client though summarizing the emotional words and emotion transition words contained in the dialogue. The agent continues the response to the client not to break/disturb the context of conversation or context respectfully by the response of such summary. This promotes self-reflection of the client, and it leads the client to self-awareness.

The summarizations keep the dialogue to continue context respectfully, in other words without disturbing the context of conversation. In particular, the agent recognizes emotional words in ongoing dialogues, and then gives the summaries using the change or transition in the emotions discovered among several dialogues. CRECA-E has three summarization patterns as shown later. With the help of these summarizations, dialogues can proceed context-respectfully, namely without ruining the context of the current dialogue. As a result, the reflection of clients are promoted and deepened, which enables them to discern themselves and then finally to have self-awareness.

4.4.1 Detecting emotion for summarization

1. Summarizing target

The agent (CRECA-E) generates the responses using the summarization by focusing on emotional statements in the dialogue. They are an important factor to promote the client's reflection. The summarization is performed when a change of emotion is detected.

2. Statement dialogue structure

Each dialogue statement ($D \in \{D1, D2, \dots, Dn\}$) is either :

an emotional statement ($E \in \{\dots, Ej, \dots, Ek, \dots\}$) or

a non-emotional statement ($NE \in \{\dots, NEl, \dots, NEm, \dots\}$).

Here, $j, k, l, m \in \{1, \dots, n\}$ $j \neq l, j \neq k, l \neq m$, each index appears in only one of the sets, emotional or non-emotional statements.

The element emotional statement (E) indicates client's feelings, e.g. anxious, worry, afraid, worry, disappointed, etc. A NE is an event statement, which does not express feelings, e.g. a fact, a reason, etc. I assume that an emotion in the latest sentence is most close to the client's current feeling in the dialogue (Ito H, 1966).

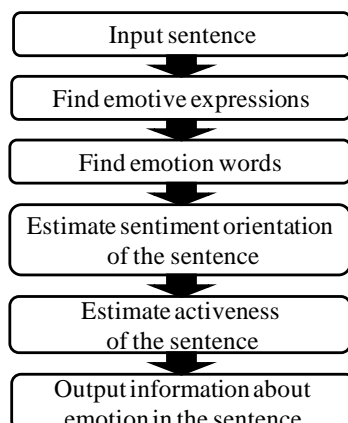


Fig. 11. Flow of emotional word analysis on dialog sentences.

3. Detection of emotion

To detect the client's emotion in the dialogue, CRECA-E uses an emotion analyzer ML-ASK (Michal P, 2011) for dialogue summarization. As for the classification of emotions, ML-ASK applies Nakamura's emotion dictionary (Nakamura A, 1993), which can distinguish 10 of the most appropriate emotion types for the Japanese language and culture. These types are the followings: *yorokobi* (joy), *ikari* (anger), *aware* (sorrow), *kowagari* (fear), *haji* (bashfulness), *suki* (liking), *iya* (dislike), *takaburi* (excitement), *yasuragi* (relief) and *odoroki* (amazement).

Fig. 11 describes the processing flow of ML-ASK. The information about emotion is output by ML-ASK. The information provided by ML-ASK are emotion categories, emotion words, intension of emotion, emotive expressions, sentiment orientation (positive vs. negative), and activation (active vs. passive). In that information, the emotion category is utilized for detecting change of client's emotion in dialogue summarization processing. To detect the change of emotion, a newly detected emotional word, namely a newly or lastly uttered word belonging to emotion categories is compared with an already uttered and detected emotional word in the previous sentences.

4.4.2 Generating Patterns for Summarization

CRECA-E performs summarization for readjustment and for providing smooth flow between statements and for bringing together what has been happening in the conversation. As shown in the sub-section 3.2.2, summarization is done at the timing c) and d).

TABLE 8. Summary response generation patterns.

Pattern	Description	Response sentence
SP1	En(in Dn)≠E1(in D1)	You said D1, And now, you are saying Dn aren't you ? あなたは、「D1」といいました。今は、Dnですね。
SP2	Client input "quit" and emotional word appears only in D1 (E1)	You said D1. And you are saying Dn. So, You are E1 ? あなたは、「D1」といいました。そして今、「Dn」といいました。あなたは E1ですね。
SP3	Emotional word appears newly in Dn(En)(n ≥ 2)	You said D1. And now Dn, aren't you? あなたは、「D1」といいました。今、あなたは Dnですね。

The generated summarization responses change depending on the state of the conversation (timing) and of the newest sentence S_n , as shown in TABLE 8.

CRECA provides summary responses for three different types of cases. Each case corresponds to a summary response generation pattern. Sentences are stacked on the history in order to compare the newest sentence with them. Each time, when CRECA creates a summary, this history is reset except S_n . TABLE 8 shows the three patterns for the summary response generation (SP1-SP3). Here, the last sentence in the client utterances is D_n . D_n may contain an emotional word E_n . The first sentence is D_1 . D_1 may contain the emotion E_1 . The history (stack) is reset, and $n=0$ after a summary is created.

The first pattern SP1 is utilized when an emotion is detected in the newest sentence D_n input by clients and the emotion is different from the one detected lastly in previous sentences such as D_1 stacked in the history. Thus, CRECA-E outputs the response generated using SP1 pattern.

The second pattern SP2 is utilized when the user wants to finish the counseling by entering the quit or the form to close the conversation. At this moment, if there is an emotion E_1 detected in previous sentences including D_1 in the history, CRECA-E outputs a response generated by using the SP2 pattern.

The third pattern SP3 is utilized when an emotion E_n is detected in the newest dialogue D_n but there is no emotional word detected in D_1 --- $D_{(n-1)}$, i.e. in any sentence stacked in the history. In this case, CRECA-E outputs a response generated by using the SP3 pattern.

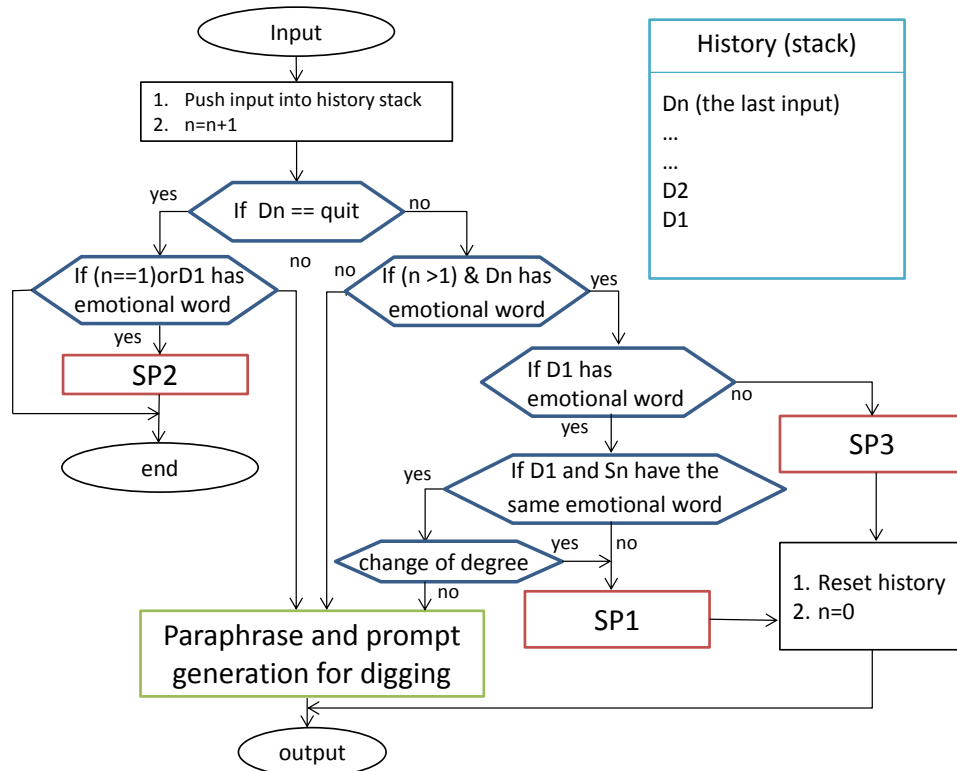


Fig. 12. Processing flow of context-respectful summarization.

Emotion focused context-respectful summarization for problem solving begins stacking the dialogue in the history as D1, and $n=0$ is set. The dialogue inputs continue, and context-respectful summarization are processing as shown in Fig 12. In case of D1 include emotion word E1, when emotional word changes are detected in Dn, i.e. SP1 type responses are generated. Continuing reset the histories and set $n=0$.

This detection of emotional changes is repeated for problem digging until Dn becomes quit, and SP2 type responses are generated, namely problems are solved, or the counseling fails. If dialogue does not satisfy anyone of these cases, CRECA-E does not generate a summary response. Then, CRECA-E routinely outputs a context-respectful response that consists of paraphrases followed by context-preserving prompts such as “Say more in detail” for digging problems. Fig. 12 shows such a process flow implementing the emotion focused context-respectful summarization and paraphrases followed by context-respectful prompts in CRECA-E’s problem solving/digging phase.

4.5. Web-based CA System for virtualization on the large-scale Web

It is required that a great number of clients can have counseling concurrently as well as responsively. The system is intended to be used by several individual clients concurrently and independently, who are distributed in several areas, organizations and enterprises. Therefore, my counseling agents are implemented as Web applications on Django in ubiquitous environments on the Web (to appear everywhere and to be used by every client at the same time).

4.5.1 Web-based CA system architecture

Fig. 13 shows the Web-based CA (Counseling Agents or Conversational Agents/bots) system architecture. Owing to this architecture, a great number of suffering IT workers can solve their problems concurrently supported by responsive as well as “context respectful” conversational agents/bots on the Web as if there were various human counselors distributed in the virtualized or cloud computer environment. For implementing this counseling agent, a so called Django Application Server on Apache 2 Web server with mod python was used as the platform as follows:

- Web server: Apache HTTP Server (Apache 2.2 including mod. python and mod_proxy_balancer) + python interpreter.
- Application server: Django 1.6 (Holovaty A, et al) is used. Django is an application

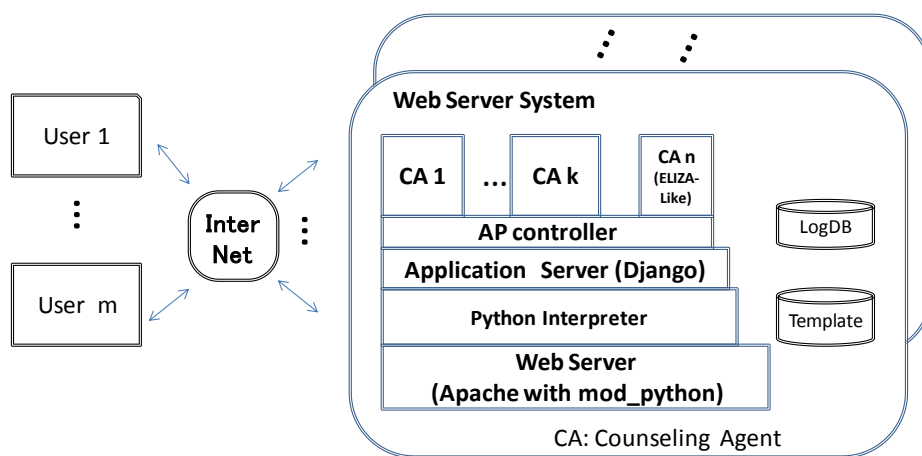


Fig. 13. Web-based CA system architecture.

server (platform) written in Python for efficient, reliable, and scalable Web-based application development. Django Application Servers are used safely by multiple clients concurrently on the Web in virtualized environments. MySQL is used for DB in my system.

- Application controller I call “AP controller” exploiting Django that handles Web applications written in Python has the followings:
 - 1) Initial processing that handles clients’ login requests for consultation and its evaluation, and the setting of available counseling agents and language selection,
 - 2) Resource assignment and management that assign and manage resources such as data transmission resources, backend DBs with the persistency mechanism for saving log data etc., and templates such as style sheets.
- Counseling agents CA1, CA2, ..., CAn as modules of a Web application for incarnation/virtualization of a human counselor, each of which consists of its dictionary for natural language text analysis, the reasoning engine, and counseling knowledge used by the engine,
- DBs for clients related data including user profiles and conversation log data, templates including style sheets and HTML files, modules for natural language input/output/analysis, and questionnaire evaluation modules.

4.5.2 System operation and execution flow

Fig. 14 shows the operation flow of my Web-based CRECA system. The counseling session starts from login, but first visit to CRECA system, the profile registration of the

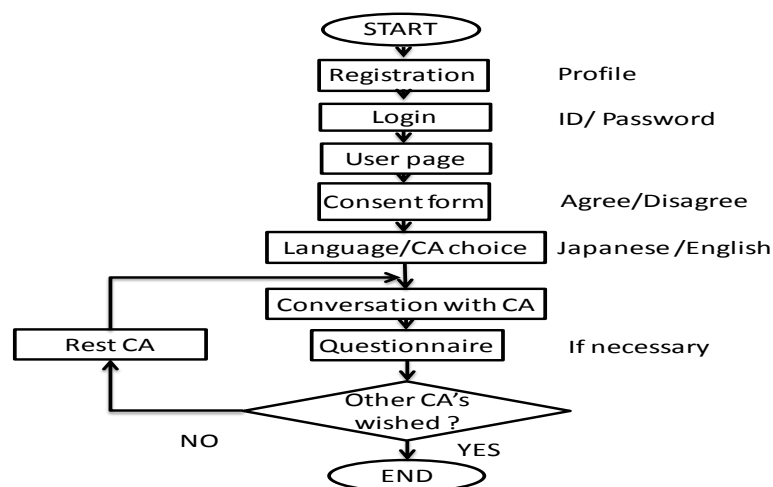


Fig. 14. Web-based CRECA Operation flow.

client is necessary , consent of use, and the selection of languages and agents that clients wish to consult with. Then it goes to the counseling dialogue. When the dialogue with an agent is over, questionnaires on current emotions of clients are taken, if they wish. If they wish to consult with another agent, the counseling dialogue with the newly selected agent continues. This is repeated until clients finish consulting with all the agents they wished or selected. Otherwise, the counseling is finished. Each session can be executed on the distributed virtual or cloud environment, i.e. many clients can request the counseling at once. This distribution/allocation request is handled by the mod_proxy_balancer of Apache (Pardeck J, 1987).

CHAPTER 5

EVALUATION

This chapter describes the evaluation experiment for two steps of the context-respectful CA called CRECA, namely the original CA with no summarization function, and the extended CRECA having emotion-focused summarization functions called - CRECA-E. The evaluation results for CRECA compared with ELIZA (-like one) are described below in 5.1 (Evaluation of CRECA). In the next step, the evaluation results for CRECA-E compared with CRECA and ELIZA (-like one) are described below in 5.2 (Evaluation of CRECA-E).

In addition, the feasibility and effects of CRECAs (CRECA, CRECA-E) on the Web is evaluated, especially together with its scalability. Namely, the evaluation results for a load simulation test results are described below in 5.3 to show that CRECAs virtualized on the (large-scale) Web enable concurrent counseling to a great number of users.

5.1. Evaluation for CRECA

5.1.1 Evaluation Methode

Evaluating conversational agents is a complex issue, and a wide range of evaluation approaches and standards have been proposed (Isbister K, Doyle P, 2005), as the responsibility of carrying out the evaluation has gradually moved away from teams of computer scientists to teams that include psychologists and other social scientists, as well as domain experts.

Some researchers focused on empirical evaluations, conducting controlled experiments to test whether their hypotheses about causes and effects hold true. An advantage of this approach is the possibility of using well-established measures when possible, so that other researchers can easily understand and replicate results. An example is the use of expert peer review and/or target audience surveys to evaluate the overall believability and effectiveness of a CA (Isbister K, Doyle P, 2005). This

approach is borrowed from the arts and media fields. The contribution of this kind of evaluation is typically bounded by the single CA instance. However, over time, these sorts of evaluations produce accumulated observations about tactics for effective design for particular audiences and contexts which can be tested and applied to similar CA projects.

Other researchers (Van der Heijden H, 2004) preferred evaluating their CAs via *outcome testing*, i.e. by observing the behavior of users interacting with a CA and measure the rate of success (and other related metrics, such as the length of interaction) in achieving particular outcome. The contribution of this sort of evaluation is the confirmation that the CA features achieve effective outcomes, allowing other CA designers to leverage their knowledge and tactics.

In evaluating my research I followed a hybrid approach. Indeed, a counseling agent that encourages self-awareness and reflection is expected to leave a trace in the participant emotional state. Therefore, emotional criteria such as counseling-training evaluation (DeMara R et al., 2008) and counseling behavior evaluation (Hung V et al., 2009; Fukushima O et al., 2007) need to be taken into account.

For measuring this effect, I set up an empirical evaluation experiment based on having a group of IT students interact with my counseling agent. Then I proposed them a survey including questions that assess the intensity of the users' emotional responses by means of a Likert scale. This method is well attested in the literature (Van der Heijden H, 2004) for testing technological systems known to have high emotional impact. In order to baseline my evaluation, I carried out a similar experiment involving a simple ELIZA-style CA. Instead of carrying out a traditional case-control study, however, I had a single group alternatively interact with both systems⁶ keeping them in the blind regarding which system they were interactive with. Following the prevalent advice of the literature (Yeh C J et al., 2012) report that in counseling training anonymity is very important to build up trust, my questionnaires were anonymous.

The same experiment was used for carrying out the quantitative outcome testing, by measuring for each conversation the number of interactions taking place between the client and the CA (Saygin A P, Cicekli I, Akman V, 2000). This measure was taken both for CRECA and for the ELIZA-style CA. In the remainder of this Chapter, I will describe my experiment in some detail.

⁶ This access shuffling technique reduces the influence of the recruitment (e.g., in terms of the participant skills and previous knowledge) on the experiment outcome (Likert R, 1932).

A. Location and subjects for the experiment

My experiment was carried out for a period of 3.5 months, from July 1, 2012 to November 16, 2012. Fifteen (15) students of the Department of Information Environment in my university participated in the evaluation as the clients. My experiment involved BSc students close to graduation (3rd or 4th year grade in the university) and likely to face anxiety in face of recruitment problems. Students were briefed about the nature of the experiment, but care was taken to include in both groups only students who claimed to be concerned about their career in IT and were interested in undergoing counseling. Namely, I took 15 students: 3 (3 females) of 4th-year undergraduates, and 11 (7 females, 4 males) of 3rd-year, and one (1 female) of 1st-year.

B. Evaluation criteria

I considered the perceived trust and self-awareness were considered *as emotional criteria*, to be assessed via the experimental survey, and the number of interactions was chosen as a testable quality of trustiness measured during the experiment.

C. Comparative evaluation method

In order to baseline the evaluation of my system, I chose a basic implementation of an ELIZA-style CA (ELIZA). Base-lining CRECA rather than providing a comparative assessment with other CAs designed for (different) vertical application is a precise methodological choice (“Empirical Evaluation Methodology for Embodied Conversational Agents” in Chapter 3 of (Van der Heijden H, 2004)) as users are known not to be reliable when comparing CA having very different domain and goals.

D. Experimental design

My experimental design set up a comparative evaluation test was done between my counseling agent (CRECA) and an ELIZA-style CA (ELIZA)..

The protocols were the followings:

- Each client talked alternatively with ELIZA and with CRECA (one conversation at a time, the order between the two was extracted randomly for each client).
- Manipulation was practiced when necessary orienting keyboard input before the conversation.

- The students were not briefed about the difference between the two agents⁷.
- After the conversation with each agent ended, the computation of the conversation length and the filling in of the questionnaire were carried out immediately.

E. Questionnaire

My evaluation questionnaire consists of 10 questions on trust, based on authorized criteria introduced in (Fukushima O et al., 2007), such as “I was able to talk to the agent comfortably”, and of 12 questions on self-awareness such as “I was able to put my problems in words”, “I was able to specify my problems”, “I was able to have more positive feelings”. Each question was to be answered on a 7-point Likert scale (Likert R, 1932) ranging from 7 (strongly agree) to 1 (strongly disagree).

I adopted (and communicated to the participants) the following definitions:

- Definition of TRUST: *Feeling of harmony and reliance on counselor, including empathic understanding* (“I was able to talk to the agent comfortably”, etc.).
- Definition of SELF-AWARENESS: *Perception of counseling effectiveness* (“I was able to have more positive feelings”, etc.), *and feelings of being able to put one’s difficulties into words* (“I was able to clarify the problem that I had ”, etc.).

5.1.2 Results

I am now ready to present in detail the results of outcome testing (in terms of dialogue interactions) and of the survey.

User profiles, normal distribution of experimented users’ properties, and processing time (less than 0.1 sec. but with pauses for self-reflection) were considered.

A. The number of dialogue interactions

The average number of interactions per conversation between students and CRECA/ELIZA was 11.7 for ELIZA and 23.7 for my agent (CRECA). Decomposing the 23.7 interactions of the dialogues with CRECA, the number of interactions of the first phase 13.1 and from there to the dialogue end was 10.6. My agent CRECA total result 23.7 (13.1 + 10.6) is twice as big as 11.7, the number of ELIZA’s dialogue continuation.

⁷ Somewhat surprisingly, few of my IT students seem to have heard about ELIZA.

TABLE 9. Results of the evaluation questionnaire on TRUST.

Sample No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average (SD)
CRECA	5.5	4.0	5.2	3.7	4.6	4.5	3.0	3.1	3.4	4.2	4.3	4.7	4.8	5.3	5.6	4.39 (.83)
ELIZA	1.0	2.2	2.8	2.4	1.6	4.6	1.3	2.6	2.3	3.2	3.4	4.7	3.0	2.6	4.3	2.8 (1.12)

B. Evaluation by questionnaire

I collected scores of each student in each question category and computed the average value and the standard deviation (SD) of TRUST and SELF-AWARENESS respectively for CRECA and ELIZA, as shown in TABLE 9 and TABLE 10.

I processed my results as follows by using SPSS V21. The difference in the CRECA's and EL's average values of 4 males' and 11 females' TRUST and SELF-AWARENESS, respectively, was checked by using nonparametric tests since each average value data group may not have normal distribution.

Accordingly, there is no gender difference in the data groups' average value of TRUST and SELF-AWARENESS as follows: TRUST in CRECA ($p=.412 >.05$ means no difference); TRUST in ELIZA ($p=.949 >.05$); SELF-AWARENESS in CRECA ($p=.280 >.05$); SELF-AWARENESS in EL ($p=.753 >.05$).

I also conducted statistical paired t-tests⁸ to assess the confidence that the difference between CRECA and ELIZA responses was not due to random fluctuations.

➤ Results of Questionnaire on TRUST:

As shown in TABLE 9, the average value (AV) questions about being able to establish building/establishing a trust relation (TRUST) in my proposed agent called CRECA showed an average of 4.39 (SD = 0.83), namely positioned on the "agree" side. Meanwhile, AV in ELIZA showed 2.80 (SD = 1.12) namely positioned on the "disagree" side.

According to the results of the paired t-test with $t(14) = 5.13$ $p < .001$, it can be said that the confidence that this difference is not due to random fluctuation is more than 99%.

➤ Results of Questionnaire on SELF-AWARENESS:

As shown in TABLE 10, the average value of the questions about self-awareness regarding CRECA (SELF-AWARENESS) showed an average of 4.5, positioned on the "agree" side. On the other hand, ELIZA showed 3.5 positioned on the "disagree" side.

⁸Normal distribution was confirmed about TRUST in CA ($p=.200 >.05$)/ EL($p=.200 >.05$) and SELF-AWARENESS in CA ($p=.200 >.05$)/ EL($p=.200 >.05$) via Kolmogorov-Smirnov analysis on the data of 15 persons.

TABLE 10. Results of the evaluation questionnaire on SELF-AWARENESS.

Sample No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Average (SD)
CRECA	5.5	3.8	4.5	4.4	5.0	4.8	3.0	2.9	3.5	4.8	4.3	5.7	4.8	5.5	5.0	4.50 (.70)
ELIZA	3.4	2.8	3.8	3.8	1.8	4.3	2.3	1.8	3.7	4.3	4.1	5.3	3.2	3.4	4.8	3.51 (1.00)

According to the results of the paired t-test with $t(14) = 4.31$ $p < .001$, it can be said that the confidence that this difference is not due to random fluctuation is more than 99%.

5.1.3 Evaluation conclusion

My counseling agent CRECA successfully builds up enough trust during the trust build-up step to convince clients to organize or summarize their experiences and accomplishments, while ELIZA interaction does not. This is largely due to this trust build-up step, where accomplishments are discussed. Experiment results clearly suggest that the trust built in the first phase encourages users to carry on the conversation in the second phase. Considering just the steps after finishing this step, the number of interactions with CRECA is 10.6 times of interactions, while the dialogue with ELIZA (having no trust-building process) had on average only 7.5 interactions.

t-tests on the trust and self-awareness questions show that CA compares favorably with EL in a statistically significant way.

In the problem solving phase, digging prompts such as “tell me more in details”, “tell me a little more”, or waiting for client’s responses for several minutes successfully promote reflection. Those utterances or silence do not destroy the current context during conversations between a client and a counselor agent, but narrow it to help the client achieve awareness of the problem’s solution through her deep reflection.

As a summary, although preliminary, my experimental results showed that my agent can indeed provide satisfactory counseling to IT related persons. Namely, compared with conventional chatterbots whose questionnaire results were positioned on the “disagree” side, the average value of questionnaire to my agent was on the “agree” side .

Thus, my agent, although rudimentary-level, can be expected to save at least 10% of IT related persons in distress

According to (MHLW, 2008), IT workers suffering from problems have reached more than 60 % of overall such workers in Japan. The number of IT workers in Japan is at least 2 millions or so (Statistics Bureau of MIC, 2012). Therefore, over millions of IT workers are in distress. There are also 100 thousands of students desiring IT workers. Thus my counseling agents are expected effective since they can save over hundreds of thousands, namely 10% of such IT related persons in distress even in only Japan whose number of suffering IT persons is over millions as mentioned above. Therefore, I claim that my agent is expected to greatly contribute as a core component in software development ecosystems.

5.2. Evaluation for CRECA-E

The comparative evaluation experiment was done in order to obtain insights about the effects of my proposed counseling agent implemented with the text summarization.

5.2.1 The evaluation settings

1. Evaluation scenario

Evaluating conversational agents is a complex issue, and a wide range of evaluation approaches and standards have been proposed (Hung V et al., 2009; Fukushima O et al., 2007), as the responsibility of carrying out the evaluation has gradually moved away from teams of computer scientists to teams that include psychologists and other social scientists, as well as domain experts.

The extended counseling agent, CRECA-E, is compared with the previously proposed one, CRECA, to verify the following hypothesis: clients deepen their reflection through summaries that depict the chronological change between emotions or the accompanied events and acquire self-awareness to organize their thoughts.

In the evaluation, the number of interactions between a client and an agent as well as the questionnaires on trust and self-awareness, which were used in the previous comparative experiment between CRECA and ELIZA, namely chatterbot, are considered.

The other evaluation items include the effect, timing, and validity of summaries, and the possibility of emotion detection, and free comments are allowed. I also take into consideration of the experiment results for CRECA and ELIZA.

In counseling, it is not possible to grasp the change in human subjective emotions simply by getting the objective information such as the interaction number between a computer agent and humans. To evaluate the effect of the computer agent's functions, it is necessary to measure the emotional changes of the client when the counseling is done.

In this measurement, the questionnaire method to humans used in psychology is valid. Especially in this research, questions on self-awareness and trust showing the effect of the interaction of counseling are considered. The measurement conditions must be the same as the ones of ordinary psychological measurement such as confidentiality (c.f., not exposing the dialog content between the computer agent and the client). When the dialog between the computer agent and the client is taken, the followings, same as ones of counseling between the human counselor and the client, must be taken into consideration: 1) it is ensured that the content of the dialog between the computer agent and the client be not exposed; 2) the client must have problems and be willing to take counseling.

To evaluate my research project, I followed a hybrid approach; questionnaires for client's subjective evaluation and counting dialogue interactions for objective evaluation. Indeed, a counseling agent that encourages self-awareness and reflection is expected to leave a trace in the participant emotional state.

In this evaluation, I compared my newly proposed CA (I call as CRECA-E), which implemented the text summarization, with my previous CA (I call as CRECA), which is not implemented the text summarization. For each CRECA, the clients are evaluated by the quantitative outcome testing, by measuring the number of interactions, the values of questionnaires on trust and on self-awareness.

I did the evaluation experiment on the following conditions:

- The clients use stand-alone PC or Web page
- After the conversation with each agent ended, the number of interactions and the client completes the questionnaires immediately

2. Evaluator's profile

16 students (15 male, 1 female) studying Computer Science, in Tokyo Denki University evaluated the systems, since my agent is intended for IT related persons. All the clients claimed to be concerned about their career in IT and were interested in undergoing counseling.

3. Evaluation Items

A questionnaire for trust and self-awareness: this questionnaire consists of 10 questions on trust, based on authorized criteria introduced in [Fukushima O et al., (2007)], such as "I was able to talk to the agent comfortably", and of 9 questions on self-awareness. Each question was to be answered on a 7-point Likert scale (Likert R, 1932) ranging from 7 (strongly agree) to 1 (strongly disagree).

A questionnaire for summarization: this questionnaire comprises 4 yes/ no questions, and free comments are allowed.

TABLE 11. Results of the number of DIALOG INTERACTIONS.

SampleNo	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Average (SD)
CRECA-E	24	27	25	30	29	27	40	35	32	24	30	30	48	24	28	29	30.1 (6.4)
CRECA	23	25	23	31	27	29	42	32	33	22	26	24	27	15	26	28	27.1 (5.9)
ELIZA	9	8	11	14	10	12	10	9	11	11	16	10	8	11	12	19	11.3 (2.9)

5.2.2 Results

1. Results of the number of dialogue interactions

TABLE 11 shows the number of interactions between each student and each agent CRECA-E, CRECA (without summarization function) and ELIZA as well as the difference among the results.

The Kolmogorov-Smirnov normality test (Chakravarti I et al., 1967) was used. Since the p-value of the CRECA-E was .006, that of CRECA was .200 and that of ELIZA was .023, the normal distribution of CRECA was admitted with hazard ratio $p < .05$, meanwhile, the normal distribution of CRECA-E and ELIZA were rejected with hazard ratio $p < .05$. Therefore, the non-parametric test was done to analyze the difference of each set of sample data.

Consequently, CRECA-E was confirmed superior to CRECA and ELIZA in the number of interactions.

2. Results of the questionnaire on trust and self-awareness

TABLE 12 shows the trust of each student towards each agent CRECA-E, CRECA and ELIZA and the difference among the results.

The Kolmogorov-Smirnov normality test was used; the p-value of CRECA-E, CRECA, and ELIZA were .006, .200, and .023 respectively. The p-value difference between CRECA-E and CRECA was .114, and the one between CRECA and ELIZA was .200. Consequently, the normality (normal distribution) of all the cases was not rejected with the hazard ratio $p < .05$, and thus the t-test was conducted. Accordingly, CRECA-E was confirmed exceeding CRECA and ELIZA in trust with the client.

TABLE 12. Results of the Questionnaire on TRUST.

SampleNo	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Average (SD)
CRECA-E	4.7	3.6	4.9	5.0	4.2	4.5	5.4	5.3	4.5	4.1	3.1	4.4	5.1	4.5	4.3	5.0	4.54 (0.61)
CRECA	4.0	3.0	3.5	3.1	4.2	4.9	4.5	4.1	2.9	4.6	3.0	3.2	4.6	4.5	3.5	3.9	3.84 (0.68)
ELIZA	2.6	1.6	2.4	3.0	3.6	3.1	3.1	3.6	3.8	2.6	4.1	2.8	3.9	2.4	1.8	3.4	2.99 (0.73)

TABLE 13. Results of the Questionnaire on SELF-AWARENESS.

SampleNo	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Average (SD)
CRECA-E	4.9	4.6	4.1	4.0	4.9	5.1	5.6	5.3	6.0	5.6	3.4	4.0	5.9	5.0	5.4		4.92 (0.73)
CRECA	4.1	4.2	3.7	4.1	5.2	5.2	4.9	4.7	5.2	4.7	3.0	3.7	4.8	4.7	5.9	4.2	4.51 (0.73)
ELIZA	2.1	1.1	3.9	3.7	2.7	5.1	3.0	3.6	3.6	1.2	4.1	2.1	3.8	4.0	3.2	5.1	3.26 (1.18)

TABLE 13 shows the self-awareness of each student after he/she talked to each agent CRECA-E, CRECA and ELIZA and the difference among the results.

The Kolmogorov-Smirnov normality test was used; the p-value of CRECA-E, and ELIZA were .200, .200, and .200 respectively. The p-value difference between CRECA-E and CRECA was .114, and the one between CRECA and ELIZA was .200. Consequently, the normality (normal distribution) of all the cases was not rejected with the hazard ratio $p < .05$, and thus the t-test was conducted. CRECA-E was confirmed superior to both of CRECA and ELIZA in self-awareness.

3. Results of the questionnaire on the summarizing function

In this item, I describe about the questionnaire on the summarizing function. The Yes/No questionnaire results on summarizing function were shown in TABLE 14.

Before the experiment, students were told that the summary responses consist of their several utterances.

1). Effect of summarization

As TABLE 14 shows, affirmative answers were obtained from the comments of 10 students for the question Q1 “Did you get better impressions/effects for and from summary responses rather than any other (e.g., just paraphrased) responses?”, which show the expected effects of the summary.

First of all, it is confirmed that the summary response led to the self-understanding (or reflection) of the students, considering “I can organize my thoughts more with my sayings summarized,” “I can check what I have said,” “Receiving the responses with my own words could lead to more self-awareness.” And also, the summary response was confirmed to play a role in leading to some kind of empathic understanding which improves the trust of the students as I got the following comments: “I felt the agent understood me well and responded right,” “The agent hit the nail on the head when it responded by words summarizing my exact worries,” “The agent understood what I was trying finally to say.”

TABLE 14. Questionnaire Results on summarizing.

Questionire item	Questiones	Answer		
		Yes	No	no answer
a. Effect of summarization	Q1 Did you get better impression for the summary responses rather than any other (e.g., just rephrased) responses?	10	0	6
	Q1a Did the agent's summary responses contribute to organizeing your thoughts?.	9	1	6
b. Summarization timing	Q2 Did the agent give you summary responses at the appropriate timing?	7	0	9
c. Appropriateness of summary	Q3 In summary responses, did the agent appropriately pick up words from your ongoing dialog history?	10	1	5
	Q3a Were you able to take a general view of the past and present events?	9	2	5
d. Emotion detecting capability	Q4 Were the emotional words in summary responses consistent with your feelings?	6	1	9

2). Summarization timing

For the timing to output the summary responses, as asked in the question Q2 in TABLE 14, “Did the agent give you summary responses at the appropriate timing?”, 7 students said yes and 2 students gave us comments: “it was good the summary responses were given just when I expressed my emotions.” and “the summary responses came at the right timing and expressed my feelings well at the end of the conversation.” Consequently, the timing of the summary response was verified appropriate enough to help students sort out their feelings.

As future work, I am going to add some appreciation words such as “Thank you for talking to me” at the end of the dialog (the timing of inserting “QUIT”).

3). Appropriateness of summary

In terms of the summary appropriateness, as asked in the question Q3 in TABLE 14 “In summary responses, did the agent appropriately pick up words from your ongoing dialog history?”, 10 students gave us affirmative answers; however, a student who gave a negative answer reported there was a case that the student’s responses with emotions where an interjection exist at the beginning (such as “uh” and “yes”) were not included appropriately, as they must have been included since they contained emotions.

With some of the comments from the students such as “I felt the agent picked up appropriate emotional words,” “my main worry got discovered through the conversation,” it was confirmed that the agent gave summary responses using the student’s utterances properly.

Nine respondents gave an affirmative reply and two gave a negative reply to the question 3a in TABLE 14, asking “Were you able to take a general view of the past and present events?” I introduce some of the comments made by respondents with an affirmative reply. “The summary was compatible with the flow of conversation.” “I noticed my weakness at the moment and in the future.” These two comments show that the summary gave the overview of their utterances. One of the other comments, however, says, “Some sentences in the summary sounded unnatural.”

As shown above, terms of the summary were appropriate, but I need to improve the sentence connection and concluding remarks in the summary.

4). Emotion detecting capability

To the question Q4 in TABLE 14, “Were the emotional words in summary responses consistent with your feelings?” six respondents gave an affirmative reply meaning that the words related to emotion in the summary are appropriate. I introduce some of the comments made by respondents with an affirmative reply. “It is acceptable since the words I had spoken were used in the summary.” “I felt like I shared a common emotion.” One comment which is not included in the comment chapter says, “I came to terms with my feelings since the summary put my thoughts into appropriate words.” It was confirmed that appropriate words related to emotion had been used in the summary.

One respondent gave a negative reply. But according to his/her comment, in some cases the words related to emotion in the summary were consistent with his/her feelings. Two respondents chose “no” as their reply. One comment says, “The strength of feelings was not appropriately expressed.” The other comment says, “The meaning of the question was difficult to understand.” Further I will add the functions dealing with adjectives and adverbs that modify emotional words and estimation of emotions.

I can see some negative comments made by respondents in the overall opinions. “Only a curt reply was given in response to my answer.” “I got no specific advice.” “I did not feel well understood.” Those comments depend on CRECAs don’t give a client any advice which is the CRECAs feature itself.

But it was confirmed that summarization function is effective in improving trust, promoting self-understanding (reflection), and leading to self-awareness on CRECAs feature itself.

5.2.3 Evaluation conclusion

The results of this experimental evaluation proved my proposed CRECA-E (With-Summarization) focusing on client's emotion in chronological order is effective as follows. As shown in TABLEs 11-13, the result of CRECA-E exceeds CRECA (No Summarization) in all evaluation criteria. CRECA-E summarizes several events and emotions, in other words, the summarization is considered as paraphrasing of not only a single sentence or a single step in a dialogue but also several or multiple sentences in a whole dialogue, which are narrated by the client in the dialogue in order to promote the client's readjustment and confirmation of the problem. Thus, my agent is able to identify emotion in the client's sentences among classes of feelings in the emotional word analysis shown in Fig. 11. This supports clients to solve their problem by their own.

Consequently, my experimental results showed that the text summarization has a fairly positive effect on computer-respectful counseling. However, detecting the emotion has room for improvement.

The experiment shows that the CRECA-E (with summarization function) is superior to CRECA (without summarization function) and ELIZA, in terms of the number of dialog interactions, trust, and self-awareness.

Specifically, CRECA-E > CRECA > ELIZA were proved in terms of the number of interactions, self-awareness, and trust.

Results of the questionnaire on the summarizing function are as follows:

- Effect of summarization: Affirmative answers were obtained from the comments of 10 students. The summary response was proved to be effective enough to improve reflection and trust.
- Summarization timing: The timing of the summary response was verified to be appropriate enough to help students sort out their feelings.
- Appropriateness of summary: 10 students gave me affirmative answers. The terms of the summary were appropriate, but I need to improve the sentence connection and concluding remarks in the summary.
- Emotion detecting capability: six respondents gave an affirmative reply and confirmed that the words related to emotion in the summary are appropriate

Those comments depend on the fact that the CRECAs (CRECA and CRECA-E) don't give a client any advice which is the CRECAs feature itself. So it was confirmed that summarization function is effective in improving trust, promoting self-understanding (reflection), and leading to self-awareness.

In this way, the following hypothesis was proven to be correct: clients deepen their reflection through summaries that depict the chronological change between emotions or the accompanied events and acquire self-awareness to organize their thoughts.

Consequently, CRECA-E is effective enough for problem solving of IT workers.

Specifically, it is verified that clients can feel they are understood and deepen their reflection and become self-aware of their problem solution through context respectful conversations focusing on emotions, that is, summaries with emotional words, paraphrases and reflection promoting prompts.

As future work, in order to lead to further reflection, the summarization function should be improved, such as 1) add some appreciation words such as “Thank you for talking to me” at the end of the dialog (the timing of inserting “QUIT”), and 2) dealing with adjectives and adverbs that modify emotional words and estimation of emotions.

5.3. Results of Load Simulation to Web-based Context-Respectful CA

5.3.1 CA on the Web

As shown in Fig. 14 and section 4.5., Web applications for implementing the context-respectful CA have many pages including the repetitive conversation pages. Web applications are waiting for the duration between each of Web pages. If the duration is very long, many clients can concurrently access. For example, registration takes more than a minutes or 100 seconds. Assuming a http server takes around 3 (in case of https practically useful for counseling that handles private information, it takes around 50) milliseconds for the connection (Zembutsu M), 30000 clients (around 2000 clients in case of https) can be connected during the time.

The access duration for each of Web pages consists of the time for sending or downloading such a page, client’s input time to such a page, and the time receiving or uploading inputted requests (transmission time + human input time). Especially the client’s input time is important to obtain the maximum response time of CA virtualized on the Web, since the human input time often including thinking time is sufficiently long e.g. second order compared with transmission time e.g. millisecond order. Therefore, such human input time was measured, using the Web-based CA system by two IT related students. The input time to the registration page was not measured since it is usually used in advance for inputting user profiles including user ID/password setting before starting the counseling session.

TABLE 15 shows such human input time or waiting time is from 1 to 30 seconds. Thus to simulate such individual difference of input time or waiting time to request the page transition, 10% of the probabilistic margin time (standard deviation) was added to

TABLE 15. Input times in the simulation test.

Page	Timefor agent's output by client's input (sec)
1 User login	2.5
2 User page	1
3 Consent form	5
4 Language select	1
5 Introduction of conversational agent or Response +Input sentence	5~30

the delay time (called Ramp-time in JMeter) by Gaussian distribution. The following computer is used in this simulation test: CPU; Intel® Core(TM) i7 1.60GHz, Memory; 4GB, OS; Ubuntu 12.04.

Fig. 15 shows the results of this evaluation test by using a JMeter. The maximum response time is 7.6 seconds in case the number of users namely clients starting counseling at once but during 10 seconds is 100. This case assumes that 100 clients use the CA with 10 seconds delay in average for the http request to each page. However, some pages have just 1 second for the waiting time. Therefore, users namely clients will possibly feel 16.6 ($=10-1+7.6$) seconds of delay. Thus, this result indicates that my context-respectful CA is practical having conversationally permissible response time (usually 3-5 seconds) if three or several Web servers are provided in case of 100 clients using the CA at once but during 10 pages.

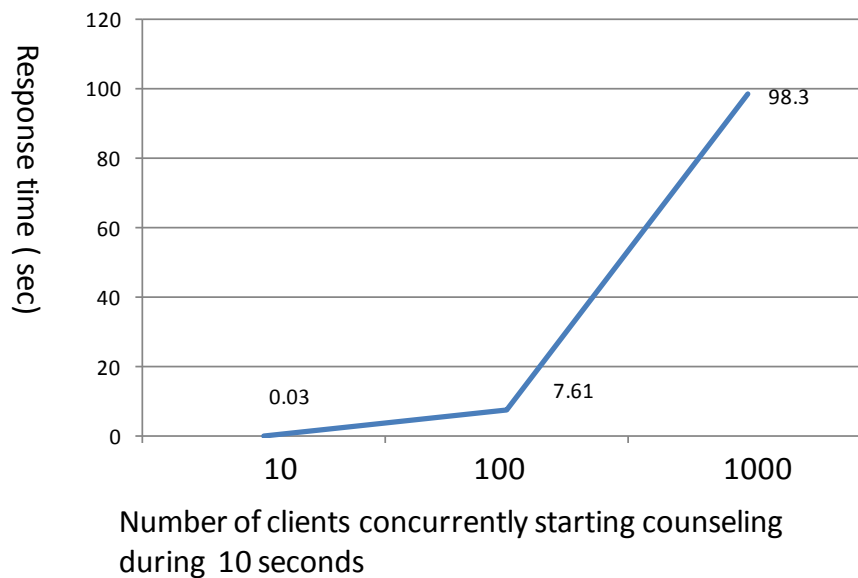


Fig. 15. Response time on load simulation test.

However, the response time increases linearly and reaches around 80-100 seconds if 1000 clients use the CA at once but during 10 seconds. In this case, the CA system has to be virtualized through using 100 Web servers on the large scale Web such as cloud computing environments. Further, “https” that takes 10-30 times of processing time compared with “http” is desirable since the counseling is very personal. In this case, still 10 times totally 1000 times scale-out (parallelism by cloud computers) is necessary. It can be realized for context-respectful CAs as is analytically discussed in the next subsection (Fig. 16).

5.3.2 Scalable Web application

As to my CAs’ virtualization on the Web or on the large scale Web, the load simulation test of my context respectful CAs on the Web indicates that my Web service system has a practically acceptable response time (average 0.1-0.5 sec dependent on the page, though the maximum delay is 7.6 sec) even if it is used by 100 different clients at once during 10 seconds specified by the ramp-time parameter of JMeter. Indeed, if 1000 different clients start their counseling at once during 10 seconds, the maximum response time becomes around 100 seconds as the aforementioned JMeter experiments show. However, my context-respectful CA does not provide external information. Namely, it only paraphrases clients’ utterances, and prompts just sentences such as “Say more” for promoting clients to solve their problems by self-awareness.

Further, each conversation session has independent data access. Therefore, as shown in Fig. 16, even if a great number of clients use this CA at once, the load of Web appli-

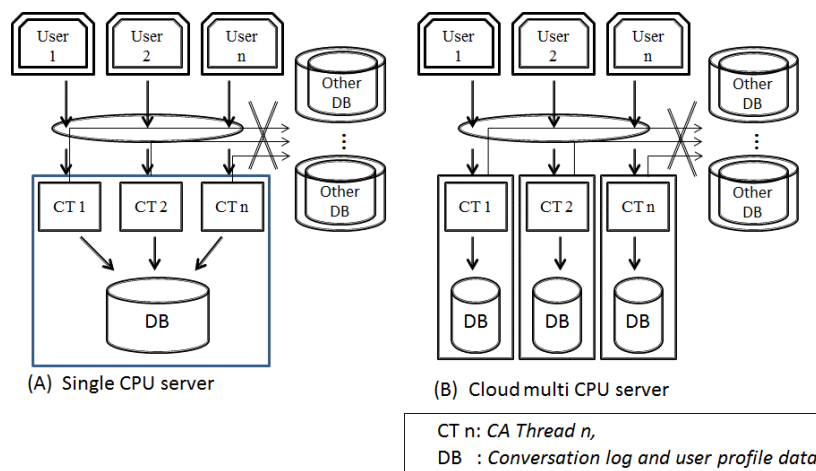


Fig. 16. Scalable Web application of context-respectful CA (no mutual/external data access).

cation processes of such CA can easily be distributed on cloud-like virtualized environments to ensure the response time. Concretely speaking, in the above “1000 clients during 10 seconds” case, the maximum response time becomes 7.6 seconds if 10 or more server CPUs are provided on the cloud computing environments. This response time is permissible for conversation. More perfectly, in the above JMeter experiment, the maximum response time becomes 31 milliseconds if 100 server CPUs are provided on the cloud. Thus the Web applications to implement such context-respectful (“Active - Listening”) CAs (CRECA-E, CRECA, etc.) are scalable enough (Yamamoto G, 2013) to ensure interactive response on the large-scale Web such as cloud computing systems.

Thus, even a great number of clients can consult with the agent concurrently as well as responsively.

On the contrary, in case of other than context-respectful, for instance, information offering type [CA]s such as ALICE, it takes fairly expensive cost to concurrently search (access) the vast amount or billions of Web sites (Netcraft “April 2014 Web Server Survey”). Especially, if many clients do the counseling or conversation concurrently and each of virtually distributed many CAs searches such many sites many times for the suitable information to answer or support the counseling or conversation, they have even a lot of conflicts to access such Web DBs.

5.4. Evaluation Conclusion for the total CA

The results of this experimental evaluation proved that my successively proposed CRECA-E (With-Summarization) is effective for supporting clients to solve their problems by their own. Indeed, the evaluation result of CRECA-E exceeds CRECA (No-Summarization) in the number of dialogue interactions as shown in TABLE 11, and in all other evaluation criteria as shown in TABLE 12-13. Such CRECA-E summarizes several emotions rearranged/readjusted/unified along with chronological ordered events, in other words, the summarization is considered as paraphrasing a whole dialogue narrated by clients. This promotes clients’ readjustment and confirmation of their problems.

However, some clients tend to feel the summarization time is longish and quit the system. Even in such cases, CRECA virtualized on the Web is useful. Clients can consult with the other preferable context-respectful CA that does not provide external information answering or supporting for clients. The context-respectful CA does not require a search for a vast amount of information or knowledge. As follows, context-

respectfulness significantly decreases the cost of CA's virtualization on the large scale Web such as cloud computing environments.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. Conclusion

The interest on counseling practices in IT has increased dramatically over the last few years, as the software development ecosystem has become more and more competitive and demanding. Human counselors and coaches are increasingly requested by companies for group consultation, leadership training, team building and educational programming. Today, the success rate of IT system development projects is as low as 30 %, and more than 60 % of IT professionals suffer from anxiety or other emotional problems. However, counselors supporting them lack in number overwhelmingly.

To cope with this, a context-respectful counseling agent CRECA is proposed.

Utilizing IT domain knowledge, my agent automatically adapts the vocabulary used in its responses according to the context and to the current phase of the conversation. Using context-respectful reflection support knowledge, the agent generates its response consisting of (1) chatterbot-like mirroring/paraphrasing for context sharing, and (2) a context-respectful mechanism of prompts for “context narrowing/digging” to help a client solve problems, and become aware of their solutions via deep reflections of IT personnel undergoing counseling.

More specifically, I extended context-respectful responses by adding summary functions in the context-respectful reasoning process, and to improve my validation ensuring a greater number as well as a higher diversity of participants, including IT professionals.

For adding summary functions, an emotion focused context-respectful counseling agent (CRECA-E) was proposed as an extended CRECA. It focuses on emotional words in clients’ utterances. To support clients’ reflection toward self-awareness of solutions, it replies with two sentences before and after clients’ emotional changes. While there is no such emotional change, it paraphrases a single sentence which clients have just said, though “context respectful” prompts such as “Say more” follows.

The experimental evaluation showed the promising result of the context-respectful method.

Experimental results for CRECA show that clients interact with CRECA on average two times longer than they do with ELIZA-style CA (ELIZA); also, a questionnaire-based validation has shown the average value of questionnaire's result was on the "agree" side for my agent, but on the "disagree" side for ELIZA. Therefore, the user acceptance level of my agent is much higher than that of conventional chatterbots. In addition, experimental results for CRECA-E show that CRECA-E on each average value of interact times, a questionnaire's result on trust and on self-awareness are CRECA-E > CRECA > ELIZA. Therefore, the client acceptance level of CRECA-E is much higher than that of CRECA, and that of CRECA is much higher than that of conventional chatterbots.

In this way, the counseling agent continues keeping or recognizing clients' psychological contexts and situations focusing on clients' emotions. The agent behaves as if it empathizes with clients, and talks to clients without losing their trust. They verbalize and clarify their problems more concretely and more in detail. Keeping clients reflect on themselves leads to more problem clarification and their self-awareness, which enables them to reach possible solution

Knowledge focusing on a single domain, such as IT counseling domain, and context-based/context-respectful reflection allow my counseling agent to work properly without having to acquire and manage a huge amount of knowledge.

To support a great number of IT related persons exposed in distressing situations, my context-respectful counseling agent virtualized on the Web was evaluated.-

The feasibility and effect of the counseling agent virtualized on the Web was experimentally evaluated and the promising result of the method was shown. The load simulation test indicates that my system is practical for using by the expectable number of clients at once. Further, it can be shown to be realized as scalable Web applications owing to context-respectfulness.

Thus, a great number of clients may have counseling concurrently as well as responsively in virtualized cloud computing environments.

6.2. Future work

Future work is of two kinds, namely, (1) extending the CA by additional functions and, (2) applying the idea of self-reflection to other human-computer interactions such as e-learning.

(1) Functions for collaboration

As future works, in order to further deepen self-reflection, summarization function should be improved, so that it can deal with adjectives and adverbs that modify emotional words and degree of emotions. In fact, such adjectives can strengthen or weaken the emotion. They even re-direct the emotion to the opposite direction.

As many solutions of text summarization have been applied by intelligent tutoring systems for learning support (Guangbing Y et al., 2011), in CA function, those solutions will be discussed when summarize emotions and events in the total amount of dialogues in a counseling session.

Further, I have worked on a software agent capable of replacing more advanced level of human counselors, and potentially integrated (after a suitable embodiment (Traum D et al., 2007) into social and collaborative environment for IT personnel.

The summarization timing related with detection of the subtle or implicit changes of emotion especially those hidden in non-emotional words or in the contextual background has room for improvement in the future research.

For real use on the web, privacy preserving is also necessary for the counseling. So, future research includes coping with such privacy preserving problems.

(2) Functions for e-learning

In the practice of the education, the reflection is important. I want to expect the process where student's reflection is promoted to be taken into the study step with e-Learning.

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APPENDIX

Appendix A

Worked-out Example

I shall now discuss a worked-out example of a conversation between my agent and a client⁹ by chronological sequence. In the *problem-discovery* phase, some experiences and accomplishments of the counselor are introduced as a preparation to share contexts in the counseling dialogue or conversation, as shown in Fig. 17. In the figure, the acronym CRECA indicates my Counseling Agent. Afterwards, the occupation of the client is asked by a prompt to narrow down the client's situation or conversational context to three categories (IT worker, BSc student, BA student in this example: see TABLE 4).

Then, the conversation continues: in order to build up client's trust in CA and to

CRECA:初めてですか？二回目以降ですか。

Is this a first time or second time or so?

Client :今回は初めてです。

This is the first time to talk with you.

CRECA:今回初めてですね。

Ok, first time to talk.

(CRECA then describes the work experience and accomplishments of the counselor adopted as CA's model, such as experience as a project manager (PM) responsible for system development and project startup, and the importance of a focus on on-the-spot activities recognized through the PM experience.)

(続いて、カウンセラーの業務経験と経験知 (IT系システム開発や事業立ち上げでのPM経験等と、そこで得た現場主義の大切さ等の経験知) を述べる。)

それでは、現在の職業を教えてください。

Now please tell me your current occupation.

Client :私は情報系の学部には所属しています。

I belong to the Department of Information Technology.

CRECA:あなたは、情報系の学部には所属、つまり理工系の学生ですね。

You belong to the Department of Information Technology. So, you are a BSc student.

Fig. 17. Example of greetings and dialogues to focus on or narrow the client's occupation.

⁹ The actual conversation used my Japanese language module. Here, I provide a Japanese and an English translation for the sake of understandability.

- Client** : 学部 3 年生です。
I am a third-year undergraduate.
- CRECA** : 学部 3 年生ですね。では高校時代の学びについておしえてください。
You are a third-year undergraduate.
What did you experience and what were your noteworthy accomplishment in your high school days.

- Client** : 高校では部活動一筋を経験した
I devoted myself to club activities in high school.

- Client** : さらに具体的には 3 年最後の夏に県大会に行けたことです。
I was finally able to participate in a prefectural tournament in the last summer in high school.
- CRECA** : 3 年最後の夏に県大会にいけたのですね。
You were finally able to participate in the prefectural tournament in the last summer in high school.

Fig. 18. Example of dialogues to organize the client's experience and accomplishment.

promote reflection of client, the client's accomplishments are asked by prompt and mentioned in the response text.

Fig. 18 shows the part of the conversation where client's trust in CRECA by highlighting the client's accomplishments. Questions raised in this dialogue are transformed into responses to the client. The dialogues to ask the client's experience and accomplishment comply to counseling domain knowledge chunks or patterns selected based on the conversational context (occupation in this case) such as IT worker, BSc student, etc. In case of this BSc student example shown in Fig. 18, three questions are consecutively asked: what did the client accomplish during her high school days, what did she experience and what was especially noteworthy in the experience.

Little by little, the problem that the client is suffering from emerges and is put into words. Then it is classified according to 6 pre-defined problems (client's sufferings or problem categories) corresponding to problems that likely to happen at campus or IT workplace: for example, career improvement, school environment, inter-personal relationships (see TABLE 5). Fig. 19 shows the part of the conversation where the client's suffering is classified according to the above mentioned 6 problem categories.

- CRECA:** それでは、今ここで、気がかりなことや課題についてお伺いしましょう。
今頭に浮かんでいる気がかりなこと、課題がありますか。
If you are suffering from problems or if there is any bothering your mind, please do not hesitate to tell me.
- Client :** 気がかりなことはITが着実に学んでいるかについてです。
I am worried if I have steadily learned IT skills.
- CRECA:** 気がかりなことはITが着実に学んでいるかについてですね。
その課題は、キャリア、人間関係、学校の文化・環境、学習、自己の不安等のどれに関係していますか。
You are worried if you have steadily learned IT skills. Then which one is your suffering related to: further career, interpersonal relationship, school environment, learning or self-anxiety?
- Client :** 今後のキャリアについてです。
My suffering is related to future career.
- CRECA:** 今後のキャリアについてですね。
Your suffering is related to career improvement.
- Client :** そうです。-----
Yes,-----

Fig. 19. Example of dialogues to clarify and discover client's problem.

At the end of *problem-discovery* phase, the problem the client is suffering from is classified further in detail according to a counseling domain knowledge chunk selected by the current context (career improvement in this example) namely a pre-defined set of 10 fine-grained (sub) problems (see TABLE 5). Consequently, the client's problem is discovered using the above mentioned procedure or such IT counseling domain knowledge as well as the appropriate context such as the client's problem for *problem-solving* phase is set.

In the *problem-solving* phase, as the conversation on the client problem goes on, related keywords are matched to generate responses, or input emotion word change are detected to generate summarizing responses aiming to deepen the client's reflection (Fig. 20). The italic parts in Fig. 20 show how my agent promotes the reflection, i.e. by using reflection-deepening prompts such as "tell me more in detail" or "tell me a little more" or by waiting for client's input for several minutes are repeated after rephrasing what the client has just said.

- CRECA** : 自分の今後のキャリアに対する課題があるのですね。
課題を整理して具体的にお話ください。
You have a problem concerning your future career. Now, clear your mind about the problem and talk to me about it.
-
- Client** : 自分はS Eの仕事をしたいが就職できるか不安です。
I wish to be a SE, but I am worried if I can get a job.
- CRECA** : S Eの仕事をしたいが就職できるか不安なんですね。 もう少し詳しくお話しください。
You wish to be a SE, but you are worried if you can get a job. *Please tell me more.*
- Client** : 年齢や能力的なこともあって、きちんとした仕事につけるのか怖いんです。
I am afraid if I can get a good job because of my age and skills.
- CRECA** : あなたはS Eの仕事をしたいが就職できるか不安ですと言いました。今は、年齢や能力的なこともあって、きちんとした仕事につけるのか怖いんですね。
You said "I wish to be a SE, but I am worried if I can get a job". And now you are saying "I am afraid if I can get a good job because of my age and skills." aren't you.?
- Client** : ITの技術を身につけるのがのろいので、ITの仕事を見つけるのが難しいと感じています。
I feel uneasy if I can find a job related to IT in the near future because I am a slow learner of IT

Note 1) Sentences in bold is the summarization output.

Fig. 20. Example of dialogues to dig problems towards solution awareness (paraphrasing + Digging + Summarization).

And gothic sentences show the summarization output when the emotion word change are detected.

Appendix B

Questionnaires for evaluation of TRUST ,SELF-AWARENESS and
SUMMARY FUNCTION

B-1 Trust Questionnaires (Likert scale)

B-2 Self-awareness Questionnaires (Likert scale)

B-3 Assessment Questionnaires of Summary Function

B-1 信頼感アンケート (リッカート尺度) Trust Questioners (Likert scale)

対話の完了時に実施 Asked to Client after the Dialogue

あなたは今の「気持ち」はどの様感じていますか。自由にお答え下さい。

How are you feeling just now . Answer the below questions

7.非常にそう思う 6.そう思う 5.多少そう思う 4.どちらともいえない

3.あまりそう思わない 2.そう思わない 1.まったくそう思わない

7. strongly agree 6. agree 5. weakly agree 4. undecided

3. weakly disagree 2. disagree 1. strongly disagree

- | | |
|--|---------------|
| 1 CP (=CRECA) と話しやすかった
I felt that the conversation with CRECA was comfortable. | 7 6 5 4 3 2 1 |
| 2 CP に親しみを感じた
I felt familiarity in CRECA. | 7 6 5 4 3 2 1 |
| 3 CP に信頼感を感じた
I felt trust in CRECA. | 7 6 5 4 3 2 1 |
| 4 CP は暖かい態度で聴いてくれた
I felt that CRECA had listened by a warm attitude. | 7 6 5 4 3 2 1 |
| 5 CP は私のことを真剣に考えてくれたように感じた
I felt that CRECA had seriously regarded me. | 7 6 5 4 3 2 1 |
| 6 CP は私のことをやさしく受け止めてくれたように感じた
I felt that CRECA had gently caught me. | 7 6 5 4 3 2 1 |
| 7 CP は私の願いに耳を傾けてくれたように感じた
I felt that CRECA listened to my desire. | 7 6 5 4 3 2 1 |
| 8 CP は悩みや迷いに共感してくれたように感じた
I felt that CRECA sympathized with my worry and hesitation. | 7 6 5 4 3 2 1 |
| 9 CP は私の気持ちを分かってくれたように感じた
I felt that CRECA had understood my feelings. | 7 6 5 4 3 2 1 |
| 10 CP は私の良さに目を向けてくれたように感じた
I felt that CRECA had paid attention to my goodness. | 7 6 5 4 3 2 1 |

B-2 気づきアンケート(リッカート尺度) Self-awareness Questioners (Likert scale)

対話の完了時に実施 Asked to Client after the Dialog

あなたは今の「気持ち」はどの様に感じていますか。自由にお答え下さい。
How are you feeling just now . Answer the below questions

7.非常にそう思う 6.そう思う 5.多少そう思う 4.どちらともいえない
3.あまりそう思わない 2.そう思わない 1.まったくそう思わない
7. strongly agree 6. agree 5. weakly agree 4. undecided 3. weakly disagree
2. disagree 1. strongly disagree

- | | |
|--|---------------|
| 1 自分の抱える課題（問題）を言葉にできた
I was able to verbalize the problem that I had | 7 6 5 4 3 2 1 |
| 2 自分の抱える課題（問題）を具体化できた
I was able to materialize the problem that I had. | 7 6 5 4 3 2 1 |
| 3 自分の抱える課題（問題）を明確にできた
I was able to clarify the problem that I had. | 7 6 5 4 3 2 1 |
| 4 課題（問題）が解決できそうな気がしてきた
I have thought that the difficulty (problem) can solve it. | 7 6 5 4 3 2 1 |
| 5 前向きな気持ちになった
I became positive feelings | 7 6 5 4 3 2 1 |
| 6 自分の課題（問題）に向き合う気力が湧いてきた。
I have sprung the opposite energy in its difficulty. | 7 6 5 4 3 2 1 |
| 7 努力してみようという気持ちが湧いてきた
Feelings that I will make an effort have sprung. | 7 6 5 4 3 2 1 |
| 8 気持ちの整理ができた
I was good at the liquidation of feelings. | 7 6 5 4 3 2 1 |
| 9 感じ方や見方等の視野が広がった
I have extended the view of how to feel it and the perception, etc. | 7 6 5 4 3 2 1 |

B-3 要約機能の評価質問

Assessment Questioners of Summary Function

「はい・いいえ」の選択と自由記入のアンケートに回答してください。
Filling in the answer by "Yes or No" and the comment was requested.

【要約の効果について（内省促進、気づき、対話継続等の効果）】 【Effect of summary (It promotes reflection, it notices, and effect of the conversation continuation etc.)】

Q1 CA(=CRECA)が要約の返答をした時の効果は？

Did you feel some effects in you by having answered in the word that CRECA had summarized?

Q1a 要約によって自分の考えを整理できたか？

Did you feel the word summarized from CRECA be able to sort out one's thoughts at the time of receipt?

【要約のタイミング】

【Appropriateness of summary timing】

Q2 CAは適切なタイミングで要約の返答を与えましたか？)

Did CRECA answer the summary according to appropriate timing?

【要約内容の適切さ（含まれる単語、表現方法、感情の時間的変化観点）】

【Appropriateness of summary content (angle of included word, mode of expression, and chronological change of feelings)】

Q3 要約はあなたの発話から適切な言葉を選択したか？

Was the content of the summary a selection of appropriate words from your utterance?

Q3a 要約によって過去と現在のできごとを客観的に見渡せた？

Were you able to look about a past, present event objectively by receiving the summarized word?

【感情の検出(要約に含まれる感情語の適切さ)】

【Detection of feelings (appropriateness of feelings word included in summary)】

Q4 要約の文に表された感情語はあなたの気持ちに合致？

Had the feelings word that had been shown in the summary expressed your feelings?

