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Self-Adapting Chatbot Personalities for Better Peer Support

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***Abstract*— Studies have shown that people relate better with other people who have similar personality characteristics as themselves. This is helpful in peer support scenarios where people should be receptive to receiving support and advice from others. In this paper we propose a chatbot personality model and an algorithm that enables the chatbot to adapt its personality in real-time as it interacts in conversation with the user. Our model is based on the Big Five personality model and we focus on two key personality traits, Extroversion and Agreeableness. The personality adaption algorithm uses an interactive genetic algorithm. We have exposed the chatbot to a controlled set of interactions and a user and the results show that the algorithms are capable of adapting personality traits to match the identified traits of the user. In the next phase of our experimentation we will expose the chatbot to healthcare professionals.**

I. Introduction

Occupational stress is a significant workplace problem with high costs for individuals and society [1]. A range of factors contribute to an increase in reported stress by workers and include, inadequate support from management, low levels of control, inappropriate task allocation [2].

According to a survey undertaken by The Japan Institute for Labour Policy and Training [3], people working in the healthcare sector are at greater risk of stress-related mental health problems than all other professions. The outcomes of exposure to workplaces stressors impacts individuals differently, but can result in depression, health related illnesses, underperformance and increase the potential for early retirement.

Although personal counselling is often used in the treatment of depression by human, support sessions with chatbots are increasing [4, 22]. Sessions with chatbots are aimed at managing emotion by performing cognitive behavioural therapy (CBT) or emotional support. Smith et al. investigated the virtual agent's emotional support, and showed that it is not as effective as human support, but it has sufficient functionality as support [5].

Personality of the person is related to whether he or she is likely to be depressed. Multiple personality theories exist, one commonly reported is the Big Five model which considers neuroticism as one of the five personality elements [6]. People with Type A behavioural patterns are also prone to depression because of anger [7]. Counselling support needs to consider individual differences and take into account personality to ensure it is appropriately targeted [8].

To measure psychological stress and stress-related mental health, then cognitive appraisal theory [9] and Sense of Coherence (SOC) [10] are commonly used. To measure physiological stress, then heart rate, brain waves and saliva offer objective indicators and are commonly used. Latest technology advancements enable wearable devices and mobile devices such as smartphones to capture both types of stress indicator [35]. In our stress management framework, we use SOC to measure stress [11].

We propose a method to adaptively change a chatbot's personality as an outcome of conversational interaction with people. In section 2, we explain related works about, specifically the idea of chatbot personalities, interactive genetic algorithms (IGA), and the use of chatbots and robots in mental healthcare. Section 3 provides a brief summarization of the stress management framework. Section 4 presents a method of user adaptation using Big Five model and IGA. Section 5 shows the experimental results of the proposed method. Section 6 gives conclusion and future works.

II. Related Work

A. Personality in human-robot interaction

In human-robot interaction, personality is considered to be an important factor to enhance the effect of interaction, and various studies have been conducted [12]. This work classified personality across four types of research area involving various combinations of robot / human actors and their work focuses on three of them: (1) *Human Personality and Human Robot Interactions,* (2) *Robot Personality and Human–Robot Interactions, and* (3) *Human–Robot Personality Similarity/Differences.*

Regarding area 2, Miwa et al. defined a sensing personality and an expressivity personality to determine the influence of facial expression on the mental state of a user. They developed a robot capable of stimulating facial expressions and were then able to develop a suit of expression methods and gestures to improve user interaction [13]. The artificial dog, Rity is a genetic robot which has genetic information. Genetic representation is proposed to evolve the personality of the artificial organism using artificial genomes and evolutionary generative algorithm [33]. Furthermore, experiments are being conducted not only with Big Five

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model but also with Myers–Briggs Type Indicator (MBTI) [34]. Masuyama et al. used personality and emotion models to make robots generate different outputs for the same input [14]. At this time, personality is generated based on gender and age using Big Five model. It was shown that it is possible to have different interactions by generating different outputs depending on different personality.

Regarding area 3, although it is human-computer interaction, Reeves and Nass describe that agents have the same personalities as people to enhance the effect of interaction, and it is more effective to gradually have the same personalities as people even though they initially have different personalities [15]. In interaction, it is important to match personalities, as it is highly appreciated when communicating with a person with the same personality. It is considered inflexible if personality is fixed at the first stage. Tapus et al. focused on extroversion-introversion of socially assistive therapist robot and the robot interacts with users with the same personalities of user's [16]. They used Eysenck's personality model and behavioural adaptation is performed using reinforcement learning algorithm.

Conversely, in another experiment, which examined whether humans like robots to have similar or different personalities to themselves, it was shown that humans seek robots that have a different personality to their own [17]. It has been proposed that the task decides whether a human will seek similar or complementary personality traits, but this has not proved [18]. The choice may also depend upon whether participants have stereotyped ideas about robots and how they should be.

B. *Interactive Genetic Algorithm in human-computer interaction*

Interactive genetic algorithm research has been used as an optimizing method for incorporating user preferences into system models. Interactive Evolutionary Computation (IEC) is used for user adaptation in Human-Robot interaction because human preferences are too subjective to fix into a single model [19]. In IEC the evaluation function is performed by the user and in [19] this method was used to interactively adapt a robot's value system to user preferences. In another study, the user was asked to evaluate the physical and facial gestures generated by a robot [20]. Through an assessment of Laban features the robot was able to successfully generate a suit of gestures tailored to the user. In addition, IEC has been applied to mental health measurements. Takagi et al. applied IEC to design happy and sad impression computer graphics, the experiments showed IEC to be a useful tool to optimise emotional responses in people with some mental health issues and showed promise as a tool for psychiatrists and therapists [21].

C. *Psychotherapy of agents or robots*

At present, a number of chatbots have been developed, such as Facebook's Messenger app. WoeBot is a chatbot based on cognitive behavioural therapy, and can interact using a smartphone [22]. More closely related to counselling with human counsellors is the virtual agent SimSensei Kiosk [23]. This virtual agent offers the advantage of being able to receive counselling even in remote areas. In robots, ApriPoco^{TM} is used for active listening for elderly people support [24]. ERICA is an android robot and is used in a counselling system [25]. In fact, it can be expected to be similar to counselling with humans. CRECA (context respectful counselling agent) performs Rogers counselling which listens to clients and promotes their reflection context respectfully [26].

III. STRESS MANAGEMENT FRAMEWORK

We are developing a stress management framework to support people at work in management of their stress levels [11] at work. It uses different agents depending on the location so that the user can have the agent as a peer at any time in which they require support. As shown in Figure 1, robots are used at home and the workplace, and a chatbot is used for all other places between home and work.

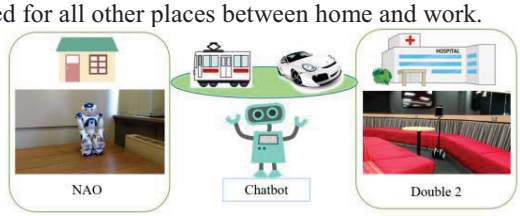

Figure 1. System configuration

The agent has software architecture as shown in Figure 2 for stress management. The user's stress condition is recognized by evaluating the input content from the user based on Sense of Coherence (SOC), and the appropriate support is selected and the interaction follows the conversation model.

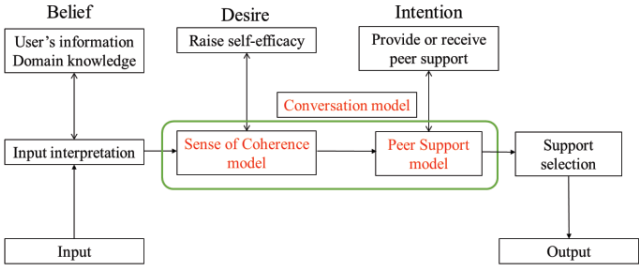

Figure 2. BDI architecture within our stress management framework

The conversation model consists of five phases, as outlined in figure 3. Phases 1 to 3 were the subject of a previous paper [11]. In this paper, we implement phase 4 and 5 and describe initial results.

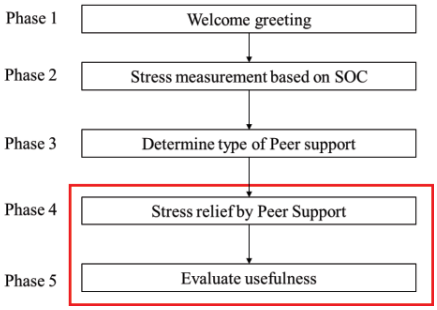

Figure 3. 5-phase conversation model

The support which the agent offers in phase 4 depends on the value of the SOC. If the SOC is low the agent imitates a peer support method. However, if the agent evaluates the users SOC as high, then agent asks the user for support. Each peer support method corresponds to a certain combination of SOC parameters, Comprehensibility (Co), Manageability (Ma) and Meaningfulness (Me) [11]. Emotional support is selected if the agent evaluates that Meaningfulness is low (Fig.4).

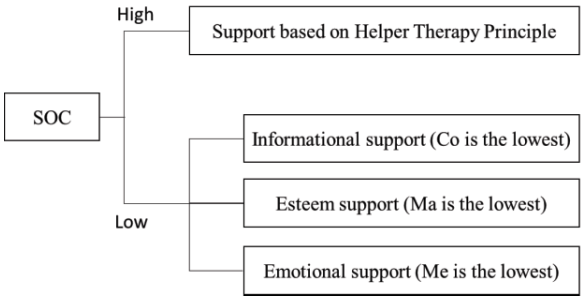

Figure 4. How to decide the support

IV. USER ADAPTATION IN EMOTIONAL SUPPORT

A. *Interactive Genetic Algorithm for user adaptation*

One example of IEC is the Interactive Genetic Algorithm (IGA). We propose an IGA to adapt the personality of the chatbot to reflect the personality preference of the user. IGA replaces the traditional fitness function of a Genetic Algorithm with human subjective judgment. This enables an IGA to accommodate user preferences that are difficult to quantify, such as likes, dislikes and sensitivity, there are many examples of studies embedded in design systems [29]. A potential drawback of IGA are their time to convergence, since the fitness function requires user input. However, the system under optimisation can adapt while in use.

In our chatbot personality model we use three key personality traits from the Big Five model: Extroversion, Agreeableness, and Neuroticism. Extroversion is the tendency to be energetic, sociable, talkative and to seek stimulation of others. Agreeableness tends to be a personality trait which is caring and supportive of others. High agreeableness is often seen as naive or obedient. Neuroticism is prone to psychological stress. It also means the degree of emotional stability. In out chatbot personality model, extroversion is used to determine the number of conversations with the user. Agreeableness determines whether the chatbot's behaviour is dominant or submissive. Neuroticism is correlated with agreeableness [8], so neuroticism is set to the same value as the agreeableness. The gene pool population size is G (=10), and the chromosome length is L (=2) corresponding to the number of personality (Extroversion and Agreeableness). The ith individual is represented by ($g_{i,1}$, $g_{i,2}$). The gene uses a real type, and takes a numerical value between 0 and 1, respectively, where a value of 0 represents low Extraversion or low Agreeableness, and 1 represents high Extraversion or low Agreeableness.

Our proposed method is shown (Fig.5). The initial gene pool of personalities are randomly generated, and one gene is randomly selected to by the current personality for the chatbot. The user then talks with the chatbot from phase 1 through to phase 5. At the end of phase 5, the user makes an assessment of the interaction and a genetic operation is performed based on the user's feedback.

The user evaluates the interaction with a value of 1 to 10. If the evaluation is 10, the current personality gene becomes the elite gene in the next generation. The elite gene then takes over the personality of the chatbot. In addition, mutation operations are performed on individuals other than elite. The mutation here is a uniform mutation, which is made by adding or subtracting a random number from 0 to 0.5.

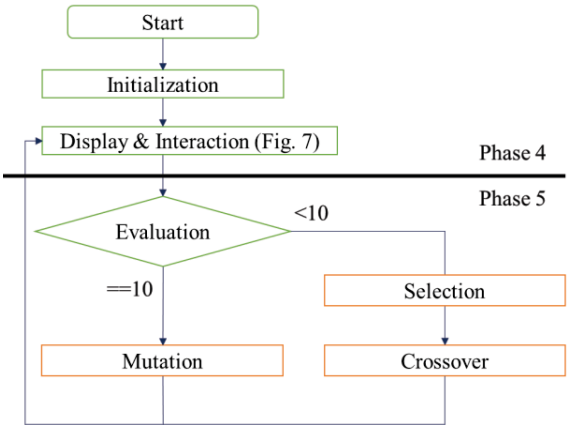

Figure 5. Flowchart of Interactive genetic algorithm in the framework

If the evaluation is less than 10, selection is done depending on the evaluation value. The fitness value of each individual is expressed as the distance of personality from the current personality gene.

$$Fit_i = \sqrt{(g_{current,1} - g_{i,1})^2 + (g_{current,2} - g_{i,2})^2} \quad (1)$$

Next, we determine the elite of next generation, as shown in the following figure.

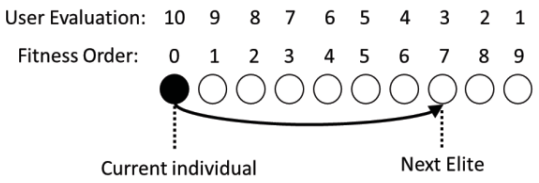

Figure 6. The method of Elite Selection

For example, if the evaluation from the user is 3, the next elite is the seventh individual when arranging the individuals in order of fitness values (Fig.6).

Then crossover will be performed between the elite and the one chose at random. Blended Crossover (BLX-a) is used as the crossover method [30]. The generated child replaces the displayed individual. In BLX-a, the element of the child is decided randomly between x and y.

$$x = \min\left(g_{elite,j}, g_{i,j}\right) - \alpha d_j \quad (2)$$

$$y = \max\left(g_{elite,j}, g_{i,j}\right) + \alpha d_j \quad (3)$$

$$d_j = \left|g_{elite,j} - g_{i,j}\right| \quad (4)$$

B. *Emotional Support*

In this system, the chatbot uses Repeating, Confirmation, Sympathy and Support messages to engage with active listening to the user's story [32]. Repeating involves repeating of the user's input. Confirmation uses questions to ensure that the user's input is understood. Sympathy uses Sentiwordnet [27] as emotion recognition, giving a positive response if the analysis is positive, and a comforting response when it is negative. The Support selects messages that match the personality selection that has been made by the chatbot. The categories of emotion support are as described by Smith et al. [28].

The flowchart is shown in Fig.7. Following input from the user, a random number selects a response from any category. In terms of support, people with low Emotion Stability (ES) tend to prefer messages from categories such as Encouragement, Deserving, and Blameless, but some data supports that high ES people prefer Praise. When agreeableness is high, the message of Praise is used. If agreeableness is low, advice for such as encouragement with a dominant attitude is used. All the messages that the chatbot uses is also deprived of Smith et al. [28]. When the response from the chatbot is performed for the determined number of times, the interaction is ended, and the process shifts to phase 5 to evaluate it. Interaction numbers are determined by the extroversion state, and range from 5 at the highest end, to 3 for introversion.

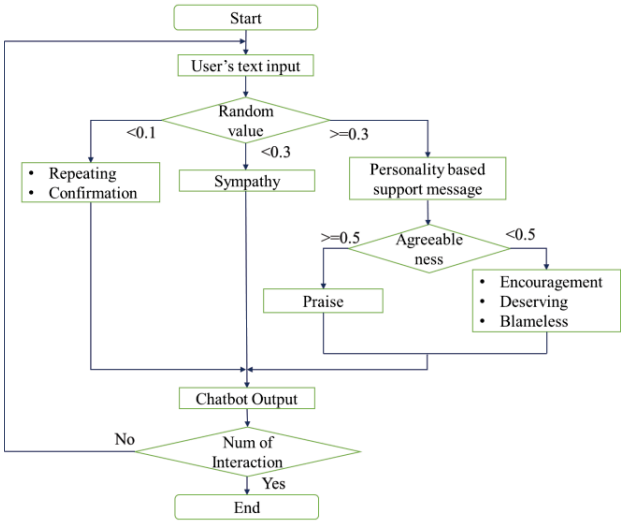

Figure 7. Flowchart of the chatbot's user interaction

V. EXPERIMENT RESULTS

We investigate whether the chatbot can adapt to the user's favourite personality as the interaction proceeds in the experiment. In conversation, active listening in emotional support is implemented. The personality of the user determines the response. Usually, the personality does not change easily, but in order to make the interaction with the user effective, the chatbot has multiple personalities. The initial population size of the gene pool is set at 10. In other words, the agent is working with 10 personality profiles and is using IGA to improve them. Table 1 shows the experimental condition. The chatbot receives text information or evaluation value from the user. User evaluation is given in the end of conversation. The chatbot sends a reply to user based on probability. The initial values of individuals are set random values.

TABLE I. EXPERIMENTAL CONDITION

Name	Content
Input	• User conversation • User evaluation of conversation from 1 to 10
Output	Reply text to user based on probability
Internal state	Random values

A. *Experiment scenario*

For these experiments we assume that phase 2 of the conversation model has been evaluated and the users SOC indicates they have low meaningfulness (Me). As a result of this, the chatbot proposes emotional support in phase 3 and the user receives support in phase 4.

The user will converse with the chat bot for a period of time controlled by the chatbots personality and are termed conversation episodes. After each episode the chatbot will ask the user to rate the conversation. This rating is used as a fitness function into the IGA. We expect initial user evaluations will be low to medium. With regard to the convergence, IGA terminates when the user is satisfied, but in this case, it is judged when an individual having the same personality emerges continuously. We use a command prompt on a personal computer to talk with the chatbot program.

B. *Experiment results*

Fig.8 shows the evaluation value given by the user, Fig.9 shows the elite individual number and Fig.10 shows the values of the elite individual. The same individuals were not selected in this interaction except the second and last generation. The selected individual at first was extroverted and submissive as the threshold is 0.5. We defined if extroversion of the elite individual is over 0.5, it is extrovert and if less than 0.5, it is introvert. In the same way, if agreeableness of the elite individual is over 0.5, it is submissive, and if less than 0.5, it is dominant. At the end of the conversation, the user gave 1 as evaluation. This is because individual at first generation was chosen at random and there may be other good individuals. Individual selected at second generation was extroverted and dominant. After this, the user gave 3 as evaluation. Individuals selected for the third time were introverted and submissive. The opposite side of personality is selected because the evaluation is 3, but it is no more extreme than first time. After

this, the user gave 5 as evaluation. Individual selected for the fourth time was extroverted and submissive. Individual changed with either personality may be selected because middle evaluation is given. The user gave 7 as evaluation after this, but it has evolved in the direction in which each personality becomes stronger. The individual selected for the 5th time was also extroverted and submissive, with both values approaching 1.0.

Regarding the determination of convergence, although it ended in 5 generations this time, it is thought that the number of times to convergence changes with distribution of the value of the initial individuals.

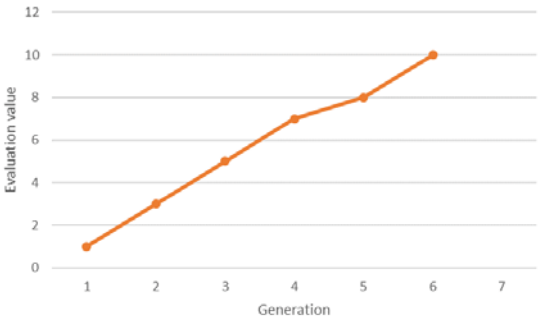

Figure 8. History of user's evaluation value

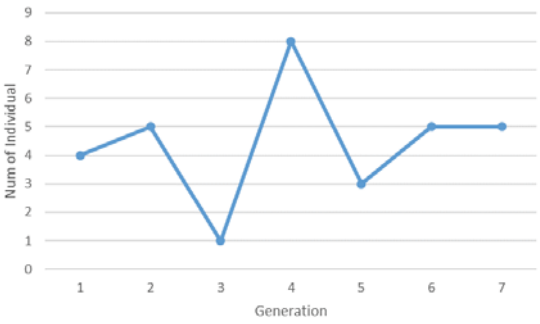

Figure 9. History of elite individual

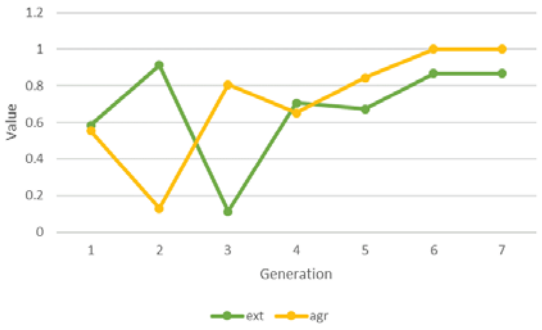

Figure 10. Changes in personality of elite individual in each generation

Next we show the result of mutation in Fig.11 and 12. These are the distribution of individuals in generation 6 and 7. As the user's evaluation value is 10, mutation is conducted except for the elite individual (Individual no.5) in generation 6. There are 7 individuals that have extroverted and submissive personality in generation 6, but after mutation there are 4 individuals in generation 7. As the interaction proceeds, similar individuals are increasing but it cannot deal with user's preference change. Therefore, the conduction of mutation is important to maintain the diversity of personality.

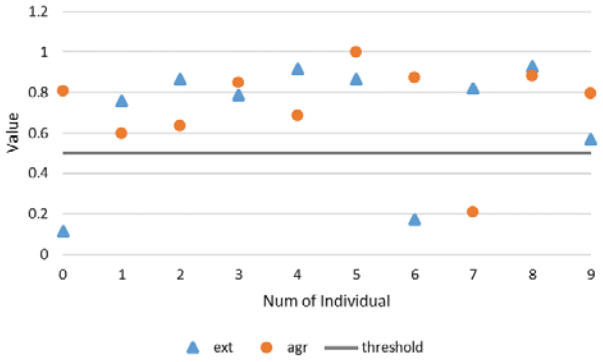

Figure 11. All individual distribution in generation 6

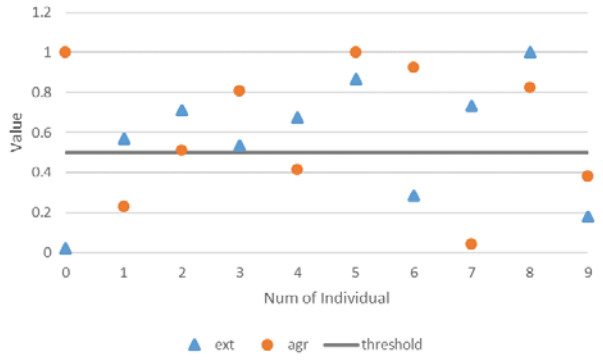

Figure 12. All individual distribution in generation 7

Next, conversation examples are shown in Fig. 13 and 14. The conversation scenario is derived from [28]. In submissive conversations, the chatbot has selected messages to praise the user. Conversely, the chatbot with dominant personalities sends advice in an imperative form. Here, we show conversations only in the case of extroverted. SYM is a sympathetic response using emotion analysis results, REP is a repeating response and PER is a support message based on personality. This time, the response content from the chatbot is randomly selected because the purpose is to show the difference of personality. However, for example, as individuals have a personal preference for the method in which they prefer to be praised, when conducting a user experience test in the future, the user is asked to evaluate the chatbot comprehensively including not only personalities but also conversation contents. It is more likely that the chatbot will learn the preferences of the user and select the response content for more effective support.

Chatbot:	Please talk about your anxiety.
User:	I had to carry out minor medical test today
Chatbot:	I understand how stressful it must be. (SYM)
User:	The test is not dangerous but the procedure is complex.
Chatbot:	You are an amazing person. (PER)
User:	Also it requires concentration
Chatbot:	You were really kind today. (PER)
User:	I was confused and very upset
Chatbot:	You said i was confused and very upset. (REP) I understand that must have been disappointing. (SYM)
User:	It's no problem if I do wrong
Chatbot:	Thanks for sharing. How do you rate this support?[1:10]
User:	3

Figure 13. Submissive conversation example

Chatbot:	Please talk about your anxiety.
User:	I had to carry out minor medical test today
Chatbot:	Ignore those things that can wait. (PER)
User:	The test is not dangerous but the procedure is complex.
Chatbot:	That's really frustrating. (PER)
User:	Also it requires concentration
Chatbot:	I understand how stressful it must be. (SYM)
User:	I was confused and very upset
Chatbot:	Do your best and prioritize. (PER)
User:	It's no problem if I do wrong
Chatbot:	Thanks for sharing. How do you rate this support?[1:10]
User:	7

Figure 14. Dominant conversation example

VI. CONCLUSION

The current study has provided support that a chatbot can interact with the user and adapt its personality to suit the user by using evolutionary computation. Our method aims to develop a chatbot to provide emotional support. This is in line with previous research which has found that chatbots which match the user's personality can provide better support than when they are not matched. Rity [33] also uses an evolutionary algorithm, but it assumes that the user knows their preferred personality from the beginning. In the future, we plan to have health professionals engage with the chatbot to explore its contribution to managing exposure to stressful conditions.

SOC and personality have been identified as related to depression [31], and for those individuals with a tendency towards neuroticism it is possible to make support easier by making adjustments such as evaluating SOC low in SOC evaluation. Therefore, peer support can be offered by developing a system that takes into account not only the user's SOC but also the user's personality.

It was possible to prepare all personality patterns in advance without using IGA because there were only two personalities which are Extroversion (Extroverted and Introverted) and Agreeableness (Submissive and Dominant) used this time. For future design significant advantages is to be able to adapt the personality by interaction with the user if personality becomes difficult to design in advance. For example, as the number of personality patterns included in the support program is increased the design process will become more challenging. For the current project, we have only used personality for conversation contents, but when integrating robot to the system, it is helpful to express robot's behaviours although additional personality might be necessary. IGA models are considered to be useful in such cases. As for the number of personalities, most research uses some of the factors from the Big Five model, but some work has focused on MBTI [34]. MBTI, includes 16 personality types, which enables a more nuanced matching of personality. In addition, to a focus on individual personality, the inclusion of social identity is also considered to be useful for enhancing the quality of support. On the other hand, the selection of appropriate messages may be difficult because of the limited data. Since the selection of the utterance content is random this time, the flow of conversation cannot be taken into consideration, but it helps to select messages. Future work will focus on the development of a system which takes into account conversation flow and the use of other personality models.

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