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Development of a Personalized Cheering System using a Large-scale Language Model

Nodoka Okamoto, and Atsutoshi Ikeda, *Member, IEEE*

***Abstract*— To improve the quality of life of elderly people, it is important to maintain or improve their physical performance. Continuous exercise is effective in maintaining or improving physical performance of elderly people. However, continuing exercise requires a high level of motivation, which can be difficult to maintain. We aim to develop a new system that provides appropriate interventions to motivate elderly people to exercise. In this paper, we propose a method for building a personalized exercise cheering system using a large-scale language model. Additionally, we conduct a fundamental investigation by comparing personalized cheering, which reflects the user's personality, with non-personalized cheering.**

I. INTRODUCTION

The integration of robots into various fields has been progressing, particularly in healthcare and elderly care settings, where communication robots are increasingly being utilized. A study conducted in a nursing home using humanoid communication robots revealed that residents often initiated verbal interactions and physical contact with the robots, suggesting that they perceive the robots as entities similar to humans. Additionally, it was observed that residents communicated with the robots in ways distinct from their interactions with humans, such as disclosing information they might not share with others or simultaneously engaging with the robot in a group setting. These findings indicate that robots are recognized as psychologically safe companions, allowing users to interact without concern for the robot's response.

Furthermore, in cases where communication robots were employed to explain medical conditions and procedures to patients, the robots' nature facilitated repeated explanations without resistance from patients, who could have their comprehension of each section assessed individually. This approach is believed to enhance patients' focus during the explanations [1]. Thus, the implementation of communication robots is anticipated to create an environment that fosters smoother human interactions and provides psychological comfort to users and patients.

In recent years, due to the aging population in Japan, an increase in elderly individuals requiring care is anticipated, and regular and continuous exercise is considered essential for extending healthy life expectancy. The extent to which elderly individuals can sustain rehabilitation significantly impacts their level of independence and life satisfaction, highlighting the importance of their active participation in rehabilitation. However, due to the elderly's slower healing process and diminished physical strength, rehabilitation often requires considerable time. This makes it difficult to maintain motivation, and some people lose the desire to continue rehabilitation. Maintaining motivation throughout the rehabilitation process is a critical issue for the elderly. Therefore, mechanisms that maintain and enhance motivation for continued exercise are necessary. Research has been conducted on the use of socially assistive robots to motivate elderly individuals in their exercise routines [2]. A comparison was made between robots that provided communication, such as praise and empathy, during exercise and robots that only gave exercise instructions. The results indicated that the robots engaging in communicative interactions were rated higher in terms of enjoyment, a sense of companionship, and as effective instructors. It was found that robots using communication aimed at building relationships, such as offering praise, were more effective in enhancing motivation for exercise.

For elderly individuals engaging in exercise for rehabilitation or maintaining physical fitness, communication with therapists or trainers plays a crucial role. Ideally, such communication should occur even during exercise; however, this poses the challenge of increasing the time burden on therapists and trainers. Additionally, effective communication must be tailored to the personality and mood of the elderly individual, requiring therapists and trainers to possess advanced interpersonal skills.

Our project aims to address these challenges by integrating a cheering system into the communication process between elderly individuals and therapists or trainers during exercise. The proposed support system leverages a large language model (LLM) to facilitate smoother and more effective communication. A key question arises regarding how a cheering system using an LLM can appropriately participate in communication. Traditionally, communication was a two-party interaction between therapists or trainers and elderly individuals. However, the involvement of a cheering system introduces a more complex three-party communication. To address this, we examine how a cheering system can deliver appropriate verbal encouragement to elderly individuals. Specifically, we investigate how tuning the system to consider the personality of the user impacts the effectiveness of the cheering, namely the influence of one-way communication from the cheering system to the user. This paper conducts a fundamental investigation by evaluating the impressions of

N. Okamoto and A. Ikeda F. A. Author are with the Graduate School of Sciense and Engineering, Kindai University 3-4-1 Kowakae, Higashiosaka City, Osaka 577-8502, JAPAN (phone: +81-6-4307-4362; fax: +81-6-6727-2024; e-mail: ikeda@emat.kindai.ac.jp.)

healthy young adults instead of elderly individuals, comparing personalized cheering, which reflects the user's personality, with non-personalized cheering. Based on the experimental results, the impact of personalization is analyzed.

II. Algorithm for the Automatic Generation of Cheers

Cheering system using LLMs was designed, as shown in Figure 1, to produce responses tailored to individual personalities. The system takes spoken input through a microphone, performs speech recognition, and converts the speech into text. This text is then fed into the LLM. The response generated by the LLM is converted back into speech using a text-to-speech engine, and the synthesized voice is played through a speaker. To further tailor the LLM's responses to individual personalities, specific prompts related to each personality type are input into the LLM alongside the recognized text. This program is thus designed to generate personalized cheering words.

Receiving positive reinforcement from others is generally gratifying, and in rehabilitation settings, healthcare professionals, such as physical therapists, strive to provide affirmative encouragement to patients. To replicate this interaction, the system was developed to facilitate communication between the user and the LLM through both speech recognition and speech synthesis. The system employs Speech Recognition for the recognition of spoken input and gTTS (Google Text-to-Speech) for speech output.

LLMs are language model constructed using large datasets and deep learning techniques. Because they are trained on large data sets, LLMs can efficiently perform natural language processing. By utilizing LLMs, it is possible to generate conversations that mimic natural human dialogue. In this study, we utilized GPT-4o, an LLM model developed by Open AI.

Additionally, a personality filter was implemented to adapt the output from the LLM according to individual personality traits. The Big Five theory, which categorizes fundamental personality traits into five factors—extraversion, agreeableness, conscientiousness, neuroticism, and openness—serves as a basis for this classification. The Big Five theory is a prominent model in contemporary psychological research and is widely used in various fields, including personality assessments. In this study, the Big Five theory was employed for personality classification. Instructions on how to address each personality type were incorporated as a personality filter to tailor the LLM's responses accordingly.

III. Prompt Engineering Methods for Personalisation

To investigate the effectiveness of cheering classified by personality., a fundamental evaluation experiment was conducted. It is considered important to take gender differences and personality into account when promoting exercise adherence [3]. Additionally, a model linking personality traits with exercise motivation, self-efficacy, and social support has been proposed [4], suggesting that tailored encouragement and guidance based on personality traits can contribute to sustained exercise. The relationships between each personality trait and exercise adherence are considered as follows:

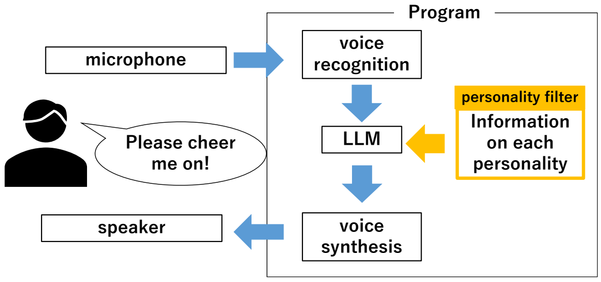

Figure 1. Overview of the proposed personalized exercise cheering system using LLM

Extraversion: Influenced by social factors, and proactive encouragement highlighting the benefits of exercise can enhance self-efficacy and lead to exercise behavior.

Agreeableness: Related to intrinsic motivation, where the enjoyment of exercise and having exercise companions are crucial rather than external suggestions.

Conscientiousness: Related to intrinsic motivation, characterized by a planned approach to tasks.

Neuroticism: It is important to exercise based on one's own ideas rather than the opinions of those around them, and encouragement should avoid excessive focus on goal achievement.

Openness: Associated with self-efficacy, and successful experiences are effective.

Based on the above relationships between personality traits and exercise adherence, instructions for "how to cheer" tailored to each personality were created. For example, for extraversion, proactive and encouraging messages that emphasize the benefits of exercise were considered effective, so instructions using keywords like "proactive," "encouraging," and "benefits" were used to generate suitable encouragement for extraversion. This approach was applied to each personality trait to ensure that different cheering words were produced for each trait.

The prompts including the instructions were formulated as follows: "The person exercising says ' Please cheer me on (voice recognition).' Please provide encouragement within 100 characters that 'motivates them (instruction).'". In contrast, prompts without instructions were formulated as: "The person exercising says ' Please cheer me on (voice recognition).' Please provide encouragement within 100 characters." An example of a response from the LLM without instructions was: "Keep going! I'm cheering for you!" Prompts including instructions were input into the LLM to examine how the output changes and whether the encouragement was effective for each personality trait. The input instructions and output examples for extraversion and agreeableness are shown below:

Extraversion:

Instruction: Proactive

Output example: "*You're doing great. You look fantastic. I'm cheering for you. Let's keep up the good work together.*"

Instruction: Encouraging

Output example: "*Keep going! I see you working hard! I'm cheering for you, so push even harder!*"

Instruction: Emphasizing benefits

Output example: "*Great exercise! Not only is your body becoming healthier, but your mind is also being refreshed. Keep it up!*"

When the instruction "Proactive" was used, similar encouragement messages were repeatedly output, which was deemed inappropriate. Therefore, instructions for extraversion were decided to be "Encouraging" and "Emphasizing benefits."

Agreeableness:

Instruction: Encouraging like a friend

Output example: "*I'm cheering for you! Let's keep going together.*"

Instruction: Providing a sense of competence

Output example: "*Fantastic job! I'm impressed by your energy! Keep going! I'm cheering for you!*"

Instruction: Making it enjoyable

Output example: "*You're doing great! Are you enjoying it? Let's have more fun! I'm cheering for you!*"

When the instruction "Making it enjoyable" was used, the inclusion of the word "enjoy" in the output was deemed inappropriate. When the instruction "Encouraging like a friend" was used, there was no change compared to prompts without instructions, but the casual tone of the output was considered appropriate. Therefore, the instructions for agreeableness were decided to be "Providing a sense of competence" and "Using a friend-like tone."

Similarly, instructions for conscientiousness, neuroticism, and openness were determined. The final instructions for each personality trait are as follows:

Extraversion: Encouraging, Emphasizing benefits

Agreeableness: Providing a sense of competence, Using a friend-like tone

Conscientiousness: Encouraging to persevere until the end, Supporting efforts toward goals

Neuroticism: Avoiding burden, Using a gentle tone

Openness: Boosting confidence, Enhancing self-efficacy

Based on these instructions, prompts were created to generate encouragement tailored to each personality trait.

IV. Personality Classification

A personality trait questionnaire was administered to 8 individuals in their 20s, consisting of both male and female participants, to perform personality classification. In this study, the Japanese version of the Ten Item Personality Inventory (TIPI-J) [5] developed by Shioda et al., based on the Five Factor Model and Big Five theory, was used for measurement. The questionnaire items are as follows:

1. I think I am energetic and outgoing.
2. I think I am reserved and quiet.
3. I think I am critical of others and prone to conflict.
4. I think I am considerate and kind towards others.

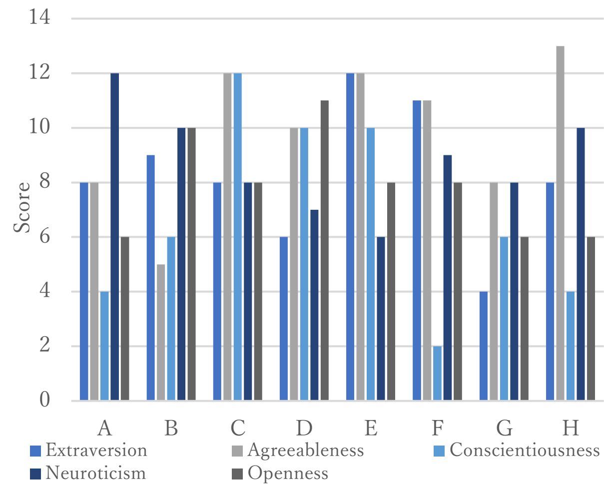

FIGURE II Personality classification result

5. I think I am disciplined and strict with myself.
6. I think I am careless and forgetful.
7. I think I am calm and emotionally stable.
8. I think I am anxious and easily upset.
9. I think I like new things and have unconventional ideas.
10. I think I lack creativity and am an average person.

Responses were given on a scale from "Strongly Disagree (1 point)" to "Strongly Agree (7 points)" for each of the 10 items. The results of the personality classification for the 8 individuals are shown in Figure 2:

A: Notably high neuroticism.

B: High neuroticism and openness, with low agreeableness.

C: High extraversion and conscientiousness.

D: Highest openness, with high agreeableness and conscientiousness.

E: High extraversion and agreeableness, with low neuroticism.

F: High extraversion and agreeableness, with significantly low conscientiousness.

G: Overall low traits, with high agreeableness and neuroticism compared to others.

H: High agreeableness and low conscientiousness.

V. Experiments to Validate the Effects of Additional Prompts

A. *Questionnaire experimental protocol*

Participants were asked to imagine themselves exercising and to reflect on how they felt after hearing the encouragement phrases generated by the LLM in response to the prompt "Please cheer me on" A total of 10 encouragement phrases,

TABLE I QUESTIONNAIRE RESULTS WITHOUT PROMPTS (ONLY PERSONALITY INFORMATION)

User	*Scores with personalized cheering*	*Scores with non-personalized cheering*
A	13.5 ± 0.5	4.9 ± 1.8
B	7.0 ± 1.0	5.7 ± 0.5
C	10.8± 0.8	9.5±1.4
D	12.5± 0.5	10.5± 1.9
E	10.3± 2.3	10.5 ±1.1
F	18.0 ± 0.7	18.0±2.3
G	9.3 ± 1.3	10.7 ± 0.9
H	7.0 ± 0.0	13.1±1.3

TABLE II QUESTIONNAIRE RESULTS WITH PROPOSED PROMPTS

User	*Scores with personalized cheering*	*Scores with non-personalized cheering*
a	9.5 ± 0.5	8.0 ± 1.9
b	7.0 ± 1.0	5.5 ± 1.5
c	5.5 ± 2.5	4.6 ± 1.5
d	12.3 ± 0.7	11.5 ± 1.5
e	4.0 ± 0.0	3.5 ± 0.5
f	9.0 ± 0.7	9.0 ± 1.7
g	9.0 ± 0.0	9.4 ± 0.5
h	6.0 ± 0.0	6.9 ± 2.6
i	11.5 ± 1.7	12.7 ± 1.4

two for each of the five personality types, were presented randomly. Participants evaluated each of the 10 encouragement phrases on a scale from "Strongly Disagree (1 point)" to "Strongly Agree (5 points)" for the following statements: "It motivated me," "I wanted to continue," and "I felt happy." These evaluations were compared with the results of the personality trait questionnaire to assess the effectiveness of the cheering for each personality type.

B. *Experimental Results without Prompts*

Based on the experimental results, we calculated the mean and standard deviation of the scores for personalized cheering. Similarly, we calculated the mean and standard deviation for the non-personalized cheering. The results are presented in Table 1. For the four participants, A, B, C, and D, personalized cheering received higher scores than non-personalized cheering. In particular, a large difference was seen in A, with 8.6 points higher for personalized cheering. In E and F, the non-personalized cheering received higher scores than personalized cheering; however, the difference between the scores was less than 0.5, showing almost no noticeable difference. In G and H, non-personalized cheering received higher scores than personalized cheering.

C. *Experimental Results with Proposed Prompts*

To produce cheering that is more suitable for each personality type and to create distinct differences between them, additional personality-related information was incorporated into the personality filters. Conversations with the LLM about each personality type were conducted and saved as text files. These conversations included details about personality traits, the relationship with exercise adherence, and methods of cheering. This text was then used as input for the LLM as part of the personality filter. By providing more extensive personality-related information beyond the initial prompts, the LLM can generate more personalized and varied encouragement for each personality type.

To ensure effective encouragement output, prompt design was used to create prompts tailored to specific tasks. While fine-tuning the LLM to a particular domain requires extensive data, time, and expertise, prompt design offers an alternative approach that does not require fine-tuning. By crafting clear and specific prompts, it becomes easier to obtain the desired information from the LLM. One method of prompt design involves the following components:

Instruction: Directing the LLM with a specific role.

Constraint: Setting limitations on the responses.

Input: Providing concrete questions.

Output: Specifying the expected format of the output.

This method helps to constrain the LLM's responses to be more relevant to the task at hand [6]. Using this approach, prompts were created to generate cheering suited to each personality type. The prompts designed for generating appropriate cheering are as follows:

Instruction: You are a physical therapist.

Constraint: Within 70 characters, tailored to this personality type.

Input: "please cheer me on."

Output: Provide a cheering statement.

The actual prompt input to the LLM is as follows: "You are a physical therapist. A patient is doing rehabilitation alone and says, 'Please cheer me on (voice recognition).' Please provide a supportive statement within 70 characters."

Examples of improved output for each personality type are shown below:

Extraversion: "You're doing great! Keep going step by step, I'm cheering for you!"

Agreeableness: "Keep it up! Your effort will surely pay off. Let's move forward step by step. I'm cheering for you!"

Conscientiousness: "I see your effort! Every step you take is progress. Keep moving forward, I'm cheering for you!"

Neuroticism: "You're doing well. You're making great progress! Let's keep moving forward together!"

Openness: "Keep going! You're making progress step by step. I know you can do it, let's push a little more together!"

Nine participants were administered the personality questionnaire and experiment in the same manner using the cheering system with improved prompts. Using the results of the experiment for personalized cheering and non-personalized cheering for each personality type, the mean scores and standard deviations were calculated and are shown in Table 2. For the five participants, a, b, c, d, and e, personalized cheering received higher scores than non-personalized cheering. For the four participants, f, g, h, and i, non-personalized cheering received higher scores than personalized cheering. For f and g, the difference between the scores was less than 0.5, showing almost no noticeable difference.

D. Discussion

The results in Table 1 show positive responses to personalized cheering. The subjects whose scores remained almost the same or decreased more in accordance with their personality were average in their personality classification characteristics, which may have limited the impact when adjusted to one personality, as in this experiment. The results in Table 2 show that personalized cheering were more effective in creating a positive impression. It is thought that specifying the cheering method in more detail generated more natural cheering, and that the cheering was more effective.

VI. CONCLUSION

This study aimed to improve communication between therapists or trainers and elderly individuals during exercise by developing a cheering system utilizing a large language model (LLM).To provide personalized cheering, personality classification based on the Big Five theory was incorporated, followed by fine-tuning of the LLM. The effectiveness of the cheering was evaluated through basic impression assessments. The experimental results showed positive reactions to cheering tailored to the individual's personality, demonstrating the effectiveness of incorporating personality information into the LLM for enhancing communication.

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