SMACS: Stress Management AI Chat System

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Abstract: The purpose of this study is to develop a stress management AI chat system that can connect users who want mental health care with counselors. By means of this chat system, a conversational AI based on a large language model (LLM) will collect data on the user's stressors through text chats with the user. The system is personalized to the user based on the collected data. This paper describes the nature of the data collected in the preliminary experiment conducted in March 2024 and the results of its analysis, and discusses considerations for the main experiment to be conducted after July 2024. The preliminary experiment was conducted with 11 students over a 3-week period. Discuss the distribution of the data collected and the issues involved in building a model for predicting stress levels.

1 INTRODUCTION

In today's society, stress has become an unavoidable part of many people's daily lives. According to the Occupational Safety and Health Survey(Ministry of Health, Labour and Welfare, 2023) conducted by the Ministry of Health, Labour and Welfare in 2022, 82.2% of workers reported feeling anxious, worried, or stressed about their current work or occupational life, and the percentage is increasing every year. In addition, while 91.4% of workers have someone they can talk to about the stresses of their current job or professional life, 69.4% of workers have actually consulted with someone, showing a gap between the two. Among them, "family/friends (62.0%)," "coworkers (63.5%)," and "supervisors (58.5%)" were the most frequently chosen consulting parties, while "psychologists such as certified psychologists (0.5%)" and "counselors (0.5%)," who are consultants who can provide professional advice from an objective perspective, were both very rare. This is due to the fact that the number of patients who consulted with a psychologist or counselor was very low. In addition to psychological problems on the part of patients, a shortage of professionals can be cited as a reason for this. There are approximately 70,000 licensed psychologists and 40,000 licensed clinical psychologists (in 2024), but more than half of them work part-time or do not work at all. These facts suggest that although many people are able to consult with those close to them, they continue to feel stress on a daily basis and have not yet reached the point of consulting with a specialist.

There are also issues related to mental health measures. According to the Occupational Safety and Health Survey conducted by the Ministry of Health, Labour and Welfare in 2022(Ministry of Health, Labour and Welfare, 2023), 63.4% of business establishments are working on mental health measures. In addition, 46.1％ of the respondents answered that they "have established an in-house counseling system for mental health measures," while 12.4 ％ answered that they "utilize medical institutions to implement mental health measures." This suggests that promoting the use of outside institutions for counseling, which is a part of mental

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health measures, remains a significant challenge. According to the Japan Inochi no Denwa Renmei (Inochi no Denwa Renmei, 2024), which operates a consultation dial for people suffering from loneliness and anxiety, there were over 540,000 telephone consultations nationwide in 2022. However, due to a lack of manpower, it is reported that calls are difficult to get through. Another reason why the number of counselors has not increased is that they have to pay the cost of attending a training course that takes more than one year to become a counselor.

According to DataM Intelligence (DataM Intelligence, 2023), the global mental health apps market reached US$5.1 billion in 2022 and is projected to reach US$14.2 billion by 2030, growing at a CAGR of 14.1% during the forecast period of 2023-2030. These are driven by factors such as the increasing prevalence of mental health disorders and rising smartphone usage. In particular, the integration of artificial intelligence and machine learning technologies is expected to boost demand for mental health apps market trends.

Based on the above, this study aims to develop a stress management AI chat system that can connect clients and counselors and support counseling operations. By developing this system and conducting user evaluations, we aim to confirm the effectiveness of the proposed method and contribute to the research and development of mental health care AI that can handle stress in an engineering manner.

This paper presents the results of the preliminary experiment focusing on the construction of a chat system. The preliminary experiment was conducted for about three weeks in March 2024, and the results of the analysis of the data collected in the system are discussed for the main experiment scheduled to be conducted in July 2024 or later.

2 RELATED WORK

2.1 Effectiveness of Text Chat

2.1.1 Consultation Through SNS

According to the interim report (Nagano Prefecture, 2017) on the consultation on bullying, etc. using LINE by Nagano Prefecture and LINE Corporation, in August 2017, as part of the "Collaborative Agreement on Measures against Bullying and Suicide of Children Using LINE," consultation on bullying, suicide, etc. was conducted for junior high and high school students using LINE. As a result, a total of 547 consultations were received from 390 junior and senior high school students in Nagano Prefecture through the "Don't Worry Alone @ Nagano" account, which was opened for two weeks from September 10 to 23, far exceeding the 259 telephone consultations received in the previous fiscal year. This indicates that there is a certain level of demand and effectiveness in text-only chats. However, text-based communication via SNS has limitations in terms of communication, and the need to switch to telephone counseling to continue the counseling has been identified as an issue.

2.1.2 Online Disinhibition Effect

Suler (Suler, 2004) states that the hurdle to self-disclosure is greatly reduced in text-based online consultations. Online deinhibition refers to a phenomenon in which inhibitions against behavior in normal face-to-face situations are relaxed or disappear on the Internet. The reasons for this are listed below.

- Because it is anonymous, there is a sense of security that individuals will not be identified even if they confess their secrets.
- Because the facial expressions and tone of voice are not transmitted to the other party in text-based communication, the embarrassment of having one's emotional reactions known when confessing a secret is reduced.
- The fear of rejection is reduced because the counselor is not visible.

2.2 Mental Health Care Apps

This section presents a selection of Japanese mental health care applications that are similar to SMACS and have more than 100,000 downloads.

2.2.1 Self

The SELF app (SELF, 2024) is an application in which AI understands and comprehends the user's life through natural conversation, and adapts to the user's needs such as mental care, stress care, life logs, and information suggestions. The seven AI characters implemented in this application not only have different personalities, but also change the content of their conversations, allowing the user to select the character that best suits his or her needs. The application has many functions to support the user's mental care. For example, the application can analyze the user's characteristics, strengths and weaknesses, and objectively communicate them to the user during the conversation with the AI, and can suggest articles based on the user's interests and concerns.

2.2.2 Awarefy

Awarefy (Awarefy, 2024) is a smartphone application based on the concept of "acquiring skills to care for the mind. The app is equipped with many practical programs and tools based on cognitive behavioral therapy, which has been proven and evidenced in a variety of fields. Awarefy AI chat utilizes the large language models GPT-3.5 and GPT-4 developed by OpenAI, Inc. The prompts have been tuned to adapt to Awarefy's user base.

2.3 Positioning of this Study

This research focuses on connecting users who wish to receive mental health care with counselors. We aim to realize a system that can provide a consistent solution from prevention of daily stress accumulation to countermeasures against serious stress. The proposed chat system aims to efficiently collect information about the causes of stress. To achieve this, our system integrates an AI chat model that collects user-specific information relevant to counseling, and adapts its responses based on this information to assist in assessment and treatment, along with a function to eliminate as much as possible utterances that are inconsistent with the past chat history. In the stress management system, a stress detection model is constructed based on the chat history, with the aim of creating a system that directs users with high stress levels to counselors, and of improving the efficiency of the counselors' counseling work. In particular, we aim to develop a user-adaptive stress detection system by adapting the stress detection model to each user's individual stress level. In addition, we aim to improve the efficiency of counseling work by collecting and visualizing necessary information from the counselor's point of view.

3 STRESS MANAGEMENT AI CHAT SYSTEM (SMACS)

3.1 System Overview

The purpose of this study is to develop a stress management AI chat system adapted to individual users that can connect users and counselors. This system will not only reduce the user's daily stress accumulation, but also improve the efficiency of counseling services. The system is mainly divided into a chat system (see Section 3.2) and a stress management system (see Section 3.3).

The system is developed using Python, JavaScript, HTML, and CSS, and can use any publicly available large language model (LLM) as a base model for AI chat. In our preliminary experiment (see Chapter 4), we use rinna, a Japanese LLM published by rinna Corporation, and gpt-3.5 published by OpenAI.

When using local LLMs such as rinna and Llama, we observed significant processing delays due to the 24GB VRAM of the GPU installed on the server running the system. On the other hand, when using external APIs such as gpt-3.5, the advantage is that multiple access requests can be handled efficiently.

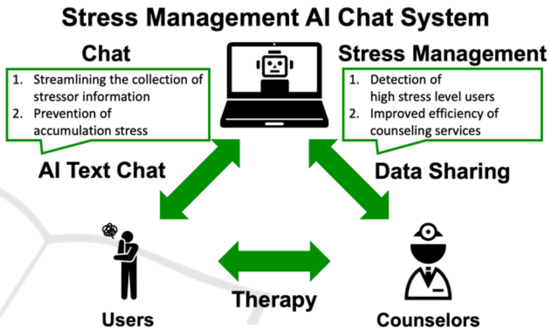

Figure 1: Stress management AI chat system overview.

3.2 Chat System

The chat system aims to improve the efficiency of data collection to identify users' stress factors and to reduce the accumulation of stress. Specifically, AI chat based on a large language model (LLM) efficiently collects data related to stress factors through user-oriented chat that can take into account user profile information and daily chat history. In addition, users can prevent the accumulation of daily stress by making it a habit to talk casually with AI chat.

Figure 2 shows an example of chatting with AI. It is a dialogue model in which system prompts (Table 1) are set to encourage self-disclosure in response to the user's statements. Based on the data collected from the chat, the user's profile (Name, Gender, Occupation, Recent Interests, Recent Challenges, Recent Enjoyments, Current Goals) in the database is updated, and the user's utterances are made in consideration of his/her profile. This allows the user to speak as if he/she understands the user even if the date changes.

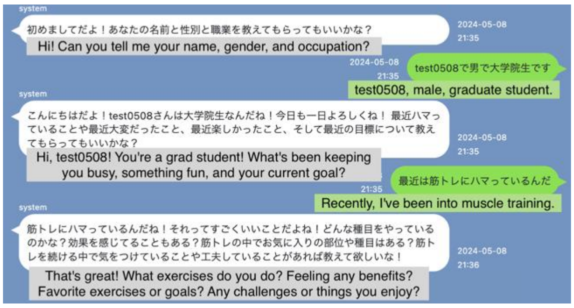

Figure 2: Example of AI chat in a chat system.

Table 1: System prompts (excerpts).

personality	・Newly born as an AI ・Already understands most of the meanings of human words, but still lacks experience and understanding of human emotions, so it wants to understand them. ・It is curious about what humans do on a daily basis, and it listens happily and happily when you talk to it.
constraint	・Do not use honorific language. ・End sentences with "dayo." ・Frequently use empathetic interjections to convey agreement. ・Show curiosity and ask questions eagerly.

3.3 Stress Management System

The stress management system is intended to improve the efficiency of self-care and the work of counselors by enabling users to become aware of their own stress. Specifically, users can check the system usage history and the visualization of the analysis results of the collected data, and notice their own stress, which is useful for self-care. In addition, a stress detection model is constructed based on the stress level and chat history collected in the database. This model automatically detects users with high stress levels and provides them with a route to a counselor. Counselors can check the results of data analysis of the chat history of the user in question, thereby streamlining the counseling work.

In the current system, users can check their stress level transition graph (Figure 3). By clicking a point on the graph, the user can view the chat history for that day. In the future, we aim to visualize the results of the automatic analysis of the collected data in an easy-to-understand format to make users aware of their stress levels.

At this point, the detection of users with high stress levels and the function to improve counseling work efficiency are still in the design stage. The stress detection model is constructed using a machine learning algorithm with the text chat history as a feature and the user's self-reported subjective stress level as the correct response data. Stress is considered to vary from user to user. Therefore, it is difficult to construct a general-purpose stress detection model that can be applied to any user, and high accuracy cannot be expected. However, it has been verified that a stress detection model adapted to each user can maintain a certain level of accuracy. We plan to design an analysis data sharing function to improve the efficiency of counseling work by referring to the work contents and judgment criteria of counselors.

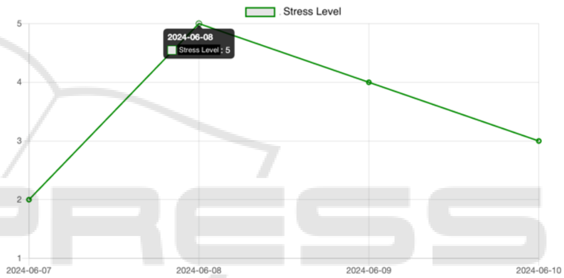

Figure 3: Stress level transition graph.

The stress detection system will be based on the predictions of five levels of stress levels by the stress level prediction model. The flow of the stress detection system is shown in Figure 4. The system processes the chat history data with the user and inputs it into the stress level prediction model to infer the predicted value of the stress level. Users with low predicted stress levels are encouraged to continue self-mental health care by using the system. Users with high predicted stress levels are preferentially directed to counselors for treatment.

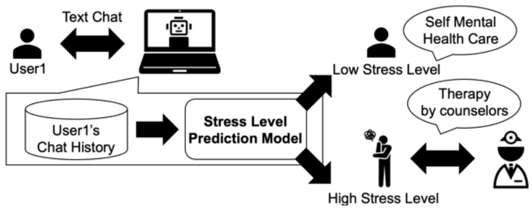

Figure 4: Stress detection system flow.

3.4 Database

The contents of the database are shown in Table 2. The database uses SQLite. The system stores user names in the user information table when a new user registers. When a user logs into the system, the system saves his/her usage history associated with the user information. The system saves data before, during, and after the chat phase, respectively, before the screen is transitioned.

In particular, the user profile in the user information table is automatically updated based on the template for each utterance from the chat history during the AI chat with the chat system. In addition, the sentences generated by the dialogue model AI are stored for system utterances during chatting. Data other than these two will be input by the user.

Table 2: Database contents of the system (excerpts).

User information	user name user profile
Before chatting	location of experiment (home or lab), stress level (1-5), emotion (free description), 3 emotions (neutral, negative, positive)
During chatting	system utterance user utterance
After chatting	degree of chat distress (1-5), degree of stress reduction (1-5), topic (free description), naturalness of chat (1-5), response speed (1-5), dissatisfaction (free description)

3.5 Stress Level Prediction Model

The procedure for constructing the stress level prediction model is shown in Figure 5. Due to the small number of data and data bias of the data obtained in this preliminary experiment, it is expected to be difficult to construct a model with high accuracy.

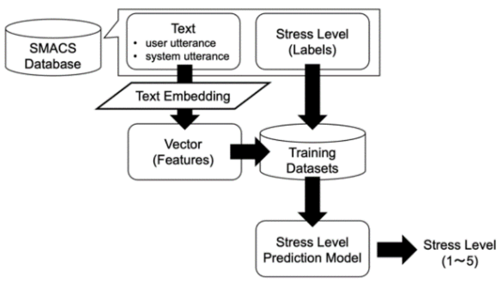

Figure 5: Stress level prediction model building flow.

4 PRELIMINARY EXPERIMENT

4.1 Outline of the Experiment

The purpose of this preliminary experiment is to consider the setting of this experiment to be conducted after July 2024, based on the results of the analysis of the data collected through the users' use of the system. The preliminary experiment was conducted for about three weeks in March 2024, targeting 11 laboratory students (all in their 20s). The experiment is conducted in the following three steps

I. A questionnaire to input the stress level and subjective feelings at the time was administered.
II. Conduct at least 10 conversations with the AI
III. Conducting a questionnaire about chatting, such as stress reduction level, naturalness of chat, topics, etc.

The dialogue model of the chat system was changed every week, and a comparison was made based on the differences in the nature of the data collected in each case. In particular, this time, the AI chat system is evaluated based on the average value of the stress reduction level in the post-chat questionnaire. In conducting the experiment, the research ethics review by the Tokushima University was conducted and approved.

4.2 Experiments and Evaluation Methods

Subjects are asked to participate in the experiment by accessing the system from a browser on their own terminals at home or in the laboratory. The only conditions presented to the subjects are that they select the chat mode of the system, answer the pre/post-chat questionnaire, and chat with the AI for 10 dialogs (about 5 minutes). In consideration of the subjects' privacy, they are instructed to refrain from entering any personal information that could lead to their identification in advance. We also recommend the use of a handle when registering as a new user.

In the preliminary experiment of this paper, we evaluate the following three dialogue models by comparing them.

I. rinna/japanese-gpt-neox-3.6b-instruction-ppo (2024/2/19 - 2024/2/25)
II. gpt-3.5 with system prompts (2/26/2024 - 3/4/2024)
III. gpt-3.5 with system prompts and user profiles (from 2024/3/5 to 2024/3/5)

For the evaluation index, we use the average value of the stress reduction level (5 levels from 1 to 5), which is data that can be collected in the post-chat questionnaire.

5 EXPERIMENTAL RESULTS

5.1 Collected Data

In a preliminary experiment, we were able to collect data for 11 subjects, each of whom was asked to enter data for a minimum of 18 days, resulting in a total of 210 days of data.

5.1.1 Distribution of Stress Level Data

The distribution of stress level data is shown in Figure 6. Most of the data are for stress levels 3 and below, with extremely few data for stress levels 4 and 5. It can be seen that most of the subjects were in a low-stress state for the experiment. It was found to be a challenge to uniformly collect data for each stress level level.

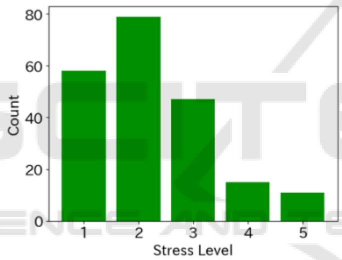

Figure 6: Distribution of stress level data.

5.1.2 Distribution of Emotion Label Data

The distribution of the emotion label data is shown in Figure 7. Most of the data is neutral, with few positive or negative data. This can be correlated with the fact that the distribution of stress level data was skewed toward stress level 3 and below. It is possible that users need to be presented with more specific and understandable emotion labels.

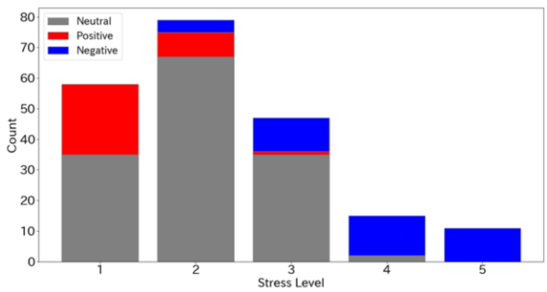

Figure 7: Distribution of emotion label data.

5.1.3 Sentence Length, Word Count and Character Count

Table 3 shows the total number of sentences/words/characters, the number of words/characters per sentence, the number of sentences/words/characters per subject, and the number of sentences/words/characters per day for one subject for the text data of system and user utterances. A word is defined as one word that has been morphologically analyzed and segmented by MeCab (Taku Kudo, 2024). Overall, it is shown that the amount of text in system utterances is larger than in user utterances. max_tokens parameter of gpt-3.5-turbo is set to 200.

Table 3: Sentence length, word count, and character count for user and system utterances.

		total	per sent.	per subject	per subject per day
user	sent.	1.640		149.1	8.3
	word	18,754	11.4	1705.0	94.7
	chara.	32,095	19.6	3066.8	170.4
sys.	sent.	1,873		170.2	9.4
	word	102,305	54.6	9300.5	517.0
	chara.	172,579	92.1	15859.2	881.1

5.1.4 Frequency of Occurrence of Each Part of Speech

The frequency of occurrence of each part of speech for the text data of system and user utterances is shown in Figure 8. The parts of speech are the results of morphological analysis by MeCab (Taku Kudo, 2024).

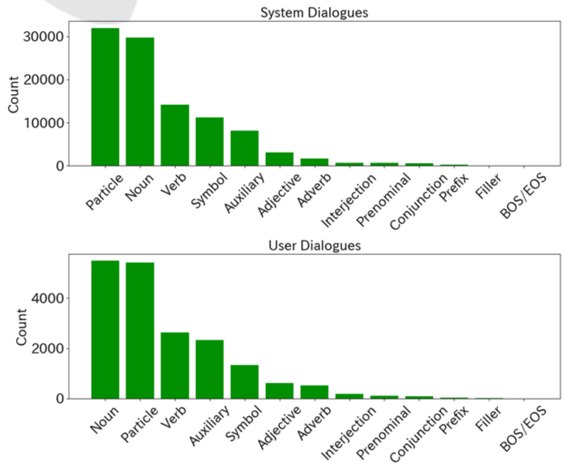

Figure 8: Frequency of occurrence of each part of speech.

5.1.5 Average Number of Words per Stress Level

The average number of words for each stress level for the text data of user and system utterances is shown in Figure 9 and 10. Stress level 1 has the lowest average word count, while stress level 4 has the highest average word count.

Figure 9: Average number of words per stress level (system).

Figure 10: Average number of words per stress level (user).

5.2 Comparison of Average Stress Reduction

The distribution and mean values of stress reduction for each interaction model are shown in Figure 11. The vertical axis represents the number of data and the horizontal axis represents the stress reduction level. As a result, the average value of the stress reduction level was the highest for the gpt-3.5 with the system prompt.

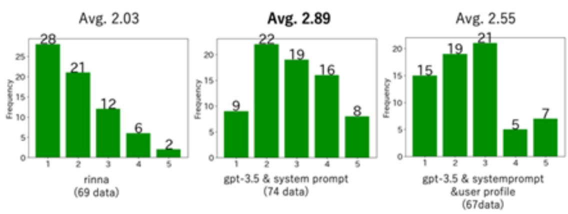

Figure 11: Distribution and mean of stress reduction levels for each interaction model.

5.3 Comparison of Stress Level Transitions by User

A comparison of stress level transitions for each user is shown in Figure 12. It can be seen that the dispersion of stress levels differs from user to user, and the tendency of stress transitions differs from user to user. This indicates that there are individual differences in the way stress is felt and the tendency of stress change.

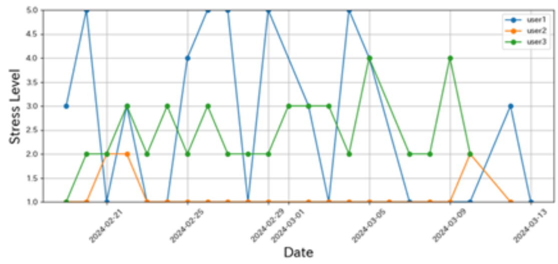

Figure 12: Stress level transitions extracted for 3 users.

6 DISCUSSION

In this study, we developed and evaluated a stress management AI chat system aimed at connecting users with counselors and adapting to individual users' needs. Our approach involved several key components: (1) conducting preliminary experiment to collect chat data, (2) implementing different dialogue models with varying system prompts and user profile integration. The following sections discuss the main findings, challenges, and implications of our research.

6.1 Stress Reduction due to Inconsistent Utterance and Response Time Delay Caused by User Profile Prompts

When we checked the complaints (descriptions) of users who had low stress reduction values during the period when we were experimenting with the dialogue model with system prompts and user profiles in gpt-3.5, we found that many of them said "the response speed was slow" and "I was asked my name repeatedly". These are thought to be caused by the time required for the task of filling in the user profile template and the fact that some of the constraints of the system prompts are ignored. A possible way to realize an AI chat system that understands user profiles and allows users to interact with it is to ask users to enter their own profiles when they register as new users. When adding the user profile to the prompts, the user should be given instructions to select utterances that are consistent with the profile.

6.2 Bias in Collected Data

In terms of stress level data, of the 210 data collected in the preliminary experiment, there were 11 data for Level 5, which is considered a high stress level, and 15 data for Level 4, which is very few. This is considered to be the case. One of the reasons for this is that many subjects did not have many opportunities to face high stress levels during the spring vacation period in March, when the preliminary experiment was conducted. In order to eliminate the bias in the data, it is necessary to conduct the experiment over a longer period of time.

7 CONCLUSIONS

In this study, in order to develop a stress management AI chat system adapted to individual users that can connect users and counselors, we collected data through the preliminary experiment and evaluated the chat system we built. The results showed that none of the dialogue models showed much effect on stress reduction. The dialogue model with relatively high average stress reduction had less inconsistency and delay in response speed during chatting than the other dialogue models.

In the future, we will develop a chat system that takes user profiles into account for this experiment. First, we will develop a method for eliminating utterances that are inconsistent with the profile information. In addition, we will add a function to collect information needed by counselors in the system. In addition to self-reported subjective stress levels, we plan to develop a method to collect objective stress levels.

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REFERENCES

Ministry of Health, Labour and Welfare. (2023). Patient Survey Report, Ministry of Health, Labour and Welfare (online), https://www.mhlw.go.jp/toukei/list/dl/r04-46-50_gaikyo.pdf, last accessed 2024/06/24

Inochi no Denwa Renmei (General Incorporated Association of Inochi no Denwa), https://www.inochinodenwa.org/?page_id=4688, last accessed 2024/06/24

DataM Intelligene, Global Mental Health Apps Market - 2023-2030. (2023). https://www.gii.co.jp/report/dmin1319134-global-mental-health-apps-market.html, last accessed 2024/06/24

Nagano Prefecture, LINE Corporation. (2017). Interim Report Material on Consultation on Bullying and Other Issues Using LINE by Nagano Prefecture and LINE Corporation, https://d.line-scdn.net/stf/linecorp/ja/pr/NaganoPrefectureReportMaterial.pdf, last accessed 2024/06/24

Suler, J. (2004). The Online Disinhibition Effect. CyberPsychology & Behavior, 7(3), 321-326, https://doi.org/10.1089/1094931041291295, last accessed 2024/06/24

SELF Corporation. https://self.software/, last accessed 2024/06/24

Awarefy Corporation. https://www.awarefy.com/, last accessed 2024/06/24

Taku Kudo, https://taku910.github.io/mecab/, last accessed 2024/06/24