Technology Reports (Special Articles) Mental Health Care Stress Cognitive Performance

Special Articles on AI for Improving Services and Solving Social Problems

Smartphone Log-based Stress and Cognitive Performance Estimation Technology

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Around the world, the number of patients with mental disorders is increasing every year, therefore prevention of deterioration of mental health has become a global problem. However, it is difficult to recognize one's own mental health state correctly because we cannot confirm it visually and objectively in daily life. To tackle this problem, we propose a method that estimates the mental state in terms of stress level and cognitive performance by extracting behavioral features from a smartphone log via passive sensing.

This technology makes it possible to visualize the user's mental health state and support self-care by encouraging users to be aware of their own stress conditions.

1. Introduction

The number of patients with mental disorders is increasing every year, and there is growing social interest in mental health care. According to the World Health Organization (WHO), more than 300 million people worldwide suffer from depression, and more than 90% of suicides are reported to be caused by mental illness [1]. Excessive stress is a known factor of mental disorders. Thus, to maintain a healthy mental state, it is important to help people to be aware of the stress they face and

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enable self-prevention, although it is difficult for people to recognize their own stress state correctly.

To address this, there have been a number of efforts to estimate the mental health of users based on logs obtained from smartphones and wearable devices [2]. Since smartphones are owned, carried and used by individuals at all times, smartphone logs reflect the daily activities of users. Assuming that the user's activity and mental health states influence each other, the mental health state of the user should be reflected in smartphone logs. Since the logs of daily smartphone usage are collected, the user does not need to perform any special operations, and the possibility that the user will be burdened is minimized. Additionally, smartphone logs are collected constantly, making it possible to continuously assess the user's mental health state.

Although stress is considered as a risk factor in mental health deterioration, moderate stress has the potential to tighten the mind and improve the efficiency of work and study [3]. However, a state of high stress and low efficiency in work and study means that the user's mental health is deteriorating. Therefore, even in high-stress states, there are situations that affect users positively and situations that affect them negatively, so it is necessary to separate and interpret the good and bad aspects of high-stress states.

In this study, in addition to estimating the degree of daily stress based on smartphone logs, we aimed to identify whether the stress a person is facing is appropriate from the perspective of the cognitive performance (concentration) by estimating the cognitive performance (response speed and accuracy of judgment), which indicates the ability for intellectual activity.

In this article, we describe the details of our proposed method and the results of demonstration experiments using the proposed method.

2. Proposed Model

Figure 1 shows an overview of the proposed model. In the proposed method, we constructed an estimation model with the smartphone log as an explanatory variable, a stress index based on heart rate data, and an cognitive performance score based on the cognitive performance measurement task (Go/NoGo task) as the respective objective variables. The stress index and cognitive performance score are used only when building the estimation model. After the model is built, estimation of stress and cognitive performance states can be done simply by collecting smartphone logs.

In this study, we collected a dataset from volunteer employees working in the R&D division of NTT DOCOMO INC. Thirty-nine employees ranging from their 20s to 50s, consisting of 34 males and 5 females, participated in the data collection. The duration of the study was three months from November 2017 to January 2018, and study participants were asked to cooperate for up to 42 days during this period.

The study was approved by the ethics committee of the Graduate School of Medicine, part of the Faculty of Medicine at the University of Tokyo (examination number: 2017-001).

2.1 Behavioral Feature Values

The smartphone logs collected and the behavioral feature values used in this study are shown in **Table 1**. A total of 1,349 days of smartphone logs

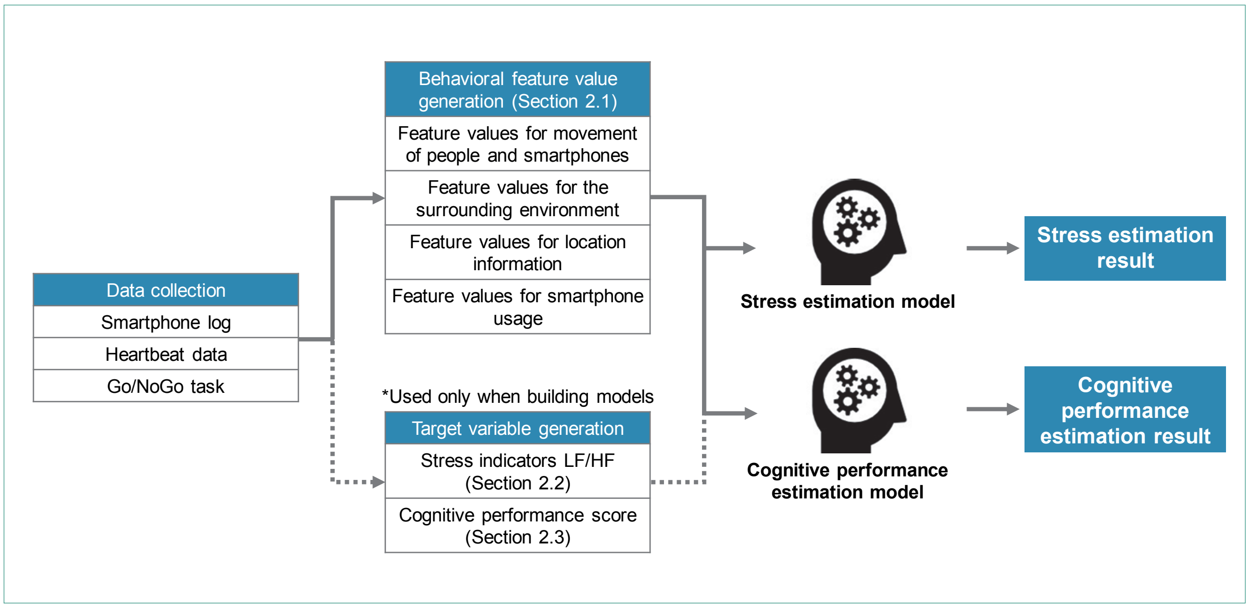

Figure 1　Stress, cognitive performance estimation model

Table 1　Behavioral feature values of stress, cognitive performance estimation model

Smartphone log	Generated feature values (excerpt)
3-axis Accelerometer Gyro sensor	Mean, variance, max, min, max-min; magnitude of vector; correlation coefficients for each axis
Ambient illumination Air pressure Battery level	Mean, variance, max, min, max-min
GPS	Max/min/max-min of latitude/longitude/altitude; the total distance traveled; the number of places visited
Earbud connections Charger attached	The number of connections; connected time per day
Screen ON/OFF	The number of times; mean, variance, max, min of screen-on times
App usage history	The number of used applications by category (games, communication tools, etc.)
Activity Recognition API	Percentage of each state (vehicle, bicycle, on foot, running, walking, still, tilting, unknown, ride, move)
Storage usage amount	Value of remaining capacity
Day of the week	Monday～Sunday; holiday

were acquired through the data collection test.

Behavioral feature values were generated under the following four perspectives.

(1) Feature values for movement of people and smartphones

We assumed that the user's mental state

would be reflected in their behavior. For example, when people feel stress they are likely to handle their smartphones more roughly.

(2) Feature values for the surrounding environment

We assumed that changes in the surrounding environment would affect the user's mental state and behavior. For example, the user may feel stress due to sudden changes in air pressure.

(3) Feature values for location information

We assumed that the user's mental state would affect how they traveled and where they visited. We also assumed that places the user visited would affect the user's mental state. For example, the user may feel stress if the total distance traveled or the number of places visited in a day becomes greater than usual.

(4) Feature values for smartphone operation

We assumed that the usage pattern and purpose of smartphones would change depending on the user's mental state. For example, if the user is feeling stressed about interpersonal relationships, the number of times he or she uses communication applications may decrease.

We estimated the daily stress and cognitive performance of users based on these feature values.

2.2 Stress Index

In this study, we collected 639 days of ElectroCardioGram (ECG) data sets using heartbeat sensor and calculated the physiological index LF/HF [4] based on the ratio of Low Frequency (LF) to High Frequency (HF)*1 components as the stress index. LF and HF represent the activity of sympathetic and parasympathetic nerves, respectively. The ratio of LF and HF is a known index that represents stress. A higher value of LF/HF means stress is felt.

In this study, we estimate the stress on a given day as either higher or lower than its standard value.

First, the daily average values of LF/HF were calculated for each day, and then the average values for all those days were calculated as the standard values for each user. Next, we labeled each day's stress state by setting high stress days as days when the daily average value of LF/HF was above the standard value and low stress days as days when the daily average value of LF/HF was below the standard value.

2.3 Cognitive Performance Index

We used the Go/NoGo task as a method to measure users' cognitive performance [5]. The Go/NoGo task application implemented on Android devices is shown in **Figure 2**.

In this task, a letter of the alphabet is displayed on the smartphone screen continuously, and the user is required to tap the screen quickly (the Go reaction) only when one of the specified letters is displayed, and not to tap the screen (the NoGo reaction) when any other letter is displayed. The displayed letter is randomly selected from eight predetermined letters to be displayed, and letters are displayed a total of 72 times in approximately one minute. The sum of the number of correct Go and NoGo responses divided by 72 is the cognitive performance score in this task.

*1 Low-Frequency (LF) and High-Frequency (HF) components: Heartbeats are known to fluctuate periodically rather than always beat at a regular interval. These are the two main components of this fluctuation.

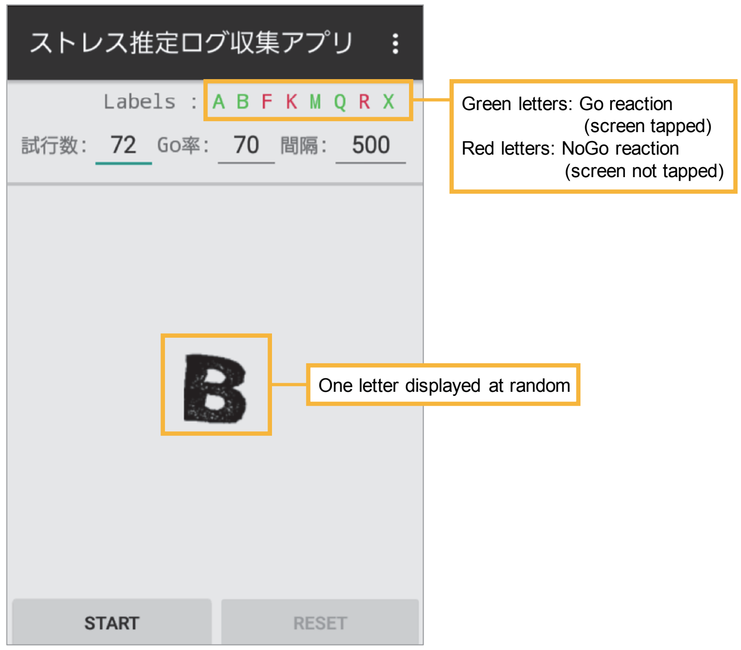

Figure 2　Go/NoGo task application

This task was performed three times a day, and the average of the scores was used as the representative value for the day. Data sets of 779 days of cognitive performance measurements were acquired through data collection test. As with stress, to label each day with a cognitive performance score, the average cognitive performance score for each user was calculated as the standard value, and days with an cognitive performance representative value above the standard value were set as high cognitive performance. and days with a value below the standard value were set as low cognitive performance.

2.4 Performance Evaluation

The estimation accuracy of stress and cognitive performance models was evaluated based on 1,349 days of smartphone logs, data sets of 639 days of ECG data and 779 days of cognitive performance measurement results. The numbers of these three types of data did not match because the wearing of the chest electrocardiograph and the implementation of the Go/NoGo task application were done voluntarily by the study participants to the extent that they did not affect their daily lives. Therefore, the performance evaluation was conducted using a total of 554 days of data, through analysis of days on which all three types of data (smartphone logs, ECG data sets, and cognitive performance measurement results data sets) were available.

We built two models to estimate stress and cognitive performance using a machine learning algorithm with the behavioral feature values as explanatory variables and stress and cognitive performance state labels as objective variables.

In evaluation, we defined one user as the target user for model evaluation and built a model based on the data sets of other users to evaluate the performance of the model for unknown users. We evaluated estimation result correctness by comparing the estimation result of the target user with the stress index based on ECG data sets and the Go/NoGo task of the target user. We evaluated each user assuming that the user is unknown and combined the evaluation results of all users to form the final evaluation results. We used three indices to evaluate the estimated results: Accuracy*2, Sensitivity*3 and Specificity*4.

Table 2 shows the estimation accuracy. The proposed method achieved an accuracy of more than 0.700 for both stress and cognitive performance. However, the sensitivity of both stress and cognitive performance was low compared to the specificity, and there is room for technical improvement to accurately estimate the high stress and high cognitive performance states.

3. External Verification Testing

3.1 Development of a Verification Application

We developed an experimental application that incorporates the stress estimation model and the cognitive performance estimation model. **Figure 3** shows the estimation results presentation screen of the application. This application constantly collects smartphone logs and stores the logs in internal storage. The stored logs are sent to the server once a day, and stress and cognitive performance are estimated on the server. The estimation results are sent to the smartphone and presented to the user through the application.

3.2 Demonstration Experiment in the METI Living Lab

1) Overview of the METI Living Lab*5

From December 2019 to March 2020, NTT DOCOMO INC. participated in the Living Lab sponsored by the Ministry of Economy, Trade and Industry (METI) (2019 Survey on Small and Medium Enterprises (Survey on the Creation of Innovative Social Problem-Solving Services in the Living Laboratory), hereinafter referred to as "Living Lab"). Based on the METI assumption that there is a causal relationship between stress and sleep, the Living Lab conducted an intervention program to improve the quality of sleep for METI employees

Table 2 Stress, cognitive performance estimation accuracy

	Accuracy	Sensitivity	Specificity
Stress	0.711	0.608	0.773
Cognitive performance	0.791	0.750	0.818

*2 Accuracy: In this article, this indicates the percentage of the total sample that is correctly classified as high stress (cognitive performance) or low stress (cognitive performance).

*3 Sensitivity: In this article, this indicates the percentage of users who should be assumed to be high stress (cognitive performance) who are correctly classified as high stress (cognitive performance).

*4 Specificity: In this article, this indicates the percentage of users who should be assumed to be low stress (cognitive performance) who are correctly classified as low stress (cognitive performance).

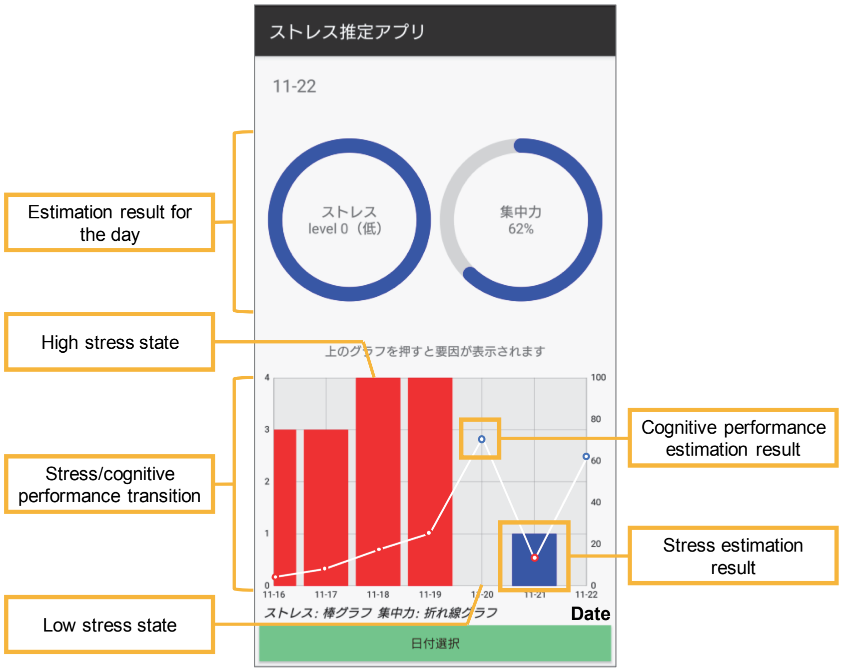

Figure 3　Stress, cognitive performance estimation application

(healthy adults) and verified the effects of the program on stress. Kodomo Mirai, Inc. was responsible for intervention and provided face-to-face and online guidance to improve sleep during the Living Lab period. In addition, a questionnaire was used to measure the stress state of participants at the beginning and end of the Living Lab.

NTT DOCOMO INC. provided the above experimental application as an instrument to measure the effectiveness of the intervention. The verification application was installed on the devices of 26 Living Lab participants. Then, 14 participants were asked to implement the sleep improvement program in accordance with the intervention, while the remaining 12 participants went about their daily lives as usual. During Living Lab, the application was used to estimate participants' daily stress and cognitive performance states.

2) Verification Results

Stress estimation results were evaluated from the following two perspectives.

(1) Intervention effectiveness

The stress states of the intervention group and the non-intervention group were compared to confirm whether there were any improvements in stress states.

(2) Validity of stress estimation results

We confirmed the degree of agreement between the results of the questionnaire at the beginning and end of Living Lab and the stress estimation results, and verified that it is possible to actually use the estimation

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*5　Living Lab: An initiative to create services and products based on the knowledge gained by repeatedly conducting experiments and evaluations in a real environment in which users and providers work together to solve social issues.

model.

In the case of (1), we conducted the following analysis assuming that stress states improved with the implementation of the intervention. Periods i and ii refer to the periods before and after the intervention, respectively.

(A) Comparison of stress states between the intervention group (period i) and the non-intervention group (period i)

(B) Comparison of stress states between the intervention group (period ii) and the non-intervention group (period ii)

In this case, the assumption may be valid when there is no significant difference in (A) and a significant difference can be confirmed in (B). We used the Mann-Whitney U test*6 as the testing method, and set the significance level to 0.05.

Figure 4 shows the analysis results. The "*" in the figure indicates that the significance level has been met. In (A), we could not confirm any significant difference in the results of stress and cognitive performance estimation between the two groups. However, in (B), a significant difference between the two groups in the results of stress and cognitive performance estimation was confirmed, suggesting the intervention may have contributed to the improvement of stress states. In addition, the intervention group showed an increase in low stress

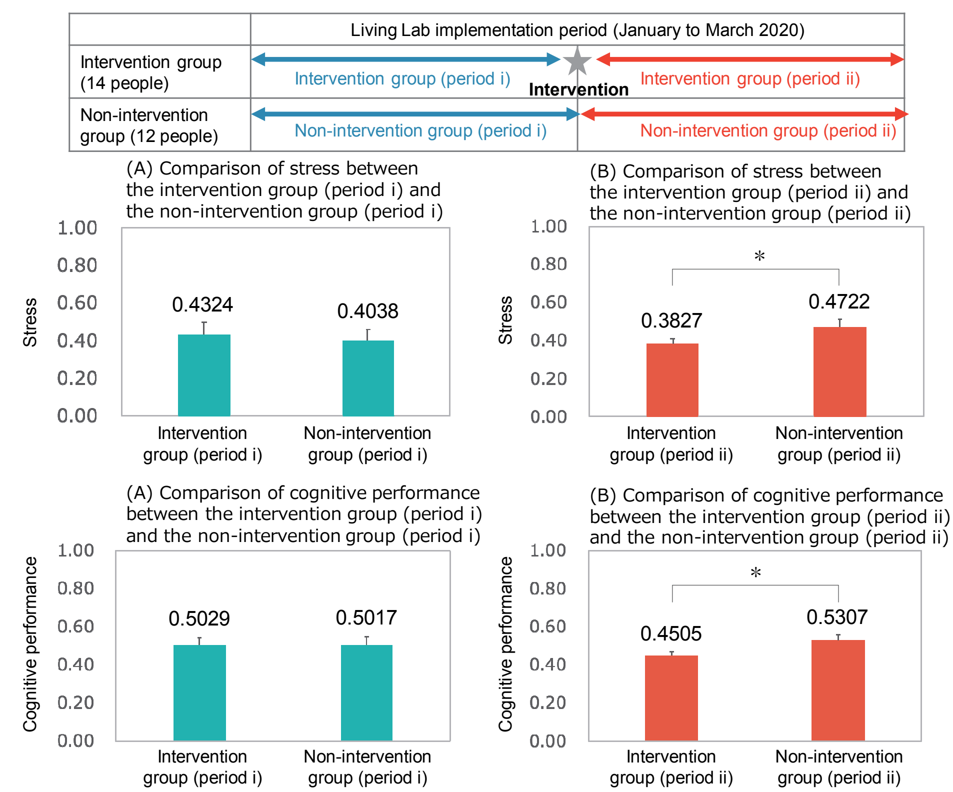

Figure 4 Changes in stress, cognitive performance due to the intervention

*6 Mann-Whitney U test: A non-parametric test for examining whether there is a statistically meaningful (significant) difference between two groups of data.

and low cognitive performance states, which can be interpreted as an increase in the relaxed state due to the intervention, which was intended to improve sleep quality.

Regarding (2), the questionnaire showed that the intervention group improved for the three items of stress response, subjective sleep quality and work results. From these results, it can be interpreted that the estimates made by the stress estimation model were reasonable. In addition, as mentioned above, we confirmed an increase in the relaxed state from the results of stress and cognitive performance estimation, while the questionnaire showed an improvement in work results. This can be interpreted as results of the intervention, which created a balance between the states of maintaining high work efficiency while feeling moderate stress, and relaxation.

4. Conclusion

In response to the growing interest in mental health care, we proposed a model for estimating the daily mental health of users based on logs collected from smartphones and described the results of a validation experiment using the model. Focusing on the advancement of the proposed technology by further verifying the results of this study, NTT DOCOMO INC. will accelerate efforts toward the practical application of the technology to support the mental health care of its customers. Going forward, we aim to provide comprehensive support for customers' physical and mental health care and contribute to extending their healthy life expectancy*7.

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*7 Healthy life expectancy: The period of life during which a person is able to spend his or her daily life without any physical or mental health problems.