International Journal of Smart Computing and Artificial Intelligence
International Institute of Applied Informatics
2024, Vol. 8, No. 1, IJSCAI760

Self-mental Care Management System by Emotion Estimation Method for Heart Rate Variability

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Abstract

This study introduces a self-mental care management system utilizing an emotion estimation technique applied to heart rate variability parameters derived from vital data. The escalating prevalence of pandemics has exacerbated the dearth of accessible mental healthcare services, underscoring the heightened significance of investing in mental health programs. However, advancements in sensor technology, marked by enhanced precision and reduced size, facilitate the rapid acquisition of vital data from users. In our approach, we capture electrocardiogram (ECG) data concurrently with the narration of emotionally evocative stories. Through the analysis of the resulting data trends, emotions strongly correlated with the newly acquired ECG data were identified and inferred to be the emotions manifested within the ECG data. Our methodology enables the estimation of user emotions based on ECG data, and is further implemented in an application featuring real-time visualization of users' emotional states through chat icons. The deployment of this application empowers users to monitor emotional fluctuations and effectively manage their mental wellbeing.

Keywords: ECG, self-mental care management system, vital data, emotion estimation

1 Introduction

The Healthy Minds Network for Research on Adolescent and Young Adult Mental Health (HMN) and the American College Health Association (ACHA) have released a report, “The Impact of COVID-19 on College Student Well-Being” [1]. The information is based on responses from 18,764 students enrolled in 14 U.S. colleges and universities. According to this report, the number of depressed college students has increased since campus closure due to coronavirus infections compared to the fall 2019 semester. This indicates that many students have been under stress since the outbreak of coronavirus infection. To alleviate stress, 41.8% of the students reported that they had attempted to seek mental health care during the pandemic. On World Mental Health Day, the WHO [2] also stated that investment in mental health programs is more important than ever before. This means that the demand for mental healthcare is increasing. However, 60%

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of the students in this report indicated that the pandemic has made it harder to access mental healthcare services. In other words, self-care is becoming more important because there are increasingly more situations in which mental health care is unavailable. Mental health care can be divided into two main categories: consultation with a specialist and consultation with a close friend. Consult. They consulted people close to them. Selfcare. However, it is difficult for people who cannot receive mental health care or have fewer opportunities to talk with others to realize that they need mental health care and to take care of themselves. Therefore, it is important to make them aware of their mental health needs and to provide them with opportunities to act.

With the advancement of ultra-small biosensors employing cardio chips [3], sensors capable of measuring vital data are progressively shrinking and simplifying. This enhancement in sensor technology has resulted in heightened precision and reduced size, enabling users to instantaneously access vital data. For this reason, there has been a surge of interest in telemedicine and telemonitoring applications that leverage vital data in recent years. An illustrative example is the development of a non-contact health management system [4] designed to assess vital signs such as SpO2 (percutaneous oxygen saturation), heart rate, respiration rate, heart rate variability, and mental stress levels solely through a smartphone. Targeted for utilization in the telemedicine, telehealth, and welfare sectors, these systems typically provide real-time output of vital data. The capability of remotely accessing real-time vital data aligns well with the contemporary era, and is witnessing a growing demand. Real-time vital data serves as an effective means of automated information dissemination to external stakeholders.

Hence, our focus was on real-time electrocardiogram (ECG) data. By developing a system capable of inferring emotions from ECG data and presenting them as icons within a chat application, individuals can monitor their emotional states during conversations. In instances where negative emotions are indicated, users may choose to conclude an interaction prematurely. Conversely, upon observing positive emotional cues, users can opt to prolong their conversation. Consequently, the use of these emotional indicators serves as a tool for self-regulating mental well-being. Moreover, as the displayed emotion icons exclusively reflect the user’s emotions and are not stored, they provide insight solely into one’s present emotional state.

As a result, self-mental care management can be achieved even when mental health care is not available because knowing one’s emotions allows one to take measures to deal with them.

In this paper, we present a self-mental care management system using an emotion estimation method for heart rate variability parameters of vital data and its application to real-time chat icon creation corresponding to the user’s emotion estimated by our method. Our method measures ECG data while listening to a story with a voice narration that evokes an emotional response. Based on the trends obtained from the measurements, the emotions that correlated well with the newly acquired real-time ECG data were estimated as emotions expressed in the ECG data. In addition, the definition of emotion was clarified using definitions in the four emotion quadrants and 15 emotion definitions. By employing our approach, the estimation of user emotions using ECG data becomes feasible. By representing these estimated emotions through facial expression icons within the chat application, users can monitor fluctuations in their emotional states, thus facilitating mental health management. Examples of the emotions depicted by icons are shown in Figure 1. In essence, the development of this application enables users to track emotional changes and respond accordingly, thereby promoting self-care for mental well-being.

The remainder of this paper is structured as follows: Section 2 provides an overview of related research. Section 3 outlines psychological research underpinning the estimation of emotions using our methodology. Section 4 details the implementation of our proposed approach using ECG data. In Section 5, we describe the construction of an experimental system for implementing our method, conduct an evaluation experiment, and present the findings. Finally, Section 6 concludes the paper.

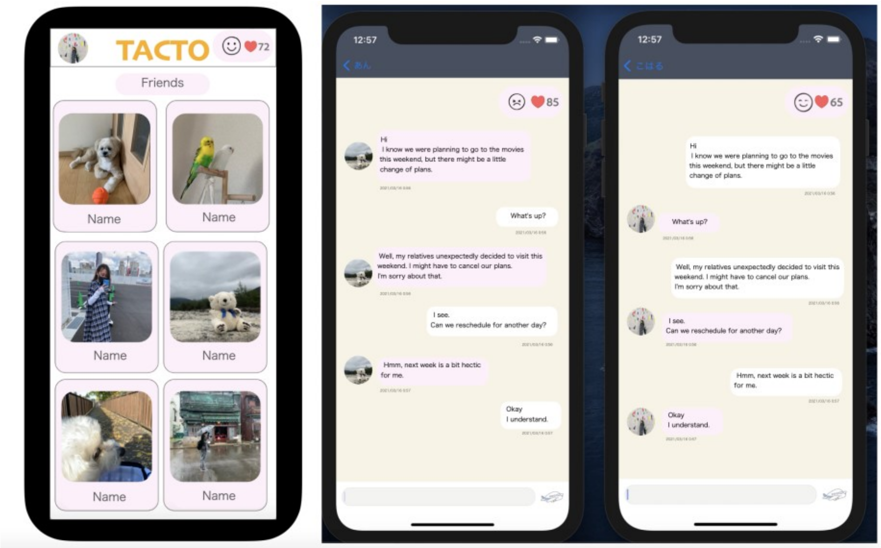


Figure 1: Example of real-time chat icon creation corresponding to the user's emotion estimated by our method: The screen on the left is the user's photo, the facial expression icon of the emotion estimated by ECG, and the heart rate. A tap on a user's photo will take you to his or her chat screen (right screen).

2 Related Works

In this section, we present research related to the proposed method.

Zhao et al. [5] have developed a system that uses electromagnetic waves to automatically detect human emotions such as excitement, joy, anger, and sadness. Body sensors such as ECG monitors are cumbersome to put on and take off, and there is a risk that the data may become inaccurate because of misalignment as the experiment is repeated. To solve this problem, it irradiates electromagnetic waves onto an individual's body and obtains heartbeat data from the reflected waves. A proprietary machine-learning algorithm analyzes the reflected waves to detect the level of excitement and emotion by capturing slight temporal changes between heartbeats. From this, they infer emotions, and although there are individual differences, they have succeeded in inferring emotions 70% of the time, even for people measuring them for the first time.

Tivatansakul et al. [6] designed a healthcare system focusing on emotional aspects to cope with negative emotions in daily life. They experimentally evaluated the efficiency and effectiveness of recognizing negative emotions in real time. This study focused on emotion recognition using ECG signals and applied and evaluated local pattern description methods, local binary pattern (LBP), and local ternary pattern (LTP), which are suitable for emotion recognition using facial expressions. The results showed that LBP and LTP can effectively extract ECG features with high accuracy. The results showed that real-time emotion recognition from ECG signals is sufficiently beneficial and efficient for emotional systems to analyze negative emotions and provide support.

Sarkar [7] et al.. proposed an ECG-based emotion recognition solution based on self-supervised deep multitask learning. This study performed emotion recognition on four public datasets:

AMIGOS, DREAMER, WESAD, and SWELL. They showed that the proposed method can significantly improve the classification performance compared to a fully supervised solution.

We conducted research on four-quadrant emotion estimation using the heart rate variability parameters of vital data [8]. In recent years, as sensors have become more precise and smaller, it has become possible to quickly obtain users' vital data in real time. In our method, electrocardiogram (ECG) data are measured beforehand while listening to a story with voice narration that evokes emotions. Based on the trends obtained through the measurement, the emotions that had a high correlation with the newly acquired ECG data were estimated as. This was expressed in the ECG data. With the implementation of our method, it is possible to estimate emotions similar to those of the current user from the ECG data.

They also considered various self-supervised transformation recognition tasks for learning ECG representations and analyzing their impact. The results show that the network learns better ECG representations that can be used for emotion classification in pretext tasks with an optimal difficulty. They also showed that multitasking CNNs improved the performance of learning ECG representations compared with single-tasking networks. Finally, an analysis of multiple datasets to train a self-supervised network showed that using multiple datasets is beneficial for the final downstream classification.

Our proposed method calculates heart rate variability parameters from ECG data and estimates emotions based on previously associated emotions to identify changes in one's own emotions and self-mental care management in response to those changes. Because the connection between ECG data and emotions differs among individuals, we developed a mobile application for emotional elicitation, performed emotional elicitation within the application, and measured ECG data during elicitation. This application allowed us to correlate the measured ECG data with the evoked emotions.

A pseudo-experience is conducted while the user listens to a story with a voice narration that elicits emotions. After listening to the voice, the user was asked to select the appropriate emotion, and the ECG data could be related to the emotion. The proposed system estimates and visualizes emotions from ECG data in real time using this relationship. The system visualizes emotions as facial expression icons in a chat application in real time. In addition, we categorized the emotions obtained during emotion elicitation into four categories and estimated a total of five emotions, including four emotions and the normal state.

3 Emotion Classification for Emotion Estimation

In our method, ECG data were used to estimate emotions. Our method aims to estimate and visualize emotions from new ECG data by correlating emotions previously elicited using an emotion-eliciting application with the measured ECG data. In this method, the emotions evoked by the stimulus, a simulated experience using voice narration, were classified into four quadrants. In addition, by selecting which of the 15 emotions apply to each of the four quadrants, we can relate the four quadrants to the 15 emotions. Roseman's primary appraisal dimensions and consequences [9] and Lazarus' emotions and their cognitive causes [9] were used for the four emotional quadrants and 15 emotions, respectively.

Roseman categorized emotions into four quadrants as primary appraisal dimensions and their consequences, as shown in Table 1. Lazarus lists fifteen emotions and their related cognitive causes themes as emotions and their cognitive causes in Table 2.

Emotion	**Core relational theme**
Anger	A demeaning offense against me and mine
Anxiety	Facing uncertain, existential threat
Fright	Facing an immediate, concrete, and overwhelming physical danger
Guilt	Having transgressed a moral imperative
Shame	Having failed to live up to an ego ideal
Sadness	Having experienced an irrevocable loss
Envy	Wanting what someone else has
Jealousy	Resenting a third party for loss or threat to another's affection
Disgust	Taking in or being too close to an indigest- ible object or idea (meta-phorically speaking)
Happiness	Making reasonable progress toward the realization of a goal
Pride	Enhancing our ego identity by taking credit for a valued object or achievement, either our own or that of some person or group with whom we identify
Relief	A distressing goal-incongruent condition has changed for the better or gone away
Hope	Fearing the worst but yearning for better
Love	Desiring or participating in affection, usually but not necessarily recip-rocated
Compas-sion	Being moved by another's suffering and wanting to help

Table 1: Emotions and their cognitive cause

In our method, these two emotional categories were applied. As for Roseman's "Primary appraisal dimensions and their consequences," since the emotions that fit into those four quadrants are the only examples, in our method, a questionnaire is conducted in the implemented application to determine which of the four quadrants is applicable. The user is asked to select one of the 15 Lazarus emotions in the implemented application to fit an emotion into one of the four quadrants of emotions. An example display of the application implemented for emotion elicitation and a questionnaire are shown in Figure 2. It allows us to classify the evoked emotions into four quadrants and 15 types, and we view the selected emotions as evoked emotions.

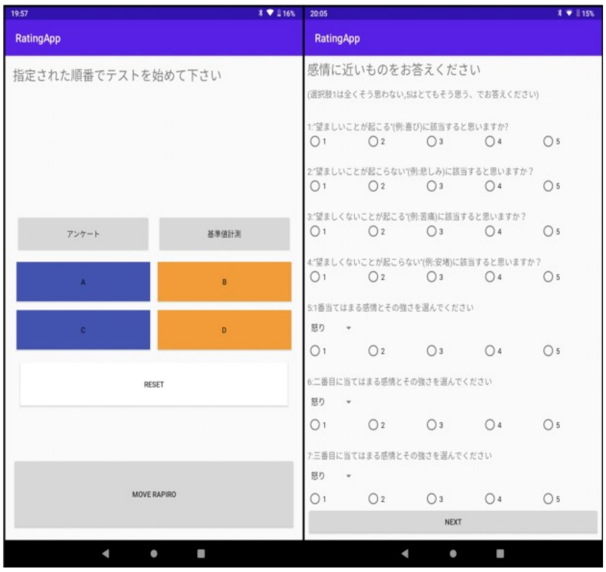


Figure 2: Application Screen: The screen on the left is the home screen of the application for emotion elicitation and questionnaire. From left to right, questionnaire of the situation, baseline measurement, negative emotion elicitation (first part), positive emotion elicitation (first part), negative emotion elicitation (second part), positive emotion elicitation (second part). The screen on the right shows a questionnaire about current emotions, based on Section 3.

	Occur	Not Occur
Desirable	Joy	Sorrow
Undesirable	Distress	Relief

Table 2: Primary appraisal dimensions and their consequences

4 Emotions Estimation Method for Vital Data and Its Application to Real-Time Chat Icons

4.1 Outline of the Proposed Method

In this section, we provide an overview of the proposed method. An outline of the proposed method is shown in Figure 3. The system calculates the values of SDNN, RMSSD, and CVSD, which are indices of heart rate variability parameters, from ECG data obtained from the ECG measurement device. In this study, we used wearable electrodes attached to the user, estimated the emotions correlated with these values, and displayed an icon that matched the emotions on the chat application.

In this study, Hitoe ® from NTT Corporation/Toray Industries, Inc. was used as the wearable electrode. Hitoe® is a composite material of the conductive polymer PEDOT: PSS and nanofibers, and was developed as a woven bioelectrode to acquire vital data, such as heart rate and electrocardiogram measurements [10]. Because biometric data can be obtained without any burden for a long time by wearing hitoe-equipped equipment, it is being used as a vital monitoring tool in many fields.

Our methodology involves the development of an application designed to evoke emotions through voice narration, facilitating the correlation of ECG data with emotional states. Additionally, a questionnaire was used to characterize these emotions. ECG data were collected during emotional elicitation via voice narration using this application. Subsequently, heart rate variability parameters, including SDNN, RMSSD, and CVSD, were computed from the acquired ECG data. By establishing a connection between the recalled emotions during emotional elicitation and the heart rate variability parameters measured concurrently, it is hypothesized that an approximation of the linked heart rate variability parameters during emotional elicitation can be obtained.

In our method, the ECG was measured in a resting sitting position with eyes closed during wakefulness, and the heart rate variability parameters were calculated. In this method, the ECG is measured in the resting position with the eyes closed for 15 seconds before the voice is elicited; this is regarded as the normal state. The ECG was measured for 15 seconds in the closed-eyed state before emotional elicitation, which was regarded as the normal state. The eyes were closed when listening to the voice narration, and a questionnaire about the current emotion was given immediately after listening to the voice narration. We can relate the ECG and emotions during emotion elicitation and estimate emotions by repeating these procedures. In our method to classify emotions, we use Roseman's "Dimensions and Consequences of Appraisal" [9] introduced in Chapter 3. We categorize users' emotions into four quadrants as defined in Roseman's work: "Desirable/Occur," "Desirable/Not occur," "Undesirable/Occur," and "Undesirable/Not Occur." Users expressed their current emotions by scoring the four emotional quadrants in the in-app questionnaire. In our method, we used two methods to classify emotions. The first uses Roseman's "Dimensions and Consequences of Appraisal" [9], introduced in Chapter 3. We categorize users' emotions into four quadrants as defined in Roseman's work: "Desirable/Occur," "Desirable/Not occur," "Undesirable/Occur," and "Undesirable/Not Occur." Users express their current emotions by scoring these four emotional quadrants in the in-app questionnaire. The second uses Laus' "Emotions and Their Cognitive Causes" [9], introduced in Chapter 3. We categorize users' specific emotions into fifteen emotions defined in Lazarus' work: "Anger," "Anxiety," "Fright," "Guilt," "Shame," "Sadness," "Envy," "Jealousy," "Disgust," "Happiness," "Pride," "Relief," “Hope,” “Love,” and “Compassion.” Users expressed their current emotions by scoring these 15 emotions using an in-app questionnaire. These “15 emotions” and “four quadrants” were used to clarify the user's emotions.

4.2 Outline of the Proposed Method

This section describes the feature extraction function for the ECG data acquired from the ECG measurement devices. This system consists of three functions: Real-time ECG acquisition, noise reduction, and Heart rate variability parameter calculation.

4.2.1 Real-time ECG Acquisition

To express emotions using a Real-Time ECG, it is necessary to acquire a Real-Time ECG. In this method, vital data are measured using a heart rate measuring device called Hitoe ® from NTT Corporation/Toray Industries, Inc. To perform real-time emotional icon expression, it is necessary to answer a questionnaire that expresses the current emotions. It is also essential to perform the analysis and calculation of ECG in real time; therefore, experiments through applications are required.

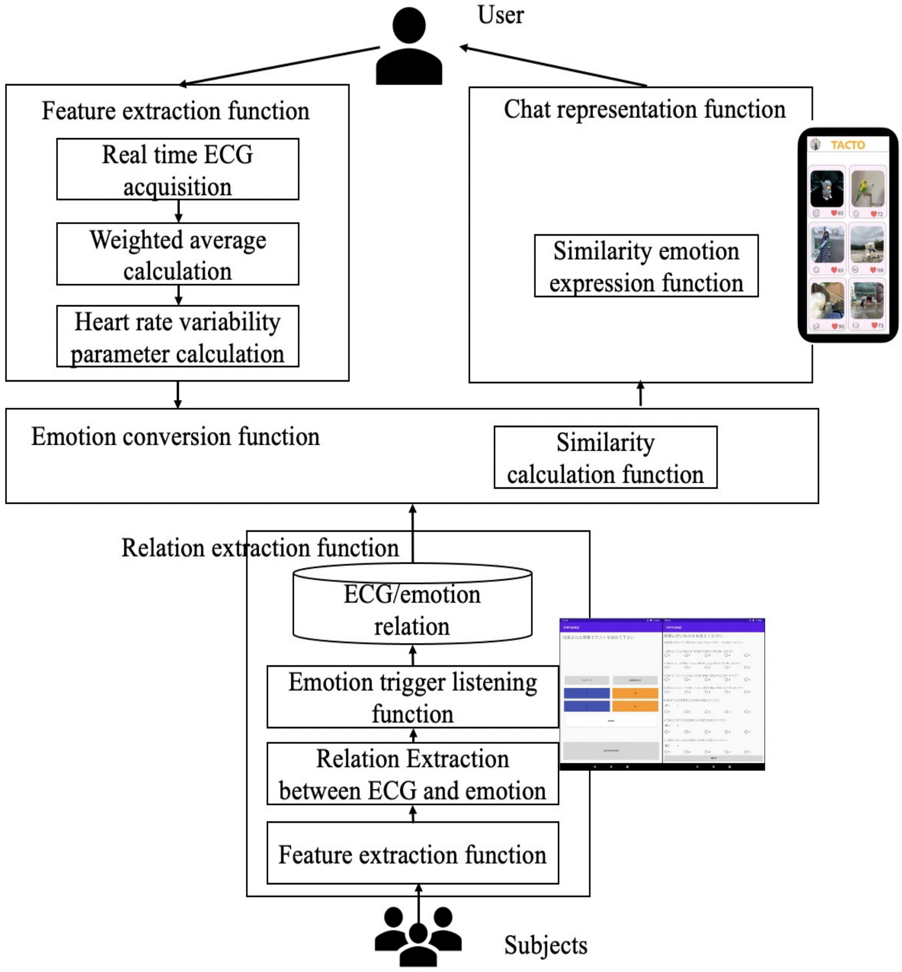


Figure 3: Overview of our proposed method

4.2.2 Noise Reduction

In typical scenarios, noise interference is a common occurrence during the measurement of ECG signals. Traditionally, noise elimination has been achieved through statistical analysis of ECG data obtained from participants. However, in the present method, data are collected in the form of "real-time data" or "individual-specific data," posing challenges in obtaining statistical insights across multiple participants. Hence, in our approach, we adopt a noise removal technique wherein RRIs (R-R intervals) less than or equal to 300 or exceeding 2000 are filtered out. Employing this threshold allows real-time noise removal processing.

4.2.3 Heart Rate Variability Parameter Calculation

Three parameters are used among the heart rate variability parameters in this study. The first is SDNN, which is the standard deviation of RRI (R-R Interval); the second is RMSSD, which is the square root of the mean of the squares of the differences between successively adjacent RRI, and is an index of vagal tone strength. A decrease in RMSSD is associated with a decrease in parasympathetic nerve activity. The third is the CVSD, which is the RMSSD divided by the mean of the NNI, and CVSD is the coefficient of variation of the continuous difference. These values were assumed to be related to emotions, and calculations were performed.

4.3 Relation Extraction Function

This section describes a method for associating emotions with an ECG used for emotional expression. This function consists of four functions: feature extraction, relation extraction between ECG and emotion, emotion trigger listening, and ECG/emotion relation.

4.3.1 Noise Reduction

Real-time ECG acquisition, noise reduction, and Heart rate variability parameter calculations were performed according to the method described in Section 4.2).

4.3.2 Relation Extraction between ECG and Emotion

In our method, the relationship between the ECG and emotion is determined by measuring the ECG during emotion elicitation. Accordingly, it is necessary to obtain an ECG signal under normal conditions. Therefore, by acquiring the ECG at rest for 15 s, an ECG at a normal state is achieved. The reference value was measured at the beginning of the experiment to avoid triggering emotions.

4.3.3 Emotion Trigger Listening Function

Our method aims to elicit emotions by having the user listening to an audio narrative story that evokes emotions. Inducing basic emotions to collect data in an experiment generally involves five methods: audiovision, imagery, music, memory recall, and situational judgment [11]. Less common methods include spontaneous conversations and discussions [12], driving [13], video games [14], and virtual reality [15]. Listening to music is another popular way to activate emotions through lyrics, melodies, and tempo changes [16]. Nevertheless, in our endeavor to evoke intense emotions, we employed storytelling as a means of emotional induction. Emotions were elicited through the recollection of memories and by immersing the participants in the narrative

through auditory stimuli. The narrative utilized in this study comprises two segments: one designed to evoke negative emotions and another intended to evoke positive emotions. To induce positive emotions, we utilized a CD accompanying the book titled “Introduction to Meditation with Yoga” (in Japanese) [17]. This CD is renowned for its ability to facilitate a sense of liberation and tranquility, liberating individuals from the burden of everyday life. Narrated by the author, the story guides listeners through meditation, directing them to adjust their posture and visualizing the inner workings of their bodies. The narrative is structured around two primary sections: “Learning to Breathe Slowly” and “Deepening Meditation by Adjusting the Seven Chakras of the Body One by One.”
In this context, “chakra” refers to energy pathways believed to run along the spine at the core of the human body, with seven distinct points along the line known as chakras purported to influence both the mind and the body. The contents of the two chapters from the book were amalgamated into a single chapter for this study.

To elicit negative emotions, we adopted the “Death Experience Lesson” (in Japanese) [18], which provides a simulated experience of one's death. This story was used in a workshop for young students to deepen their understanding of death by simulating the dying process and confirming that life shines only because of death. The story consists of 10 chapters: “stomach distress,” to be retested, “sleep due to anxiety,” family is called, “cancer is announced,” school is suspended, “treatment is stopped,” pain increases, “consciousness becomes fuzzy,” and “last breath,” which are used throughout the story. In the Death Experience Lesson for eliciting negative emotions, a third party reads the story, and the third party's voice is recorded as one of the contents for evoking emotions. In the death experience lesson used for negative emotion elicitation, a third party read the story and recorded the third party's voice, which was used as one of the contents for emotion elicitation. In addition, in the death experience lesson, the students wrote down the things that were important to them to experience loss and then erased them one by one during the story.

These two stories were divided into six chapters, with the first half being chapters 1-3 and the second half being chapters 4-6. These were divided into four sets: the first half of the positive story, second half of the positive story, first half of the negative story, and second half of the negative story.

In addition, the “Death Experience Lesson” consists of writing down important things to experience loss, and then erasing them one by one during the story. These two stories are divided into six chapters, three in the first half and three in the second half, making up four sets. (Table 3).

Story Categories	Emotional Trigger Story
Standard	standard value
A	Negative1-3
B	Positive1-3
C	Negative4-6
D	Positive4-6

Table 3: Relationship between story categories

Two patterns are prepared for the participants to prevent the order effect: “A→B→C→D,” which starts with negative emotion elicitation, and “B→A→D→C,” which begins with positive emotion elicitation. By changing the order in which emotions are elicited, the goal is to prevent the sequential effect of the question-answer function. A questionnaire on current emotions was administered at the end of each chapter to define the emotions elicited. The content of the questionnaire was selected from the four emotional quadrants and 15 emotions listed in the emotional classification in Section 3. In each of the four emotional quadrants, respondents were asked to rate the degree to which the statement was true on a five-point scale from “very true” to “not true at all.” In each of the four emotional quadrants, the participants rated the extent to which the statements were true on a 5-point scale from “very true” to “not true.” In addition, from the fifteen emotions listed in the emotion categories in Section 3, we chose three that currently apply and rate their intensity in the same way. Thus, each chapter has four questions. These tasks were performed 12 times, with six chapters each for positive and negative emotions.

4.3.4 ECG/Emotion Relation

It is necessary to divide the ECG data into scenes to relate the ECG data with emotions during emotion elicitation. ECG data that passed through the feature extraction function in Section 4.2) were saved for each scene. ECG data can be related to the emotions in each scene.

4.4 Emotion Conversion Function

This section describes a method for converting real-time ECG data into emotions using emotion-related ECG data obtained in Section 4.3. We refer to the ECG data associated with the chapter emotions conveyed in Section 4.3 as the emotional ECG data.

Real-time ECG acquisition, Noise Reduction, and heart rate variability parameter calculations were performed.

To express emotions in real time, it is necessary to estimate emotions by comparing the emotional ECG data acquired in Section 4.3) with real-time ECG. Emotional ECG data store three values of SDNN, RMSSD, and CVSD per chapter of the story. Hereafter, ECG data at normal times are included in “Emotional ECG data” as normal ECG data. Therefore, ECG data (SDNN, RMSSD, CVSD) for 13 scenes (six chapters of positive story, six chapters of negative story, and normal time) were stored in the emotional ECG data.

The similarity calculation between real-time ECG and emotional ECG was performed using SDNN, RMSSD, and CVSD. For each of the three indicators, we obtained the three scenes judged to be similar. The emotion in the scene with the highest votes among the three extracted scenes was the emotion closest to the current emotion.

4.5 Chat Representation Function

This section describes the method of expressing the emotion inferred in Section 4 as an expression icon in the chat.

To depict the prevailing emotion of a scene, determined by the highest number of votes, as established in Section 4.4), our methodology integrates facial expression icons into the chat application interface. Preliminary experiments have demonstrated that emotions elicited across chapters 1-3 and 4-6 exhibit similarities, irrespective of whether they are positive or negative. Therefore, the scene's emotion with the highest vote count is deemed as the current emotion, and the corresponding expression icon is presented within the chat application. By integrating facial expression icons associated with emotions evoked in story categories A, B, C, and D into the chat application, users were provided with real-time visual representations of their emotions. These icons serve as immediate indicators of approximate emotions, facilitating a prompt awareness of one's emotional state. Using this approach, individuals can objectively observe fluctuations in their emotions and take proactive measures to regulate them.

5 Experiment

First, we conducted an experiment using the system described in Section 4. In this section, we describe the results of the system evaluation. Section 5.1) describes the experimental setup. Section 5.2) describes the system evaluation results using four quadrants of emotion. In Section 5.3), we describe the system evaluation results using the 15 emotions. In section 5.4), we describe the evaluation results of the features from the ECG data when listening to each story. In Section 5.5), we discuss the effectiveness of the system and the evaluation results of its application to facial expression icons.

5.1 Experimental Environment

This experiment was conducted on five healthy men and women in their 20s. The number of participants in the experiment was small because the purpose was to perform emotion estimation that was specific to each individual, rather than emotion estimation that would work for everyone. The measurements were taken while sitting in a comfortable position with eyes open. During normal measurement and emotional elicitation, the application system prompts the user to close their eyes, and the ECG data are retrieved with their eyes closed. The experiments were performed in compliance with national legislation and the Code of Ethical Principles for Medical Research Involving Human Subjects of the World Medical Association (Declaration of Helsinki).

5.2 Experiment 1: Investigate the quadrant of emotions elicited by listening to stories.

In Experiment 1, we investigated the quadrants of emotions elicited by listening to the stories defined in Section 3.4. The details of this method are described in Section 3.4. The participants listened to six positive and six negative stories. Immediately after listening to each story, the participants expressed their current emotions by scoring them in four emotional quadrants, as defined by Roseman. The participants scored each story on a five-point scale from 1 to 5.

We took a questionnaire using the method described in section 4.3.3) and then calculated the sum of the five people's five-point ratings to show the percentage of emotions in the four quadrants of each scene. Figure 4 shows the results of the questionnaire. Figure 4 shows the proportion of emotions in the four quadrants of each scene, categorized into the “story categories” in Table 3. As a result, In the Positive1-3 group, “Undesirable/Not Occur” was the most frequent response, and listening to the Positive1-3 group elicited the emotion “Undesirable/Not Occur.” In the Positive4-6 group, “Desirable/Occur” was the most frequent response, and listening to the Positive4-6 group elicited the emotion “Desirable/Occur.” In the Negative1-3 group, “Desirable/Not occur” was the most frequent response and listening to the Negative1-3 group elicited the emotion “Desirable/Not occur.” In the Negative 4-6 group, “Undesirable/Occur” was the most frequent response, and listening to the Negative 4-6 group elicited the emotion “Undesirable/Occur.”

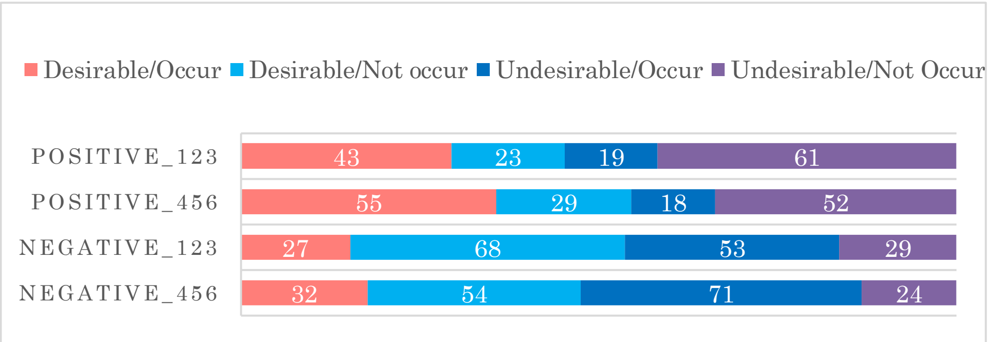


Figure 4: Relationships between the four quadrants of emotions and the story

5.3 Experiment 2: Investigations of emotions elicited by listening to stories.

The experiment investigates the emotions elicited by listening to the stories defined in Section 3.4. The details of the method are described in Section 3.4. Subjects listen to six positive stories and six negative stories. Immediately after listening to each story, the participants expressed their current emotions by scoring to find emotional emotions by Lazarus. The subjects selected three emotions for each story and rated them on a 5-point scale from 1 to 5.

Figure 5 shows the results of the questionnaire. We administered a questionnaire using the method described in (4.3.3) and then calculated the sum of five people's five-point ratings to show the percentage of emotion for each scene.

Figure 5 shows the percentage of emotions in each scene, categorized by each story. In this questionnaire, we asked them to rate, on a five-point scale, how well their feelings about each story applied to each of the viewpoints in Table 2. We administered a questionnaire using the method described in Section 4.3.3, and then calculated the sum of the five-point ratings of five people to show the percentage of emotions in each scene. As a result, the positive stories elicited overall feelings of "Relief," "Happiness," and "Hope." Negative stories elicited feelings of "Anxiety," "Fright," and "Sadness."

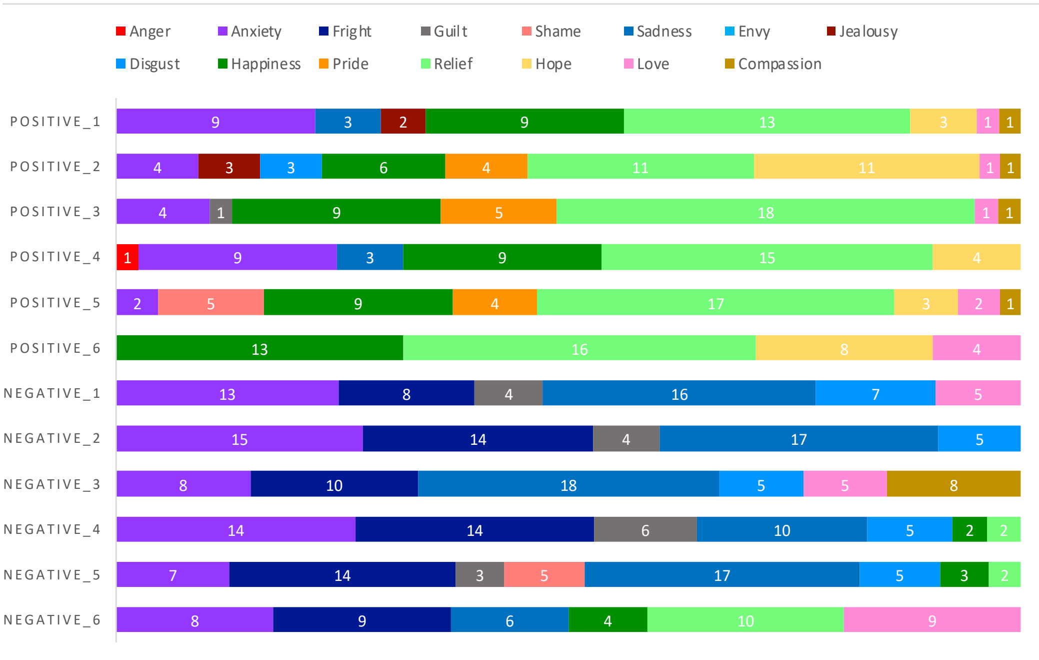


Figure 5: Relationships between emotions and the story

Figure 6 shows the percentage of emotions in each scene, categorized into the first and second halves of the story, as shown in Figure 4. In this questionnaire, respondents were asked to rate on a 5-point scale the degree to which their feelings about each story were applied to each perspective in Table 2 after taking the questionnaire using the method described in Section 4.3.3. We calculated the sum of the five-point ratings of the five respondents' 5-point ratings to show the percentages of emotional involvement in the first and second halves of the story.

The results showed that the Positive1-3 group elicited emotions that are generally considered positive, as Relief and Happiness were more frequent in the Positive1-3 group. Based on the post-experiment questionnaire, we consider that the "Anxiety" in this scene is "Anxiety" about the experiment. Thus, listening to the Positive1-3 group elicited mainly the emotions "Relief, Happiness." Similar results were obtained for the Positive4-6 group.

The Negative1-3 group elicited generally considered negative emotions, as Sadness, Anxiety, and Fright were more common. From the post-experiment questionnaire, we consider that "love" in this scene is "love toward family members or important persons." Thus, listening to the Positive1-3 group elicited mainly the emotions "Sadness, Anxiety, Fright." Similar results were obtained for the Negative4-6 groups

Figure 6: Relationship between emotions and the first half and the second half of the story

5.4 Experiment 3: Extraction of features from ECG data when subjects listened to each story.

In Experiment 3, we obtained SDNN, RMSSD, and CVSD when listening to the story defined in Section 3.4. The details of the method are described in Section 4.2.3.
Subjects listen to six positive stories and six negative stories. While listening to each story, we obtained ECG data and calculated the SDNN, RMSSD, and CVSD.

The results of the obtained indicators (SDNN, RMSSD, and CVSD) were used to relate them to the scenes in the obtained stories. By associating the sentiment of the answers to the questionnaires with the stories, we linked the questionnaires to the indicators (SDNN, RMSSD, CVSD). The indices used are as follows: SDNN is the standard deviation of the R-R Interval (RRI), RMSSD measures the strength of vagal tone, and RMSSD is CVSD divided by the mean of NNI. These values were assumed to be related to the emotions.

Figure 7 shows the results of SDNN, RMSSD, and CVSD for each subject obtained when listening to the stories defined in Section 4.3. Green points show a normal state in these figures, blue points show negative stories (Chapters 1 to 6), and red points show positive stories (Chapters 1 to 6). Because this study aims not to obtain statistical ECG data but to consider individual differences and estimate emotions specific to everyone, the results of two of the five experimenters are represented and explained.

The results for Participant 1 are shown below. In SDNN, positive stories are relatively more numerous than negative stories. RMSSD and CVSD yielded similar results. In general, a decrease in RMSSD decreases the parasympathetic nerve activity. In Positive4-6, the parasympathetic nervous system was significantly activated, and in Positive1-3, the values increased significantly. After the experiment, Experimenter 1 stated that he was puzzled first because he had no experience with meditation, which was used to elicit positive emotions. Therefore, we speculate that confusion appeared at the beginning of the experiment. As participants became accustomed to Positive 4-6, they began to experience a sense of relief. As for the changes in Negative 4-6, it is considered that the story of Negative 5 may have moved their emotions significantly because of the scene just before death.

The results for participant 2 are shown below. The values of Positive 1-6 and Negative 1-3 were relatively low, suggesting that the parasympathetic nervous system was dominant. In negative 4-6, the values were significantly higher. Therefore, it is considered that the emotions were affected considerably by Negative 4-6. SDNN, RMSSD, and CVSD yielded similar results.

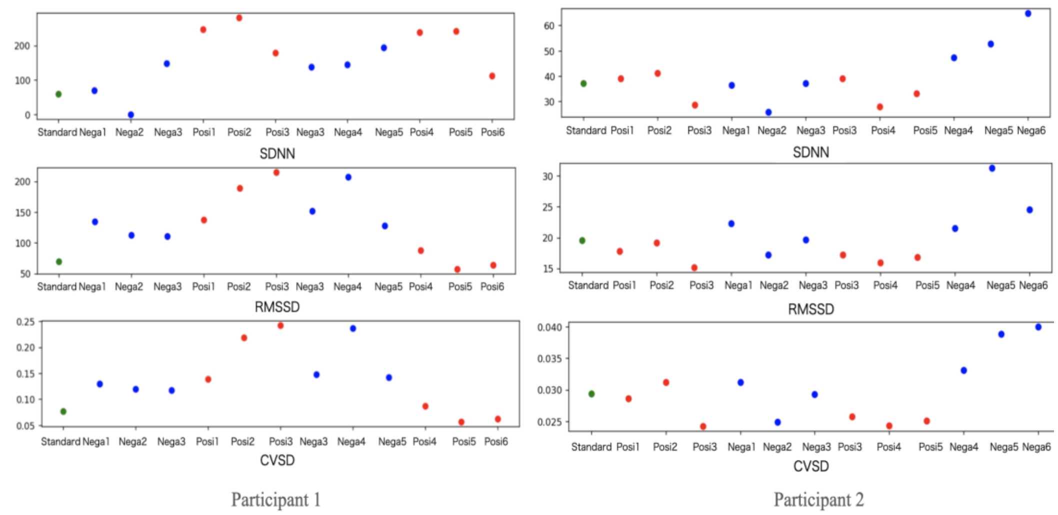


Figure 7: Experimental results for participant

5.5 Experiment 4: Application to Representation of Facial Expression Icons.

In Experiment 4, the validity of the system was investigated. This is because the subject experienced the system and after the emotion was associated with the (SDNN, RMSSD, and CVSD) values. They listen to the emotion-evoking narration again and verify whether the icons related to the story to which they are listening are displayed. The details of how they are represented as facial expression icons on the chat are described in Section 4.5. The author defined icons associated with narratives that evoked emotions based on the results shown in Figures 4 and 6. (Table 4: Defined icons). For environmental reasons, this experiment was conducted only by the author.

Table 4 shows the relationship between icons and stories and the results. The defined con shows the icons related to the story, as defined by the author. Result Icon shows the icons' results after listening to the story. This demonstrated the validity of the proposed system. Of the five icons, three stories, Positive Stories B and D, and Standard, displayed the relevant icons. However, for negative stories A and C, the icons for B and Standard are displayed, and the associated icons are not displayed for negative stories. As a result, a negative story was listened to for the second time. We speculate that the participants became accustomed to the story and felt relieved that it was proceeding as expected, because they knew how it would unfold. Therefore, the results were expected for the positive story and normal state but not for the negative story.

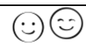
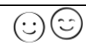
Story Categories	Emotional Trigger Story	Defined Icon	Result Icon
Standard	standard value		
A	Negative1-3		
B	Positive1-3		
C	Negative4-6		
D	Positive4-6		

Table 4: Relationship between story categories and icons displayed

6 Conclusion

In this paper, we presented a self-mental care management system using an emotion estimation method for heart rate variability parameters of vital data and its application to the display of icons corresponding to one's emotions in a chat room. In our method, ECG data are measured beforehand while listening to a story with voice narration that evokes emotions, and based on the trends obtained through the measurement, the emotions that have a high correlation with the newly acquired ECG data are estimated to be the emotions expressed in the ECG data. With the implementation of our method, it is possible to estimate the user's emotions based on ECG data.

We also present an application to chat icons that can express users' emotions in real time. By realizing this application, users will be able to check changes in their emotions and act according to those emotions, thus enabling self-mental care management.

Our future work will include realizing emotion estimation using ECG data with additional emotional elements, improving the accuracy of emotion estimation using machine learning, and combining vital data other than the ECG data. Further improvements in the accuracy can be expected by developing these methods. In addition, as a new means of mental care, we would like to consider a method of disclosing one's feelings to others and providing mental care among those close to one's heart. Once this method has been established, everyone can save on the feelings of those close to them.

Acknowledgments

I would like to thank Mr. Akitoshi Hashizume for his advice and guidance on developing the emotion-inducing application. I would also like to thank Mr. Sho Yamaguchi for his voice narration of the negative emotion elicitation. I would also like to thank the members of Musashino University's Trans Media Tech Lab for their cooperation with the experiment.

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