Regression Analyses between Physiological Indexes and Level of Understanding with VAS of a Listening Task

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Keywords: Level of Understanding, Physiological Index, Regression Analysis and Visual Analog Scale.

Abstract: This paper describes logistic regression analyses and multiple regression analyses to explain relationships between physiological signals and subjective self-reported levels of understanding of a second language listening task by using a visual analog scale (VAS) of 999 degrees. Mean contribution ratio of the logistic regression expressions was 0.72, and mean contribution ratio of the multiple regression expressions was 0.70. Power value of theta band of brain waves has a certain tendency to change according to the level of understanding. Accuracy of the regression expressions using VAS was the same or more than that of the four-level scale as our previous work.

1 INTRODUCTION

It is crucial to measure level of understanding as a metric of learning achievement, and this metric is used for self-reflective learning and also to develop heuristic guidelines to improve instruction methods and select appropriate materials. Although conventional quizzes and questionnaires are common methods for measuring the level of understanding, there are two major problems with such methods. First, these methods can impose the burden of answering a question even when the learner does not require this process because they already possess an effective level of understanding. Second, the methods interrupt learner's activity even when the learner wants to continue concentrating on that activity.

Several studies have reported that changes in physiological signals reflect changes in the levels of understanding of a learning task. For a verbal task, some results indicate that the power values of alpha and beta brain waves change relative to differences of in the difficulty level of the text in a reading task, e.g., brain blood flow increases when reading text in a secondary language compared to reading in the primary language, skin conductance response increases with greater English proficiency, and the power value of alpha waves during reading English content words is reduced compared to reading functional words.

We have previously proposed using physiological signals to validate the relationships between the signals and a learner's level of understanding, and we have developed multiple regression expressions to estimate understanding level (Omata, 2018). Using such signals allows us to observe the state of a learner without imposing a burden and interrupting activities; thus, the estimation can represent a solution to the aforementioned problems. Our multiple regression expressions could estimate the level of individual understanding while reading each second-language sentence as at least 55% and at maximum 81% on a four-level ordinal scale.

In this paper, we propose using a logistic regression model to achieve a higher-accuracy regression method. In addition, we propose the use of a visual analog scale (VAS) as a rating scale for high-resolution estimation. Previously, we reported that the contribution rate of a logistic regression model was greater than that of a multiple regression model when estimating emotion from physiological signals in a subject drawing a picture (Omata, 2014). Watanabe et al. and Yamada et al. have reported that a VAS method was more effective than Likert-scale evaluations (Watanabe 2015, Yamada 2014).

This paper describes an experiment conducted to examine the relationships between physiological signals and self-reported levels of understanding of a second-language listening task using a VAS. In addition, this paper compares a logistic regression

Omata, M. and Nakazawa, K.
Regression Analyses between Physiological Indexes and Level of Understanding with VAS of a Listening Task.
DOI: 10.5220/0006892200210029
In *Proceedings of the 5th International Conference on Physiological Computing Systems (PhyCS 2018)*, pages 21-29
ISBN: 978-989-758-329-2

model to a multiple regression model relative to contribution ratio to further explain these relationships.

The contributions of this paper are summarized as follows.

- We demonstrate that physiological signals, particularly the power of theta brain waves, are related to levels of understanding in a listening task.
- VAS is more effective to record a detailed self-reported level of understanding than a four-level scale.
- We demonstrate that the accuracy of a logistic regression model is similar to that of a multiple regression model relative to regression analyses of such relationships.

2 RELATED WORK

This section surveys previous work that studied relationship between person's responses and their physiological signals during a verbal task or e-learning.

Concerning signals of central nervous system (CNS), Mellem et al. focused on the role of oscillatory EEG dynamics in retrieving open class vs. closed class words (Mellem, 2012). Specifically, they investigated the robustness of the theta and alpha effects in different contexts and in a different population and performed time–frequency analysis based on the context or class of the word. As the results, they observed larger power decreases in the alpha waves for the open class compared to closed class words and did not observe differences in theta power between these conditions. Safi et al. studied to validate a protocol using near-infrared spectroscopy (fNIRS) for the assessment of overt reading of irregular words and nonwords with a full coverage of the cerebral regions (Safi, 2012). The results reported that total hemoglobin concentrations were significantly higher than baseline for both irregular word and nonword reading. Oishi et al. compared brain blood flow during a listening task for first language with that for second language (Oishi, 2008). The results reported that the hemoglobin concentration of the second language significantly increased than that of the first language. They interpreted that the second language needed attentional capacity more than the first language.

Concerning signals of peripheral nervous system (PNS), Harris investigated the phenomenon psychophysiologically, 32 Turkish–English bilinguals rated a variety of stimuli for pleasantness in Turkish (L1) and English (L2) by analyzing skin conductance via fingertip electrodes (Harris, 2003). The results show that the participants demonstrated greater autonomic arousal to taboo words and childhood reprimands in their L1 compared to their L2. Nomura et al. focused on the skin temperature changes and Electrocardiogram (ECG) changes of students engaged in two e-learning exercises: interactive or non-interactive (Nomura, 2012). As the result, the skin temperature showed significant decline when subjects were engaged in the interactive exercise. In addition, high frequency (0.15-0.40 Hz) values of ECG dropped just after the start of both exercises and remained low.

We conducted multiple regression analyses to investigate a trend of the relations between several physiological signals and level of understanding of second language reading of a whole text (Omata, 2016). The contribution ratio was 0.82. After that, we developed individual adaptive estimation expressions to estimate a learner's level of understanding (four-level scale) of reading each second-language sentence by analyzing the learner's physiological signals (Omata, 2018). The mean determination coefficients of the expressions was 0.69 ranged from 0.55 to 0.81.

3 PHYSIOLOGICAL SIGNALS AND INDEXES

Tables 1 and 2 list physiological signals and indexes calculated from each kind of signals, which were analyzed in the experiment. This section introduces physiological signals obtained from participants from two parts: central nervous system (CNS) and peripheral nervous system (PNS); and also explains the indexes and their pre-processing before analyzing them.

We used the ProComp Infiniti (Thought Technology Ltd.) for the measurement which is an eight channel, biofeedback and neurofeedback system for real-time data acquisition. The channels can be used with some combination of sensors described below.

Table 1: Physiological signals and indexes of CNS.

Type of signal	Calculated index	Method of calculating
EEG	Power of theta waves (4 Hz - 7 Hz)	Spectral analysis of brain waves on a forehead
	Power of alpha1 waves (7 Hz - 8 Hz)	
	Power of alpha2 waves (9 Hz - 11 Hz)	
	Power of alpha3 waves (12 Hz - 13 Hz)	
	Power of beta waves (14 Hz - 30 Hz)	
HEG	HEG ratio based on baseline	Absorptive power of oxygenated haemoglobin on a frontal lobe

Table 2: Physiological signals and indexes of PNS.

Type of signal	Calculated index	Method of calculating
BVP	Power of HF waves	Spectral analysis of BVPs on a left thumb
	LF/HF ratio	
	Pulse rate (beats / minute)	
HEG	SC ratio based on baseline	Electrical conductance between left index and middle fingers
RESP	Breaths / minute	Expansion and contraction motion of abdomen

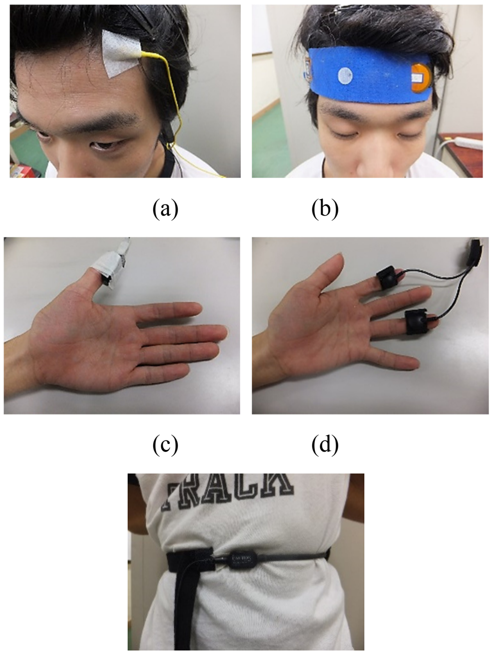

Figure 1: Sensors and electrodes for measuring physiological signals: (a) electrodes for EEG, (b) a HEG headband, (c) a BVP sensor, (d) a SC sensor and (e) a RESP sensor.

3.1 CNS Signals

3.1.1 Electroencephalogram (EEG)

EEG signals are detected on the scalp as neuronal electric fluctuations in the brain and are classified by their frequency: theta (4–7 Hz), alpha (8–13 Hz), and beta (14–30 Hz). Alpha waves are frequently detected when a person is relaxed, beta waves are commonly detected when a person is concentrating, and theta waves are detected when a person is feeling drowsy. Alpha waves are further classified into alpha1 (7–8 Hz), alpha2 (9–11 Hz), alpha3 (12–13 Hz). We recorded these data using an EEG-Z sensor (Thought Technology Ltd.), classified the frequencies and calculated the power of each frequency band (see Table 1). Figure 1a shows such electrodes on a participant's forehead (F3 of the international 10–20 system).

3.1.2 Hemoencephalography (HEG)

The HEG ratio is the ratio between oxygen-rich hemoglobin and oxygen-starved hemoglobin in cerebral blood flow (CBF), which correlates with blood flow dynamics and cellular metabolism in localized parts of the brain cortex. The level of oxygenated hemoglobin increases during brain activation due to the phenomenon of neurovascular coupling. Therefore, we subcutaneously recorded the ratio at 2 cm on the forehead by measuring the absorptive power of near-infrared and red light of the CBF because of the differences of the absorptive power of oxygen-rich and oxygen-starved hemoglobin. The HEG ratio is calculated as follows

$$HEG = 200\frac{RED}{IR} \tag{1}$$

where *RED* is the absorptive powers of oxygenated hemoglobin and reduced hemoglobin during visible red light irradiation, and *IR* is their absorptive powers during near-infrared light irradiation. We used a near-infrared headband (MediTECH Electronic GmbH; see Figure1b) on the forehead (Fp2 of the international 10–20 system) to measure HEG ratio.

3.2 PNS Signals

3.2.1 Blood Volume Pulse (BVP)

BVP, also called photoplethysmography, is a relative measure of heart rate and inter-beat interval and an index of the coarctation and angiectasis of peripheral blood vessels. The frequency characteristics of such waves reflect the tone of sympathetic and parasympathetic nerves. The high-frequency (HF, 0.15–0.4 Hz) component reflects the tone of sympathetic nerves, while the low-frequency (LF, 0.04–0.15 Hz) component reflects the tone of both types of nerves. We used a BVP sensor (Thought Technology Ltd.; see Figure 1c), which bounces infrared light against a skin surface and measures the amount of reflected light.

3.2.2 Skin Conductance (SC)

A hand's SC is a measure of the skin's ability to conduct electricity due to the eccrine sweat between two fingers. SC represents changes in the sympathetic nervous system. The value of the sensor increases when the subject is in an excitatory state or a stressful situation. We used an SC sensor (Thought Technology Ltd.; see Figure 1d) that measures SC between two fingers in micro-Siemens.

3.2.3 Respiration (RESP)

Respiratory movement consists of inspiration and expiration. The RESP rate is an index of emotion with an increase indicating tension and a decrease indicating relaxation. We used a RESP sensor (Thought Technology Ltd.; see Figure 1e) that is sensitive to stretching. When strapped around a participant's abdomen, it converts the respiratory movement into an electric signal. We also calculate the RESP rate from the data.

3.3 Pre-processing

Note that pre-processing was required for eliminating individual differences among participants, thus the data of physiological indexes were standardized using both experimental data and neutral data prior to performing experimental tasks. The indexes of EEG, HEG ratios and SC were calculated from the mean and standard deviation of the same type of data by following the equation:

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

where x is the raw data calculated from the signals obtained from a sensor, and μ and σ are the mean and standard deviation of the same kind of data, respectively, recorded before performing an experimental task in the neutral state as a baseline for each participant. The RESP and BVP indexes were standardized using the relative ratios obtained from the experimental and neutral data.

4 EXPERIMENT

This section describes a verification experiment to model the relationships between physiological indexes and participants' subjective self-reported levels of understanding when listening to English speech, which was a second language for the participants.

4.1 Objective

The main objective of the experiment was to build a regression expression to explain a learner's level of understanding more accurately than our previous model by verifying the relationships between understanding levels and physiological indexes. In addition, a second objective was to evaluate the effect of using a VAS as a rating scale by comparing it to the four-level ordinal scale used in our previous work. Therefore, our hypotheses are as follows.

H1: There is a significant relationship between the level of understanding of a second-language listening task and the listener's physiological indexes.

H2: The accuracy of a logistic regression model is significantly greater than that of a multiple regression model relative to a contribution ratio comparison.

H3: A high-resolution VAS is more useful than a low-resolution four-level scale for regression analyses.

4.2 Experimental Setup

Figure 2 shows the experimental equipment and a participant wearing the sensors used to measure physiological signals during a task. A laptop with a 17.3-inch display was used to measure and record data, and two speakers were placed approximately 30 cm from the participant. The participant's left hand was kept on a table and restrained from moving due to sensors attached to the fingers.

A slider (Phidgets Inc. Slider 60; Figure 3) for the VAS was placed near the participant's right hand. The participant reported their subjective self-reported level of understanding by moving the knob of the slider along the sulcus. The resolution of the slider was 999 degrees (0 to 998) within a 60 mm sulcus. The degrees represent "Not at all understood" (0) side to "fully understood" (998). The middle position represents "neutral" degrees and was the default position before moving. The cardboard around the equipment was used to unify the participant's sight by obscuring visual information in order to allow the participants to concentrate on the listening task.

Figure 2: Experimental equipment and a participant wearing sensors.

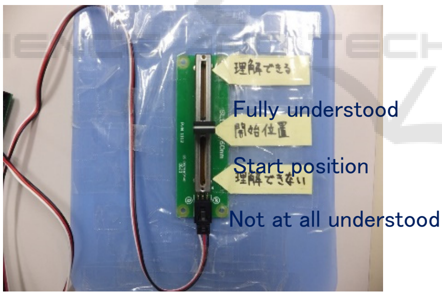

Figure 3: Slider to report level of understanding.

4.3 Task

The task was to listen to English speech and report the level of understanding of the content. In each trial, the participant first clicked the "play" button on the laptop's screen. Then, they listened to English speech played from the speakers. They then reported their level of understanding of the content by moving the slider knob and clicking the "record" button to fix and record the answer. Finally, they moved the knob back to the default start position prior to the next trial. The participant then repeated this process with another speech.

4.4 Stimuli

The speeches used for the listening task were excerpted from the Grade 1, Grade Pre-1, Grade 2, Grade Pre-2, Grade 3, and Grade 4 EIKEN tests (Eiken Foundation of Japan, online), which is one of the most widely used English-language testing programs in Japan. The speeches ranged in duration from 15 to 20 s and represented the above six difficulty grades. Each difficulty grade included ten speeches.

4.5 Participant

Ten male college students aged 21 to 23 participated in this experiment. All participants were native Japanese speakers who had studied English for over a decade. Their TOEIC (IIBC, online) listening scores ranged from 235 to 385 (mean score: 281.5) out of 495. Each participant was assigned a distinguishing ID character from A to J to facilitate explaining the results and analyses.

4.6 Procedure

A block of each difficulty grade comprised two parts: (1) recording physiological signals during rest and (2) performing a task with ten listening trials for each grade.

In the rest part, all physiological signals of a participant were measured and recorded for 60 s while the participant rested, opened their eyes, and thought of nothing.

Then, in the task performance part, the participant listened to the speeches (ten voices) of each grade and self-reported a subjective level of understanding for each trial.

All participants conducted six blocks for all six grades in a within-subject design. Therefore, each participant listened to 60 speeches. Note that the order of the blocks for each participant was counterbalanced; thus, the order of grades differed for each participant.

In addition, we obtained informed consent from all participants prior to conducting the experiment.

4.7 Results

Figure 4 shows results of the self-reported level of understanding of each participant for Grade 4, i.e., the easiest grade, and Figure 5 shows the results of the self-reported level of understanding of each participant for Grade 1, i.e., the most difficult grade.

Although the detailed results of other grades are omitted in this paper, we observed that, overall, more difficult grades resulted in lower understanding levels. In addition, because the levels of understanding were fully distributed, and several values were 999 degrees on the slider, the self-reported values and physiological indexes were useful for analyses.

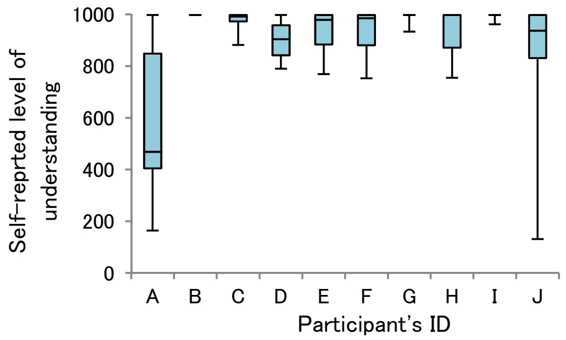

Figure 4: Distribution of self-reported levels of understanding of each participant of Grade 4.

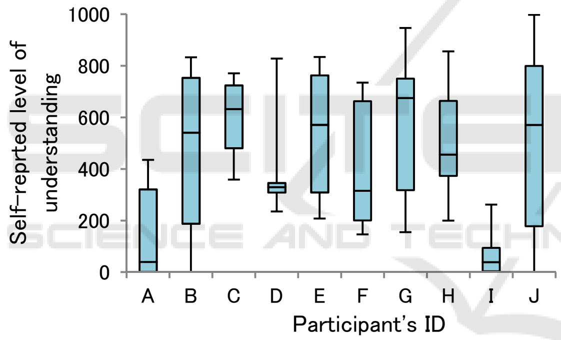

Figure 5: Distribution of self-reported levels of understanding of each participant of Grade 1.

4.8 Analyses

This section describes statistical analyses conducted to test our hypotheses (Section 4.1).

4.8.1 Correlation Analyses

Tables 3 and 4 show the correlation coefficients between the self-reported level of understanding values of each participant and the physiological index values of CNS (Table 3) and PNS (Table 4). Overall, the sign of the coefficients of the power values of each band of brain waves was negative. We observed that the power values of theta band brain waves correlate inversely with the self-reported values. The absolute values of the coefficients of participants I and J of the theta band were greater than 0.75.

Table 3: Correlation coefficients between level of understanding and CNS indexes of each participant.

ID	Power of θ	Power of α_1	Power of α_2	Power of α_3	Power of β	HEG
A	-0.45	-0.38	-0.25	-0.24	-0.29	0.33
B	-0.52	-0.51	-0.51	-0.51	-0.55	-0.35
C	-0.57	-0.31	-0.29	-0.24	-0.28	-0.27
D	-0.58	-0.58	-0.59	-0.59	-0.61	-0.12
E	-0.35	-0.24	-0.41	-0.26	-0.44	0.22
F	-0.56	-0.33	-0.42	-0.43	-0.45	0.02
G	-0.37	-0.51	-0.47	-0.49	-0.49	-0.29
H	-0.44	-0.44	-0.36	-0.40	-0.45	-0.02
I	-0.77	-0.52	-0.50	-0.52	-0.59	0.25
J	-0.75	-0.71	-0.59	-0.51	-0.63	0.19

Table 4: Correlation coefficients between level of understanding and PNS indexes of each participant.

ID	Power of HF	LF/HF	Pulse rate	SC ratio	Breaths / minute
A	-0.14	-0.29	-0.03	0.26	-0.25
B	-0.40	0.17	-0.09	0.31	0.11
C	-0.31	-0.11	-0.46	0.10	-0.21
D	-0.46	0.30	0.13	-0.66	0.21
E	0.08	-0.34	-0.58	0.10	-0.10
F	-0.62	0.39	0.56	0.25	-0.33
G	-0.39	0.19	0.19	-0.61	0.30
H	0.02	-0.07	-0.20	-0.10	-0.27
I	-0.31	-0.02	0.22	0.41	0.22
J	-0.15	0.30	-0.17	-0.08	-0.25

Figure 6 illustrates the relationships between the power values of the theta waves of participant J and his self-reported levels of understanding as a high correlation example. As can be seen, a higher level of understanding, which means the level moves toward "fully understood," is correlated with lower theta wave power. Figure 7 illustrates the power value of the theta waves of each trial for each grade of participant J. The graph shows that the power value of theta waves varies relative to the difficulty of the grade from easy (Grade 4) to difficult (Grade 1).

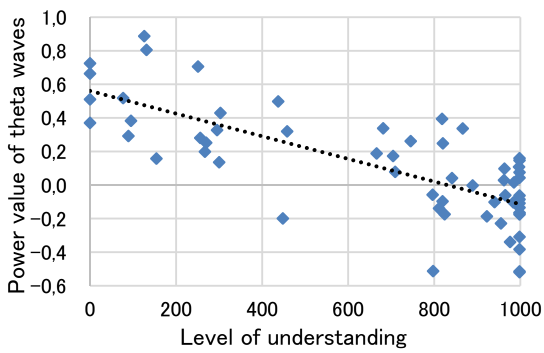

Figure 6: Correlation between level of understanding and power of theta of participant J.

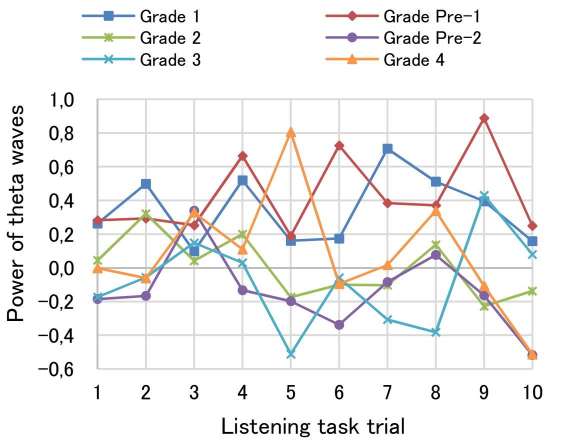

Figure 7: Level of power of theta waves of each grade of participant J.

4.8.2 Regression Analyses using Two Models

This section compares the accuracy of a logistic regression model to that of a multiple regression model to explain the relationships between the values of physiological indexes and the self-reported levels of understanding using the same recorded data.

Here, the objective variable of both regression methods is the self-reported level of understanding. However, it was necessary to convert the values from ratio scales to ordinal scale in the logistic regression; therefore, the values were divided equally by five and ranked from first to fifth because the number of samples in each division was small in greater than five equal divisions. On the other hand, in the multiple regression, the values of the self-reported levels were used as the values of the objective variable without conversion.

To avoid multicollinearity among the indexes, the explanatory variables of both regression methods are the principal components obtained by principal component analyses of the values of the physiological indexes.

The overall contribution ratio of the logistic regression expression obtained using all participant data was 0.34, and that of the multiple regression expression using the same data was 0.35. Both ratios are less than 0.5 and less accurate to explain the relationships (Donna, online).

Therefore, we built individual logistic regression and multiple regression expressions to explain the relationships of each participant using only that participant's data. Table 5 shows the contribution ratios of the individual logistic regression and multiple regression expressions of each participant. As can be seen, all ratios are greater than 0.5, the mean ratio of the logistic regression expressions is 0.72, and the mean ratio of the multiple regression expressions is 0.70. These results indicate that the regression expressions can reasonably explain the relationships between the participant's levels of understanding and the physiological indexes individually, and that there is no significant difference between logistic and multiple regression.

Table 5: Contribution ratios of two regression models for each participant.

ID	Contribution ratio of logistic regression	Contribution ratio of multiple regression
A	0.68	0.68
B	0.74	0.68
C	0.79	0.75
D	0.70	0.68
E	0.58	0.53
F	0.73	0.72
G	0.78	0.70
H	0.61	0.67
I	0.85	0.86
J	0.76	0.71

4.8.3 Analyses of Accuracy of Estimation

We compared the estimated levels of understanding using an individual multiple regression expression with the self-reported levels of understanding for each participant. The data for the comparison were classified into three difficulty grades, i.e., low (Grades 4 and 3), middle (Grades 2 and Pre-2), and high (Grades 1 and Pre-1) for the analyses. Figure 8 shows the variance of the correlation coefficients for all individual participants of each classified grade. Note that values were normalized to derive the multiple regression expressions. The graph shows that the coefficients of the high grade converge within a high range and that the mean coefficients of the high grade are greater than that of the other grades.

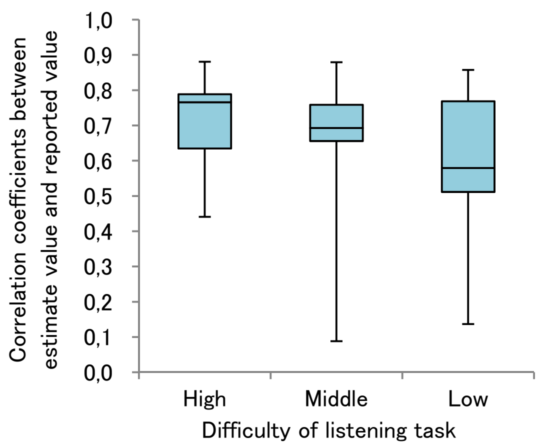

Figure 8: Correlation coefficients of three classified grades.

Figures 9 and 10 show the estimated values by the multiple regression expression and the actual self-reported values for Grade 4 (Figure 9), which is the easiest, and Grade 1 (Figure 10), the most difficult, for participant G, whose correlation coefficient is close to the mean of all participants. The graphs show that the estimated values are approximately close to the actual self-reported values.

We also compared the estimated levels of understanding using an individual logistic regression expression with the self-reported levels of each participant. Here, the mean accuracy rate of the estimation of all individuals was 0.76, and the standard deviation of the rates among the individuals was 0.10.

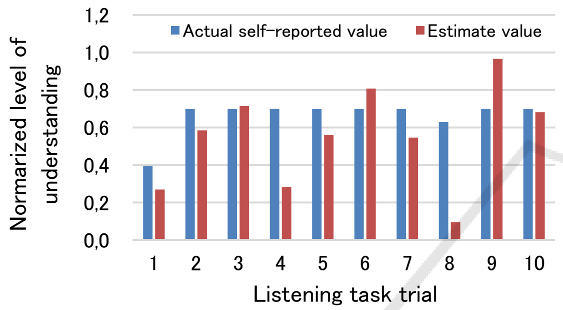

Figure 9: Comparison of estimate values with self-reported value of Grade 4 of participant G.

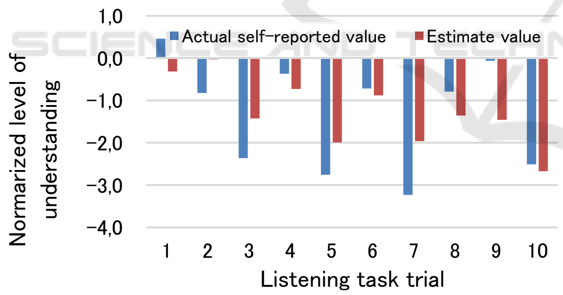

Figure 10: Comparison of estimate values with self-reported value of Grade 1 of participant G.

4.8.4 Regression Analyses using Brain Waves

We attempted to conduct regression analyses with both models using only brain wave indexes to consider whether the number of physiological signals should be reduced relative to implementation cost. These analyses were limited to brain waves because the correlation coefficients of the brain wave indexes were greater than those of the other signals, and the signs of the coefficients of all participants were the same (Section 4.8.1).

Table 6 shows the contribution ratios of the individual logistic regression and multiple regression expressions using only the values of the brain wave indexes for each participant. As can be seen, the mean ratio of logistic regression is 0.53, and the mean ratio of multiple regression is 0.53. Both mean values are less than those of the expressions using all physiological indexes (Section 4.8.2).

Table 6: Contribution ratios of two regression models using only brain wave indexes.

ID	Contribution ratio of logistic regression	Contribution ratio of multiple regression
A	0.43	0.44
B	0.70	0.62
C	0.72	0.69
D	0.58	0.43
E	0.31	0.30
F	0.46	0.48
G	0.33	0.41
H	0.39	0.46
I	0.76	0.78
J	0.59	0.64

5 DISCUSSIONS

Relative to H1, we verified a significant relationship between a listener's self-reported level of understanding in the listening task and the listener's physiological signals at an individual level. However, the contribution ratios of the logistic and multiple regression expressions using all participant data collectively were low; thus, we consider that it is difficult to develop a unified regression model to express the relationships of all learners. We surmise that this difficulty is due to the fact that kind or tendency of physiological signals that change relative to a difficulty level of understanding varies among individuals, and that each individual has a particular kind or tendency of the physiological changes when he/she is finding something difficult. On the other hand, we suggest that the power value of the theta brain waves has a certain tendency to change according to the level of understanding of all listeners.

Relative to H2, we found no significant difference between the accuracies of logistic and multiple regressions when modelling the relationships between the self-reported level of understanding and the physiological indexes. Therefore, we consider it necessary to use another statistical regression model, to combine another type of data such as English score, or to include other physiological signals such as an electromyogram to measure movement of facial muscles, in order to increase accuracy.

Relative to H3, we have verified that the accuracy of the 999-degree scale was greater than or equal to that of the four-level scale in our previous work, where the mean accuracy was 0.69 (Omata, 2018). Therefore, we propose that it is possible to estimate the level of understanding at sufficient resolution using a VAS.

6 CONCLUSIONS

We conclude that our logistic regression expressions can explain the relationships between an individual level of understanding of listening a second language and individual physiological indexes with 0.72 contribution ratio, and that our multiple regression expressions can also explain the relationships with 0.70 contribution ratio. The multiple regression expressions can explain the relationships with convergent higher correlation coefficients when the speech voices are difficult for the listener.

Additionally, we suggest that VAS is useful to answer a level of understanding and estimate it at high resolution.

We, therefore, propose that it is possible to develop an e-learning analysis system that automatically estimates a detailed level of understanding from learner's physiological signals and an e-learning content recommendation system that automatically provides a flexible and adaptable learning material based on the estimation for an individual learner.

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