Estimating Beverage Preference Based on Subjective Emotional Reactions and EEG Activity

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***Abstract*—In recent years, a new type of value called the Kansei value has been widely discussed, especially in the manufacturing industry. Many studies have tried to quantify Kansei values and found that human psychological and physiological reactions have certain effects. To further examine the relationships among psychological reactions, physiological reactions, and Kansei values, the main purpose of this study is to construct a predictive model for beverage preference evaluation. However, we found that the problem of how to obtain psychological and physiological reaction data without affecting people's Kansei value evaluations has not been solved well. Therefore, this study proposes using an arm robot instead of a human to perform a series of actions when drinking, which solves the problem of measuring psychological and physiological reactions simultaneously. Using the psychological and physiological reactions collected by this method, we completed a predictive model of people's preference evaluations. Our model's prediction accuracy is higher than that of the model using psychological evaluation or physiological reaction alone. This result proves again that psychological and physiological reactions do affect people's preference evaluation simultaneously. Through the model comparison, we also get the result that the evaluation of people's preference for beverages has been formed in tasting the beverages in the mouth.**

I. INTRODUCTION

In recent years, a new type of value called "Kansei" value has been widely discussed in the manufacturing industry. It involves all aspects of human life, including clothing [1], food [2], transportation [3], cosmetics [4], and so on. To design products better based on Kansei value, it is necessary to quantify users' psychological reactions evoked by products. There are two types of psychological reactions: conscious and unconscious. Conscious and unconscious psychological reactions each have suitable quantification methods. One method is to use reactions expressed in language [5], measuring subjective states via subjective evaluation. Another method is to use psychophysiological reactions that cannot be expressed in language, such as facial expressions and EEG activity [6][7]. These states are obtained by objective measurement.

The mechanisms that form food's Kansei values are complex because of the combined influence of many sensory modalities. To understand how conscious and unconscious reactions affect people's Kansei values when eating food, many studies have reported on the relationship between food preferences and subjective responses [2][11][12]. These studies were based on subjective evaluations obtained under natural eating behaviors, and are considered able to correctly measure the values provided by food in realistic situations. On the other hand, the unconscious state cannot be measured by subjective evaluation, and its influence has not been clarified. The relationship between preferences and unconscious states has also been studied in the field of neuroscience [8][9][10]. However, in such studies, eating methods that have little effect on measurement, such as tube injection, have typically been selected. Subjective response studies use the most natural conditions, so the subjective reactions are very close to the real situation. Still, because there are many external factors, this method is unable to get accurate objective reactions. Neuroscientific methods can obtain more accurate objective reactions because they exclude external factors. Still, because of the excessive deviation between the experimental and normal conditions, they cannot guarantee accurate subjective reactions. To sum up, measuring subjective psychological and objective physiological reactions at the same time without affecting people's Kansei values is a difficult problem.

One purpose of this study was to try to solve these problems. To measure psychological and physiological reactions simultaneously, we used an arm robot instead of a human to perform a series of actions when drinking. In this way, the participants did not have to do anything, nor did they have to remain in an extreme environment to complete the drink intake experiment. Therefore, we think this method can eliminate errors in measuring brain waves to the greatest extent. Another purpose of our study was to construct a predictive model for beverage preference evaluation. We used psychological reactions (emotional evaluation) and physiological reactions (EEG data) collected by our method to build a mathematical model to predict the preference evaluation of beverages (coffee) and analyze the psychological and physiological reactions effect on the preference evaluation. We also compared the different effects of brain waves before and after swallowing and their effects on preference evaluation.

II. Related Study

Researchers have made many attempts to measure subjective psychological and objective physiological reactions. Some of them carried out action experiments under normal drinking conditions, and others carried out fMRI experiments under extremely unnatural conditions through infusion tubes.

For example, Tanaka et al. [8] studied the effect of ERPs (event-related potential) on evaluating food image preferences. In their study, the preference for food images was related to the area of P300 components, which indicated that ERPs can be used as an index to evaluate people ' s preference for food. To analyze how overall preference evaluations of food are formed, Sagara [2] constructed a food Kansei model. This model mainly evaluated intrinsic attributes (such as fragrance) and extrinsic attributes (such as brand effect) to quantitatively evaluate how the cognition of " delicious " is generated. Among many subjects, the subject of beverages has been widely studied. Some studies examine the impact on Kansei value by measuring the subjective reactions of the participants. [11] studied preference evaluations by comparing the taste perception of drinking beverages with the ingredients contained in them [11]. Dalenberg [12] used preference evaluation and emotional factors to predict beverage choice. Dalenberg shows that a model combining preference evaluation and emotional factors has better predictive ability than one using preference evaluation or emotional factors alone. In addition, some people think that we must consider both subjective and objective reactions. Samuel [9] and John [10] used tube infusion to measure both preference and brain activity when consuming beverages. Their results showed that beverage preference is related to the frontal lobe activity of the brain [9], as well as the ventral tegmental area and striatum of the brain [10].

III. Experiment

A. Participants

First, we conducted a questionnaire survey among participants and selected 32 (24 males and 10 females) who rated their preference for coffee as "do not hate" or "general." After removing participants who were not completely measured by EEG data, the actual number of participants was 24 (18 males and 6 females). Their average age was 21.79 (SD = 1.194).

B. Stimuli

We selected five kinds of coffee with obvious differences in flavor from the market. The participants drank 15ml of each sample, and the temperature of the drinks was maintained at 4 °C.

C. Questionnaire

We selected evaluation questions from previous studies [14] to evaluate subjective emotions. There were 13 items in the questionnaire: powerful (Q1), active (Q2), agile (Q3), energetic (Q4), lethargic (Q5), not feeling like it (Q6), lifeless (Q7), tension (Q8), restless (Q9), uneasy (Q10), compatible (Q11), calm (Q12), and relaxed (Q13). Japanese - English translation is shown in Table. 1. We used a 4-point Likert scale to evaluate each item and used a visual analysis scale (total 100 points) to evaluate participants ' beverage preferences.

TABLE I
Japanese - English Questionnaire Translation

Question Num.	Japanese	Translation
Q1	気力に満ちた	powerful
Q2	活動的な	active
Q3	機敏な	agile
Q4	エネルギッシュな	energetic
Q5	無気力な	lethargic
Q6	気分ののらない	not feeling like it
Q7	生気がない	lifeless
Q8	緊張した	tension
Q9	落ち着かない	restless
Q10	気が休まらない	uneasy
Q11	ゆったりした	compatible
Q12	落ち着いた	calm
Q13	くつろいだ	relaxed

D. Apparatus

In this experiment, a Dobot Magician arm robot was used to replace the participants ' arms to complete a series of hand movements when drinking coffee. This is to avoid any unnecessary deviation of EEG measurement caused by the different habits of the participants when drinking. We used Biosemi's Active Two EEG system with a total of 64 electrode channels and 6 additional channels on participants ' heads (sampling rate 1024 Hz). To measure laryngeal movement during swallowing, we set up an ACC sensor near participants larynxes. As participants swallowed, the sensor recorded the duration of activity (Fig. 1). We set up a joystick to control the arm robot. Participants only needed to operate the joystick to complete the intake of drinks. This made their actions more uniform, reducing physiological reaction errors caused by drinking habits. To avoid the influence of noise, the whole experiment was carried out in a sound-insulated laboratory.

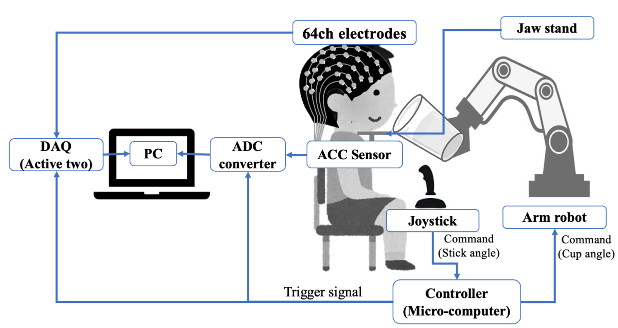

Fig. 1. Experimental equipment and data collection method

E. Procedure

Participants first placed their chins on a jaw stand. After 10 seconds of resting state adjustment (Step 1 in Fig. 2), participants were prompted to start drinking coffee. The participants drank a random cup of coffee by turning the arm robot's control stick (Step 2 in Fig. 2), and tasted the coffee for 10 seconds (Step 3 in Fig. 2). To measure physiological activity after swallowing, the participants were kept in place for 130 seconds (Step 4 in Fig. 2). After all these steps, the participants evaluated their current mood and their preference for each sample (Step 5 in Fig. 2). Finally, participants cleansed their palates with 15ml of drinking water to prepare for the next round of experiments (Step 6 in Fig. 2). The experiment was conducted for 15 trials.

We used the following method to record the drinking period: first, we calculated the angle at which the liquid flows out of the cup. When the joystick reached this angle, it sent a trigger signal to an ADC converter, and we recorded this moment as the start of drinking. Then, we divided the timing of laryngeal movement recorded by the ACC sensor by the times before and after swallowing. Finally, according to these time points, we extracted the data from the collected EEG data. (see Data Preprocessing section for detailed period division).

The present experiment with human participants was approved by the Internal Review Board of the Faculty of Letters, Kwansei Gakuin University.

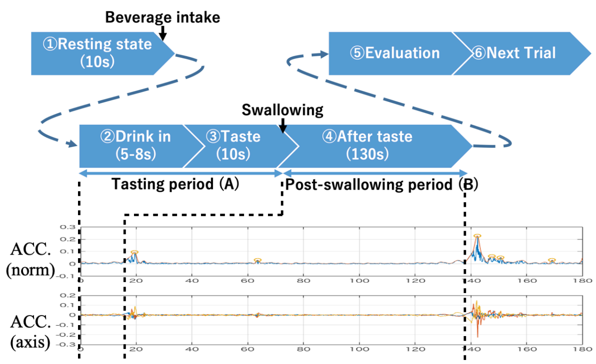

Fig. 2. Experimental procedure and different swallowing periods

F. Data preprocessing

We understood the mechanism of human swallowing based on [13]. First, when swallowing, the hyoid rises, and the epiglottis presses down to close the pharynx to prevent food from entering the trachea. During this period, the larynx rises. When food enters the esophagus, the hyoid and epiglottis return to their original positions and open the pharynx. During this period, the larynx descends. Based on this mechanism, we hypothesized that laryngeal movement could be used as a criterion to judge whether a participant was swallowing. In addition, the literature describes four stages of swallowing, each with different movement patterns. They are the cognitive stage, preparatory stage, swallowing stage (this stage is divided into mouth and pharyngeal stages), and esophageal stage. To facilitate analysis, we set up a sensor to measure laryngeal movement near participants' larynxes. According to the measured swallowing timing, we divided the process of beverage intake into the following periods (Fig. 2):

Tasting period (A period): This is the period from the mouth stage (first part of the swallowing stage) to the pharyngeal stage (second part of the swallowing stage). The EEG data corresponding to this period take the interval from drinking the beverage to before the sensor measures the first fluctuation of the larynx (Steps 2 and 3 in Fig. 2).

Post-swallowing period (B period): This is the period from the pharyngeal stage to the esophageal stage. The EEG data corresponding to this period takes the interval from after the sensor measures the first fluctuation of the pharynx to before the second fluctuation of the larynx (Step 4 in Fig. 2).

Difference between the A period and B period (AB period): Considering that the difference of reaction between the A period and B period may also be an influencing factor, we calculated the variation of brain wave activity in the A period compared with the B period.

IV. Analysis

A. Processing and analyzing subjective emotion evaluation and EEG data

To make more reasonable use of subjective emotion evaluation and EEG data, we conducted a factor analysis on the 13 self-evaluated items' responses and principal component analysis on EEG data of 24 participants after drinking five kinds of beverages.

B. Construction of mathematical model to predict preference evaluation

As shown in Fig. 3, the distributions of the five samples' preference evaluations were normal. We constructed a Bayesian regression model and choose the best model by model comparison. The best model was used to analyze the effects of emotion and EEG on preference evaluation. We also compare the EEG data before and after swallowing (A period, B period, and AB period), to clarify which period was more suitable to predict preference evaluation. The formulae of the model are shown in Equations (1) and (2).

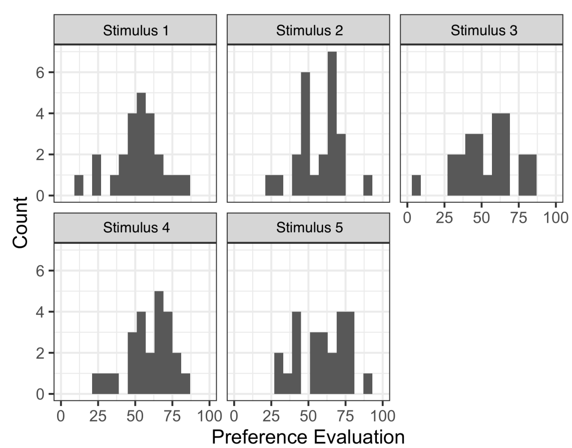

Fig. 3. Distribution of preference evaluations of five beverage samples

$$y \sim Normal(\mu, \sigma) \quad (1)$$

$$\mu = \alpha + \sum_{n=1}^{n} \beta_n V_n + r_{stimulus} + r_{participant},\ n \in 1...8 \quad (2)$$

In Equation 1, y is the result of preference evaluation, and μ and σ are the mean and standard dispersion. In Equation 2, βs represents the fixed effect and the participants' individual differences ($r_{participant}$) and individual differences in sample stimuli ($r_{stimulus}$) as random effects. $n \in 1...8$ means that the model uses up to 8 independent variables. This is because EEG produces too many principal components (see result (b)). Therefore, we carried out a single regression analysis on each principal component in advance and selected the best four parameters in A, B, and AB periods by model comparison (using WAIC as a judging standard). After adding the four subjective emotion factors (see result (a)), we got the eight independent variables used in the A, B, and AB period models. The structure of the models are as follows:

$M1_p = V1_p$
$M2_p = V1_p + V2_p$
$M3_p = V1_p + V2_p + V3_p$
...
$M8_p = V1_p + V2_p + ... + V8_p$

$M1_p$ is a model with one independent parameter, $M2_p$ is a model with two independent parameters, and so on. Finally,$M8_p$ is a model with eight independent parameters. V is the independent variable, p is the index of the period (A, B, or AB period). Finally, we calculated each models' WAIC, and the optimal model was selected.

We used RStan [15-17] for Bayesian parameter estimations. The uniform prior was used for fixed effects, and we used a weakly informative prior (gamma with α = 10, β = 10). We used RStan's default settings for MCMC sampling. For each model, there were four chains. Each chain had 1000 warm-up steps, 2000 iterations, and a thin factor of 1. Thus, there were a total of 4000 MCMC samples for each model.

To verify whether MCMC samplings had converged, we checked $\hat{R}$ values. $\hat{R}$ values for all coefficients were less than 1.1, which is a typically used criterion, and we considered that our MCMC sampling had converged.

We used the highest density interval (HDI) as a method to determine the significance of our estimation results. If the 95% HDI did not contain 0, we considered the estimation result significant. The HDI indicates which points of a distribution are most credible. Thus, the HDI specifies an interval that spans most of the distribution, such that every point inside the interval has higher credibility than any point outside the interval.

V. Results

A. Subjective emotion

We used factor analysis to analyze the participants' subjective emotion evaluations and selected the best number of factors according to Kaiser Guttman's standard (results shown in Table II). We obtained four main factors. Because the first factor was related to activity, the second factor was related to relaxation, the third factor was related to anxiety, and the fourth factor was related to low activity, we called them active, relaxation, anxiety, and negative factors.

TABLE II
Factor analysis results of subjective emotions

Index	Fac 1	Fac 2	Fac 3	Fac 4
Q1.powerful	.944	-.024	-.234	.083
Q4.energetic	.906	.125	.128	-.210
Q2.active	.881	.228	.286	-.186
Q3.agile	.665	-.195	-.074	.278
Q8.tension	.352	-.336	.146	.267
Q11.compatible	-.030	.900	-.033	.122
Q12.calm	.052	.898	.076	.000
Q13.relaxed	.203	.657	-.350	.199
Q9.restless	.032	-.046	.865	.028
Q10.uneasy	.017	-.072	.836	.071
Q7.lifeless	.009	.057	-.056	.889
Q5.lethargic	-.193	.360	.312	.645
Q6.not feeling like it	.059	-.215	.332	.341

B. EEG data

We analyzed EEG frequencies during the A, B, and AB periods. Through this frequency analysis, we obtained the frequency characteristics from time-series data via the Welch method and calculated the representative frequency bands. They are θ wave, α wave (lower α1 wave, Lower α2 wave and upper α wave), β wave and γ wave. The power calculation of each band refers to Dopplmayr's [18] results. We obtained the differences in EEG activity between each period (A period, B period, and AB period) and the calm state through this processing method. Then, we used principal component analysis to extract EEG features in each period, and the contribution ratio was 80%. To construct a more convenient model, we first selected the four most representative components from the A, B, and AB periods using WAIC as a judging standard (see Fig. 4). In the A period, A13 (lower α2 wave), A6 (θ wave), A11 (lower α1 wave) and A18 (upper α wave) were selected. During B period, B8 (lower α2 wave), B13 (β wave), B15 (γ wave), and B4 (θ wave) were selected. During AB period, ab12 (lower α2 wave), ab18 (β wave), ab21 (γ wave), and ab16 (upper α) were selected. Each circle in the picture is a top view of the head, with the face above and the back of the head below. Red areas indicate positive brain activity, and blue areas indicate negative brain activity. Many yellow areas indicate that the brain has a wide range of activities, and that the reaction involves the whole brain.

Notably, we considered the first component of the lower α2 wave the best principal component in all periods. On the whole, more than half (58.3%) of the most representative principal components selected occurred in the first component (many yellow areas). According to [19], most of these brain activities originate from the basal ganglia. Most of the activities in this area are closely related to emotion. At the same time, the reaction of the frontal lobe (A6, A18, B4) was also intriguing. This part of the activity is more closely related to cognitive processing [20]. These outcomes verified the results of [9], indicating that frontal lobe reaction is related to beverage preference evaluation.

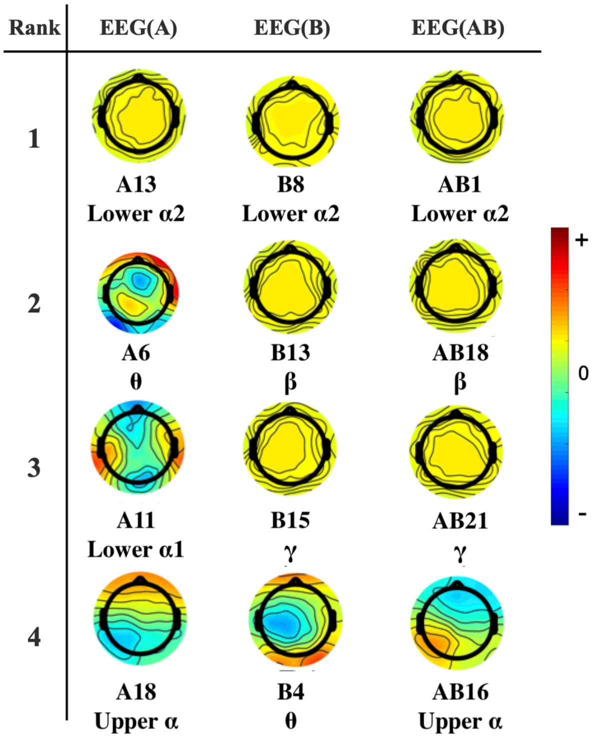

Fig. 4. Four most representative principal components by EEG model in A, B, and AB periods. WAIC used.

C. Prediction model of preference evaluation

Before analysis, we checked the Pearson correlations of all independent variables. As shown in Fig. 5, there was no obvious correlation between the four subjective emotion factors and the principal components of EEG.

As described in Analysis subsection B, we used four emotional factors from the results (a) and 12 principal EEG components (4 in each period) selected from the results (b) to construct the model according to M1 to M8. We also calculated the WAIC values for each model (see Fig. 6). The WAICs tended to be flat from M2 onward, and reached a minimum at M6. This means that M6 is the best model.

Table III summarizes the detailed structure of the best models in M2 to M8. We found that all models except M2 were an emotional factor + EEG principal components in Period A. Therefore, a model using both subjective emotion and objective physiological reactions is better than a model using subjective emotion or physiological reactions alone. Moreover, models constructed using EEG as their principal component in Period A were better than those constructed based on principal EEG components in the B or AB periods. This indicates that it is very likely that the preference evaluation of drinks is formed during the tasting period (Period A). The best model, M6, is composed of active factors (Fac1), relaxation factors (Fac2), anxiety factors (Fac3), A6 (related to frontal lobe), A13 (related to basal ganglia), and A18 (related to frontal lobe). The activity distribution of brain wave reaction is shown in Fig. 7.

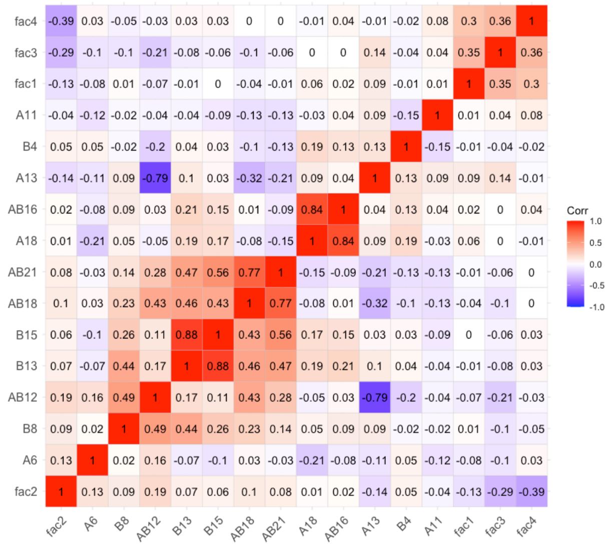

Fig. 5. Pearson correlations of all independent variables

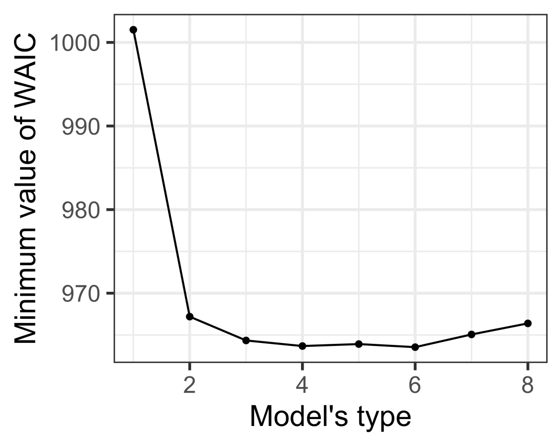

Fig. 6. Best WAIC values, models M1 to M8

TABLE III
STRUCTURE OF THE BEST MODEL AMONG DIFFERENT MODEL TYPES

Model type	Best model	Waic
subjective emotion (M2)	Fac1+Fac3	967.193
M3	Fac1+Fac3+A13	964.345
M4	Fac1+Fac2+Fac3+A13	963.678
M5	Fac1+Fac2+Fac3+A6+A13	963.913
M6	Fac1+Fac2+Fac3+A6+ A13+ A18	963.545
M7	Fac1+Fac2+Fac3+Fac4+ A6+ A13+ A18	965.064
M8	Fac1+Fac2+Fac3+Fac4+A6+A11+A13+A18	966.389

Fig. 7. Best model ’ s EEG activity

Table IV shows the results of the significant effects of the emotional factors and principal EEG components on preference evaluation as analyzed by M6. We considered an effect significant if the 95% HDI interval did not contain zero. The results showed that the higher the activity factor was, the higher the preference evaluation was; the higher the anxiety factor was, the lower the preference evaluation was. We found no significant effects between principal EEG components and preference evaluation.

TABLE IV
SIGNIFICANT EFFECT RESULTS (M6)

Predictor	Mean	95%HDI
Fac1	8.902	6.190 ∽ 11.409
Fac3	-7.740	-10.499 ∽ -4.899

Finally, we used M6 to predict participants ’ preference evaluations. As shown in Fig. 8, the x axis is participants ’ actual responses, and the y axis is the results predicted by M6. The more consistent the predicted results are with the actual answers, the more concentrated the final results will be on a diagonal line at an angle of 45 degrees. Our results show that M6 basically accurately predicts participants’ preference evaluations. However, some lower-level evaluations were still not predicted successfully. We think this is because the experimental sample size was insufficient. If we increase the number of experimental samples, this problem should be solved.

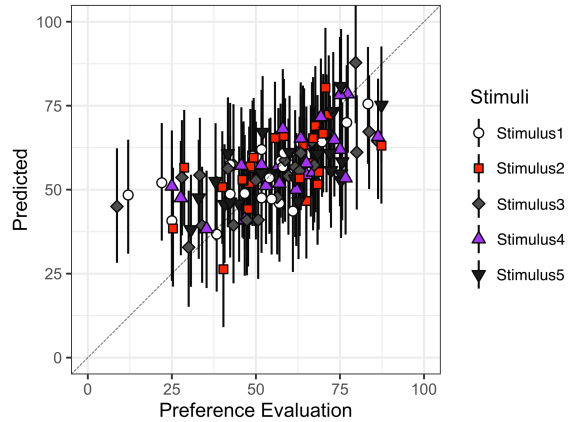

Fig. 8. Results predicted by M6 and actual participant responses

VI. DISCUSSION

This study used subjective emotion and objective physiological reactions (EEG) to build a Bayesian mathematical model to predict beverage preference evaluations. We also compared EEG data before and after swallowing in three different periods to help predict preference evaluation. Then, we used the best model to analyze the influence of various related factors on preference evaluation. First, we obtained four factors related to emotion through factor analysis. Then, we used principal component analysis to extract the principal EEG components in each period, and the contribution ratio was 80%. To construct the model more conveniently, we selected the best four principal components from the tasting period, the post-swallowing period, and the difference between the two. We selected EEG components for each period based on WAIC and positive brain activity. Notably, the best parameter selected by model comparison was the first component of lower $\alpha 2$ wave regardless of the period. More than half of the most representative principal components selected occurred in the first component (many yellow areas). This kind of brain activity is derived from the basal ganglia, and most of this kind of brain activity is related to emotion. This result shows that people ’ s preference for drinks is more subjective. At the same time, the reaction with the frontal lobe (A6, A18, B4) is also very interesting because the reaction of the frontal lobe is related to the brain ’ s cognitive processing. This result means that evaluating beverage preference also involves cognition about beverage information.

The optimal models from M3 to M8 were combinations of emotional factors and principal EEG components. All principal EEG components were reactions to the tasting period (Period A). This result shows that a model constructed using both subjective evaluation and objective physiological reaction is better than using subjective evaluation or objective physiological reaction alone. The effect of reaction in Period A on preference evaluation is better than that in B and AB periods. This result shows that people ’ s preferences for drinks are formed during the early stages of the cognitive activity of tasting.

Our model comparison results show that M6 is the best model. M6 is composed of active factors, relaxation factors, anxiety factors, A6 (related to the frontal lobe), A13 (related to the basal ganglia) and A18 (related to the frontal lobe). Although A6, A13, and A18 are related to emotion and cognition, only active and anxiety factors showed significant effects on preference evaluation. This result indicates that the evaluation of beverage preference is primarily on subjective judgement.

VII. Conclusions

In this study, we measured psychological and physiological reactions at the same time without affecting people's Kansei values by using an arm robot instead of a human to perform a series of drinking actions. At the same time, we used subjective emotional and objective physiological reactions collected via this method to build a predictive model for beverage preference evaluation and analyzed the correlations among various parameters. The relationship between brain wave and preference evaluation was the same as in previous studies. This result proves that the data collected using our measurement method is highly reliable. At the same time, our predictive model also shows that the model's predictive ability using subjective emotion and physiological reaction is greater than that of models using only subjective emotion. This result proves that both psychological and physiological reactions influence evaluation results, reflecting people's Kansei values. Next, we will adjust the parameters to continue optimizing the model and increase the sample size to check the model's credibility.

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