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Predicting Preferences for Unknown Products Toward Building Recommendation Systems Based on Collective Brain Activity

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In this study, we investigated a novel recommendation system that utilizes collective brain activity. Conventional collaborative filtering relies on conscious inputs such as user ratings, which do not necessarily capture subconscious human preferences. In this study, we propose a method that treats brain activity data obtained via near-infrared spectroscopy as a form of collective intelligence, estimates brain activity features for unobserved products through collaborative filtering, and predicts preferences using a support vector machine. Experimental findings confirm the effectiveness of the proposed method, showing only a 9.2% decrease in accuracy compared with the results obtained using actual measured brain activity features. Future enhancements may include integrating deep learning, applying majority voting across multiple models, and adapting the method for binary recommendation tasks. This method offers a promising direction for recommendation systems that incorporate human sensitivity and subconscious responses.

1. Introduction

In recent years, rapid development in sensor technologies has occurred, resulting in the use of a wide array of sensors being employed across numerous fields. With respect to neuroscience, the focus of this study, progress in noninvasive brain function measurement techniques has deepened our understanding of human brain activity. Consequently, research on brain–computer interfaces (BCIs) enabling device operation without physical motion has been actively pursued in welfare-related fields.[1] Representative examples include robotic control,[2] text entry,[3] and rehabilitation support.[4] In addition, within business and management, neuromarketing research[5] has been conducted to reveal the neural mechanisms underlying consumer decision-making. Factors such as preferences,[6] price,[7] advertising assessments,[8] branding,[9] online consumer behavior analysis,[10] and purchasing processes[11] have been examined. These studies not only enhance the understanding of the role of the brain in purchasing decisions but also

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contribute to developments in BCI technology.[12,13] For example, a BCI has been designed to distinguish between familiar and unfamiliar information and to present search results for unknown data.[14]

The expansion of network technologies such as cloud computing and advances in artificial intelligence, such as deep learning, have resulted in increasingly prominent use of big data. One notable example is the recommendation system based on collective intelligence, which is typically implemented through collaborative filtering.[15] Research has been carried out on improving scalability and precision, including the pioneering GroupLens system,[16] item-based collaborative filtering,[17] and matrix factorization approaches.[18] Various collaborative filtering methods incorporating deep learning have also been explored in recent years.[19,20]

However, the big data underlying collective intelligence largely represent conscious cognition that is expressible through ratings or language, and it remains uncertain whether this reality truly reflects human psychology. By contrast, brain activity can capture subconscious mental states such as emotions. Thus, compiling and utilizing brain activity from multiple individuals may enable the expression of collective psychology beyond conventional collective intelligence. Nonetheless, most prior studies using brain activity data, including those on BCI and neuromarketing, were focused primarily on individuals. Accordingly, aggregating collective brain activity and applying it to recommendation systems can substantially advance the development of artificial intelligence.

In this study, we focused on a recommendation system that employs collective brain activity. The strength of collaborative filtering-based recommendation systems lies in estimating and recommending ratings for unknown products using aggregated rating data. However, when brain activity is used to represent product preference, which is an essential element of recommendation, it can be recorded only for known products that are already viewed, preventing the direct evaluation of unknown items from brain data. Therefore, we propose a method to infer an individual's brain activity corresponding to an unknown product through the collaborative filtering of collective brain activity and then to use the inferred activity to predict preferences for unknown products. We verify the proposed method, which estimates brain activity for the recommended product through collaborative filtering, by comparing its accuracy with that of conventional collaborative filtering using rating values and actual measured brain activity for recommended products.

2. Data, Materials, and Methods

In this work, brain activity (changes in oxyhemoglobin concentration) was measured via an NIR spectroscopy (NIRS) device (Spectratech OEG-16) across 16 channels positioned on the prefrontal cortex, as depicted in Fig. 1. The sampling interval was set to 0.08 s. The participants were 20 students (mean age = 20.8 ± 0.7 years, 11 males, 9 females) from the University of Toyama who provided informed consent. Users of recommendation systems vary widely, but previous research also concentrated on students.[21] The participants are part of the digital native generation and comfortable with the internet and digital devices, actively using information services as efficient tools. A brain function measurement experiment involving a product

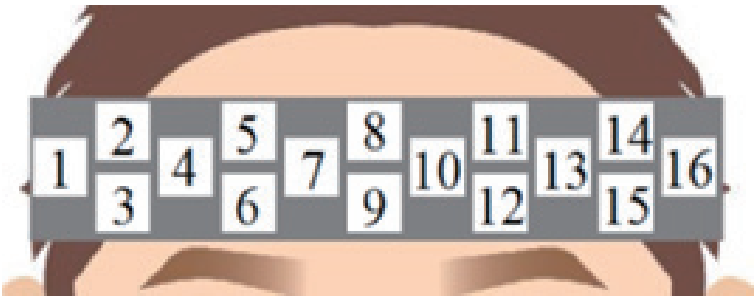

Fig. 1. (Color online) Measured regions.

evaluation task designed to capture brain activity associated with preference, which is a crucial element in product recommendation, was conducted. The specific experimental design is described below.

Product evaluation task (Fig. 2)

Step 1: Fixate on an "X" displayed at the center of the screen for 15 s.

Step 2: Observe the product images (mainly food and beverages) shown on the screen for 15 s.

Step 3: Provide a rating indicating a preference for the displayed product. The rating scale ranges from 1 (dislike) to 5 (like).

The experimental system displays images on a monitor, connects the NIRS device to a PC, and transmits brain activity data to the PC in real time via the user datagram protocol (UDP) for storage.

The following outlines the overall experimental procedure.

Experimental procedure

1. A brain activity sensor is attached to the participant's head.
2. The participant views the images presented on the screen for a total of 100 measurements (10-min breaks follow every 50 measurements).
3. After completion, the sensor is detached from the participant's head.

In this study, we utilized brain activity data recorded during the 15 s viewing period of product images in the above task. The experiment received approval from the Toyama University Ethics Committee for Nonmedical Human Studies.

3. Results

3.1 Brain activity feature extraction method

Preprocessing was performed on the raw brain activity data to predict evaluation scores via machine learning using brain activity as input features. A bandpass filter was first applied to eliminate noise. NIRS measures relative fluctuations, so the baseline brain activity value at the onset of image viewing was set to zero. Brain activity data are time series signals; thus the integrated value over the image-viewing period was calculated for each channel to obtain feature values.[22] The choice of target channel also plays a critical role in both accuracy and potential device miniaturization. The detailed procedures for bandpass filtering, integrated value, and channel selection are outlined below.

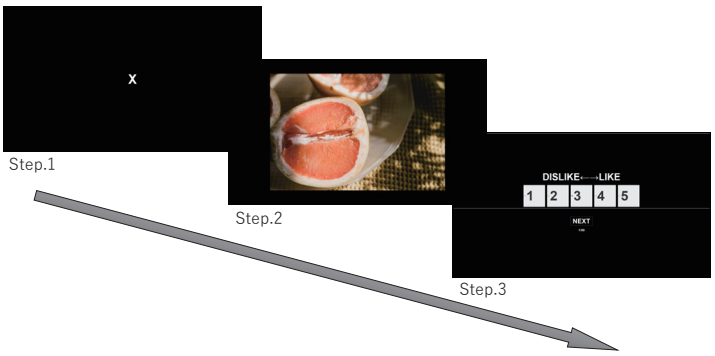

Fig. 2. (Color online) Product evaluation task.

3.1.1 Bandpass filter

Brain activity patterns vary among individuals, and the selected frequency band can affect classification accuracy. However, the optimal frequency range differs across studies. Thus, we evaluated the following six frequency bands.

- 0.01 Hz–0.05 Hz
- 0.01 Hz–0.10 Hz
- 0.01 Hz–0.25 Hz
- 0.01 Hz–0.50 Hz
- 0.01 Hz–0.75 Hz
- 0.01 Hz–1.00 Hz

3.1.2 Integrated value

The collaborative filtering method employed in this study relies on group-level rather than individual-level data; therefore, individual variability must be addressed. Accordingly, we adopted the z score as a standardization technique. Two types of integrated value data were compared to evaluate the effectiveness of z score use.

- Raw integrated values without any additional processing (raw data)
- Integrated values standardized via z scores (z score data)

Thus, the brain activity features used in this study comprised 12 patterns, combining six types of bandpass filters with two types of integrated value processing.

3.1.3 Target channels (regions)

Because this recommendation system focuses on preference, the medial prefrontal cortex (mPFC), [6,23] which is associated with the brain's reward system, is believed to play a substantial role. Therefore, the following channel sets were examined.

- All channels
- mPFC (channels 7, 8, 9, and 10)

3.2 Classification method

A support vector machine (SVM)[24] classified the rating value into five classes (1–5) using the extracted features. Two datasets were used for prediction. One consisted of brain activity features from actual product observations, as in conventional neuromarketing (referred to as the "BA-SVM method"); the other consisted of brain activity features predicted through collaborative filtering (referred to as the "BACF-SVM method"). Figure 3 shows the processing flow of BA-SVM and BACF-SVM. BA-SVM utilizes brain activity features related to products actually viewed by the subject for model creation and data verification. On the other hand, in BACF-SVM, model creation utilizes actual brain activity features, as with BA-SVM, while data verification utilizes estimated brain activity features using collaborative filtering from actual brain activity. In other words, the learning data consists of brain activity features associated with known products during viewing. The recommended products are unknown items that have not actually been viewed, and since no brain activity features exist for them, BACF-SVM uses collaborative filtering to estimate brain activity features for unknown products and utilizes them for the evaluation of unknown products. The SVM employed a Gaussian kernel, with the cost parameter (C) and Gaussian kernel parameter (γ) optimized via grid search and 10-fold cross-validation within the range of 10^{-8} to 10^{8}.

The effectiveness of the proposed method was evaluated by comparing three models: the CF method, which is the standard recommendation system method and uses collaborative filtering on rating values (predicted values are rounded to one of five classes for classification); the BA-SVM method; and the BACF-SVM method.

3.3 Feature extraction results

Figure 4 shows examples of extracted brain activity features. Figures 4(a) and 4(b) present examples from different participants, and Figs. 4(b) and 4(c) show examples from different channels of the same participant, ordered by increasing bandpass filter bandwidth. The horizontal axis represents the rating value (*RV*), and the vertical axis represents the arithmetic

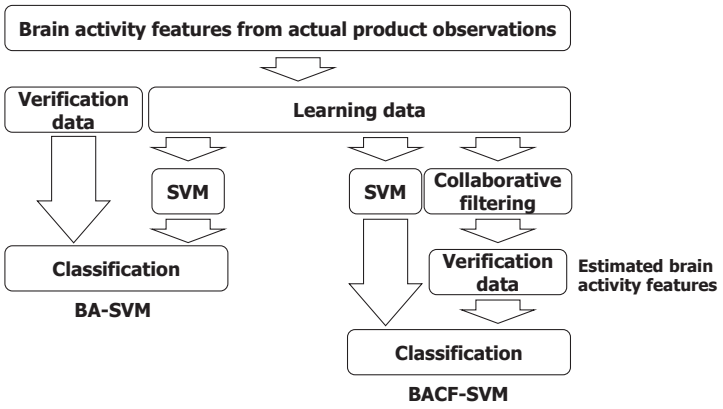

Fig. 3. Process flow diagram.

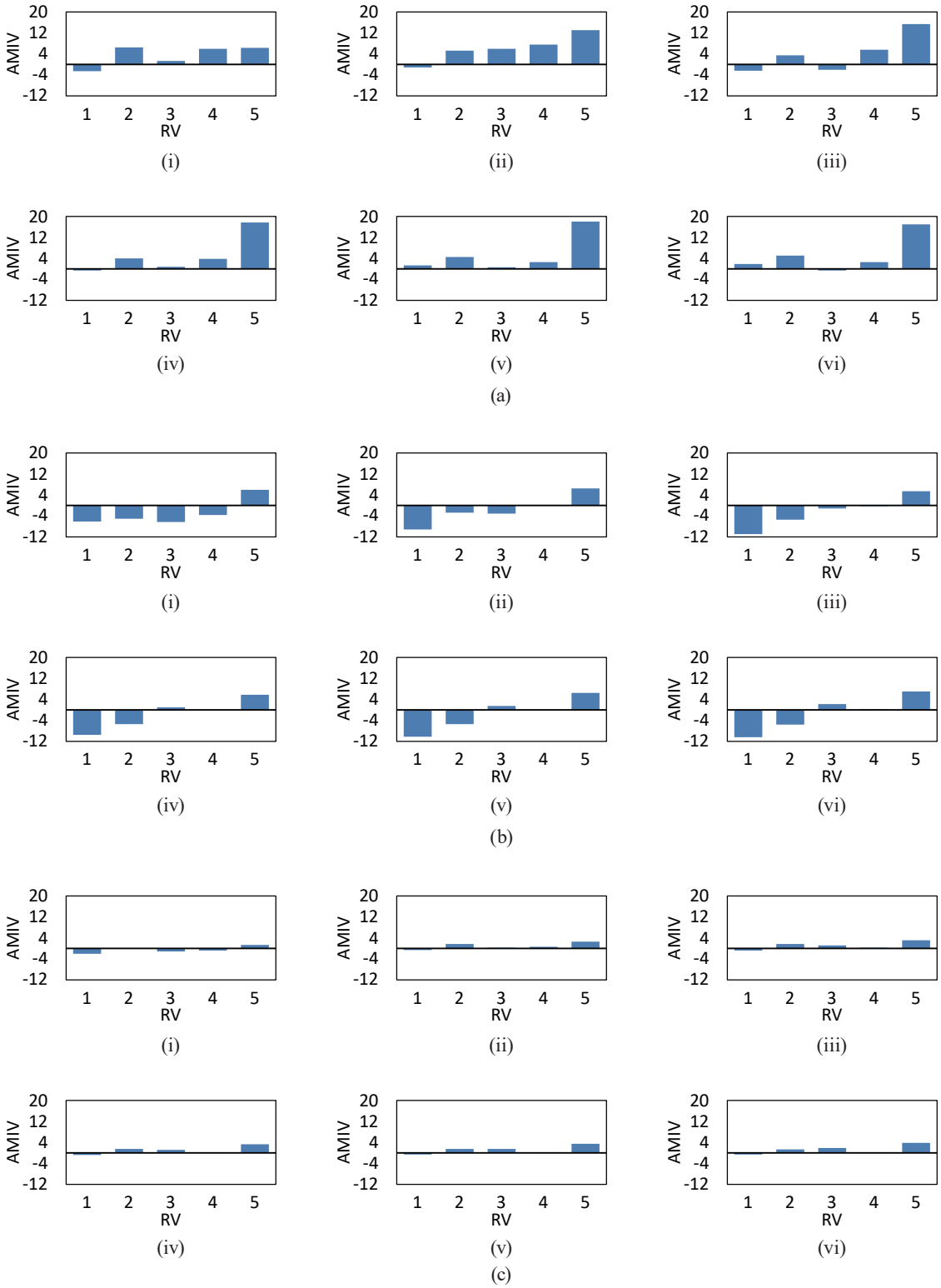

Fig. 4. (Color online) Examples of brain activity features: (a) Subject H, Channel 8; (i) 0.01–0.05, (ii) 0.01–0.10, (iii) 0.01–0.25, (iv) 0.01–0.50, (v) 0.01-0.75, and (vi) 0.01–1.00, (b) Subject J, Channel 10; (i) 0.01–0.05, (ii) 0.01–0.10, (iii) 0.01–0.25, (iv) 0.01–0.50, (v) 0.01-0.75, and (vi) 0.01–1.00, and (c) Subject J, Channel 5; (i) 0.01–.05, (ii) 0.01–0.10, (iii) 0.01–0.25, (iv) 0.01–0.50, (v) 0.01-0.75, and (vi) 0.01–1.00.

mean of the integrated values (*AMIV*) for each rating. Figures 4(a) and 4(b) demonstrate a general trend in which higher ratings correspond to stronger brain activity features. However, Fig. 4(a) indicates that features are most discernible when the upper cutoff frequency is 0.10 Hz, whereas Fig. 4(b) shows better readability at 0.25 Hz, implying that the optimal cutoff frequency varies among subjects. Additionally, Figs. 4(b) and 4(c) reveal that even within the same individual, the most readable channels differ. Therefore, it is essential to test multiple bandpass filters and brain regions.

3.4 Classification results

In this study, we used accuracy (the proportion of correct classification results) as an evaluation metric. Rating distributions differed among participants; therefore, we generated 100000 random predictions (RD method) on the basis of these distributions, and their average served as the chance level. In the experimental results shown in Tables 1–4 below, the configuration with the highest accuracy, whether from the RD, CF, or other methods, is highlighted for each subject, with (z score) and without (raw data) z score normalization.

3.4.1 BA-SVM classification results

Table 1 presents the classification outcomes for the RD, CF, and BA-SVM (all channels) methods. Table 1 shows that all the CF and BA-SVM patterns achieved accuracies above the chance level. Except for subject R, the BA-SVM method outperformed the CF method, indicating the advantage of incorporating brain activity data. The optimal bandpass filter bandwidth varied among subjects; thus, the accuracy tended to be highest when the upper cutoff frequency was set at or below 0.5 Hz. This finding serves as a useful reference for selecting the appropriate cutoff frequency. Table 2 lists the classification results for the BA-SVM (mPFC). Cells with accuracies exceeding those of the BA-SVM (all channels) configuration are underlined. Table 2 shows that, as in the all-channel case, all the results surpass chance levels and outperform those of the CF method except for subject R. Moreover, the highest accuracy is underlined for some participants, suggesting a certain degree of effectiveness in identifying the relevant area. The implications of the z score and regional identification are discussed further alongside the BACF-SVM results.

3.4.2 BACF-SVM results

Table 3 shows the BACF-SVM (all channels) results, and Table 4 shows the BACF-SVM (mPFC) results. As with BA-SVM, both tables indicate results above the chance level, with BACF-SVM surpassing the CF method except for subjects D, F, M, and R. BACF-SVM predicts brain activity features through collaborative filtering; therefore, a slight decrease in accuracy is expected. However, when comparing the averages of all patterns, this decline remains modest at 3.7 percentage points (9.2% compared with BA-SVM). These findings verify that collaborative filtering, which is the main focus of this study, can effectively predict brain activity features,

Table 1
BA-SVM (all channels) classification results.

Raw data								
Participant	RD	CF	0.01–0.05	0.01–0.1	0.01–0.25	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	**0.44**	0.40	0.40	0.41	0.40	0.41
B	0.21	0.29	0.38	0.36	0.33	**0.40**	0.39	0.37
C	0.24	0.33	0.38	0.38	**0.42**	0.37	0.38	0.37
D	0.23	0.35	0.35	0.35	**0.39**	0.34	0.31	0.34
E	0.34	0.37	**0.52**	0.49	0.49	0.49	0.49	0.49
F	0.27	0.41	0.47	0.43	0.41	0.44	0.44	**0.49**
G	0.25	0.31	0.41	0.42	0.40	**0.43**	**0.43**	0.42
H	0.23	0.19	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**
I	0.21	0.21	0.29	0.28	0.28	0.31	0.28	**0.33**
J	0.22	0.33	**0.38**	0.36	0.36	0.30	0.32	0.30
K	0.34	0.31	0.44	0.47	0.49	**0.51**	0.47	0.48
L	0.23	0.22	**0.37**	0.35	**0.37**	0.30	0.27	0.31
M	0.23	0.33	**0.38**	0.30	0.35	0.30	0.30	0.30
N	0.22	0.30	0.27	0.27	0.32	0.33	**0.34**	**0.34**
O	0.36	0.41	0.55	0.55	**0.57**	0.54	0.54	0.54
P	0.27	0.40	**0.41**	**0.41**	**0.41**	**0.41**	**0.41**	**0.41**
Q	0.31	0.31	0.48	**0.50**	0.43	0.49	0.47	0.48
R	0.31	**0.55**	0.43	0.43	0.45	0.44	0.43	0.44
S	0.25	0.28	**0.49**	0.37	0.40	0.40	0.32	0.34
T	0.28	0.36	0.39	0.40	0.42	**0.43**	0.42	0.42
Avg.	0.263	0.330	0.409	0.394	0.402	0.400	0.388	0.397
Std.	0.045	0.078	0.069	0.071	0.064	0.072	0.073	0.070
z score data								
Participant	RD	CF	0.01–0.05	0.01–0.1	0.01–0.25	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	**0.42**	0.40	0.40	0.41	0.41	0.41
B	0.21	0.29	0.36	0.35	0.34	**0.41**	0.38	0.35
C	0.24	0.33	**0.39**	0.37	0.36	0.38	0.38	**0.39**
D	0.23	0.35	0.34	0.34	**0.37**	0.36	0.36	0.36
E	0.34	0.37	**0.51**	0.49	0.49	0.49	0.49	0.50
F	0.27	0.41	0.43	0.40	0.41	**0.46**	**0.46**	**0.46**
G	0.25	0.31	0.40	**0.42**	0.39	**0.42**	**0.42**	**0.42**
H	0.23	0.19	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**
I	0.21	0.21	**0.34**	0.31	0.28	0.31	0.30	0.28
J	0.22	0.33	0.37	0.35	**0.38**	0.35	0.34	0.31
K	0.34	0.31	0.49	0.43	0.44	**0.50**	0.43	0.48
L	0.23	0.22	**0.37**	0.32	0.35	0.32	0.31	0.34
M	0.23	0.33	**0.36**	0.32	0.33	0.33	0.33	0.34
N	0.22	0.30	0.29	0.27	0.31	0.30	**0.33**	0.27
O	0.36	0.41	0.54	0.56	**0.57**	0.54	0.54	0.54
P	0.27	0.40	**0.43**	0.41	0.41	0.41	0.41	0.41
Q	0.31	0.31	0.47	0.49	0.46	**0.51**	0.50	0.50
R	0.31	**0.55**	0.46	0.43	0.43	0.43	0.43	0.43
S	0.25	0.28	**0.45**	0.35	0.43	0.39	0.36	0.33
T	0.28	0.36	0.38	**0.48**	0.43	0.42	0.43	0.40
Avg.	0.263	0.330	0.408	0.392	0.397	0.405	0.398	0.394
Std.	0.045	0.078	0.063	0.071	0.065	0.068	0.064	0.074

Table 2
BA-SVM (mPFC) classification results.

Raw data								
Participant	RD	CF	0.01–0.05	0.01–0.25	0.01–0.1	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	**0.45**	0.41	0.41	0.43	0.43	0.42
B	0.21	0.29	0.30	0.35	0.33	0.39	**0.40**	0.39
C	0.24	0.33	0.34	0.37	0.34	0.38	0.38	**0.40**
D	0.23	0.35	0.31	0.38	**0.39**	0.38	0.36	0.37
E	0.34	0.37	**0.55**	0.53	0.51	0.52	0.54	0.51
F	0.27	0.41	0.42	**0.47**	0.45	0.42	**0.47**	**0.47**
G	0.25	0.31	0.46	0.45	0.44	**0.47**	0.46	0.44
H	0.23	0.19	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**
I	0.21	0.21	**0.30**	0.28	0.28	0.28	0.28	0.29
J	0.22	0.33	**0.40**	0.34	0.34	0.31	0.34	0.34
K	0.34	0.31	**0.52**	0.43	0.45	0.43	0.46	0.42
L	0.23	0.22	0.32	0.34	0.35	**0.40**	0.39	0.35
M	0.23	0.33	0.34	0.35	0.37	0.38	**0.40**	0.38
N	0.22	0.3	0.27	**0.35**	0.33	0.34	0.34	0.34
O	0.36	0.41	0.54	0.56	**0.60**	0.56	0.54	0.56
P	0.27	0.4	**0.44**	0.41	0.41	0.41	0.41	0.41
Q	0.31	0.31	0.42	0.46	0.42	0.46	**0.49**	0.46
R	0.31	**0.55**	0.45	0.46	0.46	0.46	0.45	0.45
S	0.25	0.28	**0.42**	0.35	0.34	0.35	0.37	**0.42**
T	0.28	0.36	0.38	0.38	0.40	**0.41**	0.40	0.39
Avg.	0.263	0.330	0.399	0.401	0.398	0.406	0.413	0.408
Std.	0.045	0.078	0.080	0.068	0.072	0.065	0.066	0.062
z score data								
Participant	RD	CF	0.01–0.05	0.01–0.25	0.01–0.1	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	**0.46**	0.43	0.41	**0.46**	0.43	0.42
B	0.21	0.29	0.32	0.32	0.32	0.37	0.40	**0.41**
C	0.24	0.33	0.34	0.39	0.36	0.38	0.39	**0.40**
D	0.23	0.35	0.36	**0.38**	**0.38**	0.37	0.37	0.36
E	0.34	0.37	**0.55**	0.54	0.54	**0.55**	0.53	0.51
F	0.27	0.41	0.42	0.44	0.43	0.46	0.43	**0.49**
G	0.25	0.31	0.45	0.44	0.45	**0.46**	0.43	0.44
H	0.23	0.19	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**	**0.35**
I	0.21	0.21	0.28	0.28	**0.29**	0.28	0.25	0.28
J	0.22	0.33	**0.39**	0.33	0.34	0.31	0.33	0.32
K	0.34	0.31	**0.53**	0.46	0.46	0.46	0.49	0.43
L	0.23	0.22	0.35	0.34	0.36	0.37	**0.40**	0.33
M	0.23	0.33	0.36	0.36	0.39	**0.40**	0.35	0.39
N	0.22	0.3	0.27	**0.35**	0.33	**0.35**	**0.35**	**0.35**
O	0.36	0.41	0.56	0.56	**0.60**	0.56	0.57	0.55
P	0.27	0.4	**0.44**	**0.44**	0.41	0.41	0.42	0.41
Q	0.31	0.31	0.46	0.45	0.43	**0.48**	0.45	0.45
R	0.31	**0.55**	0.44	0.44	0.46	0.44	0.45	0.46
S	0.25	0.28	**0.42**	0.35	0.37	0.33	0.38	0.41
T	0.28	0.36	0.42	0.39	0.42	0.40	**0.44**	0.41
Avg.	0.263	0.330	0.408	0.402	0.405	0.409	0.410	0.408
Std.	0.045	0.078	0.080	0.070	0.073	0.072	0.070	0.064

Table 3
BACF-SVM (all channels) classification results.

Raw data								
Participant	RD	CF	0.01–0.05	0.01–0.25	0.01–0.1	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	0.32	0.31	**0.36**	0.34	**0.36**	**0.36**
B	0.21	0.29	0.29	0.27	0.28	0.29	0.29	**0.33**
C	0.24	0.33	0.30	0.30	0.30	0.29	0.33	**0.35**
D	0.23	**0.35**	0.30	**0.35**	0.34	0.34	0.30	0.30
E	0.34	0.37	0.49	**0.50**	0.49	**0.50**	**0.50**	**0.50**
F	0.27	**0.41**	0.39	0.38	0.38	0.38	0.38	0.38
G	0.25	0.31	0.32	0.38	0.37	0.41	**0.42**	0.38
H	0.23	0.19	0.32	0.33	0.33	0.32	**0.34**	0.32
I	0.21	0.21	0.29	0.29	**0.32**	0.28	0.31	0.29
J	0.22	0.33	0.35	**0.38**	0.31	0.37	0.36	0.36
K	0.34	0.31	**0.46**	0.43	0.43	0.45	0.45	0.45
L	0.23	0.22	0.31	**0.33**	**0.33**	0.31	0.32	**0.33**
M	0.23	**0.33**	0.28	0.28	0.29	0.31	0.31	0.28
N	0.22	0.30	0.33	0.27	0.33	0.31	**0.34**	0.33
O	0.36	0.41	0.55	0.54	**0.56**	0.54	0.54	0.54
P	0.27	0.40	**0.43**	0.41	**0.43**	0.41	0.41	0.42
Q	0.31	0.31	0.40	0.40	0.40	0.40	0.41	**0.42**
R	0.31	**0.55**	0.43	0.44	0.43	0.44	0.44	0.45
S	0.25	0.28	0.30	0.30	**0.35**	0.30	0.30	0.30
T	0.28	0.36	0.34	**0.46**	0.36	0.36	0.36	0.35
Avg.	0.263	0.330	0.360	0.368	0.370	0.368	0.374	0.372
Std.	0.045	0.078	0.074	0.076	0.069	0.071	0.068	0.069
z score data								
Participant	RD	CF	0.01–0.05	0.01–0.25	0.01–0.1	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	0.33	0.32	0.34	0.29	0.33	**0.36**
B	0.21	0.29	0.30	0.29	0.26	**0.36**	0.34	0.32
C	0.24	0.33	0.36	0.32	0.30	**0.37**	0.36	0.30
D	0.23	**0.35**	0.33	0.32	**0.35**	0.30	0.30	0.30
E	0.34	0.37	0.49	**0.50**	0.49	0.49	0.49	**0.50**
F	0.27	**0.41**	0.38	0.38	0.40	0.38	0.38	0.38
G	0.25	0.31	0.31	0.39	0.40	0.42	**0.43**	0.42
H	0.23	0.19	0.33	0.33	0.32	0.32	**0.35**	0.33
I	0.21	0.21	0.30	0.29	0.29	0.30	0.29	**0.31**
J	0.22	0.33	**0.34**	0.32	0.31	0.31	0.32	0.32
K	0.34	0.31	**0.45**	0.43	0.44	0.44	0.43	0.43
L	0.23	0.22	0.31	0.35	0.36	0.36	0.37	**0.40**
M	0.23	**0.33**	0.27	0.27	0.30	0.27	0.27	0.27
N	0.22	0.30	0.29	0.30	0.26	0.33	0.32	**0.36**
O	0.36	0.41	**0.55**	0.34	0.54	0.37	0.35	0.36
P	0.27	0.40	0.41	0.41	**0.43**	0.41	0.41	0.41
Q	0.31	0.31	**0.41**	0.40	**0.41**	**0.41**	0.40	**0.41**
R	0.31	**0.55**	0.43	0.45	0.43	0.43	0.43	0.44
S	0.25	0.28	0.33	0.34	**0.37**	0.31	0.34	**0.37**
T	0.28	0.36	0.34	**0.40**	0.35	0.36	0.36	0.38
Avg.	0.263	0.330	0.363	0.358	0.368	0.362	0.364	0.369
Std.	0.045	0.078	0.071	0.059	0.073	0.057	0.054	0.056

Table 4
BACF-SVM (mPFC) classification results.

Raw data								
Participant	RD	CF	0.01–0.05	0.01–0.25	0.01–0.1	0.01–0.5	0.01–0.75	0.01–1.0
A	0.25	0.33	**0.37**	0.33	0.35	0.33	0.34	0.34
B	0.21	0.29	0.30	0.27	**0.31**	0.27	0.26	0.27
C	0.24	0.33	0.30	**0.36**	0.30	0.31	0.30	0.32
D	0.23	**0.35**	0.34	0.33	0.30	0.32	**0.35**	0.31
E	0.34	0.37	0.49	0.49	0.49	0.49	0.49	**0.50**
F	0.27	**0.41**	0.39	0.39	0.38	0.38	0.39	0.39
G	0.25	0.31	0.31	0.31	**0.35**	0.31	0.34	0.31
H	0.23	0.19	0.32	**0.34**	0.33	0.33	**0.34**	**0.34**
I	0.21	0.21	0.29	0.30	**0.31**	**0.31**	0.29	0.28
J	0.22	**0.33**	0.29	0.30	0.30	0.30	0.29	0.30
K	0.34	0.31	0.43	**0.45**	0.43	0.43	0.43	0.44
L	0.23	0.22	0.30	0.30	0.32	0.30	0.32	**0.33**
M	0.23	**0.33**	**0.33**	0.33	0.28	0.32	0.31	0.31
N	0.22	0.30	**0.37**	0.29	0.27	0.28	0.29	0.29
O	0.36	0.41	0.54	**0.55**	0.36	0.54	0.54	**0.55**
P	0.27	0.40	**0.41**	**0.41**	**0.41**	**0.41**	**0.41**	**0.41**
Q	0.31	0.31	0.40	**0.46**	0.43	0.42	0.43	0.40
R	0.31	**0.55**	0.43	0.44	0.43	0.44	0.45	0.43
S	0.25	0.28	**0.32**	0.30	0.30	0.30	0.30	0.30
T	0.28	0.36	**0.43**	0.34	0.38	0.39	0.42	0.40
Avg.	0.263	0.330	0.368	0.365	0.352	0.359	0.365	0.361
Std.	0.045	0.078	0.069	0.075	0.059	0.073	0.075	0.074
z score data								
Participant	RD	CF	0.01–0.05	0.01–0.25	0.01–0.1	0.01–0.5	0.01–0.75	0.01–-1.0
A	0.25	0.33	0.33	0.35	**0.38**	0.35	0.37	**0.38**
B	0.21	0.29	0.29	**0.31**	0.27	0.27	0.29	0.29
C	0.24	0.33	0.30	0.30	0.33	**0.38**	0.32	0.32
D	0.23	**0.35**	0.32	0.32	0.30	0.32	0.33	0.33
E	0.34	0.37	**0.50**	**0.50**	0.49	**0.50**	0.49	0.49
F	0.27	**0.41**	0.38	0.39	0.38	0.40	0.38	0.38
G	0.25	0.31	0.32	0.31	0.31	0.35	**0.36**	0.31
H	0.23	0.19	**0.34**	0.33	**0.34**	0.32	0.33	0.33
I	0.21	0.21	0.33	0.33	**0.36**	0.31	0.33	0.32
J	0.22	**0.33**	0.30	0.33	0.31	0.26	0.32	0.32
K	0.34	0.31	0.43	0.43	0.46	0.43	**0.46**	0.42
L	0.23	0.22	0.32	0.32	0.33	0.31	0.31	**0.35**
M	0.23	0.33	0.33	0.32	**0.35**	0.31	0.33	0.27
N	0.22	0.30	**0.34**	0.32	0.31	0.30	0.32	0.30
O	0.36	0.41	0.55	**0.56**	0.55	0.35	0.54	0.54
P	0.27	0.40	0.42	**0.43**	0.41	0.42	0.42	0.41
Q	0.31	0.31	0.44	**0.48**	0.46	0.47	0.45	0.44
R	0.31	**0.55**	0.44	0.43	0.43	0.45	0.43	0.43
S	0.25	0.28	**0.42**	0.34	0.35	0.32	0.34	0.31
T	0.28	0.36	**0.37**	0.34	0.34	0.34	0.34	0.36
Avg.	0.263	0.330	0.374	0.372	0.373	0.358	0.373	0.365
Std.	0.045	0.078	0.070	0.073	0.071	0.065	0.067	0.069

demonstrating the validity of the proposed method. However, no significant differences in accuracy were observed between conditions, such as features. Therefore, to understand the tendencies of our proposed method, we verified the effects of *z* scores and the region as described in the following sections.

3.4.3 Effect of *z* score

The effect of *z* score was assessed by comparing the maximum accuracies achieved with and without *z* scores in BA-SVM and BACF-SVM and then determining whether the difference was positive or negative. A negative difference indicates improved performance with respect to the *z* score, and the results were evaluated by counting the number of participants exhibiting each outcome. Table 5 summarizes these counts. Table 5 shows that, for BA-SVM, a higher accuracy was consistently achieved without a *z* score across all channels. BA-SVM predictions do not need the features of other subjects and rely solely on individual data; thus, it is plausible that not using the *z* score preserves unique individual characteristics more effectively. By contrast, BACF-SVM yielded significant differences when focusing on the mPFC, suggesting that *z* score is advantageous in this context. BACF-SVM estimates brain activity features for target products using data from multiple subjects; therefore, the *z* score likely enhances performance by mitigating interindividual variability.

3.4.4 Effect of region

The impact of the analyzed region was examined by comparing differences in the maximum values obtained via all channels versus only the mPFC for both BA-SVM and BACF-SVM and determining whether the difference was positive or negative. A negative difference indicates that using only the mPFC yields better results, and the evaluation was again based on participant counts. Table 6 provides a summary of these comparisons. Table 6 shows that, for BA-SVM, identifying and isolating specific brain regions produced superior results. For BACF-SVM,

Table 5
Effect of *z* score.

Raw–*z* score	BA-SVM		BACF-SVM	
	all channels	mPFC	all channels	mPFC
>0	10	5	7	3
=0	4	10	5	4
<0	6	5	8	13

Table 6
Effect of regional identification.

	BA-SVM		BACF-SVM	
All – mPFC	Raw	*z* score	Raw	*z* score
>0	5	3	8	7
=0	3	3	6	4
<0	11	13	5	8

although the *z* score generally improved outcomes, the effect was not substantial. This is likely because limiting the analysis to a smaller region reduces the amount of available information, thereby requiring more accurate estimation of the brain activity features. This suggests that the accuracy of brain activity feature estimation may be insufficient. Collaborative filtering, the method used for estimating brain activity features, depends on correlation strength. Thus, estimation performance is affected by how well evaluation values correlate with brain activity features, highlighting the need for further refinement. Reducing the number of channels required for brain activity features can also facilitate the miniaturization of measurement devices.

4. Discussion

The classification accuracy remains modest, but the experimental results consistently exceeded the chance level, demonstrating that the method of predicting brain activity features through collaborative filtering, which is the main focus of this study, is effective, with only a 9.2% loss relative to the use of brain activity features obtained during actual product viewing. Preprocessing choices such as setting the bandpass filter cutoff frequency to 0.5 Hz or less also proved beneficial, and the *z* score further improved the performance and enabled region-specific identification. However, individual differences exist. When comparing maximum accuracy with BA-SVM and BACF-SVM, the following cases show particularly significant changes. BACF-SVM achieved higher accuracy: Subject I showed increases of 6 percentage points in raw data and 7 percentage points in *z* score data when specifying the region. Subject R showed an increase of 9 percentage points when using *z* score data across all channels. BACF-SVM achieved lower accuracy: Subject G showed decreases of 11 percentage points in raw data and 10 percentage points in *z* score data when specifying the region; Subject S showed decreases of 14 percentage points in raw data and 8 percentage points in *z* score data when specifying the region; Subject T showed decreases of 8 percentage points in all channels and 7 percentage points in specifying the region when using the *z* score; Subjects A, F, and K showed average decreases of 7, 7, and 6 percentage points, respectively. Given these various individual differences, we need to make some improvements. These results apply to students, so they need to be verified for a broader age range.

On the basis of the experimental results, we calculated the probability distribution of predictions for each user rating using the confusion matrix that summarized data from all subjects and patterns. The results are shown in Table 7. Table 7 shows that the higher user ratings exhibit greater accuracy, but BACF-SVM demonstrates reduced accuracy for user rating 5 compared with BA-SVM. Here, assuming we recommend products with predicted ratings of 4 and 5, the proportion of products recommended for each user rating is as shown in Fig. 5. The horizontal axis represents the user ratings, and the vertical axis represents the recommendation rate. Figure 5 shows that products with higher user ratings are more likely to be recommended. Therefore, this result shows that the proposed method functions as a recommendation system.

For practical application, it will be necessary to increase the accuracy of the baseline method, which uses brain activity features obtained during actual product viewing. For example, with larger datasets, model accuracy can be improved by adopting more advanced methods than

Table 7
Predicted probability for each user rating.
(a) BA-SVM

		Predicted ratings				
		1	2	3	4	5
User ratings	1	0.165	0.091	0.270	0.242	0.232
	2	0.041	0.216	0.276	0.306	0.160
	3	0.050	0.104	0.441	0.265	0.140
	4	0.035	0.081	0.206	0.501	0.177
	5	0.018	0.061	0.169	0.251	0.501

(b) BACF-SVM

		Predicted ratings				
		1	2	3	4	5
User ratings	1	0.157	0.152	0.263	0.252	0.177
	2	0.039	0.203	0.275	0.364	0.118
	3	0.042	0.109	0.407	0.324	0.118
	4	0.036	0.089	0.197	0.531	0.147
	5	0.018	0.073	0.155	0.348	0.406

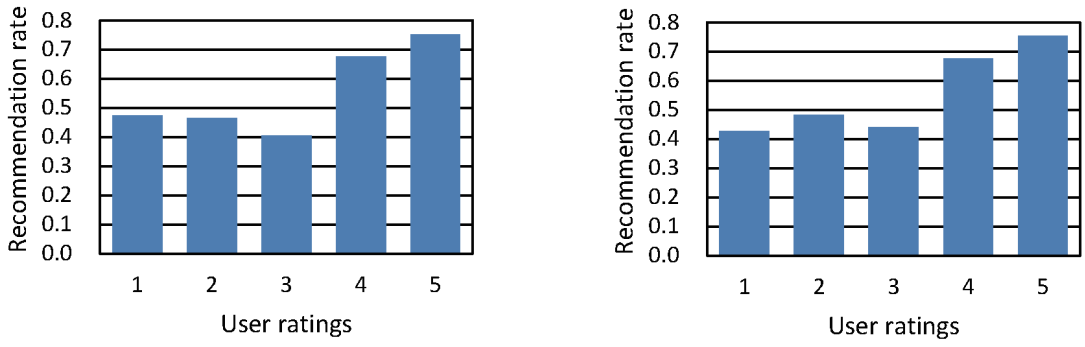

Fig. 5. (Color online) Recommendation rate for each user rating: (a) BA-SVM and (b) BACF-SVM.

SVMs, such as deep learning, by performing preprocessing across multiple frequency bands, as in this study, or by combining multiple machine learning techniques (e.g., majority voting) that use various patterns of brain activity features, such as those in areas other than the mPFC that are relevant to neuromarketing, such as the orbital frontal cortex (OFC) and dorsolateral prefrontal cortex.[25] This would also improve the accuracy of the proposed method in this study. Furthermore, although we predicted evaluation values on a five-point scale in this study, simplifying the problem to binary classification (e.g., recommend or not recommend) can improve accuracy and facilitate implementation.

In the future, as devices become smaller and more affordable, enabling a society where they are connected to networks and can be used easily, it will become possible to collect vast amounts of data. For example, by intentionally omitting some actual brain activity data when creating a learning model and verifying how this omission affects accuracy, we can determine the necessary amount of brain activity data for known products required to estimate the brain activity data of unknown products, enabling more concrete system design. In those cases, the proposed method has potential as a novel recommendation system distinct from conventional models.

5. Conclusions

In this study, we proposed a recommendation system that uses brain activity, which represents subconscious group-level information, instead of conventional systems that rely on consciously expressed evaluations. The proposed method estimates brain activity features for unknown products through the collaborative filtering of collective brain data and uses those features to predict individual preferences.

Experimental results demonstrated that the proposed BACF-SVM method achieved only a 9.2% decrease in accuracy relative to the BA-SVM method, which uses actual measured brain activity data, confirming the viability of recommendation systems that estimate brain activity features through collaborative filtering. Additionally, *z* score normalization effectively reduced individual differences, and focusing on specific brain regions, such as the mPFC, suggests the potential for device miniaturization. However, since the optimal approach varies from person to person depending on individual differences, improvements regarding to this issue are necessary.

With ongoing advancements in sensors and network technologies, leveraging subconscious collective intelligence derived from brain activity can become a powerful alternative to conventional systems based on explicit evaluations. If further enhanced through deep learning, ensemble modeling, or binary classification frameworks, the proposed system may evolve into a next-generation recommendation platform that integrates human sensitivity and subconscious cognition.

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