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PHENOMENON OF BOREDOM BY REPETITIVELY LISTENING TO THE SAME MUSIC
OBSERVATION THROUGH EEG

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ABSTRACT

The sustainable business must develop the fundamental technology for strategies that ensure people are interested in the information and contents for long periods of time. To contributes to this goal, this study was that a more realistic sense of boredom was evoked by the action of repeatedly listening to music in situations of repetitive consumption, based on the Meaning and Attentional Components (MAC) model defined psychologically boredom as two separate components of meaning and attention. Our experiment was the repetitively listening to the same music which had the highest or lowest level of preference, which was conducted over seven days respectively. Through electroencephalogram (EEG) measurements, decreased attention was measured by the increased alpha wave and the decreased beta wave. In addition, decreased meaning was measured by the increased gamma wave. In conclusion, measuring boredom must include factors of the temporal changes and the conditions of preference, particularly for EEG.

Keywords: *Attention, Bored, Interest, Meaning, Preference*

1 INTRODUCTION

In recent years, information services are popular business because of the increase of the quantity of information due to the development of the Internet. Considering the intensification of the competition for the services, one of the important issues is when sellers will resupply additional information and contents to consumers, in other words, how consumers will not be got bored. For example, the consumers may get bored for not only the products but also the

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services if the similar products are recommended repetitively. Therefore, the sustainable business must develop the fundamental technology for strategies that ensure people are interested in the information and contents for long periods of time. This study aims to contributes to this goal by incorporating psychology and informatics, in which a more realistic sense of boredom is evoked by the action of repeatedly listening to music in situations of repetitive consumption.

In general, interest of information and contents decreases over time and eventually boredom arises. People avoid boredom by not repeatedly consuming something, and therefore, boredom may spoil the expected selling schedule and recommendation. Although there is a general consensus on how to modulate boredom (e.g., by supplying a new item), it is challenging for humans to apply the idea in real time. Thus, in order to optimize the recommendation for the push timing and the selection of similar contents, which has the consideration to the state of interest of consumers changing dynamically over time, we propose that artificial intelligence predicts boredom through human information (i.e., subjective evaluation, action history, and biosignals).

In informatics, Inamura et al (2010) and Kapoor et al (2015) researched the mathematical model to introduce the state of mind of boredom by subjective evaluation or action history. Their study showed the possibility to predict boredom; however, they were unable to modulate boredom. Evaluation and action are evoked following the psychological and physiological response, and therefore, the data may not reflect the state of mind at that time. Thus, in order to achieve this study's proposition, biosignals have been used to measure boredom in real time.

In psychology, as shown in Table 1, Westgate & Wilson (2018) proposed the Meaning and Attentional Components (MAC) model for boredom as aversive emotion. Their model showed that boredom is composed of two separate components of attention and meaning. The attention component was defined as whether there is successful cognitive engagement in the current task. The meaning component was defined as whether the current task, regardless of engagement, is valuable and thus worth pursuing. Based on this definition, boredom may be measured by a decrease in attention or meaning. In addition, Raffaelli, Mills & Christoff (2018) measured a loss of attention by the increased power spectrum of the alpha wave and the decreased power spectrum of the beta wave. Moreover, Tsuji et al (2019) measured the level of preference of music by the increased power spectrum of the gamma wave. Therefore, in our study, we measured boredom through corresponding measures of attention and meaning using an electroencephalogram (EEG).

According to Westgate & Wilson (2018), previous studies have not focused on the temporal change component of human information that may reflect boredom. To observe temporal change and hence infer boredom, this study used music as the stimuli that would be consumed repeatedly. Finally, the purpose of this research was to test the following hypotheses.

What temporal changes and psychological components indicate boredom that arises from listening to music repeatedly?

(i) Is decreased attention measured by an increased alpha wave and a decreased beta wave?

(ii) Is a decreased meaning measured by an increased gamma wave?

Table 1. MAC model (adapted from Westgate & Wilson (2018))

	Meaning component	
Attention component	**Low Meaning** Task is INCONGRUENT with valued goals	**High Meaning** Task is CONGRUENT with valued goals
Understimulation: Demand < Resources	(A) ***Meaningless + Attentional boredom*** *Seek interesting activity*	(E) ***Attentional boredom*** *Increase demand*
Low-level Engagement Low demand + Low resources	(B) ***Meaningless boredom*** *Seek enjoyable activity*	(F) ***Enjoyment*** ***(Low boredom)***
High-level Engagement High demand + High resources	(C) ***Meaningless boredom*** *Seek interesting activity*	(G) ***Interest*** ***(Low boredom)***
Overstimulation: Demand > Resources	(D) ***Meaningless + Attentional boredom*** *Seek enjoyable activity*	(H) ***Attentional boredom*** *Increase resources*

2 METHODS

2.1 Stimuli and Procedure

Ten university students were asked to participate in the experiment. They were people who enjoyed listening to music and can easily spend an hour doing so. Eight genres of music were chosen from the database created by Santana et al (2020) and used as stimuli. The music stimuli were all instrumental and had a length of 30 seconds. To measure the participants' preference for music, they were asked to answer the following questions after listening to the 8 types of music stimuli.

(A) How do you intuitively favor this music? (1: Least favorite ~ 10: Most favorite)

(B) How early do you get bored of this music if you listen to it repeatedly? (1: Very late ~ 10: Very early)

We defined a preference for a particular kind of music as the score that resulted from subtracting the answer to (B) from the answer to (A). Within this experiment, each participant within the experiment or control group listened to the music of their highest or lowest preference, respectively. Specifically, the participants were asked to play the file and listen to the music repeatedly. The files were each composed of sections (S) and (Q), as depicted in Figure 1, where (S) represents a stimulation for 30 seconds, 6 times, after a rest for 60 seconds, and (Q) represents the participants answering questions about boredom for 180 seconds.

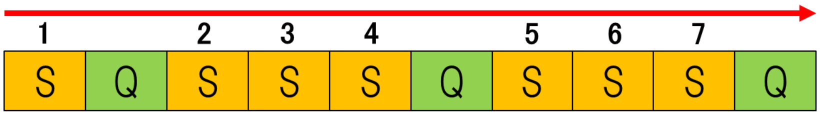

Figure 1. The composition of the music file allowing for repeated listening

2.2 Questionnaire and Apparatus

To relate the findings to the results of EEG, the participants were asked to subjectively evaluate their state of mind after listening to the music. According to Raffaelli, Mills & Christoff (2018), the following questionnaires were prepared. These are subjective evaluations, namely the state of emotion, the impression of the music, and the state of listening to the music. Incidentally, as shown Figure 2, the state of emotion was measured by a self-assessment Manikin test (10 points scale) according to Bradley & Lang (1994), as either: (1) Pleasure, (2) Arousal, or (3) Dominance. In addition, the impression of the music and the state of mind when listening to the music were measured by Visual Analog Scale (40 points scale), as follows.

The impression of the music:

(4) Preference

Do you have a preference for the music? (Do not prefer ~ Prefer)

(5) Boredom

Are you bored by the music? (Not bored ~ Bored)

The state of mind when listening to the music:

(6) Attention

How much did you pay attention when listening to the music? (Not paying attention ~ Paying attention)

(7) Time perception

When the music was a length of 3 minutes, how long did you the music was, subjectively? (Short ~ Long)

When participants listened to the music, an EEG was measured. Within this experiment, the wearable device “Muse2” (Interaxon) was used, which recorded the EEG using the application “Mind Monitor” (by James Clutterbuck). The electrodes of the device were located on the frontal lobes (AF7, AF8) and temporal lobes (TP9, TP10). The sampling rate of the device was 256 Hz.

After an EEG was measuring with Muse2, filters were applied to reduce the noise associated with the raw data, according to Hiraki et al (2020). A Fourier transform was then applied to the cleaned data, and therefore, the power spectrum with respect to time and frequency was obtained. The resolution of time was taken to be 400 points, over which the epoch was defined to be from 30 seconds before to 180 seconds after the stimulation. In addition, the resolution of frequency was 4673 points, from 7.5 Hz to 44 Hz, where the alpha wave was defined between 7.5 to 13 Hz, the beta wave between 13 Hz to 30 Hz, and the gamma wave between 30 Hz to 44 Hz. The average of the time and frequency power spectrums were calculated for all electrodes, and the averages for each wave were defined as (8) Alpha, (9) Beta, and (10) Gamma.

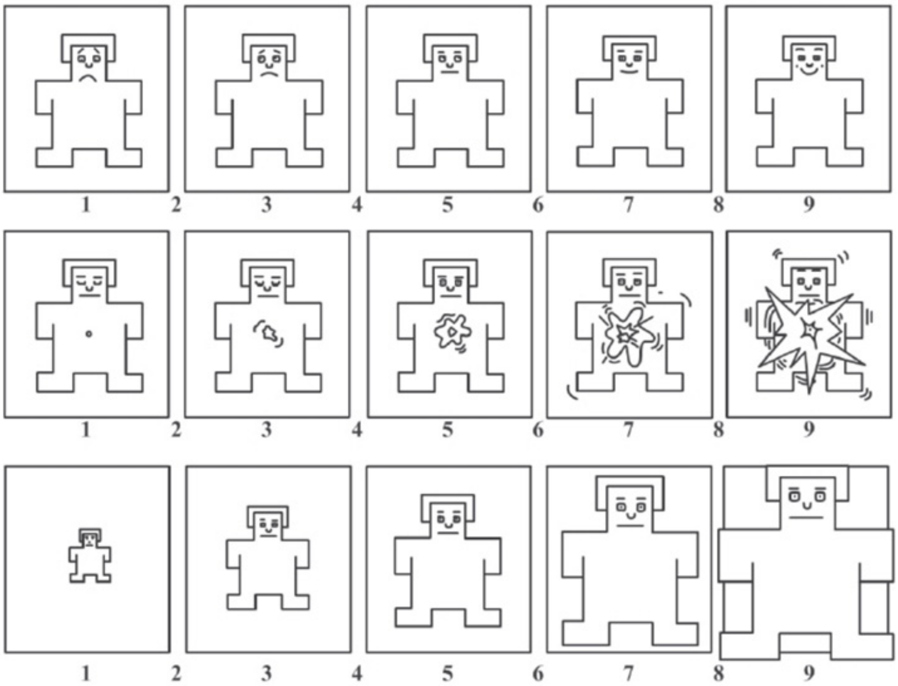

Figure 2. Self-Assessment Manikin test regarding Pleasure (top), (2) Arousal (middle), and (3) Dominance (bottom) (adapted from Bradley & Lang (1994))

2.3 Experimental Design and Analytical Method

The experiment was carried out according to the above explanation. While participants repeatedly listened to the music of their highest/lowest level of preference, their state of mind, including boredom, was measured with EEG, namely (1) Pleasure, (2) Arousal, (3) Dominance, (4) Preference, (5) Boredom, (6) Attention, (7) Time perception, (8) Alpha, (9) Beta, and (10) Gamma. The same experiment was conducted for seven days per piece of music. The experiment had seven sections for stimulation, and therefore, seven data points (1) Pleasure ~ (10) Gamma were acquired within the experimental and control group.

The temporal changes were analyzed from the data, both regarding long-term and short-term. As shown Figures 3 and 4, long-term was taken to be the full seven days, and short-term included seven points a day. First, the data was scaled with robust Z-scores for each participant in a day and a point. Second, based on the analyses for long-term and short-term, the bootstrap method was used and estimated a value "*t*" over 2500 times with bias-corrected and accelerated percentile method. Third, as shown in Figure 5, the temporal changes regarding (1) Pleasure ~ (10) Gamma in both long-term and short-term were observed based on the following definition.

Incidentally, the data for (4) Preference and (5) Boredom were used to check whether boredom was evoked by the experiment. Firstly, two-factor repeated non-parametric measures ANOVA were applied, in which a p-value of less than 0.05 was considered statistically significant. In detail, the first factor included the temporal changes that occurred for seven days or over seven points a day, and the second factor involved the conditions that resulted in highest/lowest level of preference.

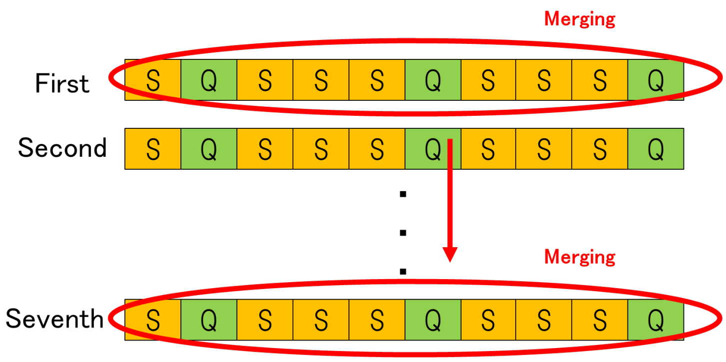

Figure 3. Long-term measurement

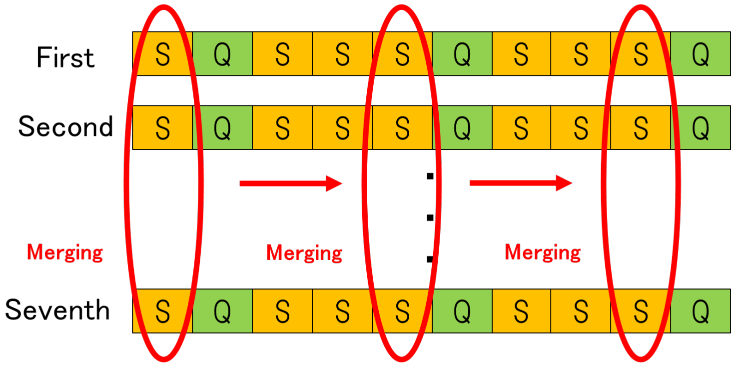

Figure 4. Short-term measurements

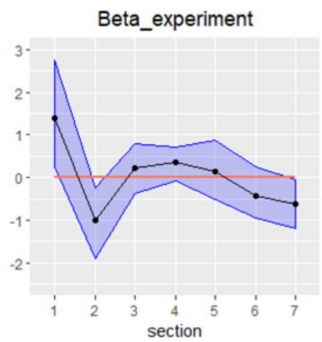

Figure 5. Analysis of temporal change

t : the bootstrap-estimated value after scaling with a robust Z-score

- $t < -0.5$ → minus (-)
- $t <= |0.5|$ → zero (0)

- $t > 0.5$ → plus (+)

E.g.,) Figure 5 shows that (9) Beta changed from plus to minus while the experiment took place.

3 RESULTS

First, applying ANOVA for data involving (4) Preference and (5) Boredom showed that the conditions of preference had significant differences in both the long-term and short-term. However, for (4) Preference and (5) Boredom, there were no significant differences between long- and short-term in the temporal changes.

Table 2. The temporal changes for indices

Temporal Change	Long-term		Short-term	
Condition	Experiment	Control	Experiment	Control
①Pleasure	+→-	0→0	0→0	0→0
②Arousal	0→0	0→0	0→0	0→0
③Dominance	0→0	0→0	0→0	0→0
④Preference	+→-	0→0	+→0	0→0
⑤Boredom	-→+	-→0	-→+	-→+
⑥Attention	0→-	0→-	+→-	+→-
⑦Time perception	0→0	-→0	-→0	-→0
⑧Alpha	0→0	-→0	+→0	+→0
⑨Beta	0→0	-→0	+→-	+→0
⑩Gamma	0→0	-→0	+→0	+→0

Second, as shown the Table 2, because of the temporal changes for (1) Pleasure ~ (10) Gamma, we found some differences between long-term and short-term. (1) Pleasure (+ → -), (4) Preference (+ → 0), (5) Boredom (- → +), (6) Attention (0 → -), and (7) Time perception (- → 0) had a similar trend on subjective evaluation. On the other hand, compared to hypotheses (i) and (ii), (8) Alpha, (9) Beta and (10) Gamma demonstrated the most different trend through the EEG. In the long-term, results for (8) Alpha (- +) and (10) Gamma (- → 0) were similar to hypotheses (i) and (ii), however, those of (9) Beta (- → 0) was different to hypothesis (i). Conversely, in the short-term, the results for (9) Beta (+ → -) were similar to hypothesis (i), however, those of (8) Alpha (- → +) and (10) Gamma (- → 0) were different to hypotheses (i) and (ii).

Third, there were some differences regarding preference in the long-term. For the condition of highest level of preference, (1) Pleasure (+ → -) and (4) Preference (+ → -) had the strongest trends, although for the condition of lowest level of preference, their indices followed no trend. Conversely, it was only on the condition of the lowest level of preference that (8) Alpha (- → +), (9) Beta (- → +), and (10) Gamma (- → +) had the strongest trends, although on the condition of the lowest level of preference their indices followed no trend.

4 DISSCUSION

First, for (4) Preference and (5) Boredom, there were significant differences between the conditions of preference in both the long-term and short-term. Therefore, this experiment may have evoked different types of boredom depending on preference in both long-term and short-term. In addition, due to the results from (4) Preference and (5) Boredom showing no significant temporal changes, the temporal changes must be further analyzed in detail.

Second, (1) Pleasure (+ → -), (4) Preference (+ → 0), (5) Boredom (- → +), (6) Attention (0 → -), and (7) Time perception (- → 0) followed a similar trend in both long-term and short-term. In addition, the temporal change of their indices was similar to Raffaelli, Mills & Christoff (2018). Thus, this experiment may evoke boredom in long-term and short-term, respectively. On the other hand, in the long-term, (8) Alpha (- → +) and (10) Gamma (- → 0) were similar to hypotheses (i) and (ii). Moreover, in the short-term, (9) Beta (+ → -) was similar to hypothesis (i). This result suggests that observations of boredom in the long-term and short-term show different characteristics. In other words, the indices of EEG may be effective or ineffective for indicating boredom in long-term or short-term. Incidentally, some results were different to hypotheses (i) and (ii), which suggests that this experiment may evoke other psychological phenomenon expect for boredom.

Third, because (1) Pleasure (+ → -) and (4) Preference (+ → -) were the indices for preference, their indices may follow more remarkable trends only on the condition of the highest level of preference. Therefore, if the stimuli has more meaning, it may evoke stronger boredom, particularly for subjective evaluation in the long-term. On the other hand, (8) Alpha (- → +), (9) Beta (- → +), and (10) Gamma (- → +) followed the most different trends as compared to previous study. According to Westgate & Wilson (2018), MAC model has independent components of attention and meaning. In other words, even if the condition for preference is different, attention is not different. However, within this experiment, (8) Alpha and (9) Beta were the attentional indices from the EEG, which only followed different trends in the condition of the lowest level of preference. Therefore, this result suggested that meaning is interrelated with attention against the previous definition for boredom, particularly for EEG in long-term. In other words, this study suggested that consumers feel bored as aversive emotion for the information and contents which have the interest or preference when the similar things are supplied repeatedly.

5 CONCLUSION

We measured the temporal changes of psychological components regarding boredom through the act of repeatedly listening to music. Part of the results confirmed hypotheses (i) and (ii). Decreased attention was measured by the increased alpha wave and the decreased beta wave. In addition, decreased meaning was measured by the increased gamma wave. However, particularly for EEG, the indices regarding boredom were different between long-term and short-term, and between the highest and lowest level of preference. In conclusion, measuring boredom must include factors of the temporal changes and the conditions of preference, particularly for EEG.

This study was conducted based on the MAC model. The model was correct when compared to results from a subjective evaluation, however, it was incorrect when using results from an EEG. As boredom must be measured in real time, future development will have to use biosignals such as EEG, which can ultimately improve the MAC model. In addition, the difference in data between subjective evaluation and biosignals must be considered, as subjective evaluation is the conscious data, while conversely, biosignals are unconscious data.

This study for boredom has the limitation because EEG is not the realistic measurement for many consumers. In other words, the technology measuring boredom by EEG may be useful for not consumers but sellers in the situation of the experimental developing such as selling schedule and recommendation. In addition, the confidence of our study had been insufficient yet because the number of participants was ten and some individual difference was detected. Thus, our study will be improved through evaluating human interface which has the issue about boredom, such as “When boredom is evoked?”, and “What the feedback modulate boredom?”. Moreover, this study was the fundamental research which measured the temporal change of emotion related to cognitions of habituation and reward. In the future, our study will be developed to the human interface and intelligent agent which have nudge to change human behavior by cognitive bias, modulating the boredom for nudge automatically, based on the values and lifestyle for individuals.

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