1. INTRODUCTION

Listening to music is one behavior people use for the induction of emotions (e.g., relaxing or uplifting) and mood modulation [1-3]. For example, people listen to music to reduce boredom or to energize and empower themselves [4]. Playlists are becoming an increasingly crucial element for people using music streaming services to induce emotions and search for new music [5, 6]. For instance, listeners may select and listen to a “relaxation” playlist to reduce tension. Many good playlists have been made by professional disc jockeys (DJs) or music specialists. Playlists made by these professionals have a central theme, or organizing principle, or coherence to the audio tracks [6]. It is difficult for listeners lacking musical knowledge to create such playlists themselves, although they may wish to listen to such playlists for emotional induction through new music.

This study assumes that for many listeners, playlist requirements for emotional induction with new music are: (1) matching the listener’s purpose (e.g., mood uplifting or relaxing), (2) being pleasant and listenable (e.g., smooth transitions of audio tracks), (3) having musical diversity and serendipity in the tracks. In this study, “serendipity” means the chance of finding a new audio track that can place a listener in a positive mood.

However, these techniques categorized into three approaches have some problems fulfilling the playlist requirements for emotional induction with new music.

The first and most popular method is to create a playlist composed of similar music. This method adapts to the requests to match a “purpose” and can generate a listenable playlist. However, the diversity and serendipity of such music can be low. Therefore, a listener may have the impression that such a playlist is monotonous. Consequently, it is challenging to create a significant change in the positive mood of the listener.

The second method for creating a playlist consists of adapting the playlist to the feedback of online listeners. Listeners judge whether an audio track in a playlist is suitable for their preferences or not, and the method chooses their favorite audio tracks from a music pool. This method also suits requests to match the listener’s purpose. Moreover, this playlist is listenable for a listener in the context of matching their preferences. However, this playlist is not suitable for listeners wanting to discover new songs that are not similar to their favorite music. Therefore, to fulfill the playlist requirements, this playlist needs to mix favorite and new songs and organize them to shift the listener toward a positive mood.

The third method involves learning from manually generated playlists, e.g., by a music therapy method or by a professional DJ. In the realm of music therapy, Altschuler has proposed the ISO-principle technique, which helps people feel better using music. In this technique, the first audio track in a playlist is matched with the mood of a listener and is then gradually altered...
to influence the desired mood state. The authors of this technique describe in detail the effect of the smooth transition of audio tracks to put the listener in a positive mood [10]. To create a playlist, a therapist selects musical pieces suitable for the playlist theme, based on aspects of musical impression. Therefore, the music used in the playlist must be fixed and specified [11, 12]. Thus, it is difficult for listeners lacking expertise in music therapy to select the appropriate music. Playlists mixed by a professional DJ are designed to fit a purpose, such as an event, activity, message, story, or mood. They also propose several types of smooth transitions between audio tracks to affect the listener’s mood [6]. Therefore, this approach is useful for advising transition methods of audio tracks in a playlist. However, it is not clear how to create a playlist with smooth transitions to switch a listener toward a positive mood.

This study proposes an impression-based playlist generation method that fulfills the abovementioned requirements and places the listener in a positive mood. The proposed method belongs to the method of learning from manually generated playlists. This study defines a playlist as a sequence of audio tracks. Additionally, it is explained that playlist generation comprises the selection of audio tracks from a music pool and the organization of a series of them. Therefore, song order is significant in this study.

This method addresses two types of playlists for two corresponding purposes: mood-boosting, and mood-stabilizing. This study defines a positive mood state of a listener as a boosting (uplifting) state or a stabilizing (relaxing) state. Both of the mood-boosting and mood-stabilizing playlists have four smooth transition patterns, with different structures that influence the listener’s mood. This method uses the ISO-principle technique and the mixed playlists of a professional DJ as references for fulfilling the need for smooth transitions of audio tracks.

To bring the diversity and serendipity to a playlist, this method estimates the impression of all tracks in the music pool by using a machine learning method. The method calculates the probability of impressions of all audio tracks by using a multinomial mixture model adopting a Bayesian approach [12]. Moreover, it chooses the audio tracks for the playlist using this probability. Moreover, it chooses the audio tracks for the playlist using this probability. This study extracts 30 types of musical features from about 1,000 sample track pieces to evaluate the model. Moreover, this study also receives tagged data expressing five impressions of these tracks from 13 Japanese subjects. In this way, a song is selected for use in a playlist based on the expected impression, resulting in a smooth change in the listener’s mood. Subsequently, a playlist is created by gradually changing the impressions of the audio tracks.

Afterward, the four patterns designed in both playlists were evaluated to determine if they led Japanese listeners toward a positive mood, using two psychometric evaluations: the multiple mood scales method [13] and the Positive and Negative Affect Schedule (PANAS) [14]. Statistical significance (p < 0.05) between the control group (without a playlist) and the experimental group (with a playlist) were examined by the nonparametric multiple tests for many-to-one comparisons applying the stepwise procedure by Gao [28]. This method is rank-based multiple stepwise procedures for the Dunnett-type multiple comparisons. After listening to the four patterns in the mood-boosting and mood-stabilizing playlists, all liveliness scale and three well-being scale in the experimental group were significantly higher than the control group scale. The results indicate that the proposed method can design mood-boosting and mood-stabilizing playlists that can positively influence a listener’s mood.

Section 2 describes how this method generates impression-based playlists and shifts the listener toward a positive mood. Section 3 explains two psychometric evaluation results concerning the playlists. Section 4 discusses the performance of the method in placing listeners into a positive mood. Finally, Section 5 provides some concluding remarks on this research.

2. METHOD

2.1 Estimation of impressions concerning an audio track

Music with a high arousal potential leads to significant activation. Music with a low arousal potential leads to significant deactivation [17, 18]. People who are exercising choose to listen to loud, fast music to move their arousal level to high, whereas those who are relaxing choose to listen to quiet music to move their arousal level to low [19, 20]. The circumplex model of affect expresses emotion in two-dimensions, that together are called the “core affect” [15, 16]. The core affect expresses feelings in moods and emotions at a point in time mainly by a combination of two types of feelings: pleasure, and activation. In that regard, this method focuses on the activation-deactivation of emotion by music, and expresses impressions of music by the differences in activation levels of the music.
The method uses five words/phrases to represent the impressions of the musical contents of audio tracks concerning the activation-deactivation level of the music. The five words are “Low” (very inactive), “Low-Middle” (moderately inactive), “Middle” (slightly inactive and slightly active), “Middle-High” (moderately active), and “High” (very active). This method calculates every probability of the five impressions that a listener will perceive in a single audio track, using some clustering models based on the multinomial mixture model and adopting a Bayesian approach. This study used Stan [26] to create the clustering models. In concrete terms, and as shown in Figure 1, this method makes ten clustering models, and selects four of the ten models to estimate the impression of an audio track. The four models are related to the impression for which the method wants to predict the probability. It calculates the probability of the impression of the track by all four models and computes the average of the probability. It applies the average probability of the four clustering models as the probability of the impression of the track.

### Table 1: Ten clustering models created and used in this study to estimate the probability of an impression concerning a single audio track

| The clustering model | Precision | Recall | F-measure |
|----------------------|-----------|--------|-----------|
| LL or MM             | 0.82      | 0.95   | 0.88      |
| MM or HH             | 0.85      | 0.91   | 0.89      |
| LM or MM             | 0.96      | 0.61   | 0.75      |
| MH or MM             | 0.92      | 0.64   | 0.76      |
| LL or HH             | 0.86      | 0.73   | 0.79      |
| LL or LM             | 0.84      | 0.53   | 0.65      |
| LL or MH             | 0.83      | 0.92   | 0.87      |
| LM or HH             | 0.94      | 0.96   | 0.95      |
| MM or HH             | 0.85      | 0.87   | 0.86      |
| MH or MH             | 0.91      | 0.86   | 0.89      |

Note) LL: Low, LM: Low-Middle, MM: Middle, MH: Middle-High, HH: High

For example, the probability that the impression of the audio track will be “Low” (very inactive) is obtained based on the average of four possibilities, namely, “Low or Low-Middle,” “Low or Middle,” “Low or Middle-High,” and “Low or High.” This study defines the impression with the highest probability in the five impressions as the primary impression of the track. For creating the clustering models, the method receives tagged data expressing the five impressions of the tracks from 13 Japanese subjects. It also extracts 30 types of audio feature data from 1,500 pieces of sample tracks using jAudio [21] and the MIR toolbox [22]. The data are compressed using principal component analysis, and the compressed data are applied to create a model.

### 2.2 Design of playlist used to shift to a positive state

The method designs two types of playlist: mood-boosting, and mood-stabilizing. A mood-boosting playlist raises a depressed mood into a lively one. The mood-stabilizing playlist brings a restless mood down to a calm mood. Figure 2 shows the structure of the four patterns, for both playlist types. Table 2 also shows the structure for shifting the primary impression of an audio track within the four patterns in the mood-boosting type. Pattern 1 is a straight shifting of the primary impression. The number of primary tracks of every impression is approximately the same. Pattern 2 is where the “Low” and “Low-Middle” impression parts are weighted. Therefore, the numbers of tracks of the low and low-middle category are greater than other levels of impressions, and the playing time of a moderate-level impression is longer than other different types. Pattern 3 is where the “Middle-High” and “High” impression parts are weighted. Therefore, the numbers of tracks of the high and middle-high category are greater than other levels of impressions, and the playing time of an arousal-
level impression is longer than other different types. Pattern 4 is a wave type. This type has been used in a mixed playlist by a professional DJ. This technique is sometimes used for giving variety to the playlist, or for preventing a user from losing interest, and engaging the impression in the playlist.

The policy of this method is to gradually change the impression of the audio tracks in a playlist, to achieve a pleasantly listenable playlist. The gradual change of audio tracks is designed based on the gradually changing impressions of an audio track, and the probability of them. For example, in a case where the first track has the “Low” impression as the primary impression, this method selects a next track that has a probability of the “Low” impression that is lower than the first track, and in which the “Low-Middle” impression is higher than the first track. The “Low-Middle” impression is the next arousal level for the impression of the “Low” impression in the mood-boosting type.

The method randomly selects a single audio track from candidate tracks that are most appropriate for the structure of the impression transition in the playlist. The selection method for the candidate tracks is based on the following two rules, for adapting the policy mentioned above.

**First rule**

The first rule concerns the first track, and the part in which tracks of the different given impression occur in series in the playlist.

In this case, the candidate tracks that also have the probability of the primary impression must be higher than 0.8 or 0.9. The probability of 0.8 or 0.9 is a threshold defined in this study. Most listeners perceive the same impression as the primary impression for audio tracks for which the primary impression has over 0.8 probability. This study uses 0.9 as the threshold in a case where there are a large number of candidates tracks over 0.8.

**Second rule**

The second rule concerns the part in which tracks of the same given impression occur in series in the playlist. In this case, the candidate tracks must have a probability of the primary impression of the audio track that is lower than that of the previous audio track, and that is at least higher than 0.8. Moreover, the candidate tracks also must be those whose probability concerning the next level of impression is higher than that of the previous track. By way of exception, if there is no next level of impression, i.e., if the impression is “Low” or “High,” the method selects an audio track that has the probability of the primary impression being higher than that of the previous track. The next level of impression of the mood-boosting type means an impression that is higher activation than the current level impression; the next level of impression of the mood-stabilizing type means an impression that is lower activation than the current level impression. The current level of impression means the given impression in the playlist that is being referred to for determining the audio track.

For example, as shown in Table 3, i.e., the pattern of one of the mood-boosting types, the first, second, and third track of the given impression are respectively “Low,”

| Track Number | Pattern | 1   | 2   | 3   | 4   |
|--------------|---------|-----|-----|-----|-----|
| 1            | LL      | LL  | LL  | LL  | LL  |
| 2            | LL      | LL  | LM  | LL  | LL  |
| 3            | LM      | LL  | MM  | LM  | LM  |
| 4            | LM      | LM  | MM  | LM  | LM  |
| 5            | LM      | LM  | MH  | MM  | MM  |
| 6            | MM      | LM  | MH  | MM  | MM  |
| 7            | MM      | LM  | MH  | MM  | MM  |
| 8            | MM      | LM  | MH  | MM  | MM  |
| 9            | MH      | MM  | MH  | MM  | MM  |
| 10           | MH      | MM  | HH  | MM  | MH  |
| 11           | HH      | MH  | HH  | HH  | HH  |
| 12           | HH      | HH  | HH  | HH  | HH  |

Note: LL: Low, LM: Low-Middle, MM: Middle, MH: Middle-High, HH: High
Impression-Based Music Playlist Generation Method for Placing the Listener in a Positive Mood

Table 3: Example of an impression and its probability for the selected track, suitable for the given impression of the pattern in one of the mood-boosting playlists

| Track number | Given impression | Probability of the impression of the selected track |
|--------------|------------------|-----------------------------------------------------|
|              |                  | Primary | Next level |
| 1            | LL               | 0.98 (LL) | 0.56 (LM) |
| 2            | LL               | 0.86 (LL) | 0.80 (LM) |
| 3            | LM               | 0.81 (LM) | 0.42 (MM) |
| ...          | ...              | ...     | ...        |
| 12           | HH               | 0.98 (LL) | ---        |

Note) LL: Low, LM: Low-Middle, MM: Middle, MH: Middle-High, HH: High

“Low,” and “Low-Middle.” The first track is selected based on the first rule. The first track of the playlist pattern is an audio track having a primary impression that is the “Low” impression, and a 0.98 probability concerning that impression. In addition, in this track, the probability concerning “Low-Middle” is 0.55. The first and second tracks in the playlist occur for the same given impression in series. Therefore, the second track is selected based on the second rule. The second track has an impression of “Low” as the primary impression. The track has a 0.86 probability concerning the impression of “Low,” and thus the probability of the impression is lower than that of the first track. The track also has a 0.79 probability concerning the “Low-Middle” impression, and the probability of this impression is higher than that of the first track. The “Low-Middle” impression is the next level of impression for the “Low” impression. The second and third tracks occur for the different given impressions in series in the playlist. Therefore, the third track is selected based on the first rule. The third track of the playlist pattern is an audio track having a primary impression that is the “Low-Middle” impression, and a 0.81 probability of the impression.

Figure 3 shows the algorithm for making playlists of mood-boosting and mood-stabilizing types.

```
// Playlist: This has the five impression (LOW, LOW-MIDDLE, MIDDLE, MIDDLE-HIGH, HIGH) in every sequence number of the four patterns of the mood-boosting and of the four patterns of the mood-stabilizing playlist.
// TrackPool: This has all audio tracks.
// Candidate tracks: The audio tracks suitable for the rule
// num: The sequence number of the playlist
// track: A single audio track
// Impression (Primary) of track: The primary impression of the track. The primary impression is one of five impressions.
// Impression (Given) of num: The given impression in every sequence number of a playlist pattern. The given impression is one of five impressions.
// Maximum activation level: LOW (mood-stabilizing type) or HIGH (mood-boosting type)
// Probability of Impression (Primary) of track: The probability of the primary impression of the track.
// Probability of Impression (Next Level) of track: The probability of the next level impression of the track.
Threshold: 0.8 (or 0.9)

FOR num in Playlist DO
    // First rule
    IF num = 1 OR Impression (Given) of num != Impression (Given) of (num - 1) THEN
        FOR track in TrackPool DO
            IF Impression (Primary) of track == Impression (Given) of num AND
                Probability of Impression (Primary) of track >= Threshold THEN
                Put the track into the Candidate tracks
            ENDIF
        ENDFOR
        Select randomly a track from the Candidate tracks
        Set the track at the point in the playlist
    ENDIF
    ELSE IF Impression (Given) of num == Impression (Given) of (num - 1) THEN
        FOR track in TrackPool DO
            IF Impression (Primary) of track == Impression (Given) of num THEN
                IF Impression (Primary) of track == Impression (Maximum activation level) THEN
                    IF Probability of Impression (Primary) of track > Probability of Impression (Primary) of (track - 1) THEN
                        Put the track into Candidate tracks
                    ENDIF
                ELSE
                    IF Probability of Impression (Primary) of track < Probability of Impression (Primary) of (track - 1)
                        AND Probability of Impression (Primary) of track >= Threshold
                        AND Probability of Impression (Next Level) of track > Probability of Impression (Next Level) of (track - 1) THEN
                            Put the track into the Candidate tracks
                        ENDIF
                    ENDIF
                ENDIF
            ELSE
                IF Probability of Impression (Primary) of track < Probability of Impression (Primary) of (track - 1)
                    AND Probability of Impression (Primary) of track >= Threshold
                    AND Probability of Impression (Next Level) of track > Probability of Impression (Next Level) of (track - 1) THEN
                        Put the track into the Candidate tracks
                    ENDIF
                ENDIF
            ENDIF
        ENDFOR
        Select randomly a track from the Candidate tracks
        Set the track at the point in the playlist
    ENDIF
ENDFOR
```

Figure 3: Algorithm used for designing a playlist for shifting a listener into a positive mood
3. EVALUATION

This study used two psychological evaluations to assess a control group and an experimental group to determine whether playlists in both types could have shifted a Japanese listener toward a positive mood (uplifting or relaxing) or not. Subjects in the experimental group listened to all four patterns on both playlists. Subjects in the control group did something (e.g., work or study) without listening to a playlist.

The subjects of the experimental group were 11 men and 2 women. The average age of the 13 subjects was 22 (SD=1.2), and they were all college students. Each subject listened to a playlist of four mood-boosting and four mood-stabilizing patterns. The audio tracks in each playlist were selected based on the impression of 1,500 pieces of tracks from the database. The audio tracks used in each playlist were different for each listener. The length of the playlists ranged from 50 min to 60 min. The subjects had no restrictions on listening to the four playlists, except to set a listening interval of more than one hour and to refrain from falling asleep. They selected playlists in any order from eight playlists and listened to the playlist using their favorite device (headphone or speaker). The order of the playlists for each of the participants was varied. These experiments were performed over a period of two to five days. Each participant chose the best time to do the experiment. Finally, they answered two psychological evaluation methods before and after listening to every playlist.

On the other hand, the subjects of the control group (i.e., those who did not listen to music) were nine men and two women aged 22 (SD=0.9), all of whom were college students. The subjects included the same individuals as the experimental group. Likewise, they answered two psychological evaluation methods before and after doing something within one hour without listening to a playlist. The subjects had no restrictions on the control group, except from refraining from falling asleep and not to listen to music. For example, they studied, played a game, or watched a movie.

Under both groups, this experiment gave them no instruction or description for controlling the subjects to the same psychological condition.

This study used two psychological evaluation methods for Japanese listeners: the multiple mood scales method and the PANAS. Furthermore, this study investigated two statistical differences by using R: One is the statistical difference (p<0.05) between the control group and the experimental group using the nonparametric multiple tests for many-to-one comparisons applying the stepwise procedure by Gao. Another statistical difference (p<0.05) is between the relevant pattern playlists in both types using the two-sided Wilcoxon-Mann-Whitney test that is a nonparametric test.

The multiple mood scales method is a self-reporting instrument having eight 10-item mood scales to measure multiple mood states for the Japanese. These eight scales are depression (anxiety), hostility, boredom, liveliness, well-being, friendliness, concentration, and startle. The scales are constructed with four categories: feeling very much, feeling a little, feeling not much, and not feeling at all. These responses are converted to numerical values for computational purposes, from feeling very much (4) to not feeling at all (1). The final score of the multiple mood scales method is the sum of the ten items on all eight scales. The result of using this method is similar to that of using the English mood scales [13, 23-25]. If a playlist in the mood-boosting can put a listener in a positive mood, the liveliness scale increases. Similarly, if a playlist in the mood-stabilizing can put a listener in a positive mood, the well-being scale increases.

The PANAS is one of the mood scales for measuring positive and negative affect. The PANAS is two 10-item mood scales. This study used the Japanese version of the PANAS. The scales are constructed with six categories: it applies very much, it applies a lot, it applies a little, it does not apply a little, it does not apply a lot, and it does not apply at all. These responses are converted to numerical values for computational purposes, from it applies very much (6) to it does not apply at all (1). The final score of the PANAS scale is the sum of the ten items on the positive scale and the sum of the ten items on the negative scale.

The study also asked the subjects whether each track in the playlist was a favorite or a known track using a five-rating scale. The scale is from “It applies very much (5)” to “It does not apply at all (1).”

Table 4 shows the results of the multiple mood scales method and PANAS concerning the control group and the experimental group. The negative feelings in the multiple mood scales method were composed of three scales: depression (anxiety), hostility, and boredom. For all playlists, the results showed that the scale of a negative mood after listening to a playlist decreased from that existing prior to listening to it. Moreover, the liveliness scale of the mood-boosting playlist and the well-being scale of the mood-stabilizing playlist both increased. As for the statistical difference (p<0.05) between the two groups, all liveliness scale concerning the mood-boosting
Table 4: Results of the multiple mood scales method and PANAS concerning the mood-boosting and mood-stabilizing playlists.

The transition of the negative feeling, the liveliness feeling, the well-being feeling, the positive affect (PA), and the negative affect (NA).

| Playlist Pattern | Negative Feeling Scale | Liveliness Scale | Well-being Scale | PANAS |
|------------------|------------------------|------------------|------------------|-------|
|                  | Ave. | S.D. | p   | Ave. | S.D. | p   | Ave. | S.D. | p   |
| Control Without a playlist (N=11) | -1.91 | 9.74 | -- | -0.18 | 2.12 | -- | -0.45 | 3.03 | -- |
| Mood-Boosting (N=13) | B1 | -5.23 | 5.13 | 0.31 | 2.38 | 2.13 | 0.01 | -3.13 | 3.13 | 0.13 |
|                    | B2 | -3.08 | 7.50 | 0.83 | 2.69 | 2.46 | 0.00 | -0.23 | 2.19 | 0.83 |
|                    | B3 | -1.08 | 2.89 | 0.61 | 2.15 | 2.28 | 0.03 | -0.08 | 2.81 | 0.81 |
|                    | B4 | -4.31 | 4.44 | 0.38 | 3.00 | 2.11 | 0.00 | 0.77 | 3.74 | 0.78 |
| Mood-Stabilizing (N=13) | S1 | -3.46 | 3.71 | 0.49 | -0.08 | 3.29 | 0.74 | 4.08 | 3.02 | 0.00 |
|                    | S2 | -4.69 | 4.37 | 0.26 | 1.08 | 1.49 | 0.10 | 4.15 | 2.98 | 0.00 |
|                    | S3 | -2.92 | 3.75 | 0.71 | -0.85 | 1.96 | 0.66 | 3.85 | 4.07 | 0.01 |
|                    | S4 | -2.46 | 4.29 | 0.93 | 0.77 | 1.19 | 0.19 | 3.00 | 5.22 | 0.10 |

Comparison with relevant patterns: Liveliness Scale and Well-being Scale

|                  | Live (p) | Well (p) |
|------------------|----------|----------|
| B1 (Boosting) = S1 (Stabilizing) | 0.02 | 0.00 |
| B2 (Boosting) = S2 (Stabilizing) | 0.08 | 0.00 |
| B3 (Boosting) = S3 (Stabilizing) | 0.00 | 0.04 |
| B4 (Boosting) = S4 (Stabilizing) | 0.01 | 0.36 |

Note: (1) The average and S.D. value are calculated based on the response value after listening to the playlist minus the response value before listening to it, except for the control condition (i.e., without a playlist).

(2) The average and S.D. value in the control group (i.e., without a playlist) are calculated based on the response value after doing something without a playlist minus the response value before doing it.

(3) The statistical difference (p < 0.05) between the control group and the experimental group was determined by the nonparametric multiple tests for many-to-one comparisons by Gao et al. This method was conducted using the “nparcomp” package in R [29].

(4) The statistical difference (p < 0.05) between the relevant pattern playlists in both types was determined by the two-sided Wilcoxon-Mann-Whitney test. This method was conducted using the “coin” package in R [30].

As for the statistical difference (p < 0.05) concerning liveliness and wellbeing score between the relevant pattern playlists in both types, the result in Table 4 shows that three patterns in the mood-boosting playlists and three patterns in the mood-stabilizing playlists have a different effect.

The results from Table 4 indicate that the proposed method can design both mood-boosting and mood-stabilizing playlists that can lead a listener toward a positive mood. However, the average concerning the PA scale of Pattern 1 in mood-stabilizing in Table 4 is -1.23. This result shows that some subjects disliked the playlists. Five subjects obtained a negative value regarding the PA scale average. For instance, the scales of the two subjects were -11 and -16. Therefore, the results indicate that the proposed playlists did not suit them.

Table 5 shows the effect of shifting a listener to a positive mood by the playlists with serendipity. It shows that approximately 75% of the listeners (9/12 subjects) in the experimental group shifted their mood in a positive mood by the playlists with serendipity. It shows that the proposed method was able to shift a listener to a positive mood and moreover to provide the listener with serendipity in the music.

Table 6 shows the concordance rate between the primary impression that 13 subjects felt from an audio
The purpose of this study was to design a method that automatically generates many impression-based playlists with musical diversity and serendipity for placing listeners into a positive mood. The study designed four pattern playlists for each of the mood-boosting (uplifting) and a mood-stabilizing (relaxing) type.

This study conducted two psychological evaluations to assess the difference in the effect of shifting a listener into a positive mood between an experimental group listened to the playlist and a control group listened not to the playlist. The results indicated that the proposed method could generate many playlists to match a purpose for uplifting or for relaxing and shifted a listener toward a positive mood.

It was found that playlists not including many favorite tracks were able to shift a listener to a positive mood. Moreover, it was found that playlists generated by the proposed method could provide diversity and serendipity of tracks to a listener. Interestingly, approximately half of the listeners felt that the mood was shifted to a positive mood when listening to a playlist.

### Table 5: The effect of shifting a listener to a positive mood by the playlist with the least number of favorite tracks in both playlist types

| Mood-Boosting Playlist (N=12) | Mood-Stabilizing Playlist (N=12) |
|-------------------------------|----------------------------------|
| Subject | Pattern | i | ii | iii | iv | v | vi | vii | Pattern | i | ii | iii | iv | v | vi | vii |
|-------------------------|---------|----|----|-----|----|--|----|----|---------|----|----|----|----|--|----|----|
| A | 2 | 0 | 0 | 1 | 2 | 3 | 5 | False | A | 4 | 1 | 0 | 4 | 0 | 1 | -2 | True |
| B | 2 | 2 | 0 | 0 | 5 | -1 | 6 | False | B | 1 | 2 | 0 | 4 | -5 | 3 | 0 | True |
| C | 4 | 5 | 5 | 4 | -5 | 8 | -6 | True | C | 2 | 1 | 2 | 0 | 4 | 3 | True |
| D | 3 | 0 | 1 | 0 | -3 | 8 | 5 | True | D | 3 | 1 | 2 | -3 | -3 | 2 | 0 | True (weak) |
| E | 1 | 2 | 1 | 3 | -13 | 14 | -5 | True | E | 2 | 3 | 3 | 1 | 3 | 4 | -5 | True (weak) |
| F | 2 | 3 | 3 | 3 | -4 | 15 | -5 | True | F | 0 | 2 | -3 | 0 | 6 | 0 | True |
| G | 2 | 0 | 0 | 0 | 0 | 0 | -2 | True (weak) | G | 0 | 0 | 4 | -4 | 8 | -2 | True |
| H | 1 | 5 | 4 | -1 | -5 | 14 | 14 | True | H | 2 | 2 | 0 | 0 | 0 | 0 | 0 | True |
| I | 1 | 0 | 0 | 2 | -7 | 11 | -6 | True | I | 2 | 10 | 0 | 7 | 13 | 18 | -11 | True |
| J | 2 | 10 | 0 | 7 | -13 | 18 | -11 | True | J | 0 | 0 | 4 | 0 | 4 | 0 | True |
| K | 3 | 2 | 2 | 1 | 3 | 3 | 0 | True | K | 0 | 0 | 5 | -2 | 3 | 0 | True (weak) |
| L | 1 | 2 | 2 | 4 | -2 | -1 | -5 | True | L | 4 | 1 | 3 | 5 | 8 | 6 | -5 | True |

Note: One subject out of 13 subjects did not answer this question.
1. Number of favorite tracks of the subject
2. Number of known tracks by the subject
3. Liveliness Feeling scale, (iv) Negative Feeling scale
4. PA scale, (v) NA scale
5. Effectiveness of the playlists. This value was obtained as follows:
   (1) If the value obtained by subtracting the negative feeling scale from the liveliness feeling scale is greater than zero and the value obtained by subtracting the NA scale from the PA scale is greater than zero, this study defines the effectiveness of the playlist as true.
   (2) If one of the values is greater than zero, this study defines that the effectiveness of the playlist is weak.
   (3) If both values are under zero, this study defines that the effectiveness of the playlist is false.

The value of (ii), (iv), (v) and (vi) based on the response value after listening to the playlist minus the response value before listening to it.

### Table 6: The concordance rate between every impression that 13 subjects felt from the audio track in the playlist and the impression of the audio track in the playlist

| Mood-Boosting type | Track No. | Pattern One | Pattern Two | Pattern Three | Pattern Four |
|--------------------|-----------|-------------|-------------|--------------|-------------|
| Ave. | 0.51 | 0.39 | 0.49 | 0.48 |
| SD | 0.15 | 0.23 | 0.17 | 0.11 |

| Mood-Stabilizing type | Track No. | Pattern One | Pattern Two | Pattern Three | Pattern Four |
|-----------------------|-----------|-------------|-------------|--------------|-------------|
| Ave. | 0.63 | 0.54 | 0.49 | 0.58 |
| SD | 0.15 | 0.23 | 0.25 | 0.13 |

Note: LL: Low, LM: Low-Middle, MM: Middle, MH: Middle-High, HH: High

4. DISCUSSION

The purpose of this study was to design a method that automatically generates many impression-based playlists with musical diversity and serendipity for placing listeners into a positive mood. The study designed four pattern playlists for each of the mood-boosting (uplifting) and a mood-stabilizing (relaxing) type.

This study conducted two psychological evaluations to assess the difference in the effect of shifting a listener into a positive mood between an experimental group listened to the playlist and a control group listened not to the playlist. The results indicated that the proposed method could generate many playlists to match a purpose for uplifting or for relaxing and shifted a listener toward a positive mood.
all subjects could recognize the smooth transitions of the impressions of audio tracks.

However, this method would benefit from some potential improvements. The value of the standard deviation in Table 4 was considered in all patterns in both playlists. The values indicate that there was a suitable playlist type per individual. In future work, it is necessary to find an appropriate playlist type for placing each listener into a positive mood. It should be noted that the playlists made by the proposed method are not personalized and that the impression evoked from music is different for each individual. Therefore, personalization should be performed to raise the concordance rate of impressions.

Finally, evidence showed that the proposed method was able to design both mood-boosting and mood-stabilizing playlists with serendipity, that was capable of moving a listener toward a positive mood.

5. CONCLUSION

This study proposed an impression-based music playlist generation method with diversity and serendipity to place a listener in a positive mood using specifically designed mood-boosting and mood-stabilizing playlists. The results from two types of self-report mood questionnaires indicated that the proposed method could generate many impression-based playlists from a vast music database. Additionally, the generated playlists could positively influence a listener’s mood with the serendipity of the tracks.

From the results, we can conclude:

1. The mood-boosting playlists placed the listeners in an uplifting mood, while the mood-stabilizing playlists placed the listeners in a relaxing mood. However, it is necessary to find the best playlist type (transition pattern) for an individual for placing the listener into a positive mood.

2. Playlists based on the proposed method can estimate impressions of audio tracks in the playlists. However, this method needs to improve the estimation rate regarding some impressions and improve customization regarding the prediction of impressions in the music.

3. Playlists offered diversity and serendipity of audio tracks to the listeners. Playlists not including many favorite audio tracks placed many subjects into a positive mood. However, some subjects did not shift their mood to positive. Therefore, there is a need to investigate the relationship between the ratio of favorite audio tracks and the effectiveness of shifting a listener to a positive mood.

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