HOW MUSIC ALTERS DECISION MAKING - IMPACT OF MUSIC STIMULI ON EMOTIONAL CLASSIFICATION

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ABSTRACT

Numerous studies have demonstrated that mood can affect emotional processing. The goal of this study was to explore which components of the decision process are affected when exposed to music; we do so within the context of a stochastic sequential model of simple decisions, the drift-diffusion model (DDM). In our experiment, participants decided whether words were emotionally positive or negative while listening to music that was chosen to induce positive or negative mood. The behavioral results show that the music manipulation was effective, as participants were biased to label words positive in the positive music condition. The DDM shows that this bias was driven by a change in the starting point of evidence accumulation, which indicates an a priori response bias. In contrast, there was no evidence that music affected how participants evaluated the emotional content of the stimuli. To better understand the correspondence between auditory features and decision-making, we proceeded to study how individual aspects of music affect response patterns. Our results have implications for future studies of the connection between music and mood.

1. INTRODUCTION

There is robust evidence that one's mood can affect how one processes emotional information. This phenomenon is often referred to as mood-congruent processing or bias, reflecting the finding that positive mood induces a relative preference for positive emotional content (and vice versa). The goal of the present study was to use a popular model of simple decisions, the drift-diffusion model (DDM; [9]), to explore how music-induced mood affects the different components of the decision process that could drive mood-congruent bias. The model, described below, can differentiate two types of bias: a) Bias due to an a priori preference for one response over the other; and b) Bias due to a shift in how the stimuli are evaluated for decision making. This class of models has been successfully employed to differentiate these biases in perceptual and memory tasks, but to our knowledge has never been used to investigate effects of music on emotional classification. We consider the following to be our key contributions: a) We provide meaningful evidence that decision making is indeed affected by music stimuli, and analyze the observed effects; b) we study evidence of how specific auditory features are correlated with aspects of decision making.

Studies that induce mood, either through listening to happy/sad music or having participants write passages or see pictures based on a particular emotion, have shown mood-congruent bias across a range of tasks. Behen et al. [4] showed participants happy and sad faces while they listened to positively- or negatively valenced music and underwent fMRI. Participants rated the happy faces as more happy while listening to positive music, and the fMRI results showed that activation of the superior temporal gyrus was greater when the face and music were congruent with each other. In a study of mood and recall, De l'Etoile [3] found that participants could recall significantly more words when mood was induced (through music) at both encoding and retrieval. Similarly, Kuhbandner and Pekrun [6] had participants study emotional words that were printed in either black, red, green, or blue, with the hypothesis that congruent words (e.g., negative words in red, positive words in green) would show enhanced memory at test. Their findings supported the hypothesis, as memory was better for negative words shown in red and positive words shown in green.

Previous work at the intersection of musicology and cognitive science has also studied the connection between music and emotion. As Krumhansel points out [5], emotion is a fundamental part of music understanding and experience, underlying the process of building tension and expectations. There is neurophysical evidence of music being strongly linked to brain regions linked with emotion and reward [1], and different musical patterns have been shown to have meaningful associations to emotional affectations [8]. Similarly, studies have indicated that mood also affects the perception of music [12]. Not only is emotion a core part of music cognitive processing, it can also have a resounding impact on people's mental state, and aid in recovery, as shown for instance by Zumbansen et al. [15] in the case of people suffering from Brocas aphasia. People regularly use music to alter their moods, and evidence has been presented that music can alter the strength of emotional negativity bias [2]. All this evidence indicates a deep and profound two-way connection between music and emotional perception.

The structure of the paper is as follows. In Section 2 we outline the characteristics of the drift-diffusion model, which we use in this study. In Section 3 we discuss our experimental design and how data was collected from participants. In Section 4 we present and analyze the results of our behavioral study. In Section 5 we further analyze how individual auditory components correlate with the behavioral patterns observed in our human study. In Section 6 we recap our results and discuss them in a broader context.

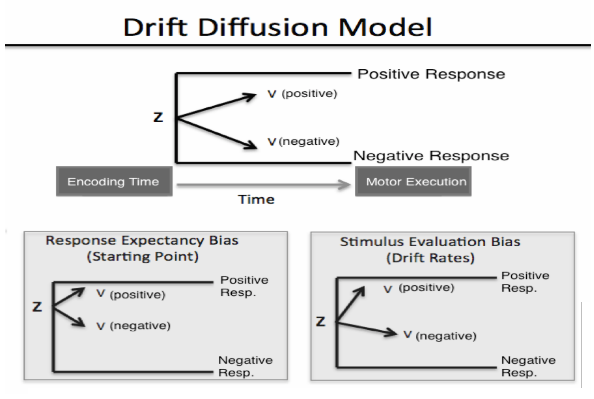

Figure 1. An Illustration of the Drift-Diffusion Model.

2. THE DRIFT-DIFFUSION MODEL

This study employs the DDM of simple decisions to relate observed decision behavior to the underlying decision components. The DDM, shown in Figure 1, belongs to a broader class of evidence accumulation models that posit simple decisions involve the gradual sequential accumulation of noisy evidence until a criterial level is reached. In the model, the decision process starts between the two boundaries that correspond to the response alternatives. Evidence is accumulated over time to drive the process toward one of the boundaries. Once a boundary is reached, it signals a commitment to that response. The time taken to reach the boundary denotes the decision time, and the overall response time is given by the decision time plus the time required for processes outside the decision process like encoding and motor execution. The model includes a parameter for this nondecision time (Ter), to account for the duration of these processes.

The primary components of the decision process in the DDM are the boundary separation, the starting point, and the drift rate. Boundary separation provides an index of responses caution or speed/accuracy settings; wide boundaries indicate a cautious response style where more evidence needs to be accumulated before the choice is made. The need for more evidence makes the decision process slower, but also more accurate as it is less likely to hit the wrong boundary by mistake. The starting point of the diffusion process (z), indicates whether there is a response bias. If z is closer to the top boundary, it means less evidence is required to reach that boundary, so “positive” responses will be faster and more probable than “negative” responses. Finally, the drift rate (v) provides an index of the evidence from the stimulus that drives the accumulation process. Positive values indicate evidence for the top boundary, and negative values for the bottom boundary. Further, the absolute value of the drift rate indexes the strength of the stimulus evidence, with larger values indicating strong evidence and leading to fast and accurate responses.

In the framework of the DDM, there are two mechanisms that can drive behavioral bias. Changes in the starting point (z) reflect a response expectancy bias, whereby there is a preference for one response even before the stimulus is shown [7,14]. Experimentally, response expectancy bias is observed when participants have an expectation that one response is more likely to be correct and/or rewarded than the other. In contrast, changes in the drift rate (v) reflect a stimulus evaluation bias, whereby there is a shift in how the stimulus is evaluated to extract the decision evidence. Experimentally, stimulus evaluation bias is observed when there is a shift in the stimulus strength and/or the criterion value used to classify the stimuli. Thus responses expectancy bias, reflected by the starting point in the DDM, indicates a shift in how much evidence is required for one response relative to the other, whereas stimulus evaluation bias, reflected by a shift in the drift rates in the DDM, indicates a shift in what evidence is extracted by the stimulus under consideration. Importantly, both mechanisms can produce behavioral bias (faster and more probable responses for one choice), but they differentially affect the distribution of response times. In brief, response expectancy bias only affects fast responses, whereas stimulus evaluation bias affects both fast and slow responses (see [14]). It is this differential effect on the RT distributions that allow the DDM to be fitted to behavioral data to estimate which of the two components, starting point or drift rates, is driving the bias observed in the RTs and choice probabilities. The DDM has been shown to successfully differentiate these two bias mechanisms from behavioral data in both perceptual and recognition memory tasks [14].

This study used the DDM approach described above to investigate how music-induced mood affects the different decision components when classifying emotional information. Participants listened to happy or sad music while deciding if words were emotionally positive or negative. The DDM was then fitted to each participant’s behavioral data to determine whether the mood induction affected response expectancy bias, stimulus evaluation bias, or both.

3. METHODS

Participants were shown words on the computer screen and asked to classify them as emotionally positive or negative while listening to music. The words were emotionally positive, negative, or neutral. After a fixation cue was shown for 500 ms, each word was presented in the center of the screen and remained on screen until a response was given. If no response was given after 3 seconds, the trial ended as a "no response" trial. Responses were indicated with the "z" and "/" keys, and mapping between the key and response was counterbalanced across participants. The task consisted of 4 blocks of 60 trials with 20 stimuli from each word condition (positive, negative, neutral). A different song was played during each block, alternating from positive to negative music across blocks. The order of the songs was counterbalanced across subjects. The entire experiment lasted less than 30 minutes. To ensure that the results were not specific to the particular choice of songs, the entire experiment was replicated with a new set of music.

The stimuli consisted of emotionally positive (e.g., success, happy), negative (e.g., worried, sad), and neutral words (e.g., planet, sipped) taken from a previous study [13]. There were 96 words for each stimulus condition, which were matched for word frequency and letter length. From each wordpool, 80 items were randomly chosen for each participant to use in the task. Words were randomly assigned to appear in the positive or negative music blocks with the constraint that 20 of each word type appeared in every block of trials.

Publicly available music was surveyed to isolate two clear types - music that is characterized by slow tempo, minor keys and somber tones, typical to traditionally "sad" music, and music that has upbeat tempo, major scales and colorful tones, which are traditionally considered to be typical to "happy" music. Our principal concern in selecting the musical stimuli, rather than their semantic categorization as either happy or sad, was to curate two separate "pools" of music sequences that were broadly characterized by a similar temperament (described above), and show they produced consistent response patterns.

To ensure that the selected music was effective for inducing the appropriate mood, a separate set of participants rated each piece of music on a 7-point Likert scale, with 1 indicating negative mood and 7 indicating positive mood. There were 21 participants that rated the songs for Experiment 1, and 19 participants for Experiment 2. This mood assessment was done outside of the main experiment to eliminate the possibility that the rating procedure would influence the participants' classification behavior in the primary task. The ratings showed that the music choices were appropriate. The positive songs in Experiment 1 led to more positive ratings than the negative songs. Similar results were found for the songs in Experiment two, with higher ratings for the positive songs than the negative songs. The differences between the positive and negative song ratings were highly significant for both experiments (p-values $< .001$ using a paired t-test, with $t(20) > 7.3$). The means and standard deviations of the scores for the songs in the two experiments are presented in table 1.

The DDM was fitted to each participant's data, separately for positive and negative music blocks, to estimate the values of the decision components. The data entered into the fitting routine were the choice probabilities and response time (RT) distributions (summarized by the .1, .3, .5, .7, and .9 quantiles) for each response option and stimulus condition. The parameters of the DDM were adjusted in the fitting routine to minimize the χ^2 value, which is based on the misfit between the model predictions and the observed data (see [10]). For each participant's data set, the model estimated a value of boundary separation, nondecision time, starting point, and a separate drift rate for each stimulus condition. Because of the relatively low number of observations used in the fitting routine, the variability parameters of the full DDM were not estimated (see [9]). This resulted in two sets of DDM parameters for each participant, one for the positive music blocks and one for the negative music blocks.

	—Experiment 1—		—Experiment 2—	
song	average	SD	average	SD
happy 1	5.14	1.24	5.15	1.29
happy 2	5.00	1.22	5.42	1.17
sad 1	2.24	1.00	2.26	1.24
sad 2	2.33	0.97	2.11	0.99

Table 1. Aggregated Likert scale results for the 8 songs used in the two experiments.

4. RESULTS

The RTs and choice probabilities in Figure 2 show that the mood-induction successfully affected emotional bias. The left column shows the response probabilities, and the right column shows an RT-based measure of bias, which is taken as the median RT for negative responses minus the median RT for positive responses for each condition. Thus RT values above 0 indicate faster positive than negative responses for that condition, and vice-versa. In Experiment 1 (top row), happy music led to more "positive" responses overall. This difference was significant for neutral words and positive words, but not for negative words. For RTs, positive responses were generally faster than negative responses in the happy compared to sad music conditions, though the difference was only significant for positive words . The results from Experiment 2 largely mirror those from Experiment 1. Participants were more likely to respond "positive" in the happy music condition. This difference was significant for the negative and neutral words, but not the positive words (though there is a trend in that direction). Likewise, positive responses were relatively faster than negative responses in the happy compared to sad music conditions, though the difference was only significant for neutral and positive words.

Overall, the behavioral data show that the mood induction was effective in influencing participants' emotional classification: positive responses were more likely and faster in the happy compared to sad music condition. These behavioral data are next decomposed with the DDM.

Figure 3 shows the DDM parameters for each experiment. Although the two bias-related measures (starting point and drift rates) are of primary interest, all of the DDM parameters were compared across music conditions.

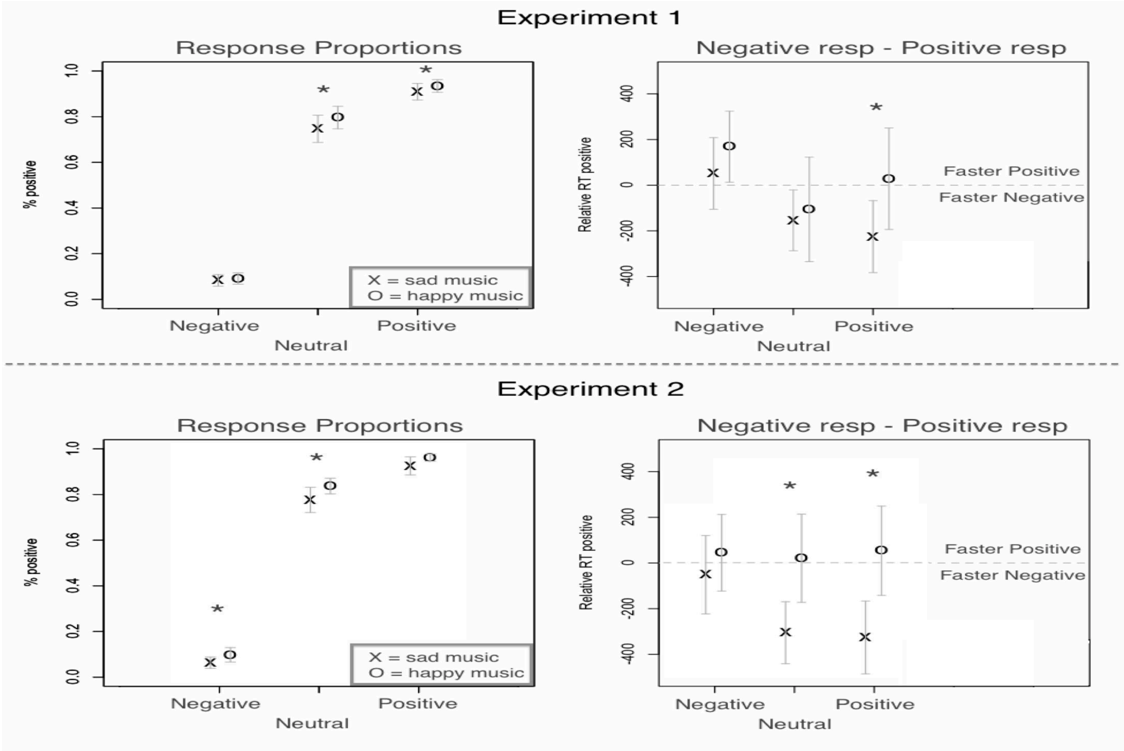

Figure 2. Response patterns for the two experiments. 1st column shows proportions of classification for the three word types. 2nd column shows normalized response time difference between positive and negative classifications for the three word types. X marks the sad music condition, O marks the happy music condition.

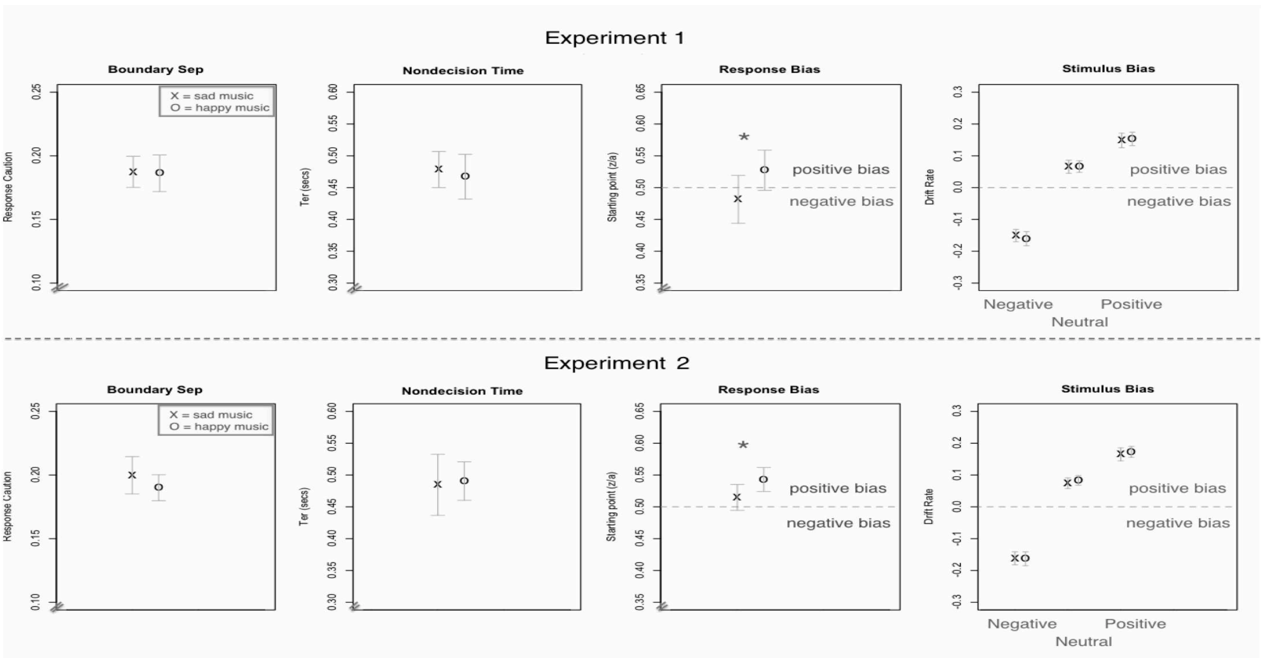

Figure 3. DDM fitted parameters - boundary separation, nondecision time, response bias and stimulus bias. X marks the sad music condition, O marks the happy music condition. Response bias indicates a statistically significant difference between the sad and happy music conditions.

It is possible that the different music conditions could affect response caution and nondecision time. For example, the slower tempo of the sad songs could lead participants to become more cautious and have slower motor execution time. Thus all parameters were investigated. As the left columns of Figure 3 shows, the music conditions did not differentially affect response caution or encoding/motor time, as neither boundary separation nor nondecision time differed between happy and sad music blocks. Of primary interest were the starting point and drift rate parameters, which provide indices of response expectancy and stimulus evaluation bias, respectively. For starting point, there was a significant shift in response bias for both experiments, with participants favoring the "positive" response more heavily in the happy compared to sad music. This indicates that the music induced an a priori bias for one response over the other. In contrast, the music conditions had no reliable effect on the drift rates for positive, negative, or neutral words. Thus music did not influence the stimulus evaluation of the items. The DDM results show that the music-based manipulation of mood had a targeted effect on the starting point measure, which reflects an a priori response expectancy bias. There were no effects of music on response caution, nondecision time, or drift rates (stimulus evaluation bias). Thus the results show that the mood-congruent bias was driven by a change in participants' expectancy about the appropriate response, rather than a change in how the emotional content of the words was evaluated.

5. CORRELATING RESPONSES AND MUSICAL FEATURES

The partition between "positive" and "negative" mood-inducing songs is intuitively understandable, and is indeed sufficient in order to observe the effects discussed in the previous section. This partition, however, is still somewhat arbitrary. It is of interest then to identify, on a more fundamental auditory level, how specific aspects of music affect response patterns. To this end, we considered the 8 musical segments used in this experiment, extracted key auditory features which we assume are relevant to the mood partitioning, and examined how they correlate with the participant responses we observed.

5.1 Extracting Raw Auditory Features

We focused on three major auditory features: a) overall tempo; b) overall "major" vs. "minor" harmonic character; c) average amplitude. Features (a) and (c) were computed using the Librosa library [11]. To compute feature (b), we implemented the following procedure. For each snippet of 20 beats an overall spectrum was computed and individual pitches were extracted. Then, for that snippet, according to the amplitude intensity of each extracted pitch, we identify whether the dominant harmonic was major or minor. The major/minor score was defined to be the proportion of major snippets out of the overall song sequence. We can easily confirm that these three features were indeed associated with our identification as "positive" vs. "negative". Having labeled "positive" and "negative" as 1 and 0 respectively, we observed a Pearson correlation of $0.7 - 0.8$ with p-values ≤ 0.05 between these features and the label. Significance was further confirmed when we applied an unpaired t-test for each feature for positive vs. negative songs (p-values $< .05$, $|t(3)| > 3$).

5.2 Processing Participant Responses

For each observed song we first aggregated all relevant subject responses. We focused on three measurements - time delay for classifying positive words as positive, time delay for classifying negative words as negative, and likelihood of classifying neutral words as positive. Time delays were normalized to a z-score per user. This alternative perspective helps verify the robustness of the effects observed in the previous section. Following this analysis step, we proceeded to fit the DDM parameter decomposition as we did in sections 3 and 4, but rather than for each song condition ("sad"/"happy"), to each song separately.

5.3 Observed Correlations

In this section we consider the effects observed when analyzing response patterns with respect to each of the three auditory features discussed in the previous subsections. Only statistically significant correlations are reported, though it's worth noting that with a relatively small sample size in terms of songs, potentially meaningful effects might be missed due to outliers.

5.3.1 Correlation with Response Times and Bias

When we consider how the three auditory features correspond with the normalized delays when classifying positive or negative words as such, we see an interesting pattern. For all three features, there was a statistically significant negative correlation (p-value ≤ 0.05) between the average normalized response time and the feature values. Intuitively speaking, the faster the song was, the louder it was, or the more it was major in mode overall, the faster people classified positive words as positive (see Figures 4a-4c). However, no such clear correlation was observed for negative songs. This observation supports our key finding when using the drift-diffusion model, that participants were biased to label words positive in the positive music condition. When we analyzed the likelihood of associating neutral words as positive with respect to each auditory feature, the only effect that is borderline significant (p-value ≤ 0.1) is the correspondence between major mode dominance and the likelihood of associating a neutral word as positive (the more major-mode oriented the song is, the more likely people are to associate neutral words as positive) - see Figure 4d.

5.3.2 Correlation with DDM Decomposition

We analyzed the correlation between the extracted auditory features and the DDM parameters fitted for each song separately: nondecision time, response caution, response bias, and stimulus evidence (drift rate) for each word type.

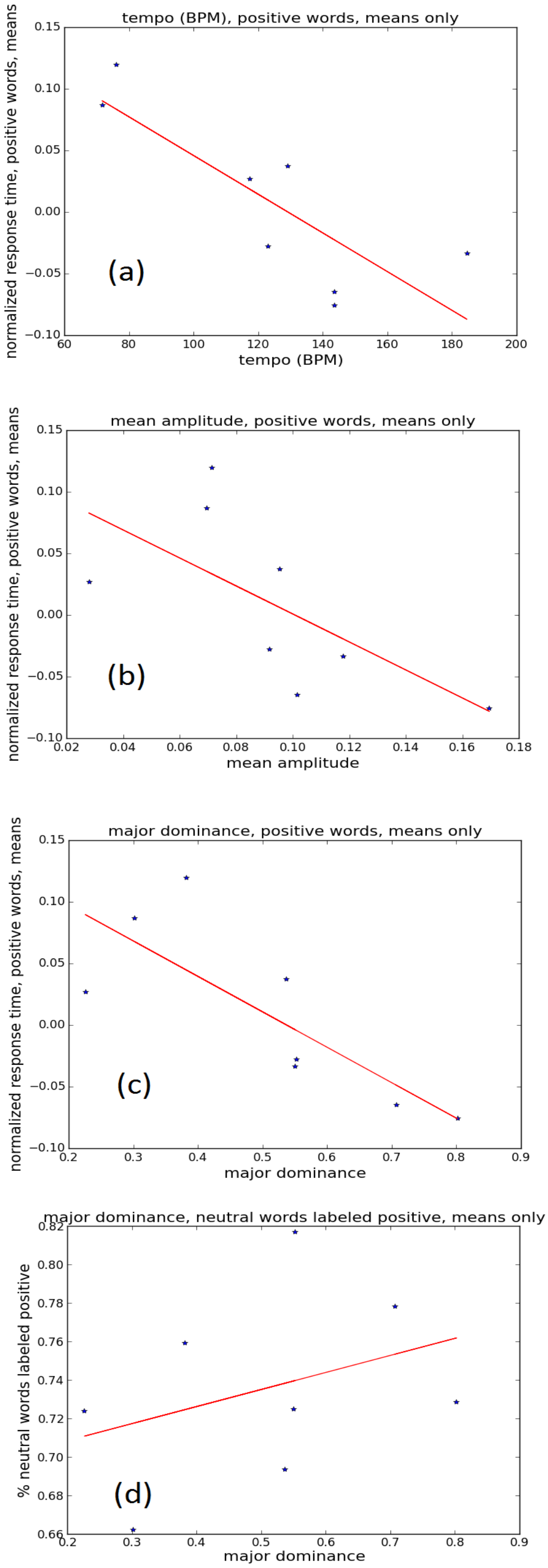

Figure 4. Scatter plots reflecting the correlation between musical features and response patterns: (a) average tempo (as BPM) in a song vs the normalized average delay in classifying positive words as positive; (b) average amplitude in a song vs. the normalized average delay in classifying positive words as positive; (c) the percentage of major-mode harmonies (major dominance) in a song and the normalized average delay in classifying positive words as positive. (d) the percentage of major-mode harmonies (major dominance) in a song vs. the likelihood of associating neutral words as positive.

We found a statistically significant correlation ($r = 0.7 - 0.8, p < 0.05$) between the major dominance feature and the bias and positive drift rate parameters (see Figures 5a, 5b). A borderline correlation ($r = 0.62, p < 0.1$) was observed between major dominance and the neutral drift rate. These findings support the previous observations in the paper. Interestingly, we've also observed a borderline significant negative correlation ($r = -0.67; p < 0.1$) between mean amplitude and response caution, implying people are less cautious the louder the music gets (see Figure 5c).

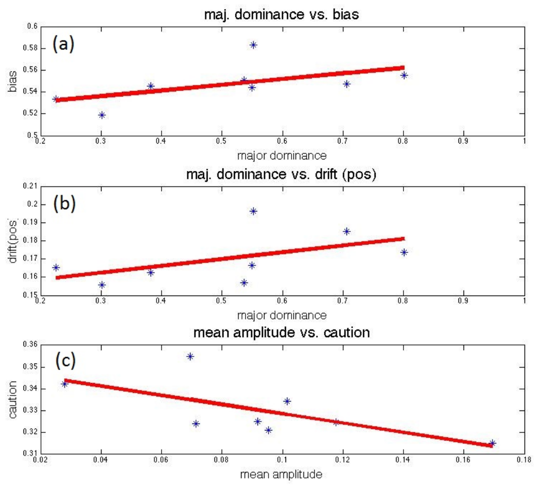

Figure 5. (a) Scatter plot of the correlation between the percentage of major-mode harmonies (major dominance) in a song and the bias component of the DDM. (b) Scatter plot of the correlation between the percentage of major-mode harmonies (major dominance) in a song and the stimulus evidence component (drift rate) for positive words in the DDM. (c) Scatter plot of the correlation between the average amplitude of a song and the response caution component of the DDM.

6. DISCUSSION

There is great interest in understanding how music affects emotional processing. This study advances our understanding of this relationship through the use of the drift-diffusion model, which was used to decompose the behavioral data into meaningful psychological constructs. Participants classified words as emotionally positive or negative while listening to music that induced a happy or sad mood. The behavioral data showed small, but reliable effects of mood congruent emotional bias based on the music conditions. The DDM analysis of those data showed that music-induced mood had a targeted effect on the decision components, affecting response expectancy bias but not stimulus evaluation bias, response caution, or encoding/motor time. Further analysis of how specific musical traits correspond with response patterns confirmed these findings and led to interesting additional observations.

These results suggest that music-induced mood does not significantly affect how participants evaluate the emotional content of the stimuli, but rather it affects how they favor one response option independent of the actual stimulus under consideration. In other words, a negative word is just as negative while listening to sad compared to happy music, even though the classification behavior differs. Thus the mood-congruent bias appears to be driven more by the selection of the response, rather than the emotional processing of the stimulus. The distinction between these two processes is only identifiable through the DDM analysis, as it can capitalize on the RT distributions to dissociate the two decision components.

Acknowledgments

This work has taken place in the Brain and Behavior Lab, The Department of Psychology, Syracuse University, and in the Learning Agents Research Group (LARG) at the Artificial Intelligence Laboratory, The University of Texas at Austin. LARG research is supported in part by grants from the National Science Foundation (CNS-1330072, CNS-1305287), ONR (21C184-01), AFRL (FA8750-14-1-0070), AFOSR (FA9550-14-1-0087), and Yujin Robot.

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