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Decision mechanisms underlying mood-congruent emotional classification

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ABSTRACT

There is great interest in understanding whether and how mood influences affective processing. Results in the literature have been mixed: some studies show mood-congruent processing but others do not. One limitation of previous work is that decision components for affective processing and responses biases are not dissociated. The present study explored the roles of affective processing and response biases using a drift-diffusion model (DDM) of simple choice. In two experiments, participants decided if words were emotionally positive or negative while listening to music that induced positive or negative mood. The behavioural results showed weak, inconsistent mood-congruency effects. In contrast, the DDM showed consistent effects that were selectively driven by an a-priori bias in response expectation, suggesting that music-induced mood influences expectations about the emotionality of upcoming stimuli, but not the emotionality of the stimuli themselves. Implications for future studies of emotional classification and mood are subsequently discussed.

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Research on the effects of mood on cognitive processing often focuses on the presence or absence of mood-congruent effects, which are reflected when positive mood induces a relative preference or facilitation for positive emotional content (and vice versa). Often a specific mood is induced, for example by listening to happy music or reading a sad literary passage, and then processing of emotional information is tested. Many studies in this domain have shown mood-congruent processing across a range of tasks, including implicit priming (Mohan et al., 2016), memory recall (Varner & Ellis, 1998), emotion ratings (Carroll & Young, 2005; Lemmens, De Haan, Van Galen, & Meulenbroek, 2007), facial recognition (Jeong et al., 2011), pain processing (Berna et al., 2010), issue interpretation (Mittal & Ross, 1998), and lexical processing and word recognition (Niedenthal, Halberstadt, & Setterlund, 1997; Olafson & Ferraro, 2001). However, other studies have failed to show mood-congruent processing (Sereno, Scott, Yao, Thaden, & O'Donnell, 2015; Weaver & McNeill, 1992) or only found it for certain mood induction (Varner & Ellis, 1998) or certain subsets of participants (Roiser et al., 2009). Given the problem of publication bias against null effects, it is likely that there are many more unpublished studies with null effects that have been relegated to the "file drawer" (Etz & Vandekerckhove, 2016). Finally, mood-*incongruent* effects are sometimes found whereby stimuli of the opposite valence of the mood are preferentially processed. For instance, Schwager and Rothermund (2014) showed that mood-incongruent processing can occur when remembering affectively hot (active) events, whereas mood-congruent processing can occur when remembering events to which the participant has already become accommodated. This suggests that affective intensity is a potential moderator of mood-congruency effects. Overall the literature on mood-congruent affective processing shows a range of empirical effects, thus it is unclear to what

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extent mood influences affective processing, and how robust mood-congruency effects are across different tasks, mood-induction techniques, populations, and cognitive processes.

There are myriad factors that can influence the presence/absence of mood-congruency effects in a study. The induction of mood itself can be accomplished in multiple ways, like playing emotional music or having participants recall an emotional memory, and undoubtedly these methods have different levels of effectiveness. Thus a null effect of mood-congruency could reflect an ineffective mood induction rather than evidence against an effect on cognitive processing. Further, different cognitive processes are likely to be more or less sensitive to mood-congruency effects; for example we might expect affective processing to be affected more than memory or lexical processing. Finally, mood-congruency is likely to affect certain cognitive components that drive behaviour in a given task; for instance when classifying stimuli as emotionally positive or negative, mood could influence affective processing of the stimuli, response bias for the choice options, or both. This study focuses on this last aspect of mood-congruency experiments and attempts to improve our understanding of whether and how mood influences different components of the decision process.

The goal of the present study was to shed light on mood-congruent processing by investigating the cognitive mechanisms that could be influenced by mood in an affective classification task. Participants classified words as emotionally positive or negative while listening to music that was chosen to induce a happy or sad mood. A popular model of simple decisions, the drift-diffusion model (DDM; Ratcliff & McKoon, 2008), was used to explore effects of mood on different components of the decision process that drive affective classification behaviour. The model, described below, can differentiate effects due to response caution, encoding/motor processes, response biases, and affective processing itself. For studies of mood-congruent processing, the DDM can differentiate processing biases that are driven by expectations about the upcoming response from those that are driven by changes in the actual affective processing of the stimuli (see below). In this regard, the DDM allows us to identify which, if any, of these decision components are affected by induced mood. This class of models has been successfully employed to differentiate decision components in perceptual and memory tasks, but to our knowledge has never been used to investigate effects of music on emotional classification.

DDM and bias

The primary advantage of using the DDM to analyse data in mood-congruency tasks is the ability of the model to distinguish bias due to changes in the evaluation of the stimuli and bias due to expectations about the response. These biases are conceptually distinct in the DDM framework and have theoretically different interpretations. To understand the difference in these biases, it is first important to understand how the DDM accounts for simple decision behaviour.

The DDM, shown in Figure 1, belongs to a broader class of evidence accumulation models that posit simple decisions involve the gradual accumulation of noisy evidence until a threshold level is reached. The decision process starts between the two boundaries that correspond to the response alternatives, and evidence is accumulated over time to drive the process until a boundary is reached, signalling 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.

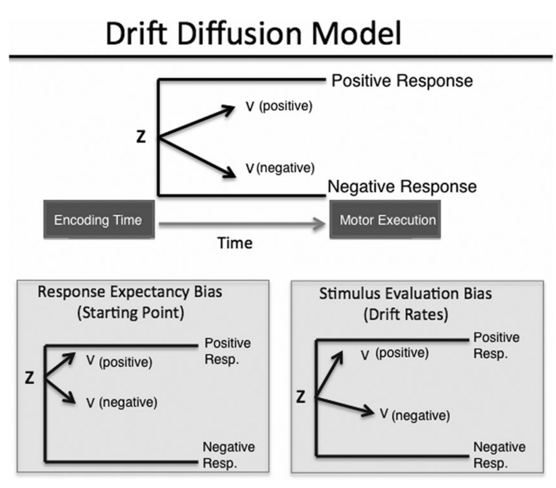

Figure 1. Schematic of the DDM. The top panel shows unbiased diffusion process, and the bottom panels show bias in starting point and drift rates. See text for details.

The primary components of the decision process in the DDM are the boundary separation, the starting point, and the drift rate. Boundary separation provide an index of response 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 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.

In an affective classification task, mood-congruency would typically be shown as participants being faster and/or more likely to label stimuli as positive when in a positive mood (and vice versa for negative mood). In the framework of the DDM there are two mechanisms that can lead to this behaviour: changes in response bias or changes in stimulus (affective) processing. 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 (Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012; van Ravenzwaaij, Mulder, Tuerlinckx, & Wagenmakers, 2012; Voss, Rothermund, & Brandtstaedter, 2008; Voss, Rothermund, & Voss, 2004; White & Poldrack, 2014). 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 subjective evaluation of the stimulus. For instance if the word "failure" was experienced as more extremely negative when in a negative compared to positive mood, this would be reflected in the drift rates by the former providing stronger evidence for the negative response than the latter. For these two types of bias in an affective classification task, response bias would indicate a difference in expectation about the affective nature of the upcoming stimulus, whereas stimulus evaluation bias would indicate a shift in the affective evaluation of the stimulus itself. These two effects can be distinguished with the DDM because they produce differential effects on the distributions of RTs for positive and negative responses. In brief, response bias (starting point) affects the fastest responses and has small effects on response probabilities, whereas stimulus evaluation bias (drift rates) affects both fast and slow responses and tends to have larger effects on response probabilities (see White & Poldrack, 2014).

The present study used this DDM approach to investigate how induced mood affects response expectancy and stimulus evaluation bias when classifying emotional information. It is critical to analyse both of these components because they could counteract each other. For instance, if participants showed mood-congruent response bias paired with mood-incongruent stimulus bias, these processes could cancel each other out and result in null effects of mood in the analysis of RTs and/or response rates. The DDM analysis circumvents this problem by allowing separate analysis of both response and stimulus bias.

In the study, 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 behavioural data to determine whether the mood induction affected response expectancy bias, stimulus evaluation bias, or both. Although there were no hypothesised effects of mood on other components of the decision process, the DDM also allows investigation of mood effects on response caution and motor/encoding time. These additional model parameters were analysed for completeness, but are not directly related to the primary focus on mood-congruency because differences in response caution or nondecision time would only affect the overall speed and accuracy of the responses, but not the presence or absence of mood-congruent bias.

Methods

Two experiments were conducted that differed only in the stimuli that were used and the timing of the trials. The second experiment served as a conceptual replication of the first.

Procedure

Participants were shown words on the computer screen and asked to classify them as emotionally positive or negative while listening to music. In Experiment

1, the words were emotionally positive, negative, or neutral, whereas in Experiment 2 only the positive and negative words were shown. Although there were three categories of words (positive, negative, and neutral), participants were forced to classify them as either positive or negative. This was done to increase the likelihood of observing a music-induced bias since the neutral words had to be assigned to the positive or negative response that was either congruent or incongruent with the music. Note that in Experiment 2 the neutral words were removed and similar pattern of results were obtained. After a fixation cue was shown for 500 ms, each word was presented in the centre of the screen and remained on screen until a response was given. Participants were given up to 3 s to respond in Experiment 1. The response window was shortened to 2 s in Experiment 2 based on the finding in Experiment 1 that nearly all responses were given within 2 s. 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 condition (neutral, positive, negative) for Experiment 1, and 4 blocks of 48 trials with 24 stimuli from each condition (negative, positive) for Experiment 2. 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. Each experiment lasted less than 30 min.

Participants

The study and procedures were approved by the Syracuse Institutional Review Board. All participants were Syracuse University undergraduates who participated for course credit. The aim was to have approximately 75 participants in each of the 2 experiments. Note that the comparisons of interest were within-participant (happy vs. sad music), so the sample size should be sufficient for detecting differences. In Experiment 1, 5 participants were excluded for not finishing the entire experiment and 2 for responding at chance (50%), leaving 68 total participants. In Experiment 2, 3 participants were excluded for not finishing the entire experiment, 1 was excluded for responding at chance, and 3 were excluded for having more than 10 non-response trials, resulting in 67 total participants. Excluding participants for non-response trials was based on the DDM fitting procedure guidelines that recommend having at least 40 observations per condition for parameter estimation (see below).

Stimuli

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 (White, Kapucu, Bruno, Rotello, & Ratcliff, 2014). The words had been previously rated for valence and arousal to create the different word pools (Dougal & Rotello, 2007). There were 96 words for each stimulus condition, which were matched for word frequency and letter length. From each word-pool, 80 items (Experiment 1) or 96 items (Experiment 2) 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 an equal number of each word type appeared in every block of trials.

Music

Publicly available music was surveyed to isolate two clear types – music that is characterised by slow tempo, minor keys, and sombre tones, typical to traditionally "sad" music, and music that has upbeat tempo, major scales, and colourful tones, which are traditionally considered to be typical to "happy" music. Our principal concern in selecting the musical stimuli, rather than their semantic categorisation as either happy or sad, was to curate two separate "pools" of music sequences that were broadly characterised by a similar temperament (described above), and show they produced consistent response patterns. The full list of songs, categorised by type, is listed in Appendix A in Supplemental data.

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 behaviour in the primary task. The ratings showed that the music choices were appropriate. The positive songs in Experiment 1 led to more positive ratings (song 1: mean = 5.14, SD = 1.24; song 2: mean = 5.00, SD = 1.22) than the negative songs (song 1: mean = 2.24, SD = 1.00; song 2: mean = 2.33, SD = 0.97). Similar results were found for the songs in Experiment 2, with higher ratings for the positive songs (song 1: mean = 5.15, SD = 1.29; song 2: mean = 5.42, SD = 1.17) than the negative songs (song 1: mean = 2.26, SD = 1.24; song 2: mean = 2.11, SD = 0.99). The differences between the positive and negative song ratings were highly significant for both experiments (p's < .001).

Drift-diffusion model (DDM)

The DDM was fitted to each participant's data, separately for positive and negative music blocks, to estimate the values of the decision components. For all analyses including the DDM fitting, RTs faster than 250 ms were trimmed from the data (less than 0.8% of the data). The upper bound for RTs was determine by the response window (3 s for Experiment 1, 2 s for Experiment 2). The fast-dm package (Voss, Voss, & Lerche, 2015) was used for model fitting, using the maximum likelihood estimation procedure which is best suited for the relatively low number of trials per condition (~40–48). For each music condition and participant, the model estimated a value of boundary separation, nondecision time, starting point, and a separate drift rate for each stimulus condition (positive, negative, or neutral). This resulted in two sets of DDM parameters (boundary separation, nondecision time, starting point, and drift rates) for each participant, one for the positive music blocks and one for the negative music blocks.

Results

Behavioural data

A repeated measures ANOVA was conducted on data from each experiment with music type (happy, sad) and stimulus type (negative, neutral, happy [Experiment 1] or negative, happy [Experiment 2]) as within-subject factors. *Post hoc* comparisons of each stimulus type were then performed using paired *t*-tests between happy and sad music blocks. A Bayes Factor (BF) for each comparison was calculated using the Bayesian *t*-test package (pcl.missouri.edu/bayesfactor) to quantify the strength of evidence for or against the null hypothesis. Reported BFs used the Jeffrey–Zellner–Siow prior and a scale of $r = 0.5$ to reflect expectation of fairly small effect sizes (see Rouder, Speckman, Sun, Morey, & Iverson, 2009). With this analysis, a BF_a of 3, for example, indicates the data were 3 times more likely under the alternative (effect of music), whereas a BF_0 of 2 indicates the data were 2 times more likely under the null (no effect of music). In general, BFs of 1–3 provide anecdotal evidence, BFs 3–10 provide moderate evidence, and BFs > 10 provide strong evidence.

In Figure 2, the raw response rates are plotted in Panel A, and the difference between happy and sad music is plotted in Panel B for visual clarity, with values above 0 indicating more negative responses in the happy compared to sad music (and vice versa). In Experiment 1, the ANOVA showed a main effect of music type ($F(1,67) = 5.68$, MSE = 0.058, $p = .018$, $\eta^2 = 0.014$) and stimulus type ($F(2,134) = 2921.44$, MSE = 29.84, $p < .001$, $\eta^2 = 0.935$), but no interaction ($p = .633$). *Post hoc* comparisons for each stimulus type showed more positive responses were given in the happy compared to sad music for negative words ($t(67) = -2.341$, $p = .022$, $BF_a = 2.10$, $d = 0.370$), neutral words ($t(67) = -2.57$, $p = .012$, $BF_a = 3.40$, $d = 0.359$), and positive words $t(67) = -2.344$, $p = .022$, $BF_a = 2.12$, $d = 0.355$). In Experiment 2, the ANOVA showed a significant main effect of stimulus type ($F(1,66) = 5396.04$, MSE = 44.20, $p < .001$, $\eta^2 = 0.954$) but no main effect of music type ($F(1,66) = 0.771$, MSE = 0.01, $p = .38$, $\eta^2 = 0.005$) or interaction ($p = .47$). *Post hoc* comparisons for each stimulus type confirmed that the difference in response rates for happy compared to sad music did not reach significance for negative $t(66) = -1.845$, $p = .069$, $BF_0 = 1.16$, $d = 0.287$) or positive words $t(66) = -0.156$, $p = .876$, $BF_0 = 5.34$, $d = 0.025$). For comparisons of median RTs (Figure 2(c,d)), none of the main effects of music type nor interactions were significant (p's > .4), and *post hoc* comparisons showed that the only significant difference between happy and sad music were for positive responses to neutral words in Experiment 1 ($t(67) = 2.50$, $p = .015$, $BF_a = 2.92$, $d = 0.338$). All other comparisons of median RT were not significant (p's > .05, $BF_0 > 2$, $d < 0.2$).

The traditional comparisons of response proportions and median RTs show weak or no evidence for mood-congruency effects: response rates were affected in Experiment 1 but not Experiment 2, and although the differences were significant at the $p < .05$ level in Experiment 1, the BFs (2–3.5) provided anecdotal evidence at best. Further there was no evidence of mood-congruency in the median RTs, which would typically be shown as faster "positive" responses under happy compared to sad music (and

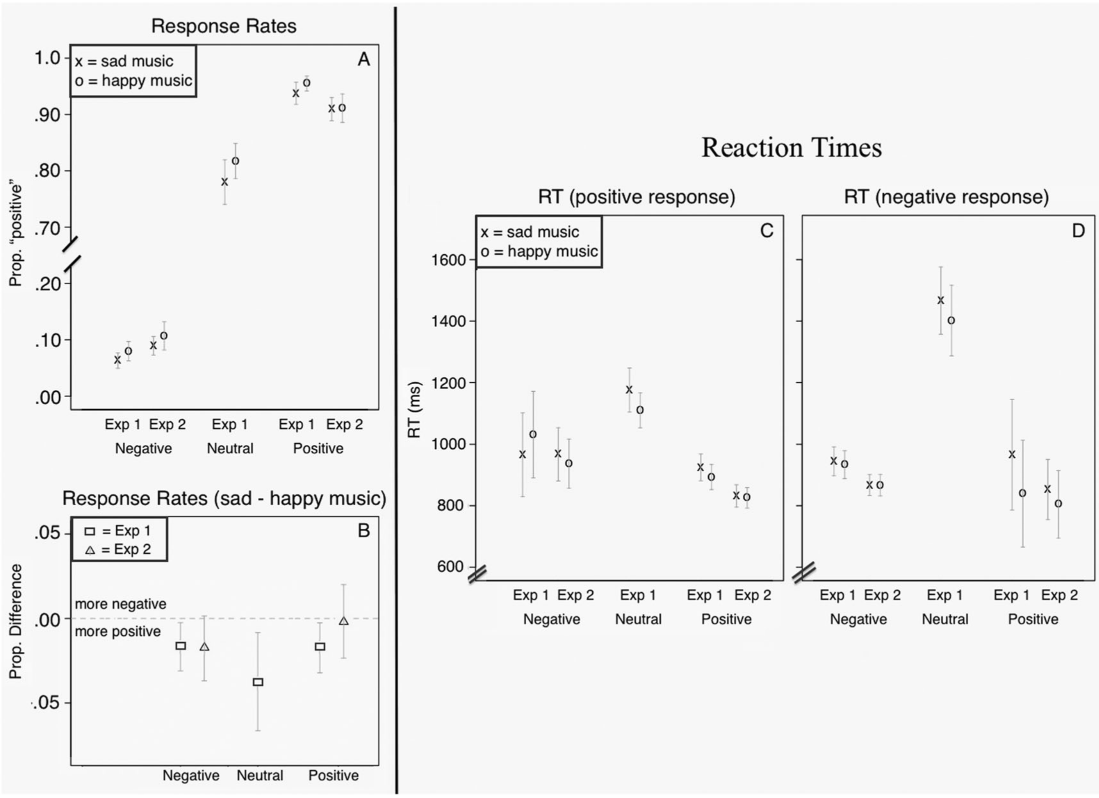

Figure 2. Behavioural data from experiments. (a) Response proportions for each word condition. (b) Difference in response proportions between happy and sad music conditions. (c) Median RTs for positive responses. (d) Median RTs for negative responses. See text for details. Error bars indicate 95% confidence intervals.

likewise for negative responses under sad compared to happy music). However, as mentioned in the introduction, if mood-congruency effects manifested as response bias (DDM starting point) rather than stimulus evaluation bias (DDM drift rates), the behavioural effects would be most pronounced in the fastest responses (not the median RTs).

Taken together, the standard analyses of response rates and median RTs showed weak to no evidence for mood-congruent bias, as the differences were only significant for response rates in Experiment 1 (but not Experiment 2), and the BFs were small and in the anecdotal range. However, comparisons of the fastest responses, which are most affected by changes in response bias, showed consistent mood-congruency effects for both experiments. This analysis of the fastest responses is crucial to assessing the mood-congruency effects in this case, as standard analyses based on response rates and median RTs would suggest no reliable effects of the mood induction on emotional classification. We now turn to the DDM analyses to corroborate the behavioural analyses and determine which decision components were affected by the mood induction.

DDM results

Before interpreting the estimated parameters from the DDM, it is crucial to demonstrate that the model actually fits the data successfully. Figure 3 shows a plot of the predicted data from the best-fitting DDM parameters and the observed data from the experiments. For visual clarity the response rates and RTs were collapsed across music condition. The figure shows that the model successfully captures the data, as the predicted response probabilities and RT quantile values are similar to the observed values. Further, the fit quality, as quantified by the Maximum Likelihood values, did not differ between happy and sad music blocks for either experiment (both p's > .4). This gives confidence in the interpretation of the recovered parameter values.

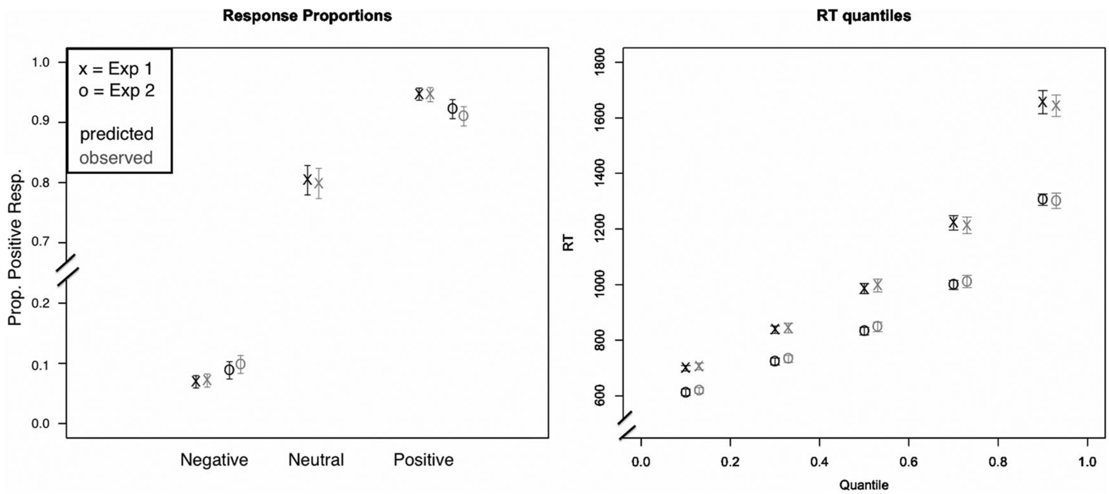

Figure 3. Observed and predicted data from the best-fitting diffusion model parameters. The left panel shows the response proportions and right panel shows RT quantiles. Error bars indicate 95% confidence intervals.

Figure 4 shows the DDM parameters for each experiment. Of primary interest were the starting point and drift rate parameters, which provide indices of response expectancy and stimulus evaluation bias, respectively. However, boundary separation and nondecision time were compared for completeness but there were no effects of music condition on either parameter (Appendix B in Supplemental data).

For starting point, there was a significant shift in response bias for both experiments, with participants favouring the "positive" response more heavily in the happy compared to sad music (Experiment 1: $t(67) = 2.968$, $p = .004$, $BF_a = 8.56$, $d = 0.569$; Experiment 2: $t(66) = 2.794$, $p = .007$, $BF_a = 5.65$, $d = 0.536$). 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 negative (Experiment 1: $t(67) = 0.927$, $p = .358$, $BF_0 = 3.67$, $d = 0.127$; Experiment 2: $t(66) = 0.381$, $p = .705$, $BF_0 = 5.05$, $d = 0.056$) or positive words (Experiment 1: $t(66) = -1.70$, $p = .09$, $BF_0 = 1.47$, $d = 0.244$; Experiment 2: $t(66) = 1.24$, $p = .220$, $BF_0 = 2.68$, $d = 0.178$). There was a trend for more positive drift rates for neutral words in the happy compared to sad music, but the effect was not significant (Experiment 1: $t(67) = -1.98$, $p = .051$, $d = 0.264$) and the BF was

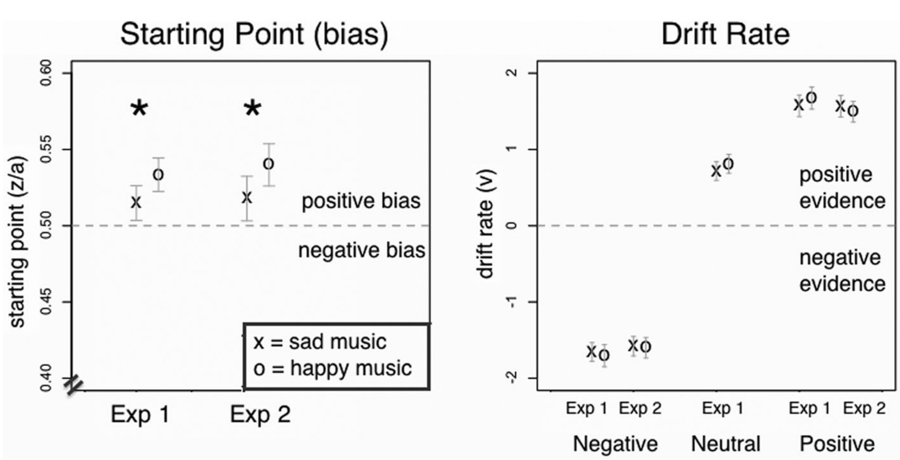

Figure 4. Diffusion model parameters for quantifying mood-congruent bias. See text for description of parameters. Error bars indicate 95% confidence intervals; * indicates significant difference as a function of music condition ($p < .05$).

extremely small ($BF_a = 1.06$). Thus there was no evidence that music influenced 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 affective content of the words was evaluated.

Discussion

There is great interest in understanding how mood affects emotional processing. The present study advanced our understanding of this relationship through the use of the DDM, which was used to decompose the behavioural data into meaningful psychological constructs. The DDM provides an analytical tool to explore underlying cognitive processes based on observed behaviour. Participants classified words as emotionally positive or negative while listening to music that induced a happy or sad mood. The behavioural data showed small, inconsistent effects of mood-congruent affective based on the music conditions. Importantly, traditional analyses of response rate and median RTs would have provided no meaningful evidence for mood-congruency effects, but these behavioural measures can be contaminated by conflicting effects of the different DDM parameters, and thus do not provide an accurate measure of processing biases. However, a subsequent analysis of the fastest RTs, which are most reflective of changes in response bias, showed mood-congruent effects consistent with changes in the starting point parameter (see Appendix B in Supplemental data). 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. Although these effects were not large, the fact that they were consistent across two experiments with different procedures suggests that they are meaningful and robust.

These results suggest that music-induced mood does not significantly affect how participants evaluate the emotional content of the stimuli, but rather how they favour 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 behaviour differs. Thus the mood-congruent bias appears to be driven more by the selection of the response, rather than the affective processing of the stimulus. The distinction between these two processes is identifiable through the DDM analysis, as it can capitalise on the RT distributions to dissociate the two decision components.

One limitation of this study is that there was no direct assessment of the mood-induction procedure. Although a separate test of the chosen songs indicated that they differentially mapped onto positive and negative emotion, we did not measure their effect on mood for participants in the emotional classification task. As mentioned above, the experiment alternated between happy and sad music, so online assessment of mood could have drawn attention to the aims of the experiment. Nonetheless, this leaves the possibility that the bias effects were not driven by mood, but rather the surface qualities of the music itself. Our interpretation of these effects is that the music affected participants' mood, which then affective their response bias for affective classification. However it is possible that the mood component of this relationship was absent and the observed bias effects were directly driven by the music stimuli. Thus although consistent effects of mood-congruency were shown with the DDM analysis, there remains an open question of precisely how effective the mood-induction procedure was. Future research is needed to validate the purported mood differences in this study.

Another interesting finding was that participants showed an overall positivity bias, whereby the starting point of the DDM was biased for the positive response even for the sad music condition (Figure 3). We are cautious to interpret this finding because it is likely specific to the stimuli that were presented. That is, if the positive words were more strongly positive than the negative words were negative, an overall positive bias would be expected. Thus it is conceivable that a different set of stimuli would result in a more neutral (or even negative) overall response bias.

We turn now to the question of the source of this mood-congruent expectancy bias. One explanation is that the emotional bias is based on a lifetime of experience with music and emotional events. The music-induced bias observed in this study is consistent with what has been termed response expectancy bias (White & Poldrack, 2014), which is typically observed when there is an a-priori expectation about which response is likely to be correct. A straightforward interpretation of this is that the happy and sad music influenced participants' expectations about which type of emotional stimuli would occur in each music condition, leading them to favour one response over the other. In fact, this expectation is consistent with everyday experiences with emotional music and media consumption. When watching a show or movie, the tone of the background music provides information about the emotionality of the events that will occur. Sombre, sad music is usually accompanied by a negative emotional event (e.g. danger or failure), whereas upbeat, happy music is usually accompanied by a positive emotional event (e.g. winning the big game). Thus it is possible that a lifetime of experience with such music–emotion associations drives participants to predict or expect emotional events based on the tone of the music. This would produce precisely the effect we observed, where participants bias their responses based on an expectation about the emotional content of the upcoming stimulus.

Alternatively, the emotional response triggered by certain types of music could be an innate physiological property. Even in other species like dogs, the tone and pitch of sound carries emotional information. Deep, low sounds are associated with negative emotions like aggression and displeasure, whereas higher pitched tones are associated with positive emotions like playfulness and pleasure. Thus there might be an innate, biological associations between sound qualities and emotional responses, meaning such associations exist independent of experience and cultural norms. Whatever the root cause of such perceptions may be, it seems to pose something of a feedback loop – film and television repeatedly exploit the emotional connotations of different types of music to enhance or affect the way we perceive the visual and textual content, and this, in turn, only reinforces these connotations.

In closing, we found that music-induced emotional bias is driven by expectations about which response or outcome is more likely to occur under happy compared to sad music. In contrast, there was no evidence that the music affected the actual emotional evaluation of the stimuli under consideration. Thus our results suggest that the emotional content of music influences behaviour through mechanisms related to expectations about the upcoming events, rather than mechanisms related to evaluating the emotional content of the item or event. That is, sad music induces expectations of upcoming negative emotional events, but does not affect how negative those events actually are to the participant. This distinction was made possible through the use of DDMs to relate the observed behaviour to underlying cognitive constructs. Future work in this domain would benefit from applying such models to enhance the ability to investigate different decision components and how they are influenced by experimental manipulations.

Disclosure statement

No potential conflict of interest was reported by the authors.

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