IMPACT OF MUSIC ON DECISION MAKING IN QUANTITATIVE TASKS

Elad Liebman
Department of Computer Science
The University of Texas at Austin
eladlieb@cs.utexas.edu

Peter Stone
Department of Computer Science
The University of Texas at Austin
pstone@cs.utexas.edu

Corey N. White
Department of Psychology
Syracuse University
cnwhite@syr.edu

ABSTRACT

The goal of this study is to explore which aspects of people's analytical decision making are affected when exposed to music. To this end, we apply a stochastic sequential model of simple decisions, the drift-diffusion model (DDM), to understand risky decision behavior. Numerous studies have demonstrated that mood can affect emotional and cognitive processing, but the exact nature of the impact music has on decision making in quantitative tasks has not been sufficiently studied. In our experiment, participants decided whether to accept or reject multiple bets with different risk vs. reward ratios while listening to music that was chosen to induce positive or negative mood. Our results indicate that music indeed alters people's behavior in a surprising way - happy music made people make better choices. In other words, it made people more likely to accept good bets and reject bad bets. The DDM decomposition indicated the effect focused primarily on both the caution and the information processing aspects of decision making. To further understand the correspondence between auditory features and decision making, we studied how individual aspects of music affect response patterns. Our results are particularly interesting when compared with recent results regarding the impact of music on emotional processing, as they illustrate that music affects analytical decision making in a fundamentally different way, hinting at a different psychological mechanism that music impacts.

1. INTRODUCTION

There is plentiful evidence that one's mood can affect how one processes information. When the information being processed has emotional content (words, for instance), this phenomenon is referred to as mood-congruent processing, or bias, and it's been found that positive mood induces a relative preference for positive emotional content and vice versa [2,7]. However, what effect does music have on non-emotional decision making? This study focuses on the impact of music on risky decision behavior which requires quantitative reasoning. To this end, we design an experiment in which participants decide whether to accept or reject gambles with different win-loss ratios (meaning they have different expected payoff).

Previous work in this area shows robust effects of loss aversion, whereby participants put more weight on potential losses than potential gains. Loss aversion in this context manifests as subjects being unwilling to accept gambles unless the potential gain significantly outweighs the potential loss (e.g., only accepting the gamble if the gain is twice as large as the loss [12, 13]). The present study focuses on whether and how emotional music influences such risky decision behavior.

Not much work has studied the direct connection between music and risky decision making. Some previous work has studied the general connection between gambling behavior and ambiance factors including music [1, 3, 11] in an unconstrained casino environment. Additionally, Noseworthy and Finlay have studied the effects of music-induced dissociation and time perception in gambling establishments [6]. In this paper, we take a deeper and more controlled look at how music impacts decision making in this type of risk-based analytical decision making. To this effect, we use a popular model of simple decisions, the drift-diffusion model (DDM; [8]), to explore how music-induced mood affects the different components of the decision process in such tasks. Our results indicate that music indeed has a nontrivial and unexpected effect, and that certain types of music led to better decision making than others.

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 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.

2. THE DRIFT-DIFFUSION MODEL

This study employs the Drift Diffusion Model (DDM) of simple decisions to decompose the observed decision behavior into its underlying decision components. The DDM, shown in Figure 1, belongs to a family of evidence accumulation models which frame simple decisions in terms of gradual sequential accumulation of noisy evidence until a decision criterion is met. 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 marks the choice of a specific response. The time taken to reach the boundary represents the decision time. The overall response time is the sum of the time it takes to make a decision 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 represents response caution or the speed vs. accuracy tradeoff exhibited by the participant. Wide boundaries indicate a cautious response style where more evidence needs to be accumulated before a decision is reached. The need for more evidence makes the decision process slower, but also more accurate, since it is less likely to reach the wrong boundary by mistake. The starting point of the diffusion process (z) reflects response expectancy. If z is closer to the top boundary, for instance, 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) represents the processing of evidence from stimulus which drives the accumulation process. Positive values indicate evidence for the top boundary, and negative values for the bottom boundary. Furthermore, the absolute value of the drift rate represents 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 an a-priori preference for one response even before the stimulus is shown [5,14]. 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 response 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 [14]), 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

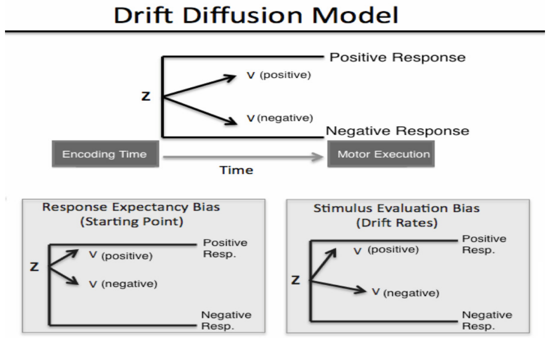

Figure 1. An Illustration of the Drift-Diffusion Model.

(see [14]). It is this differential effect on the response time (abbreviated RT) distributions that allows 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 performing a quantitative task. Participants listened to happy or sad music while deciding whether to bet or fold as bets with different win-loss ratios were proposed to them. 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 presented with simple binary gambles and were asked whether to accept (bet) or reject them (fold). Each gamble had a 50%-50% chance of success, with varying win to loss ratio, reflecting how much was to be gained vs. lost. For example, a 15:5 win-loss ratio reflect a 50% chance to win 15 points and a 50% chance of losing 5 points. After a fixation cue was shown for 500 ms, each gamble was presented in the center of the screen and remained on screen until a response was given. If no response was given after 3.5 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 gamble stimuli were partitioned to very negative (win-loss ratio in range $[0.33, 0.66)$), negative (win-loss ratio in range $[0.66, 1)$), positive (win-loss ratio in range $[1, 2)$), and very positive (win-loss ratio in range $[2, 3]$). The actual values of the bets were randomized in the range of $[3, 60]$. Each experiment comprised 20 batches of 20 gambles, such that in each batch each stimuli condition was repeated 5 times (gamble order was randomized). Subjects were not shown the outcome of their gambles immediately as that would be distracting. Instead, between each batch subjects were shown the overall score they accrued for the previous batch (whereas each batch score starts as 0). To encourage competitive behavior, they were also shown the expected score for that batch. A different song was played during each block of 5 batches, 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 repeated with a large sample of participants ($N = 84$), and two separate sets of songs to assess result reliability.

The music used for this experiment is the same as that used in [4]. It is a collection of 8 publicly available songs which 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. The principal concern in selecting these 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. In [4], it has been shown experimentally that the selected music was effective for inducing the appropriate mood. This was done by selecting a separate pool of 40 participants and having them rate each song on a 7-point Likert scale, with 1 indicating negative mood and 7 indicating positive mood. It was then shown that the songs designated as positive received meaningfully and statistically significantly higher scores than those denoted as sad.

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 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 [9]). 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 [8]). This resulted in two sets of DDM parameters for each participant, one for the positive music blocks and one for the negative music blocks.

4. EXPERIMENTAL RESULTS

The response times and choice probabilities shown in Figure 2 indicate that the mood-induction successfully affected the decision making behavior observed across participants. The left column shows the response proportions, the center column shows normalized response times for betting decisions, and the right panel shows normalized response times for the folding decisions. The betting proportions and response time (or RT) measures for the two conditions - the happy songs and the sad songs - indicate a clear difference between the conditions. Generally speaking, happy music led to more "correct" behavior - participants were more likely to accept good bets and reject bad bets under the happy song condition than the sad song condition. These trends are evident across all gamble proportions and bet-fold decisions, but were only shown to be statistically significant for some of the settings; the difference in betting proportions is shown to be significant for very negative, positive and very positive gambles, whereas the difference in response times is only shown to be significant for folding decisions in very positive gambles. Significance was evaluated using a paired t-test with $p \leq 0.05$.

Figure 3 shows the DDM parameters fitted for the 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. 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 top-left and top-center panels of Figure 3 show, 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. Interestingly, as apparent in the top-right and bottom-right panels of Figure 3, overall, we did not observe any stimulus (evidence processing) bias nor starting point (response expectancy) bias in the two music conditions. However, the key difference lied in the drift rates themselves. Fitting parameters for the drift rates for the four gamble types indicate an overall change in evidence processing in the happy vs. the sad music conditions, which is statistically significant for all gamble proportions. This outcome is shown in the bottom-left panel of Figure 3. In other words, people were faster to process the evidence and make betting decisions for good gambles and folding decisions for bad gambles in happy vs. sad music. This difference is summarized in the bottom-center panel of Figure 3, which presents the discriminability factor in the happy vs. the sad condition. Discriminability is defined as the sum of the drift rates for good bets minus the sum of the drift rates for the bad bets, $(d_{positive} + d_{very-positive} - d_{negative} - d_{very-negative})$. This measure represents the "processing gap" between good evidence (good bets) and bad evidence (bad bets). The discriminability was dramatically higher for happy songs compared to sad songs.

The DDM results show that the music-based manipulation of mood affected the overall processing of information in the quantitative task of deciding when to bet and when to fold, rather than any single bias component. There were no effects of music on response caution, nondecision time, or response or stimulus bias, meaning that people weren't

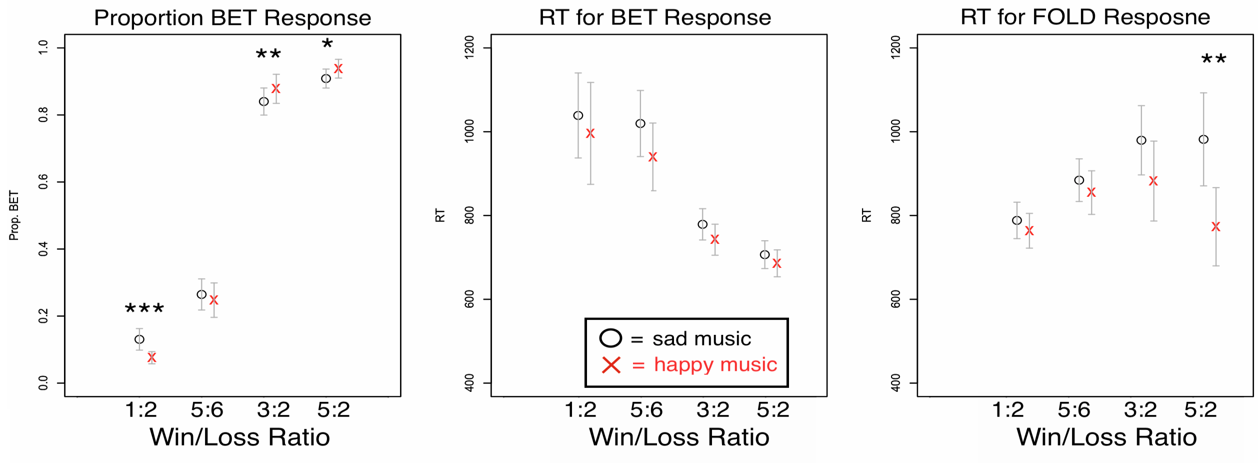

Figure 2. Response patterns in terms of response times and bet-fold proportions for the behavioral experiment. A statistically significant difference between the happy song and the sad song conditions is evident for betting proportions given the four clusters of betting ratios (very negative, negative, positive and very positive). There is also a large statistically significant difference between response times for folding in the two different conditions. Error bars reflect 95% confidence intervals. $* = p < .05$; $** = p < .01$; $*** = p < .001$.

more likely to accept bets or reject them in one condition or the other, but rather the change impacted the entire decision process. In other words, the mood change induced by music neither affected the a-priori inclination of people to bet or to fold, nor has it led to a relative difference in processing one type of bet vs. the other, but rather simply made people make better decisions (more likely to accept good bets and reject bad ones).

5. CORRELATING RESPONSES AND MUSICAL FEATURES

The partition between "positive" and "negative" mood-inducing songs is easy to understand intuitively, and in itself is enough to induce the different behavioral patterns discussed in the previous section. However, similarly to the analysis performed in [4], we are interested in finding a deeper connection between the behavior observed in the experiment and the different characteristics of music. More exactly, we are interested in finding the correspondence between various musical features, which also happen to determine how likely a song is to be perceived as happy or sad, and the gambling behavior manifested by participants. To this end, we considered the 8 songs used in this experiment, extracted key characterizing features which we assume are relevant to their mood classification, and examined how they correlate with the subject gambling behavior 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, representing loudness. Features (a) and (c) were computed using the Librosa library [10]. To compute feature (b), we implemented the following procedure, similar to that described in [4]. 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 identified 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. Analysis done in [4] confirms these three features were indeed associated with our identification as "positive" vs. "negative". Having labeled "positive" and "negative" as 1 and 0 respectively, a Pearson correlation of $0.7 - 0.8$ with p-values ≤ 0.05 was observed between these features and the label. Significance was further confirmed by applying an unpaired t-test for each feature for positive vs. negative songs (p-values $< .05$).

5.2 Processing Observed Gambling Behavior

Given the complexity of the behavioral experiment discussed in this paper, several behavioral breakdowns of participant behavior were extracted. Normalizing the response times (RTs) for each participant, we separately considered the average response times for betting and for folding for all four gamble types and songs (64 values overall). Subsequently, we aggregated these average response times per decision (bet or fold), per gamble type (very negative, negative, positive and very positive), per song (4 happy songs, 4 sad songs overall), to obtain 64 average response times and response time variance per $\langle$decision, gamble type, song$\rangle$ configuration. Then we could correlate these values per $\langle$decision, gamble type$\rangle$ setting with the features extracted for each song. Similarly, we extracted the average bet-fold ratio and bet-fold variance across all participants for each $\langle$decision, gamble type, song$\rangle$ configuration as well. As a result we were also able to examine the relationship between bet-fold ratios per $\langle$decision, gamble type$\rangle$ setting with the features extracted for the songs.

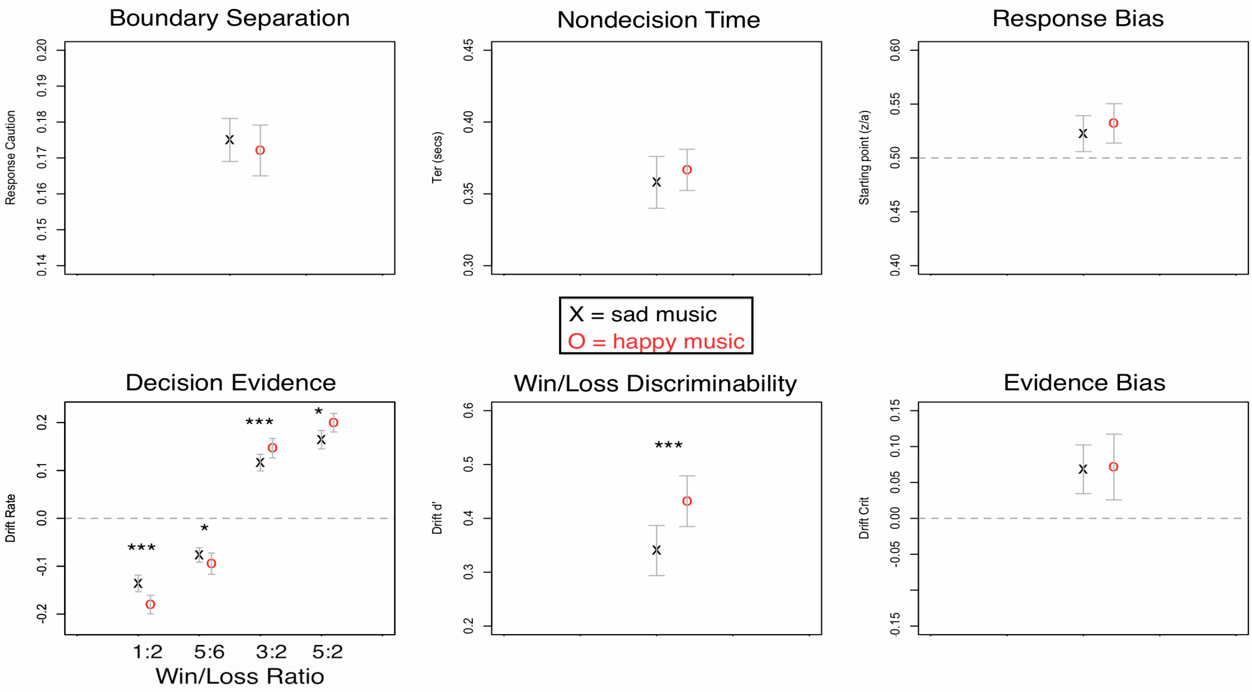

Figure 3. Drift-Diffusion Model parameters fitted for the behavioral experiment. A statistically significant difference between the happy song and the sad song conditions is evident for betting proportions given the four clusters of betting ratios (very negative, negative, positive and very positive). There is also a large statistically significant difference between response times for folding in the two different conditions. Error bars reflect 95% confidence intervals. * $= p < .05$; ** $= p < .01$; *** $= p < .001$.

Decision	Gamble	RT Avg	RT Var.	Avg. p-val	Var. p-val
bet	v. negative	**-0.73**	**-0.61**	**0.03**	**0.1**
bet	negative	**-0.65**	0.48	**0.07**	0.22
bet	positive	**-0.77**	**-0.64**	**0.02**	**0.07**
bet	v. positive	**-0.78**	-0.59	**0.02**	0.11
fold	v. negative	**-0.81**	**-0.65**	**0.01**	**0.07**
fold	negative	**-0.78**	-0.56	**0.02**	0.14
fold	positive	-0.45	-0.45	0.25	0.25
fold	v. positive	**-0.77**	**0.76**	**0.02**	**0.02**

Table 1. Correlation values between tempo and response times (average and variance). Results with p-value ≤ 0.1 are marked in bold.

5.3 Observed Correlations

In this section we discuss how the auditory features corresponded with the normalized response time and bet-fold ratio information extracted from the behavioral experiment. We proceed to analyze the more exact correspondence between the DDM parameters as extracted per song individually and the auditory features of the songs. We note that since we are correlating continuous scalar aggregates across users with continuous auditory features, using the assumptions implicit in a standard Pearson correlation is reasonable.

5.3.1 Correlation with RTs and Bet-Fold Ratio

Examining the relationship between the features extracted per song and the response time and bet-fold ratio data discussed in 5.2 reveals a compound and interesting picture.

Tempo was consistently and in most cases statistically significantly inversely correlated with response times. This was true for all gamble types and decision combinations. Tempo also tended to be inversely proportional to the observed response time variance. Again, this result was consistent across all gamble type and decision combinations. In other words, generally speaking, not only people responded faster (lower response times) the faster the music was, the variance in response times also tended to be reduced. The observed Pearson correlations for average normalized response times and response time variances across the 8 gamble type and decision combinations is provided in Table 1.

Tempo was also inversely correlated with the average bet-fold ratio for very negative gambles ($r = -0.74, p = 0.03$). This also manifested in the correlation with the bet-fold variance ($r = -0.66, p = 0.06$). However, it was linearly correlated with the bet-fold ratio in the very positive gambles case ($r = +0.71, p = 0.04$). Furthermore, in the very positive gambles case, the variance was still reduced, leading to a negative correlation ($r = -0.71, p = 0.04$). In other words, the faster the music, the more people are likely to bet on very good bets, and more consistently (reducing variance). Furthermore, the faster the music, the more likely people are to fold on bad bets, and more consistently (reducing variance). This is a strong signal for how tempo improves the quality of decision making in quantitative tasks.

There is evidence that the major dominance feature (determining the major to minor chord proportion in each song) is inversely correlated to the average bet-fold ratio and the bet-fold ratio variance in the very negative gambles case (average: $r = -0.6, p = 0.11$, variance: $r = -0.61, p = 0.10$). Similarly, there is some evidence that major dominance is linearly correlated with the average bet-fold ratio and inversely correlated to the bet-fold variance in the strong-positive case, but this result wasn't as convincing (average: $r = +0.42, p = 0.29$, variance: $r = -0.58, p = 0.14$). This result, though inconclusive, hints at the possibility that the more major chords there are in a song, the better the analytical decision making that subjects manifest.

Interestingly, the major dominance feature (determining the major to minor chord proportion in each song) was inversely proportional to the variance in response times when folding on a very positive bet ($r = -0.71, p = 0.04$). Major dominance was also inversely proportional to variance in response times betting on a very negative bet ($r = -0.65, p = 0.07$). In other words, the more major chords appeared in a song, the less variability people displayed in the time it took them to make a poor decision. This could be a side effect of people making fewer such mistakes in these gamble - decision combinations, as was documented in previous sections.

The average amplitude was inversely correlated to the average bet-fold ratio and the bet-fold ratio variance for negative and very negative gambles. These observations seem borderline significant (average: $r = -0.59, p = 0.12$ for negative, $r = -0.53, p = 0.17$ for very negative, variance: $r = -0.58, p = 0.13$ for negative, $r = -0.7, p = 0.05$ for very negative). This would imply that the louder the music, the less likely people are to make betting decisions on bad gambles, and variance is also reduced.

5.3.2 *Correlation with DDM Decomposition*

Finally, we were also interested in examining how the individual DDM parameters fitted for each song separately corresponded with the song features. Comparing the DDM parameters per song with the tempo, major dominance and amplitude data, we observed a statistically significant correlation between the tempo and the drift rate for very positive gambles (Figure 4(a), $r = -0.72, p = 0.04$), tempo and very negative gambles (Figure 4(b), $r = +0.79, p = 0.01$), and, interestingly, between the mean amplitude and the response caution, a connection that was also suggested in [4] (Figure 4(c), $r = -0.67, p = 0.06$). These observations corroborate both the observations in Section 5.3.1, and in Section 4.

6. SUMMARY & DISCUSSION

In this paper, we study how music-induced mood affects decision making in risky quantitative tasks. Subjects were presented with gambles and needed to decide whether to accept or reject these gambles as different types of music were played to them. Our results show that while there is no evidence for music-induced bias in the decision making process, music does have a differential effect on decision making behavior. Participants who listened to music categorized as happy were faster to make decisions than people who listened to music categorized as sad. Moreover, the decisions participants made while listening to happy music were consistently better than those made while listening to sad music, implying increased discriminabilty. Further analysis indicates there is a correlation between tempo and the speed and quality of decision making in this setting. Interestingly, previous work on gambling behavior has found a connection between the tempo and the speed of decision making, but was unable to isolate further impact on the quality of decision making, due to a fundamentally different design and different research questions [1].

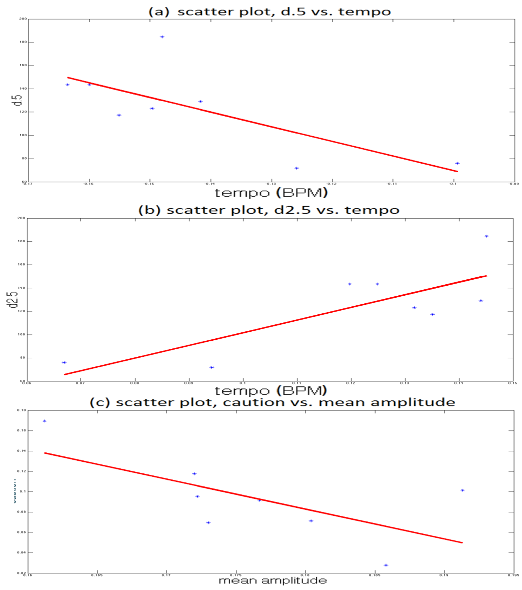

Figure 4. (a) Correlation between tempo and the drift rate for very negative gambles. (b) Correlation between tempo and the drift rate for very positive gambles. (c) Correlation between mean amplitude and the overall response caution (boundary separation).

Of particular note is the comparison between the results of a recent paper studying the connection between music-induced mood and mood-congruent bias [4]. In that paper, participants were requested to classify words as happy or sad as music categorized as happy or sad was played. Results indicated a clear expectancy bias, meaning music affected people's a-priori tendency to classify words as happy or sad. This paper, which uses the exact same set of songs, has reported no such bias effect, or any bias effect, for that matter. This difference suggests the psychological mechanisms involved in emotional classification and risky analytical decision making are inherently different.

This paper is a meaningful step towards a better understanding of the impact music has on commonplace cognitive processes which involve quantitative reasoning and decision making. In future work, additional tasks and other music stimuli should be studied to better understand the relationship between music and this type of cognitive processing.

7. REFERENCES

[1] Laura Dixon, Richard Trigg, and Mark Griffiths. An empirical investigation of music and gambling behaviour. *International Gambling Studies*, 7(3):315–326, 2007.

[2] Rebecca Elliott, Judy S Rubinsztein, Barbara J Sahakian, and Raymond J Dolan. The neural basis of mood-congruent processing biases in depression. *Archives of general psychiatry*, 59(7):597–604, 2002.

[3] Mark Griffiths and Jonathan Parke. The psychology of music in gambling environments: An observational research note. *Journal of Gambling Issues*, 2005.

[4] Elad Liebman, Peter Stone, and Corey N. White. How music alters decision making - impact of music stimuli on emotional classification. In *Proceedings of the 16th International Society for Music Information Retrieval Conference, ISMIR 2015, Málaga, Spain, October 26-30, 2015*, pages 793–799, 2015.

[5] Martijn J Mulder, Eric-Jan Wagenmakers, Roger Ratcliff, Wouter Boekel, and Birte U Forstmann. Bias in the brain: a diffusion model analysis of prior probability and potential payoff. *The Journal of Neuroscience*, 32(7):2335–2343, 2012.

[6] Theodore J Noseworthy and Karen Finlay. A comparison of ambient casino sound and music: Effects on dissociation and on perceptions of elapsed time while playing slot machines. *Journal of Gambling Studies*, 25(3):331–342, 2009.

[7] Kristi M Olafson and F Richard Ferraro. Effects of emotional state on lexical decision performance. *Brain and Cognition*, 45(1):15–20, 2001.

[8] Roger Ratcliff and Gail McKoon. The diffusion decision model: theory and data for two-choice decision tasks. *Neural computation*, 20(4):873–922, 2008.

[9] Roger Ratcliff and Francis Tuerlinckx. Estimating parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability. *Psychonomic bulletin & review*, 9(3):438–481, 2002.

[10] Brian McFee ; Matt McVicar ; Colin Raffel ; Dawen Liang ; Douglas Repetto. Librosa. *https://github.com/bmcfee/librosa*, 2014.

[11] Jenny Spenwyn, Doug JK Barrett, and Mark D Griffiths. The role of light and music in gambling behaviour: An empirical pilot study. *International Journal of Mental Health and Addiction*, 8(1):107–118, 2010.

[12] Sabrina M Tom, Craig R Fox, Christopher Trepel, and Russell A Poldrack. The neural basis of loss aversion in decision-making under risk. *Science*, 315(5811):515–518, 2007.

[13] Amos Tversky and Daniel Kahneman. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323, 1992.

[14] Corey N White and Russell A Poldrack. Decomposing bias in different types of simple decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 40(2):385, 2014.