Current and Expected Affective Valence Interact to Predict Choice in Recurrent Decisions

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Abstract

Research on the role of affect in decision-making indicates that both predecisional current and expected affective valence predict choice. However, the exact role of current and expected affect for recurrent decision-making is still a matter of debate. We used a generalized mixed effect model to predict gambling responses in an experience-based learning task from ratings of current and expected affective valence. Results indicate that current and expected affective valence interact to predict choice. While expected valence had the biggest effect size, current valence and the interaction still contributed significantly to the prediction of choice. Resolving the interaction showed that participants relied more on the current valence if expectations were unclear or positive. These findings are discussed in the context of dual-process accounts and the affective signalling hypothesis. In conclusion, current and expected valence depend on one another and interact to predict choice in recurrent decision tasks.

Keywords: predecisional affect, decision-making, current affective valence, expected affective valence

Introduction

In the past decades an expanding body of literature provides evidence for the emotional involvement in judgement and decision-making (Bechara et al., 1997; Dunning et al., 2017; Lerner et al., 2015; Loewenstein & Lerner, 2003; Mellers et al., 1999; Schlösser et al., 2013). Most researchers agree to separate predecisional and postdecisional affect (Lerner et al., 2015). There are three different theories on how affect guides choice. First, direct causation approaches assume that it is the actually felt affect which guides choices and behaviour (Bechara et al., 1997). Second, expectancy approaches posit that cognitive expectations of future emotional consequences of outcomes predict choices (Charpentier et al., 2016; Jäger et al., 2020; Mellers et al., 1999). Third, interaction approaches argue that current feelings and emotional expectancies work together to guide choices (Lerner et al., 2015; Loewenstein et al., 2001; Reimann & Bechara, 2010). Moreover, dual process models do not focus on an affective involvement but rather distinguish between rapid autonomous processes (Type 1) and higher order reasoning processes (Type 2). These processes work in the way that Type 1 processes yield default responses unless intervened on by Type 2 processes (for a comprehensive review see Evans & Stanovich, 2013).

Evidence either favors the direct causation approach (Schlösser et al., 2013) or the expectancy approach (Charpentier et al., 2016; Jäger et al., 2020). When looking more closely at the employed measures it appears that results converge. Asking participants "how they feel when considering a decision option" – termed immediate affect for some groups (e.g. Schlösser et al., 2013) – predicts subsequent choice across a variety of tasks. The same holds for asking participants "how they expect to feel after receiving the outcome of the decision" - termed expected affect (Charpentier et al., 2016; Jäger et al., 2020). However, anticipating the emotional consequences of a particular outcome (e.g. "Consider winning 5 € in this gamble, how would that make you feel?") does not have the same predictive power (Schlösser et al., 2013). Taken together, decision options elicit a current feeling and at the same time an expectation of future feelings that both predict subsequent choice based on winning probabilities and winning amounts (Jäger et al., 2020; Mellers et al., 1999; Schlösser et al., 2013). An alternative interpretation of these findings posit that these two different types of questions actually measure the same construct, which would make the theoretical distinction superfluous.

We still think that the distinction could be useful. However, in most experimental paradigms immediate affect and cognitive expectations align. In everyday life, this is often not the case. To most decisions there are past experiences that are no longer relevant to the current choice. Some groups proposed to separate background from immediate emotions that are integral to the decision problem (Dunning et al., 2017). There are good theoretical and empirical reasons to make this distinction; however, feelings are based on an average of all available information (Asutay et al., 2021; Efendić et al., 2020). Cognitive expectations, past emotional experiences, and other information types serve as inputs to current feelings and predict valuation judgements (Efendić et al., 2020). Hence, for the affective system there seems to be no distinction between relevant and irrelevant information in decision problems, which means a measurement of immediate background emotions would be an artificial category. For choice prediction, it is more plausible to measure a variable that summarizes all current feelings. This is the reason we speak of current affect, which we define as the current self-reported feeling that incorporates immediate background as well as integral affect (Lerner et al., 2015).

In the present experiment, we tried to disentangle current feelings and cognitive expectations. Thus, we used a gambling task similar to the one employed by Jäger et al. (2020). In this task, there are four symbols. Two symbols have an overall positive reinforcement balance while the other two have an overall negative reinforcement balance. Over several trials, participants have to decide for each symbol if they want to gamble or have a pass. Hence, participants can learn symbol-outcome contingencies and adjust their current affect and expectations accordingly. Second, we manipulated participants' expectations. After a learning phase, we informed them that symbol contingencies for two symbols were exchanged but not for the other two. We changed contingencies in the way that a previously positive symbol resulted in a loss of points afterwards and vice versa. Participants continued the gambling task and rated their current and expected valence before making the decision. Previous research has shown that arousal measures are not reliable (Asutay et al., 2021) and that the predictive value of arousal measures is negligible (Jäger et al., 2020), which is why we just measured the valence dimension of affect. Thus, participants should now have a learning experience differing from their expectations. We wanted to show three things: First, current feelings and cognitive expectations measure different constructs. Second, each construct has its own predictive power. Third, if the confound is resolved, cognitive expectations and current feelings interact to predict choice as interaction models (Lerner et al., 2015) and default-interventionist dual process models (Evans & Stanovich, 2013) propose.

Method

Participants

Sample size was determined by simulating data of a pilot study using the SIMR package in R (Green & MacLeod, 2016). Alpha was set at 0.05, interaction and main effect slopes for choice prediction were set at 0.75, which corresponds to a medium effect size (predicted from earlier results of Jäger et al., 2020). For 50 simulations, the power remained above 0.8 for all effects and indicated an optimal sample-size of thirty-five participants ($M_{\text{age}} = 23.7$ years, $SD = 3.72$; 31 right-handed; normal or corrected to normal vision). All participants were students at the University of Bamberg and received course credit for participation. As an additional incentive, the best five participants each gained 20 euros. All of them gave their written informed consent and were debriefed afterwards. The local ethics commission approved the study protocol.

Materials

The experiment consisted of two parts: A Learning Phase and Predecisional Valence Questionnaire blocks. For stimulus presentation, we used the NBS Presentation software. For answer collection, we used a two-keyed Cedrus Response Box (RB-380).

Gambling Task. Starting with a balance of 500 points, the participants of the gambling task were instructed to earn as many points as possible. In each trial, one of four different symbols was presented, and participants had to decide whether to gamble or not. If a participant decided to pass, the score always remained unaffected (+/- 0). If a participant decided to gamble, they could either win or lose points (+/- 15 points), depending on constant probability pairing for each symbol. The fundamental objective of the learning phase was to acquire and consolidate the symbols´ probability pairings. While two of the four symbols gained points in 90% of the cases, the remaining two resulted in a loss of points with 90 % certainty. Symbol-probability pairings were randomly assigned for each participant. However, we did not inform participants about the incentive values of the symbols. They had to obtain insight into the task structure via trial and error (for trial structure and timing parameters see Figure 1, for symbol-contingency pairings see Table 1). A reasonable strategy would be to gamble on positive symbols and pass on the negative ones. Eight learning blocks encompassing five presentations of each symbol were administered (i.e. 20 trials per block). Symbols were displayed in a randomized order.

Predecisional Valence Questionnaire Task. In the questionnaire blocks, participants continued the gambling task, aware that contingencies for two symbols had been exchanged. We measured self-reported predecisional valence using a digital questionnaire format. Each time a symbol was presented, participants rated their current and expected valence before making the decision (see Figure 1). Using a Self-Assessment Manikin Scale (Bradley & Lang, 1994), they marked their individual position on the visual analog scale by moving the mouse. The computer recorded the chosen point in a value ranging from -255 for a very unpleasant feeling to +255 for a very pleasant feeling. Starting point was always in the middle of the scale. Taken together, we recorded three different question perspectives of valence for each symbol. The first perspective asked participants to rate their current valence *("How did you feel seeing this symbol?")*. The other two question perspectives referred to the expected valence: One in relation to the decision to gamble ("*Please imagine, you decide to gamble. How will you feel after you received the outcome of your decision?*") and the other one to the decision to pass (“*Please imagine, you decide to pass. How will you feel after you received the outcome of your decision?*”). The presentation of these questions and the respective symbols was randomized. Participants did not receive immediate feedback after responding, they merely obtained aggregated feedback by receiving their current score after each block. In total, questionnaire blocks consisted of three blocks, including 16 trials each, which means that we collected 48 ratings per questionnaire block.

Procedure

Participants gave their written informed consent and completed a demographic questionnaire. Afterwards, they received instructions for the experimental task. In total, the experiment consisted of two rounds. In each round, participants completed the Learning Phase and the Predecisional Valence Questionnaire Task. The initial balance for each participant was 500 points. Moreover, they received their current score after each block and had the opportunity for a brief self-timed pause. Participants performed a practice block that did not affect their balance. Afterwards, they started the first of the eight learning blocks. After completing the Learning Phase, a notification appeared on the screen, which informed participants that outcome contingencies for two symbols were from now on exchanged, i.e. one of the previous positive symbols mainly resulted in a loss of points and vice versa. We ensured that participants had properly understood this information and handed them a note sheet to write down the corresponding symbols. Thus, participants knew and wrote down which symbols changed contingencies. Subsequently, participants processed the predecisional valence questionnaire task. The whole procedure was repeated with different symbol – outcome pairings. Taken together, the study lasted 60 minutes.

Results

Manipulation Check

To analyze how the experimental manipulation influenced gambling frequencies, current and expected affective valence ratings, and the correlation between both affective constructs, we conducted several analyses. For the expected valence perspectives, we computed a difference score (Expected Valence Difference = "Expected Valence if gambling" – "Expected Valence if passing", possible values ranging from -510 to +510). For post-hoc t-test, Bonferroni-corrected p-values are reported.

Gambling Frequencies. To ensure that our experimental manipulation was successful, we conducted a 2 x 2 x 2 ANOVA for repeated measures analyzing the gambling frequencies before and after the exchange. Thus, the factor TIME had two levels: Pre-Exchange, and Post-Exchange. The factor BALANCE had two levels: positive, for symbols that won on average, and negative, for symbols that lost on average. The factor EXCHANGE had the levels yes, for symbols that changed contingencies, and no, for symbols that did not change contingencies. The three-way interaction TIME x EXCHANGE x BALANCE was significant, $F(1, 34) = 47.2$, $p < 0.001$, $\eta_p^2 = 0.581$. For resolving this interaction, we used the pre-exchange data to conduct a 2 x 2 ANOVA with the factors BALANCE and EXCHANGE. The results showed a significant main effect of BALANCE, $F(1, 34) = 1005.2$, $p < 0.001$, $\eta_p^2 = 0.967$. Gambling frequency was significantly higher for positive symbols, $M = 0.94$, $CI = [0.90, 0.97]$, than for negative ones, $M = 0.11$, $CI = [0.07, 0.15]$. Next, we conducted a repeated measure ANOVA with the factors Balance and Exchange for the post-exchange data. There was a significant BALANCE x

EXCHANGE interaction effect, $F(1, 34) = 44.8$, $p < 0.001$, $\eta_p^2 = 0.569$, describing a disordinal interaction. Positive-changed-to-negative symbols, $M = 0.34$, $CI = [0.23, 0.45]$, showed a significantly lower gambling frequency than non-exchanged positive ones, $M = 0.80$, $CI = [0.68, 0.91]$, $p < 0.001$. In contrast, negative-changed-to-positive symbols, $M = 0.85$, $CI = [0.73, 0.96]$, indicated a significantly higher gambling frequency than non-exchanged negative ones, $M = 0.35$, $CI = [0.23, 0.46]$, $p < 0.001$. Besides, gambling frequency did not significantly differ between positive-changed-to-negative and non-exchanged negative symbols, $p > 0.05$; such as between negative-changed-to-positive and non-exchanged positive ones, $p > 0.05$.

Expected Valence. For expected valence difference scores we computed a 2 x 2 ANOVA for repeated measures. There was a significant interaction effect BALANCE x EXCHANGE, $F(1, 34) = 100.1$, $p < 0.001$, $\eta_p^2 = 0.746$, describing a disordinal interaction. Post-hoc t-tests demonstrated that difference scores of positive-changed-to-negative symbols, $M = -141$, $CI = [-182, -99.6]$, were significantly lower than negative-changed-to-positive symbols, $M = 144$, $CI = [140, 221.9]$, $p < 0.001$. In contrast, expected difference scores for positive non-exchanged symbols, $M = 181$, $CI = [140, 221.9]$, were significantly higher than negative non-exchanged ones, $M = -174$, $CI = [-215, -133.4]$, $p < 0.001$. Besides, expected valence difference scores did not differ significantly between positive-changed-to-negative and non-exchanged negative symbols, $p > 0.05$; such as between negative-changed-to-positive and non-exchanged positive ones, $p > 0.05$.

Current Valence. For current valence ratings, we computed a 2 x 2 ANOVA for repeated measures. The interaction BALANCE x EXCHANGE was significant, $F(1, 34) = 43.7$, $p < 0.001$, $\eta_p^2 = 0.562$, describing a disordinal interaction. Current valence ratings for positive-changed-to-negative symbols, M = -1.0, CI = [-23.3, 21.3], did not differ from negative-changed-to-positive symbols, M = 23.0, CI = [0.7, 45.3], $p > 0.05$. For all symbols with unchanged contingencies, current valence ratings for positive symbols, M = 96.9, CI = [74.6, 199.2], were significantly higher than for negative ones, M = -60.7, CI = [-83.0, -38.4], $p < 0.001$, than for all exchanged symbols, for both $p < 0.001$. Furthermore, negative symbols differed significantly from positive-changed-to-negative symbols, $p = 0.002$, and from negative-changed-to-positive symbols, $p < 0.001$.

Correlation between Current and Expected Valence. To analyse how the experimental manipulation changed correlations between Current Valence and Expected Valence we used the R package correlation (Makowski et al., 2020) to account for the multilevel structure of our data. Expected and Current Valence ratings for symbols that did not change contingencies were highly correlated, $r = .75$. For symbols that did change contingencies the correlation dropped to, $r = .37$.

The manipulation check showed that participants adapted their choices according to the new expectations and adjusted their expected and current valence ratings in the predicted way. Furthermore, the analysis of the note sheets showed that all participants noted the contingency change correctly. Moreover, the manipulation considerably lowered the correlation among current and expected valence. Thus, the experimental manipulation was successful.

Choice Prediction

To test how Expected and Current Valence predict choice, we ran a generalized mixed effects model (Bates et al., 2015). Thus, as data fitting procedure the maximum likelihood method and a logit link function were used. We modelled expected valence and current valence as fixed effects. In addition, we entered an interaction term that included the interaction of expected valence, current valence and the contingency change factor. We included Participant ID and the Symbol ID as random factors and started modelling with the maximal random effect structure, which did not converge. Hence, we reduced the random effect structure until we arrived at an intercept only structure that eventually converged. This resulted in the formula: Choice ~ Expected Valence + Current Valence + Expected Valence:Current Valence:Contingency Change + (1| Participant ID) + (1| Symbol ID). In addition to model inherent significance indicators, we assessed significance via model comparison with an Alpha of 0.05. For details regarding odds ratios, fixed and random effect structure see Table 1. The predictor Expected Valence had the highest *Odds Ratio* above 1, $X^2(1) = 598.1$, $p < .001$, meaning that the higher the Expected Valence the higher the probability of gambling and vice versa. The predictor Current Valence had an *Odds Ratio* above 1, $X^2(1) = 35.65$, $p = .001$, meaning that the higher the Current Valence Ratings the higher the probability of gambling and vice versa. The interaction of Expected Valence and Current Valence for changed contingencies had an *Odds Ratio* above 1, $X^2(1) = 9.03$, $p = .011$. Figure 1 shows choice prediction functions for Current Valence in the changed contingency condition including *CI*s for different values of Expected Valence. The predictive power of Current Valence depended on Expected Valence Ratings for changed contingencies. Specifically, if Expected Valence was around or above 0, Current Valence Ratings predicted choice. For Expected Valence Scores below 0, Current Valence did not predict choice. Finally, choice prediction functions of Expected Valence were not different from one another for different Current Valence values.

Discussion

We studied the role of current and expected affective valence in recurrent decision-making. Participants learned outcome contingencies of four different symbols in an experience-based learning task. Hence, they learned which symbols to approach as they won on average and which symbols to avoid as they lost on average. After a learning phase, we told participants that we switched outcome contingencies of one advantageous with one disadvantageous symbol. Participants knew which symbols switched; however, they did not receive immediate feedback anymore. Results indicate that current and expected valence are sufficiently distinct from one another and both predicted choice. However, expected valence demonstrated a much bigger effect size compared to current valence. In addition, we found that expected valence and current valence interact to predict choice. Hence, current valence has the strongest predictive power if future valence expectations are unclear or positive. This is in line with an interaction approach of the affective involvement in recurrent decision-making (Lerner et al., 2015) and integrates previous findings of the other two theory classes (Bechara et al., 1997; Charpentier et al., 2016; Jäger et al., 2020; Schlösser et al., 2013). Taken together, we showed that previous findings for single decisions also hold true for recurrent decision making.

Other groups have repeatedly found that immediate affect is the strongest predictor of subsequent choice (Schlösser et al., 2013; Schlösser et al., 2016). We want to point out that our findings do not contradict these results, as these groups measured immediate affect in a similar way as we measured expected affect (for more details see introduction). The fact that changed expectations also changed current feelings adds more evidence to the interpretation that expectations produce immediate affect (Jäger et al., 2020). In other words, expected and immediate affect both measure a similar construct that has both a cognitive and an immediate affective nature. The results propose that this construct is the strongest predictor of choice. At the same time, an average of current feelings that are attached to a decision cue independently predicts choice, too.

In the present study, current valence predicted decisions when expectations were positive, but not when expectations were negative. Hence, one possible interpretation could be that for negative expectations the predictive influence of expected valence on choice predominates the predictive power of current valence. Furthermore, our findings are compatible with a dual process account (e.g. Evans & Stanovich, 2013), which means that negative valence expectations trigger increased self-monitoring. Thus, system two becomes more active which pushes the influence of current valence processed by system one to the background. This interpretation reminds of the affective signalling theory which posits that a control system notices negative affect driving adaptive changes in attention and performance (Dignath et al., 2020).

There are some limitations to the generalizability of our findings. First, in human decision making and reward learning a large part of the variability is attributable to computational noise, which increases in volatile environments (Findling & Wyart, 2021). In the present task, we had almost sure losses and gains and clear instructions, which means that our findings are only valid for this kind of environment. Second, other studies (e.g. Schlösser et al., 2013) have incorporated a subjective probability measure to show the predictive power of affect variables beyond subjective probability. This was not our main research question, which is why we decided not to incorporate that measure. However, it could be possible that our measures do not predict choice beyond subjective probability. Given previous research findings, we do not think this is a major issue.

In conclusion, current and expected valence depend on one another and at the same time interact to predict choice. Further examining their dependency and interaction are promising avenues for future research.

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Table 1. Example of Symbol-Feedback contingencies depending on the average feedback balance in the learning phase and when Symbol-Feedback contingencies were exchanged in the Predecisional Affective Questionnaire Phase. P refers to the probability of obtaining the respective outcome if the participant decides to gamble. Please note that symbol-feedback condition mapping was randomly assigned for each participant.

			Pre-Exchange		Post-Exchange	
Average Learned Balance	Exchange	Symbol	P = 0.9	P = 0.1	P = 0.9	P = 0.1
positive	yes	■	+15	-15	-15	+15
positive	no	▲	+15	-15	+15	-15
negative	yes	●	-15	+15	+15	-15
negative	no	✚	-15	+15	-15	+15

Table 2. Generalized linear mixed effect estimates of the choice prediction model for symbols with changed contingencies. Fixed Effects: Odds Ratios, Confidence Intervals (CI), and p-values. Random Effects: σ^2 = within-person residual variance, $\tau_{00\ \text{Participant}}$ = between-person variance, ICC = Proportion of variance explained by between-person differences; Marginal R^2 = variance explained by fixed effects, Conditional R^2 = variance explained by fixed and random effects; Significant results are printed in bold;

	Response		
Predictors	*Odds Ratios*	*CI*	*p*
(Intercept)	2.57	1.05 – 6.33	**0.040**
Expected Valence	5.59	4.75 – 6.58	**<0.001**
Current Valence	2.68	1.94 – 3.71	**<0.001**
Expected Valence x Current Valence x No Contingency Change	0.78	0.51 – 1.21	0.267
Expected Valence x Current Valence x Contigency Change	1.95	1.17 – 3.24	**0.010**
Random Effects			
σ^2	3.29		
$\tau_{00\ \text{Subject\_ID}}$	6.34		
$\tau_{00\ \text{Symbol\_Code}}$	0.18		
ICC	0.66		
$N_{\text{Subject\_ID}}$	35		
$N_{\text{Symbol\_Code}}$	8		
Observations	3360		
Marginal R^2 / Conditional R^2	0.255 / 0.750		

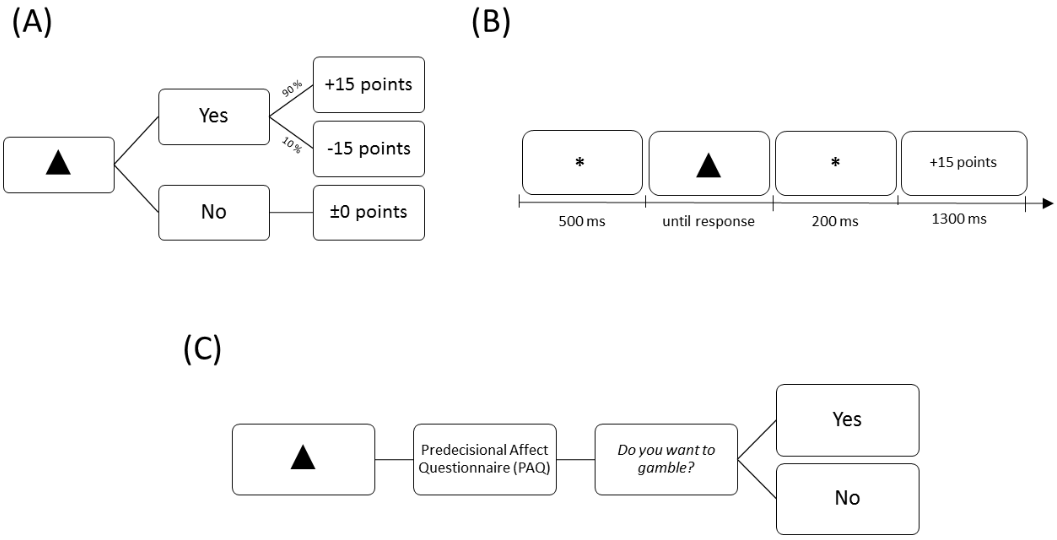

Figure 1. Example of the trial structure and possible feedback depending on gambling decision for a positive symbol (A) in the learning blocks and (C) the Predecisional Affective Questionnaire (PAQ) blocks. (B) Example trial to illustrate the timing of the Gambling Task. Numbers characterize presentation durations in ms. In this case the participant would have chosen to gamble and subsequently won 15 points. * Indicates a fixation dot.

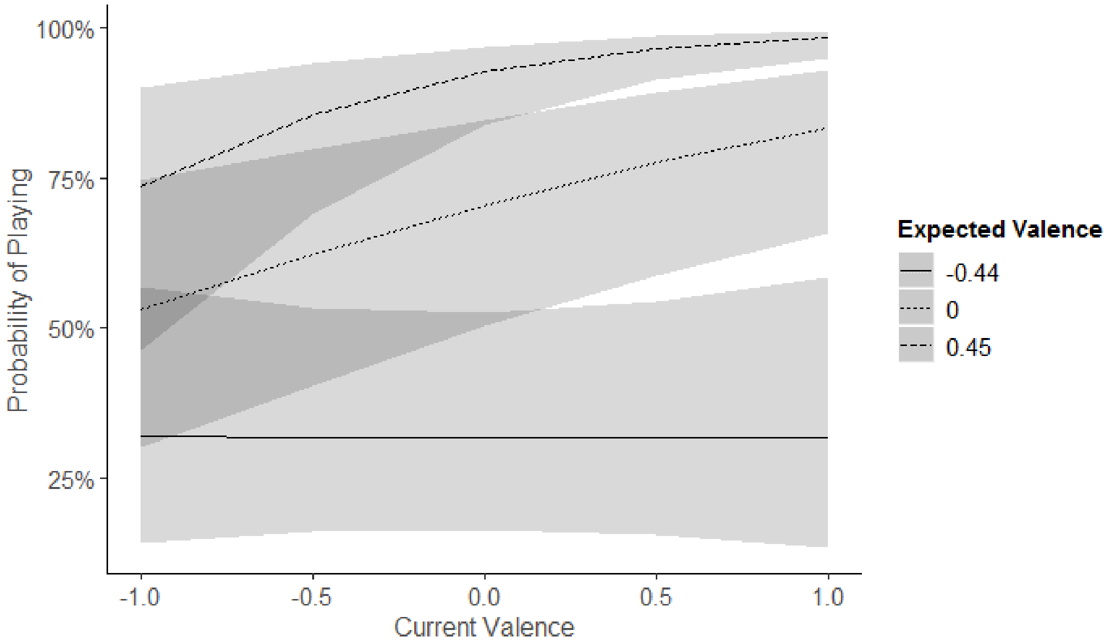

Figure 2. Choice Prediction function of Current Valence based on different Expected Valence Ratings; grey shades indicate Confidence Intervals.