Why Songs Are Like Monetary Losses: Leveraging Insights from the Neurophysiology of Memory to Strengthen Our Understanding of Consumer Experiences

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While many studies have explored risk preferences for money, few have systematically assessed risk preferences for everyday consumer experiences. We have proposed a conceptual model that, in contrast to a typical "zero" reference point for monetary gambles, reference points for experiences are set at more extreme outcomes, leading to concave utility for negative experiences but convex utility for positive experiences (Martin, Reimann, & Norton, 2016). As a result, consumers are risk-averse for negative experiences such as dentist visits—as for monetary gains—but risk-seeking for positive experiences such as desserts—as for monetary losses.

We have already gathered behavioral evidence from several experiments, showing that these risk preferences for experiences (vs. money) are robust to different methods of elicitation (Martin et al., 2016). For example, in one experiment, we showed that consumers are generally more risk-averse for negative categories of experience and risk-seeking for positive categories of experience, a reversal of the relationship between valence and risk preferences observed for money. In another experiment, we clarified that this reversal in risk preferences is due to a fundamental difference between risk in the quality of experiences and risk in the quantity of money. We observed similar risk preferences for quantities of experiences and quantities of money of the same valence, but again the opposite pattern for experiential quality, which is the type of experiential risk more commonly encountered in everyday life. In yet another experiment, we ruled out alternative explanations relating solely to the manner in which consumer use rating scales for experience quality: when participants list equivalent experiences and monetary outcomes, from which we construct "equivalent" risky choices, they exhibit different risk preferences depending on whether these choices are expressed as experiential outcomes or their monetary equivalents (Martin et al., 2016).

However, little empirical evidence exists to show what exactly causes these differences in risk preferences for experiences (vs. money). If our theorizing is correct, and consumers indeed use more extreme reference points for choices of experiences (vs. money), then we would expect to see a greater involvement of consumers' explicit memory of facts and events because experiential choices could—to a greater extent than monetary choices—be based on extreme reference points, which could ultimately tap the decision maker's explicit memory of facts and events. The present research aimed to make several important contributions to literatures in marketing and consumer research as well as the psychology and neuroscience of memory:

(1) We intended to broaden our understanding of consumer experiences by showing if and why consumers set and utilize extreme reference points when making choices of experiences. To do so, we leveraged insights from cognitive neuroscience to directly measure the degree of involvement of explicit memory by conducting a functional magnetic resonance imaging (fMRI) experiment. The brain area that processes explicit memory—the medial temporal lobe, located right "above" and "behind" both ears— has been well researched (e.g., Kandel, 2007; Milner, Squire, & Kandel, 1998; Squire & Zola-Morgan, 1991). We built on this discovery to better understand if consumers set extreme reference points for product and service experiences and, in doing so, access explicit memory for choices on experiences (but less so for choices on money).

(2) Our research is directed at expanding the extant marketing knowledge by taking an existing insight from the cognitive neurosciences (i.e., the medial temporal lobe memory system, including the hippocampus) to study how consumers process product and service experiences and make choices about them. By doing so, we aimed to extend existing neuromarketing research that has studied the neurophysiological utility of food experiences (Plassmann,

O'Doherty, Shiv, & Rangel, 2008; Reimann, MacInnis, & Bechara, 2016) and package experiences (Reimann, Zaichkowsky, Neuhaus, Bender, & Weber, 2010), but, so far, has provided only little insight into the role of memory in the marketing and consumption of experiences (Esch et al., 2011).

(3) It is surprising that little is known about the role of memory for experiences in predicting future choice of consumer experiences in light of the fact that marketers strive to design experiences that are inherently memorable, and given research examining the role of forgetting in enhancing subsequent consumption and the desire to "protect" previous experiences by not revisiting them (Zauberman, Ratner, & Kim, 2009; Zhang, Kim, Brooks, Gino, & Norton, 2014). The proposed work aimed to close this knowledge gap. In doing so, we hope to better comprehend both cognitive (memory) and affective (valence) determinants of consumer experiences (Verhoef et al., 2009), and gain further insights into how marketing practitioners and experience designers can leverage consumers' reference points in memory to guide them toward buying and enjoying their products and services.

Conceptual Background

How can marketing researchers predict, when consumers make choices in everyday life, whether they will be risk-seeking or risk-averse? If these choices relate to money, the answer is known relatively well. Decades-long research devoted to risk preferences for money exists, revealing that consumers are risk-seeking when choosing between monetary losses and risk-averse when choosing between monetary gains (e.g., Kahneman & Tversky, 1979; Rabin & Thaler, 2001; Stewart, Chater, Stott, & Reimers, 2003; Wang & Johnson, 2012). As an example,

most consumers will take a 50/50 chance of losing either $1 or $5 over a sure loss of $3, but choose a sure gain of $3 over a 50/50 chance of gaining either $1 or $5 (Martin et al., 2016). Notwithstanding this important work on risk preferences for money, remarkably little research has focused on risk preferences for non-monetary experiences, either negative ones (e.g., disgusting foods and visits to the dentist) or positive ones (e.g., desserts and visits to the movies) (Martin et al., 2016). In our prior work, we asked, when consumers face a choice between listening a "safe" music song that receives many 3-star ratings and a "risky" song that receives many 5-star but also many 1-star ratings, how they judge the potential risks and rewards?

Provided the well-documented contrast between risk preferences for positive and negative monetary gambles, valence offers a plausible prediction about risk preferences for experiences: negative experiences could be similar to monetary losses, whereas positive experiences could be similar to monetary gains, implying risk-seeking for negative experiences and risk-aversion for positive experiences (Martin et al., 2016). Contrariwise, we have predicted that consumers are generally risk-seeking for positive experiences and risk-averse for negative experiences, the mirror image of choices for money (Martin et al., 2016).

Previously, we had suggested that this reversal exists because of the contrasting reference points that are commonly drawn upon for experiences and money (Martin et al., 2016). Specifically, reference points are crucial for understanding risk preferences because they serve as the basis against which possible outcomes are compared. Namely, outcomes are treated as losses whenever they fall below some reference point but as gains when they exceed that reference point (Heath, Larrick, & Wu, 1999; March & Shapira, 1992; Payne, Laughhunn, & Crum, 1980). For monetary prospects, zero change in wealth serves as a salient reference point, such that monetary gambles with positive values are treated as gains and those with negative values are

treated as losses (Kahneman & Tversky, 1979; Rabin & Thaler, 2001; Tversky & Kahneman, 1992). Instead, for experiences, one can infer from prior research that reference points could be determined not by neutral values but rather by extreme values (e.g., the best song one has every listened to and the worst one, too). Indeed, consumers asked to recall typical occurrences of past experiences in positive and negative domains in fact seem to recall the most extreme positive and negative experiences they have had in those domains (Gershoff, Mukherjee, & Mukhopadhyay, 2003; Morewedge, Gilbert, & Wilson, 2005), and these apparently readily available memories offer suitable reference points (Koszegi & Rabin, 2006; Novemsky & Dhar, 2005; Thaler & Johnson, 1990). Should the best song one has listened to represent a reference point when choosing between two songs, then many of the available positive options could be treated in prospect as comparative losses, and should the worst song come to mind when choosing between two songs, many of the available options—despite being negative experiences—could be treated in prospect as comparative gains (Martin et al., 2016).

In the present work, we are curious to know whether consumers access extreme reference points in memory in order to make choices on experiences (vs. money). Neurophysiologically, consumers have the ability to acquire new ideas from experiences and to retain these ideas in memory (Kandel, 2001). Explicit memory for facts and events (also called declarative memory) is stored in the medial temporal lobe (Milner et al., 1998; Squire & Zola-Morgan, 1991). If our hypothesis—that reference points for experiences are set at more extreme outcomes but "zero" reference points for money—holds true, then we would expect to see activation in the medial temporal lobe (particularly, the hippocampus) for choices on experiences (vs. money). As such, we are eager to understand: Which neurophysiological changes can we observe in the brain when consumers make choices on experiences (vs. money), and why? Are extreme reference points for

experiences (vs. "zero" reference points for money) stored in the medial temporal lobe and, if yes, can we leverage this insight to design better experiences and manage them more effectively? Which events and facts of an experience lead to the most extreme reference points in explicit memory? The proposed research attempts to provide preliminary insights into some of these questions.

Specifically, we set out to test whether experiential choices (vs. monetary choices) are associated with explicit memory and its associated brain region—the medial temporal lobe (e.g., Milner et al., 1998; Squire & Zola-Morgan, 1991).

Materials and Method

Participants. Forty-six adult volunteers were recruited from the subject pool of a large university, invited to the functional neuroimaging facility, and were engaged in a behavioral decision-making task in which they had to repeatedly choose between two music songs (i.e., two experiences) or two monetary gambles. While participants were engaged in the task, their neurophysiological responses were recorded.

Procedures. Upon arrival at the functional neuroimaging facility, participants were welcomed and asked to provide written informed consent to a protocol approved by an institutional review board. An experimenter also checked subjects' medical eligibility for participation. Before entering the functional neuroimaging scanner (i.e., a Siemens Skyra 3 Tesla scanner), participants were engaged in a practice version of the behavioral task to familiarize them with the task structure. All visual stimuli (e.g., written instructions, choice options) were presented to participants through the presentation software E-Prime, which has successfully been

used in previous fMRI experiments in both consumer psychology (e.g., Reimann et al., 2016; Reimann et al., 2010) and general psychology (e.g., Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Knutson et al., 2008). Any questions participants may have about the procedures of the experiment were answered during this phase of the experiment.

Also, before being positioned inside the scanner, participants indicated their most preferred music genre from a list of 22 genres (e.g., classical, hip-hop, jazz, rock; see full list in Figure 1). In accordance with Prospect Theory (Breiter et al. 2001, Kahneman and Tversky 1979, Tversky and Kahneman 1992) to put the participants into a state of monetary gains, they were provided with a $25 cash endowment and were asked to put the bills in their pocket and take them inside the scan room with them. We aimed to make the subsequent monetary choices incentive-compatible in the sense that participants made real monetary choices from their own endowment. Next, participants were told that we would like them to make monetary choices in different games of chance, and that during these games, they might either lose some or all of their $25 stake, retain it, or increase it. These instructions were adapted from prior research on eliciting risk preferences for monetary gambles (Breiter, Aharon, Kahneman, Dale and Shizgal 2001).

Next, following prior research (Martin et al. 2016), participants received the instructions on how to interpret their subsequent monetary and experiential choices (also see Figures 2 and 3). Specifically, participants were asked to read the following instructions: "*To make these choices, we will need to introduce you to the following charts: Today's task is designed to find out how you make choices between different games of chance based on the actual losses/winnings of other people. For each game of chance, we will show you a chart where the heights of the bars above a specific loss or winning indicate the number of people who lost or*

won, respectively. Please read the following example carefully: 57 UA students participated in different games of chance with outcomes from -$5 to +$5, -$5 being the worst, +$5 being the best. In this chart, five people lost $5, twelve people lost $4, and so on. Please study this chart for a minute:" (see chart is shown in Figure 2). Participants then read more instructions: "*In addition to choices on games of chance, today's task is also designed to find out how you make choices between different music songs based on the actual ratings other people have given. You will make choices on different music songs, for this music genre: [AN EXPERIMENTER FILLED IN THE PREFERED GENRE, WHICH PARTICIPANTS HAD STATED EARLIER] Today, you will choose between 5 different sets of songs and get to take home your 5 chosen ones. For each music song, we will show you a chart where the heights of the bars above a number indicate the number of people who gave the song that rating. Please read the following example carefully: 57 UA students rated different songs on a scale from -5 to +5, -5 being the worst, +5 being the best. In this chart, five people gave the song a rating of -5, twelve people gave the song a rating of -5, and so on. Please study this chart for a minute:*" (see chart is shown in Figure 3).

Participants were then guided to the fMRI scanner, placed horizontally on a bed, and moved inside the scanner. The behavioral task was projected onto a mirror that was placed right above participants' eyes. Like in the practice version of the behavioral task, all visual stimuli were shown in E-Prime. Participants were able to provide all behavioral responses via a standard button box. For a more detailed description of standard fMRI experimental procedures see the primer by Reimann, Schilke, Weber, Neuhaus, and Zaichkowsky (2011).

Once comfortably situated inside the scanner, participants were asked to make five monetary choices and five experiential choices in pseudorandom order. They were prompted to evaluate the two choice options, which always had a low-variance choice (risk-averse option)

and a high-variance choice (risk-seeking option). The high- and low-variance options were identical in their expected value set to zero. Each of these ten product choices followed the trial structure shown in Figure 4. In particular, participants were initially shown a fixation cross to focus their attention on the center of the screen ("fixation" phase, timed between two and four seconds long). Participants were then provided a prompt telling them whether to expect two song options or two monetary gamble options ("trial introduction" phase, timed two seconds long). Next, participants were provided with the actual two options, a low-variance choice and a high-variance choice and given ample time to interpret the given options ("risk judgement" phase, timed twelve seconds long). Participants were then prompted to choose one option from the choice set ("choice" phase, timed two seconds long), followed by a brief confirmation of their choice ("choice confirmation" phase, timed two seconds long) before the next trial started. In summary, the repeated-measures design yielded a dataset containing 460 individual choices (46 subjects × 10 choices). Because the behavioral task is precisely timed, we were able to analyze the brain activity during the time frame in which participants judged the experiential or monetary options, followed by participants' actual choice response. We were thus able to test our prediction that making choices on experiences will result in greater neurophysiological activity (i.e., greater blood-oxygen-level-dependent responses) in the medial temporal lobe compared to making choices on money, possibly because participants are using extreme reference points stored in explicit memory to a greater extent under experiential choices than monetary choices. In summary, the present experiment yielded both behavioral choice data as well as functional neuroimaging data.

Neuroimaging data collection specifications. Neuroimaging data consisting of a time series of 441 volumes with 33 slices in the transverse plane were obtained using single shot

gradient-echo planar imaging (TR = 1,000ms, TE = 30ms, flip angle = 90°, resolution = 2.5mm × 2.5mm × 2.5mm, and FOV = 240mm). All functional neuroimaging runs were automatically motion-corrected during data collection as per Siemens' head motion correction protocol. For anatomical neuroimaging, we obtained a high-resolution image of the brain using a 3-D T1-weighted MPRAGE sequence (echo time (TE) / repetition time (TR) / inversion time = 2.32 / 2,300 / 900ms, flip angle = 8°, matrix = 256 × 256, field of view (FOV) = 240mm, slice thickness = .9mm without gap).

Analyses and Results

Behavioral results. Participants chose high-variance over low-variance experiences (56.94% vs. 43.05%) more often than high-variance over low-variance monetary gambles (50.72% vs. 49.27%).

Neuroimaging data prepreocessing. Neuroimaging data were preprocessed and analyzed using the BrainVoyager QX 20.6 analyses software (Goebel, Esposito, and Formisano 2006). In particular, each participant's functional dataset underwent standard pre-processing steps, including slice-scan time correction, three-dimensional motion correction, and temporal high-pass filtering. Each participant's anatomical data underwent intensity inhomogeneity correction, ISO-voxel (1 x 1 x 1mm) transformation, followed by normalization to a standard Montreal Neurological Institute (MNI) brain template. Next, the preprocessed functional and anatomical data were co-registered. Initial and fine-tuning alignment were completed and a volume time course information file was created for each participant.

Feature extraction. We were interested in the neurophysiological activity in the medial temporal lobe and, therefore, extracted neurophysiological activity data especially from the hippocampus. Additionally, we extracted data from the thalamus and from the amygdala for reasons of comparison and validation. The BrainVoyager analyses software offers pre-defined volume of interest (VOI) files that map voxel coordinates to subcortical regions. The coordinate system used is native to the BrainVoyager analyses software. In order to adapt to the MNI coordinate system, we overlaid the pre-defined VOI template on an MNI template and manually fine-tuned it to get MNI-adapted VOI files. We also used the functional coverage information, while creating the VOI files to avoid extracting data at voxels where there is no functional data available.

Then, we made use of the NeuroElf module (http://neuroelf.net) and MATLAB to extract time course of intensity values from the volume time course file at every voxel specified in the MNI-adapted VOI file. The MATLAB script extracts time course of intensity values one region at a time. We later combined these regions by concatenating the individually extracted time course of intensity values into one big matrix containing 441 volumes of intensity values for 12910 voxels. Figure 5 illustrated an exemplary time course at one such voxel. Moreover, because blood oxygenation differs from individual to individual, we standardized the intensity values. Feature standardization makes the intensity values at each voxel have zero mean and unit variance. This method is widely used for normalization in many machine learning algorithms. The general method of calculation is to determine the distribution mean and standard deviation at each voxel, subtract the mean then divide the values at each voxel by its standard deviation.

Duration of each trial of the behavioral task lasted approximately twenty seconds (fixation phase length varied). In the "risk judgment" or "compare" phase of each trial (compare

Figure 4), participants were shown two choice options to choose from within a twelve-second time frame. This time frame corresponds to twelve volumes of intensity values at every voxel specified in the VOI. The twelve volumes of intensity values corresponding to every choice were extracted and stored in a separate comma-separated values (CSV) file. We also experimented with varying the time frame window by including and excluding other phases in the same trial (fixation, stimuli, choice, and feedback) while extracting volumes of intensity values.

Each participant made ten choices, hence yielded ten comma-separated values files numbered 1 to 10 corresponding to the order in which they made the choice.

Machine learning approach. We used a machine learning approach to analyze the data. In particular, we submitted the data to a support vector machine, representing a useful technique for data classification (i.e., a non-probabilistic binary classifier). The standard support vector machine uses a linear decision boundary, given by $\omega^T x_{new} + b$, to classify new data objects. Objects lying on one side of the decision boundary are put into class $t_{new} = 1$ and objects on the other side into $t_{new} = -1$.

$$t_{new} = sign(\omega^T x_{new} + b)$$

Each comma-separated values file consisted of twelve to twenty columns of voxel intensities, which correspond to normalized functional data extracted at a specific region of interest for one choice. Since we are dealing with time series data as input, we used the below approaches to convert the time series data to feature vectors:

(a) *all data*: We rolled out the columns (time axis) of the voxel intensity matrix into a single vector. Every value in the matrix was treated as an individual feature. For example, if we

had extracted 20 volumes (20 seconds) at 12910 voxels for each choice, then our training data

for each choice had 258,200 features (high dimensional).

(b) *average*: We took the average of intensity values across time at each voxel. Our

training data for each choice ended up having 12,910 features, one corresponding to every voxel.

(c) *variance*: We took the variance of intensity values across time at each voxel. Our

training data for each choice ended up having 12,910 features, one corresponding to every voxel.

Given our training set of instance-label pairs *(x$_i$, y$_i$), i = 1, 2… n* where *x$_i$* is the vector of

temporal voxel intensities corresponding to a particular choice *and y$_i$* belongs to *{1, -1}* (1 if the

participants chose high-variance choice and, -1 if the participants chose low-variance choice), the

support vector machine requires the solution of the following optimization problem:

$$\min_{\mathbf{w},b,\boldsymbol{\xi}} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i$$
$$\text{subject to} \quad y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i,$$
$$\xi_i \geq 0.$$

Results revealed prediction accuracies between 50.2% and 60.2% for the hippocampus.

Table 1 summarizes the results. When the dataset was divided into experiential choices and

monetary choices and the data were separately subjected to the support vector machine, results

revealed prediction accuracies between 57.7% and 70.1% for the hippocampus for experiential

choices (see Table 2) and prediction accuracies between 64.2% and 66% for the hippocampus for

monetary choices (see Table 3).

Discussion

The present work provided interesting preliminary insights into the possible underlying neurophysiological and psychological mechanisms of experiential (vs. monetary) decision making. It seems that participants in this study preferred high-variance options more often than low-variance options for experiences but less so for gambles. Importantly, a key structure of the medial temporal lobe—the hippocampus—predicted high-variance choices to some extent (however, note that, as shown in Table 1, some prediction accuracies were closer to chance, while others were around 60%). When experiential and monetary choices were analyzed separately, results revealed up to 70% prediction accuracy for experiences but only up to 66% prediction accuracy for monetary choices. While these results only allow cautious interpretation regarding the differential involvement of explicit memory in experiential versus monetary choices, they nonetheless pave the way for future studies that could hone the experimental design or apply other machine-learning approaches to the data to possibly obtain higher prediction accuracies. While future work is warranted, the behavioral and neuroimaging results of the present research provided a glance into the possible existence of "extreme" references points for experiences when compared to monetary gambles.

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Figure 1:

Materials: Music genres

Which is your <u>most preferred</u> music genre? Please check one.

- ☐ Alternative Music
- ☐ Blues
- ☐ Classical Music
- ☐ Country Music
- ☐ Dance Music
- ☐ Easy Listening
- ☐ Electronic Music
- ☐ European Music (Folk / Pop)
- ☐ Hip Hop / Rap
- ☐ Indie Pop
- ☐ Inspirational (incl. Gospel)
- ☐ Asian Pop (J-Pop, K-pop)
- ☐ Jazz
- ☐ Latin Music
- ☐ New Age
- ☐ Opera
- ☐ Pop (Popular music)
- ☐ R&B / Soul
- ☐ Reggae
- ☐ Rock
- ☐ Singer / Songwriter (inc. Folk)
- ☐ World Music / Beats

Figure 2:

Materials: Instructions to interpret monetary gamble options

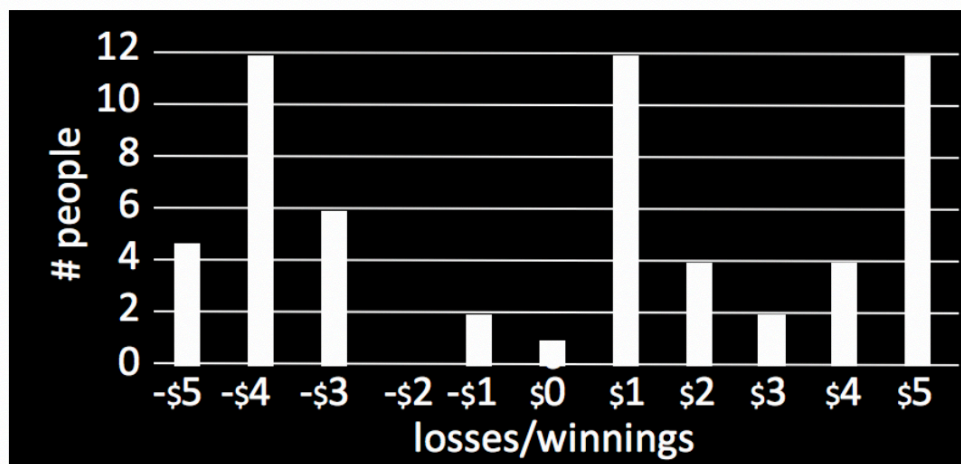To make these choices, we will need to introduce you to the following charts:

Today's task is designed to find out how you make choices between different games of chance based on the **actual losses/winnings** of other people.

For each game of chance, we will show you a chart where the heights of the bars above a specific loss or winning indicate the number of people who lost or won, respectively.

Please read the following example carefully:

57 UA students participated in different games of chance with outcomes from -$5 to +$5, -$5 being the worst, +$5 being the best.

In this chart, five people lost $5, twelve people lost $4, and so on. Please study this chart for a minute:

Please turn the page for more information.

Figure 3:

Materials: Instruction to music song options

In addition to choices on games of chance, today's task is also designed to find out how you make choices between different music songs based on the **actual ratings other people** have given.

You will make choices on different music songs, for this music genre:

_____

Today, you will choose between 5 different sets of songs and **get to take home your 5 chosen ones**.

For each music song, we will show you a chart where the heights of the bars above a number indicate the number of people who gave the song that rating.

Please read the following example carefully:

57 UA students rated different songs on a scale from -5 to +5, -5 being the worst, +5 being the best.

In this chart, five people gave the song a rating of -5, twelve people gave the song a rating of -5, and so on. Please study this chart for a minute:
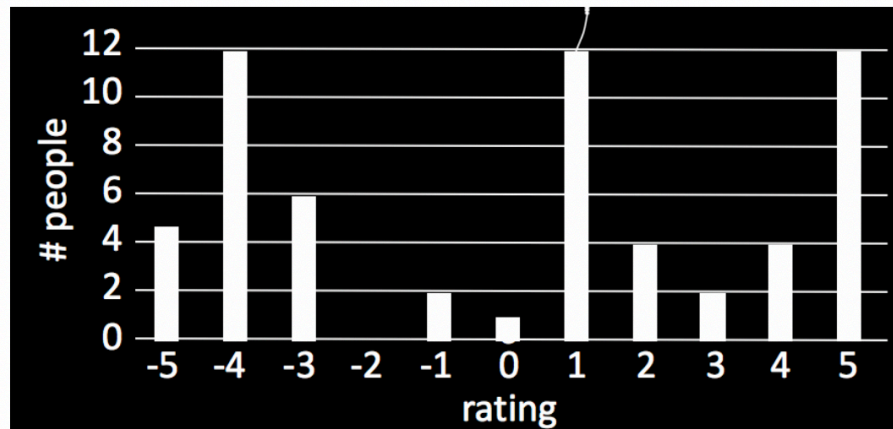
Thank you! Please hand the package over to the researcher.

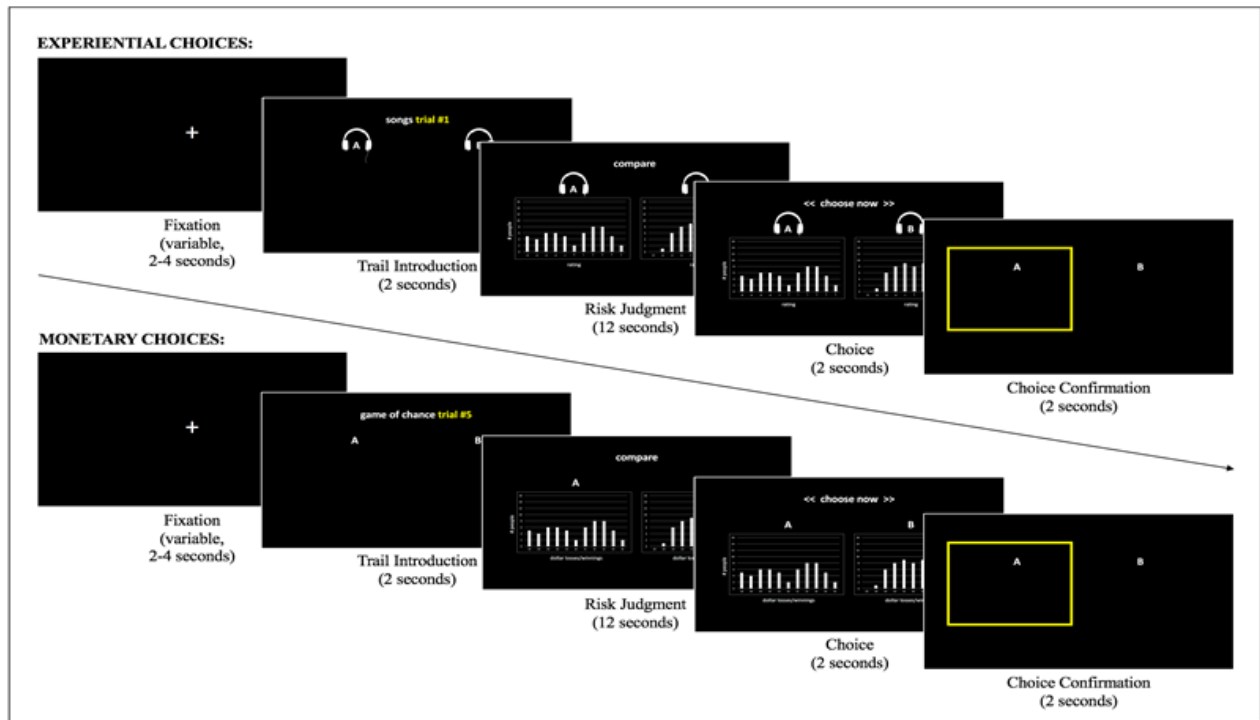**Figure 4:**

Trial structure of the behavioral task

Figure 5:

Exemplary time course of voxel intensities extracted at voxel (x: 1, y: 44, z: 49)
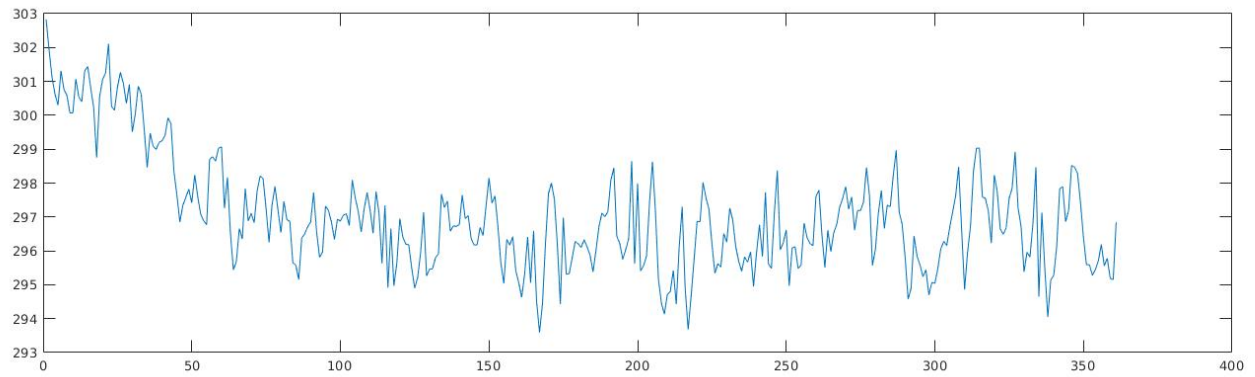
across the behavioral task

Table 1:

Prediction accuracies for support vector machine classifier for different kernels, features, and sub-cortical regions under consideration

Feature	VOI	Linear	Polynomial (d=3)	RBF
All Data	All Regions	73.4	57.5	50.2
	Hippocampus	50.2	60.2	57.5
	Amygdala	57.5	52.5	53.2
	Thalamus	49.6	52.3	52.3
Average	All Regions	56.4	53.2	51.6
	Hippocampus	50.7	53.9	55.8
	Amygdala	55.8	53.9	50.4
	Thalamus	46.8	50.1	52.1
Variance	All Regions	56.4	53.2	53.2
	Hippocampus	53.2	53.9	55.7
	Amygdala	55.8	53.9	55.7
	Thalamus	46.8	50.1	52.1

Table 2:

Experiential choices: Prediction accuracies for support vector machine classifier for different kernels, features, with Hippocampus region under consideration

Feature	VOI	Linear	Polynomial (d=3)	RBF
Average	All Regions	62.37	67.52	64.98
	Hippocampus	57.73	70.10	69.58
	Amygdala	61.85	68.04	63.91
Variance	All Regions	63.91	56.18	56.18
	Hippocampus	60.31	56.18	56.18
	Amygdala	57.73	56.18	56.18

Table 3:

Monetary choices: Prediction accuracies for support vector machine classifier for different kernels, features, with Hippocampus region under consideration

Feature	VOI	Linear	Polynomial (d=3)	RBF
Average	All Regions	65.56	63.67	63.67
	Hippocampus	66.03	64.62	64.15
	Amygdala	62.73	67.92	66.50
Variance	All Regions	54.24	50.47	50.47
	Hippocampus	52.83	50.47	50.47
	Amygdala	59.43	50.47	50.47