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Hippocampal blood oxygenation predicts choices about everyday consumer experiences: A deep-learning approach

Chinmai Basavaraj[a], Martin Reimann[b,c,1], Kobus Barnard[a], and Lynn Nadel[c,1]

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This research investigates the neurophysiological mechanisms of experiential versus monetary choices under risk. While ventral striatum and insula activity are instrumental in predicting monetary choices, we find that hippocampal activity plays a key role in predicting experiential choices, which we theorize is due to its role in retrieving autobiographical memories. This neurophysiological differentiation clarifies observed variations in risk preferences between experiential and monetary prospects and highlights the importance of domain-specific neurophysiological processes in shaping human decision-making.

experience theory | decision-making under risk | hippocampus | consumer neuroscience | marketing

When people make choices under risk, what can brain activity reveal about these choices? For monetary choices, the answer seems clear. Activity in the ventral striatum, including the nucleus accumbens, has been reported to precede risky monetary choices (1, 2), while activity in the insula seems to precede riskless monetary choices (1, 3). However, it is unclear whether the same subcortical activity patterns apply to choices about everyday experiences. This gap in knowledge is striking, especially considering that most people make experiential choices daily, such as deciding between different songs to listen to, movies to watch, or restaurants to eat at. Intuitively, one could predict that the neurophysiological mechanisms of monetary choices may generalize to those of choices about everyday experiences. However, this intuition may be flawed as monetary decision-making is often driven by abstract, temporally proximate risk–reward assessments, which are believed to engage the ventral striatum and insula (4), whereas experiences frequently draw upon temporally distant emotional memories (5–7), which may rely on other subcortical circuits.

This lack in the neuroscientific understanding of human decision-making prompts a closer look at the behavioral research on choices under risk. Focusing on monetary choices, seminal work in behavioral economics—prospect theory—has consistently demonstrated that people tend to exhibit risk aversion for prospective monetary gains but display risk-seeking for prospective monetary losses (8, 9). However, experience theory suggests that people demonstrate opposite risk preferences for experiential (versus monetary) prospects of the same magnitude, riskiness, and expected value—specifically, risk-seeking for prospective experiential gains but risk aversion for prospective experiential losses (10). Drawing from this theory, we expect that in experiential choices, people are likely to use extreme "best" or "worst" memories as personalized reference points. Consequently, they treat many positive experiences as shortfalls from the best memorable outcome—leading to risk-seeking in the positive domain—and most negative experiences as improvements over the worst-case memory—leading to risk-aversion in the negative domain. These memory-based reference points, therefore, diverge from prospect theory's neutral status quo and, thus, offer an explanation for why risk preferences systematically reverse between monetary and experiential choices (10).

For our purposes, an experiential choice option marks the subjective value people expect to gain or lose from engaging in a (nonmonetary) experience, such as listening to a song. We acknowledge that experiential domains are vast, ranging from everyday activities like music selection to high-stakes experiential pursuits such as freehand rock climbing and acrobatic flying, and the mechanisms we describe may not generalize to all such contexts—especially when outcomes become highly consequential. Here, we focus on moderate-stakes everyday choices (i.e., deciding on a potentially enjoyable or disappointing song) where memories of prior positive or negative encounters form salient reference points. Specifically, we expect that when choosing between different positive experiential options varying in riskiness, people are more likely to prefer the riskier choice if it promises a highly enjoyable

Significance

What is going on in the brain when people make decisions, particularly when it comes to everyday experiences such as choosing between different songs to listen to? This study investigates the role of the hippocampus, a key memory region, in predicting choices involving such everyday experiences. Using deep-learning models that integrate natural-language-processing approaches and neuroimaging data, we identify a neurophysiological mechanism linked to people's *experiential* risk-taking behavior—hippocampal activity—and compare this finding to the established literature on people's *monetary* risk-taking behavior.

Author affiliations: [a]Department of Computer Science, The University of Arizona, Tucson, AZ 85721; [b]Department of Marketing, Eller College of Management, The University of Arizona, Tucson, AZ 85721-0108; and [c]Department of Psychology, The University of Arizona, Tucson, AZ 85721

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[1]To whom correspondence may be addressed. Email: reimann@arizona.edu or nadel@arizona.edu.

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outcome rather than settle for a safer, modestly pleasant one (10). This behavior arises because the reference point for an experiential choice is shaped by recalling the "best" or "worst" experiences that come to mind—a process we propose hinges on the hippocampus's role in autobiographical memory retrieval (11–15). The vividness of these recalled experiences (16) can effectively tilt the decision frame, and thus heighten risk-seeking for prospective experiential gains yet prompt risk aversion for prospective experiential losses.

In contrast, a monetary choice option reflects the subjective value people expect to gain or lose from engaging in a financial transaction, typically referenced against one's current wealth (8, 9). While risk preferences in these monetary scenarios may appear superficially similar to those seen in experiential situations, the underlying mechanism differs. Prospect theory improves on classical expected utility theory (17) by recognizing separate gain/loss value functions, but it still does not explicitly account for memory-shaped reference points that can dominate in experiential decision-making. The present work thus attempts to offer a glimpse into how memory retrieval and autobiographical salience might recalibrate perceived gains and losses in an experiential context—thus moving beyond both classic expected utility theory's uniform utility function and prospect theory's status-quo-based approach.

Drawing from experience theory (10), we expect that it is more probable that consumers choose the risky option when making experiential (vs. monetary) choices in the realm of gains. We hypothesize that hippocampal activity selectively predicts experiential choices, distinguishing them from the monetary decision domain and highlighting a neurophysiological pathway for understanding risk preferences for the experiential decision domain. By bridging established findings on hippocampal function in autobiographical memory retrieval (11–15), we theorize that hippocampal activity specifically tracks the memory-shaped reference points guiding experiential choices. In particular, because the hippocampus can recall "best" or "worst" prior outcomes, there is a conceptual link to the vividly remembered contexts that shape experiential risk preferences. This region's connectivity with affective and reward networks further supports the integration of emotional memory. Consequently, we theorize that heightened hippocampal activation would predict risk-seeking for positive experiential prospects and risk aversion for negative ones, which illustrates how this subcortical mechanism influences risk-taking behavior beyond traditional monetary frameworks.

To test the hypotheses, participants were engaged in a series of behavioral choices while a time series of functional magnetic resonance images (fMRI) recorded their brains' blood oxygenation. We then employed deep-learning models that capture voxel-level activation patterns in the hippocampus—rather than a single aggregated activation metric—to predict participants' choice behavior (18). For reasons of consistency, our study employed gain framing (19), where participants were told to anticipate both positive experiential and positive monetary outcomes.

Experimental Design

Our study employed a within-subjects, repeated-measures experimental design with decision domain (experiential vs. monetary) as the independent variable and choice between a relatively riskier and a relatively safer option as the dependent variable. Choice between two experiential options was operationalized as choice between two songs in each participant's preferred music genre and choice between two monetary options was operationalized as choice between two games of chance. The different choice options were identical in magnitude, riskiness, and expected value across the two decision domains. Blood-oxygen-level-dependent (BOLD) responses of the brain at specific regions of interest were assessed while participants made their choices.

Participants

Fifty-two human subjects were recruited to the neuroimaging lab at the University of Arizona in exchange for course credit, a $25 cash endowment, and a selection of songs from their preferred music genre, which participants received after the study. Subjects were students at the university with backgrounds in business administration and/or economics. All subjects had normal or corrected-to-normal vision and were later determined by two independent MRI scientists (S.S. and A.H.) to have normal brain anatomy. We excluded seven participants from the analysis, leaving us with a usable dataset of 45 participants (M_{age} = 21.67, SD_{age} = 2.17; 51% female). The *SI Appendix* details the exact reasons for exclusion (see the section titled *Neuroimaging Data Collection*), which were independently determined and verified by the two MRI scientists.

Experimental Procedures

Upon arrival at the neuroimaging lab, participants were guided to a waiting room and handed a paper-and-pencil study package. Participants were screened for MRI eligibility based on factors such as prior medical conditions, pregnancy, or the presence of implanted ferrous materials, any of which could prevent them from undergoing scanning, and provided written informed consent to a protocol approved by the University of Arizona's Institutional Review Board. Participants were then asked to indicate their most preferred music genre from a list of 22 genres such as classical, hip-hop, jazz, and rock.

In order to put participants into a state of monetary gains, we then provided each with a $25 cash endowment. Our provision of money to participants meets extant guidelines on how to induce a state of monetary gains (9, 20) and also closely follows previously established procedures aimed to ensure incentive compatibility (20). Participants read on their paper-and-pencil study package: "The experimenter will provide you with $25 now. Please put the two bills in your pocket and take them inside the scan room with you. This money is yours to take. In one of the tasks today, we would like you to make monetary choices in different games of chance. During these games of chance, you might lose some or all of your $25 stake, retain it, or increase it." Participants then responded to whether they had understood these instructions (yes/no; 100% of participants said yes) and to the question of how much of their $25 endowment they could potentially lose (72% of participants responded to the correct answer that they could lose some or all of it). Participants then read: "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:". Fig. 1 shows the monetary histogram that participants then studied.

Next, in order to put participants into a state of experiential gains, we had them anticipate that they would receive songs from their preferred music genre, which they had indicated earlier. The operationalization of experiential choices as choices between music

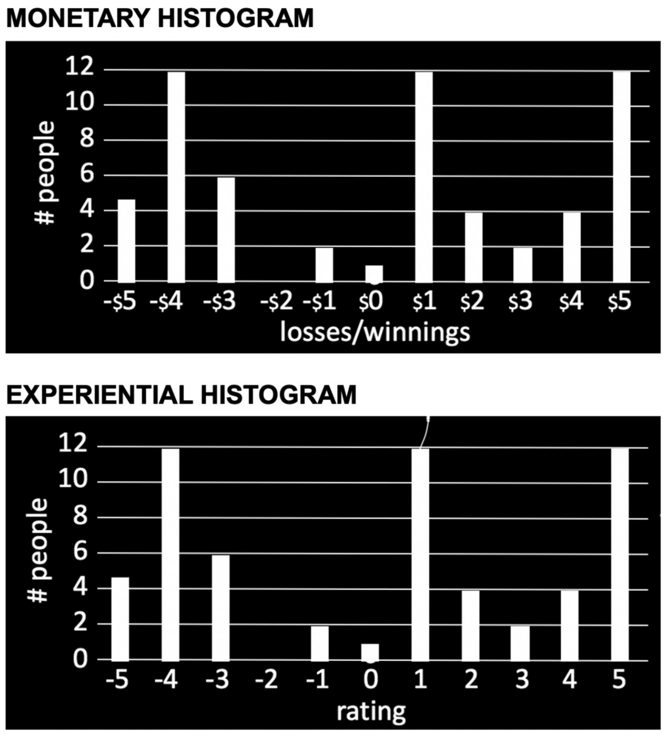

Fig. 1. Participants were shown histograms depicting previous consumers' monetary or experiential outcomes. For monetary choices, the heights of the bars above a specific loss or winning indicate the number of people who lost or won, respectively. For experiential choices, the heights of the bars above a number indicate the number of people who gave the song that rating. In the main version of the behavioral choice task and unknown to participants, the different choice options were identical in magnitude, riskiness, and expected value across the two decision domains—experiential versus monetary.

songs follows previously established practices (10) and our provision of songs to participants again aimed to ensure incentive compatibility as well as commensurability with any gains in the monetary condition. Participants read: "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." Participants were then asked to fill in their preferred music genre, and then continued to read that they will choose between five different sets of songs and get to take home their 5 chosen ones. They were also shown a histogram where the heights of the bars above a number indicate the number of people who gave the song a particular rating, based on 57 students having rated different songs on a scale from -5 to +5 (Fig. 1). The experimenter then verbally asked each participant whether they had understood the histograms.

Participants were then engaged in a practice version of the behavioral choice task on a laptop computer. The practice version of the task ensured that participants fully understood how the task worked and also guaranteed they did not feel time-pressured to make their decisions while in the scanner. Only when all their open questions were answered and participants provided their consent to proceed were they allowed to continue with the main task and placed horizontally inside the Siemens 3 T Skyra scanner. The behavioral choice task was projected onto a mirror right above the eyes and participants provided all behavioral responses via a standard button box.

The behavioral choice task comprised ten trials in total, with five experiential trials and five monetary trials presented to participants in pseudorandom order. Similar behavioral choice task designs have been used in both consumer neuroscience (e.g., 21, 22–27) and neuroeconomics (e.g., 2, 28, 29). For each trial, participants first saw a fixation cross to center their attention on the middle of the screen. Then, participants were prompted to the decision context (either experiential or monetary), shown two options to choose from, asked to make their choice, and finally shown a confirmation of their choice. Each choice involved a selection between two histograms, a high-variance (i.e., relatively riskier) option and a low-variance (i.e., relatively safer) option. *SI Appendix*, Fig. S1 in the Supporting Information (*SI*) depicts all histograms. Our operationalization of high-variance histograms as relatively riskier option and a low-variance histograms as relatively safer option is based on the notion that variance reflects the level of risk surrounding potential outcomes (30). Accordingly, a high-variance option can produce drastically better or worse outcomes, indicating greater unpredictability and thus higher risk. Conversely, a low-variance option typically yields outcomes that are more consistent and closer to an expected value, making it comparatively less risky. In the context of consumer ratings, a high-variance rating profile implies that previous consumers had significantly divergent experiences. This unpredictability introduces greater risk about one's own outcome. Meanwhile, a low-variance rating profile indicates more consistent experiences, lowering the chance of extreme disappointment or unexpectedly poor outcomes. In the experiential decision domain condition, the scale of the histograms was labeled from -5 to +5, signifying the rating outcomes. Participants could only view the histograms and did not hear the songs otherwise. They had to make their choices solely based on other consumers' rating outcomes, similar to consumers choosing digital music products based on previous consumers' rating outcomes in the Apple iTunes store. In the monetary condition, the scale of the histograms was labeled from -\$5 to +\$5, signifying the dollar outcomes. Participants could only view the histograms and did not receive feedback otherwise. They had to make their choices solely based on other consumers' prior monetary outcomes, similar to consumers choosing digital financial products based on past consumers' monetary outcomes on financial websites. The section titled *Design, Piloting, and Presentation of the Behavioral Choice Task* in the *SI Appendix* reports how we designed and presented the task. Likewise, the *SI Appendix* section titled *Development and Validation of the Histograms for the Behavioral Choice Task* discusses in detail how the experiential ratings and, respectively, monetary outcomes were calculated and how the histograms were developed and then validated. Fig. 2 illustrates the trial phases of the behavioral choice task. The original materials, including the study package and the behavioral choice task stimuli, as well as data and code for obtaining the reported prediction accuracies, are available through the Open Science Framework (OSF): https://doi.org/10.17605/OSF.IO/PKBV2.

Methodological Approach

We built several different deep-learning models and subjected the behavioral and neurophysiological datasets to them in an effort to detect differences in the data between experiential and monetary choices on a voxel level. There are several reasons why we chose this approach over traditional univariate and multivariate analyses in functional neuroimaging research. First, conventional methods assume linear relationships between the focal variables, which may oversimplify the complexity of decision-making. Deep-learning models, by contrast, capture nonlinear interactions, which can offer a more nuanced understanding of the effect

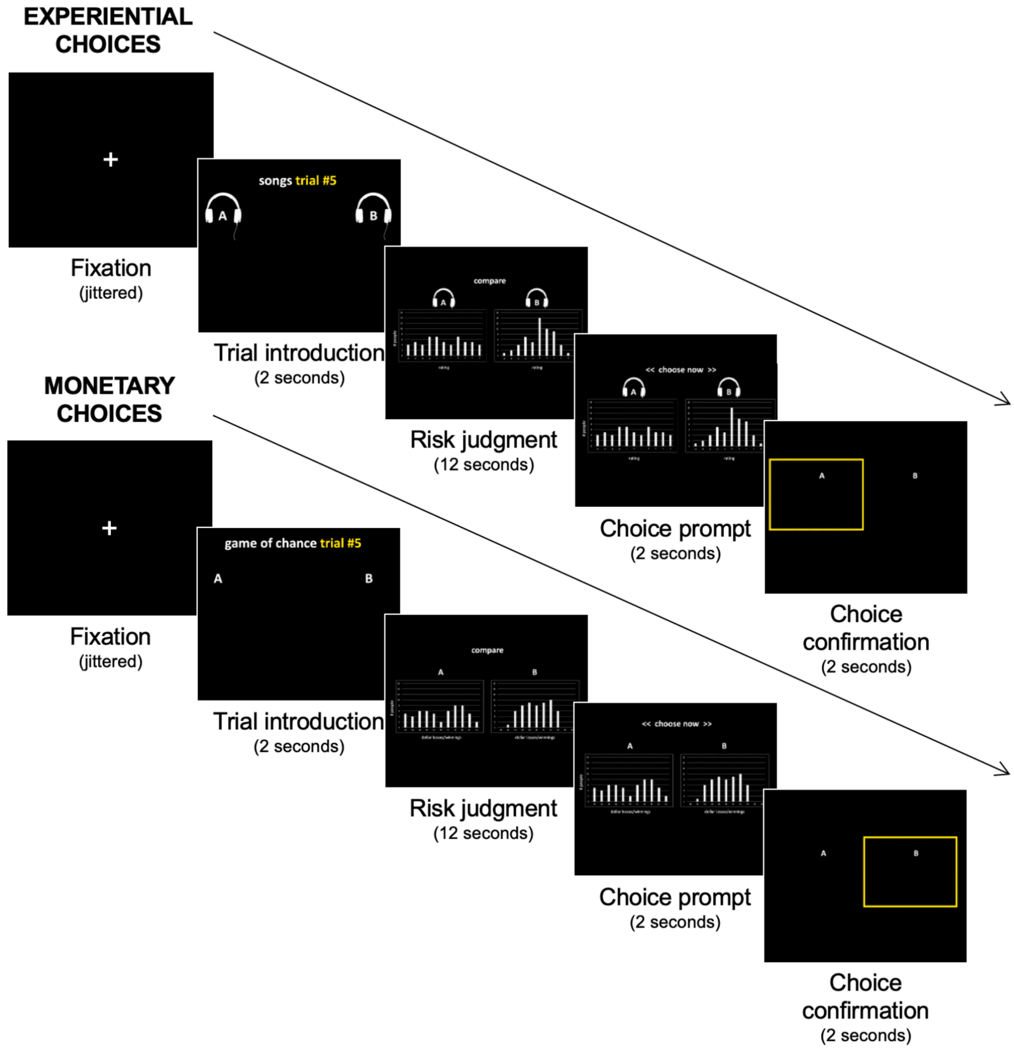

Fig. 2. Illustration of an experiential and a monetary trial of the behavioral choice task. For each of ten trials of the behavioral choice task, participants were first shown a fixation cross, were then prompted to the specific decision domain—either experiential or monetary—for 2 s, were then given 12 s to evaluate a high-variance, relatively riskier option and a low-variance, relatively safer option, were then asked to make their choice between the two options for 2 s, and were eventually shown a confirmation of their choice for 2 s.

of the experimental manipulations on neurophysiological activity and behavior. Second, traditional approaches aggregate BOLD signals into static measures, which essentially discard critical temporal information, while deep-learning models are able to retain the temporal structure of the data. Third, univariate and multivariate analyses focus on group-level metrics, such as means and *P*-values, which cannot assess individual-level predictive accuracy. Deep-learning bridges this gap by directly linking neurophysiological signals to individual choices. Finally, conventional methods lack the ability to compare the predictive power of neuroimaging data versus behavior. Our approach enables such comparisons, which allows us to gauge how much better fMRI data predict choice outcomes relative to past behavior.

The section titled *Support Vector Machine* (SVM) in the *SI Appendix* discusses the traditional machine-learning technique we use as baseline model to compare our deep-learning models to. The SVM analyzes the activity of multiple voxels in a so-called pattern classification task, in contrast to conventional statistical analyses (31–33). We demonstrate that our deep-learning models yielded substantial improvement in prediction accuracy over the SVM, highlighting the magnitude to which these deep-learning models perform better than a traditional machine-learning approach (*SI Appendix,* Table S3). Also in the *SI Appendix*, the description of the SVM is followed by a description of the input and output formats for each of the four deep-learning models and the parameters involved in training each of them. Refer to the *SI Appendix* titled *Four-Dimensional Convolutional Neural Network* (4D-CNN), *Bi-Directional Long Short-Term Memory Networks* (Bi-LSTM), *Bi-Directional Long Short-Term Memory Network with Conditional Random Field* (Bi-LSTM-CRF), and *Four-Dimensional Convolutional Neural Network with Conditional Random Field* (4D-CNN-CRF).

To provide an overview of our analyses and the following results, first, we compare the hippocampus finding to those of the ventral striatum, a key brain area previously implicated in monetary choices. Second, we analyze the data separately for two distinct parts of the hippocampus in order to further scrutinize the role of autobiographical memory. Third, to check for the robustness of our hypothesis test, we contrast the hippocampus finding with results from two brain areas previously linked to risky choices—the insula and amygdala. Fourth, also as a robustness check, we compare the hippocampal predictions against behavioral data to gauge the added predictive performance of neuroimaging data over the predictive performance of behavioral data. Fifth, again as another robustness check, we evaluate the hippocampus finding against a brain area

Table 1. Experiential choices are most accurately predicted using data from the hippocampus, whereas monetary choices are most accurately predicted using data from the ventral striatum

	Percentage prediction accuracies and SE	
Brain areas	Experiential choices	Monetary choices
Hippocampus	**71.3 ± 3**	56.7 ± 3
Ventral striatum	66.3 ± 3	**61.3 ± 3**
	Ratios of percentage prediction accuracies between brain areas	
Hippocampus/ventral striatum	1.08	0.92

Note. Prediction accuracies of best-performing brain areas are highlighted in bold. Results are based on using the Bi-LSTM sequential model (cf. *SI Appendix*, Fig. S4, panel *B*).

not previously associated with either experiential or monetary choices, the visual cortex. We then proceed to a series of methodological evaluations to scrutinize our deep-learning modeling approach and results interpretation. First, we perform model comparison to identify the best predicting model available for the type of behavioral and neuroimaging data available; second, we validate our best-performing model using data from an independent research group (34); third, we apply cross-subject validation; and fourth, we conduct reverse-inference meta-analyses.

Behavioral Results

To scrutinize our theorizing that it is more probable that consumers choose the risky option when making experiential (vs. monetary) choices in the realm of gains, we conducted a random-intercept logistic regression with participant as clustering variable and a fixed-effects approach (35). The choice in each trial (risky = 1, safe = 0) served as the dependent variable and the decision domain (experiential = 1, monetary = 0) served as the independent variable. Missed choices were excluded from the analysis. Given our directional hypothesis derived from prior research (10), we used one-tailed testing (36). Results revealed that experiential (vs. monetary) decision domain predicted the choice of the risky option (b = 0.42, SE = 0.23, z = 1.86, P = 0.03, odds ratio = 1.52). Thus, ceteris paribus, the odds of choosing the risky option were 52% higher in the experiential versus the monetary decision domain. Further, to account for the potential effect of individual differences, when allowing the effect of decision domain to vary across participants in a mixed-effects logistic regression with a random-effects approach, results were highly similar (b = 0.37, SE = 0.22, z = 1.65, P = 0.0498, odds ratio = 1.45), showing that results are robust.

Table 2. Experiential choices are more accurately predicted using data from the posterior part of the hippocampus when compared to data from its anterior counterpart

	Percentage prediction accuracies and SE	
Brain areas	Experiential choices	Monetary choices
Posterior hippocampus	**67.7 ± 3**	54.2 ± 3
Anterior hippocampus	60.2 ± 4	52.6 ± 3
Ventral striatum	64.9 ± 3	**58.6 ± 3**
	Ratios of percentage prediction accuracies between brain areas	
Posterior/anterior hippocampus	1.12	1.03
Posterior hippocampus/ventral striatum	1.04	0.92
Anterior hippocampus/ventral striatum	0.93	0.90

Note. Prediction accuracy of best-performing brain area is highlighted in bold. Results are based on using the Bi-LSTM individual model (cf. *SI Appendix*, Fig. S4, panel *A*) for prediction.

Table 3. Compared to other brain areas and compared to participants' actual behavior, experiential choices are most accurately predicted using data from the hippocampus, whereas monetary choices are most accurately predicted using data from the ventral striatum

	Percentage prediction accuracies and SE	
Brain areas	Experiential choices	Monetary choices
Behavioral benchmark 1 (BB1)	58.0 ± 5	49.7 ± 4
Hippocampus	**68.3 ± 3**	54.7 ± 3
Amygdala	61.1 ± 4	55.4 ± 4
Insula	60.8 ± 4	53.5 ± 4
Ventral striatum	64.9 ± 3	**58.6 ± 3**
	Ratios of percentage prediction accuracies between brain areas and BB1	
Hippocampus/BB1	1.18	1.10
Amygdala/BB1	1.05	1.11
Insula/BB1	1.05	1.08
Ventral striatum/BB1	1.12	1.18

Note. Prediction accuracies and percentage improvements over BB1 of best-performing brain areas are highlighted in bold. Results are based on using the Bi-LSTM individual model (cf. *SI Appendix*, Fig. S4, panel *A*) for prediction. BB1 represents a simple algorithm that predicts the most common choice in held-out behavioral data based on behavioral data (see the *SI Appendix* for the exact definition of BB1).

Table 4. Experiential choices are more accurately predicted using data from the hippocampus when compared to data from the visual cortex

	Percentage prediction accuracies and SE	
Brain areas	Experiential choices	Monetary choices
Hippocampus	**68.3 ± 3**	54.7 ± 3
Visual cortex	57.1 ± 4	54.0 ± 4
	Ratios of percentage prediction accuracies between brain areas	
Hippocampus/visual cortex	1.20	1.01

Note. Prediction accuracy of best-performing brain area is highlighted in bold. Results are based on using the Bi-LSTM individual model (cf. *SI Appendix*, Fig. S4, panel *A*) for prediction.

Neurophysiological Results

We then proceeded to test our neurophysiological hypothesis. For details on *Neuroimaging Data Collection, Voxel Selection and Definition of Volumes of Interest*, and *Neuroimaging Data Extraction*, refer to the respective sections in the *SI Appendix*.

Neurophysiological Hypothesis Test 1: Hippocampal Versus Ventral Striatal Contributions in Experiential Choices. To test our theorizing that activation in the hippocampus selectively predicts experiential choices, in the realm of gains, when compared to monetary ones, we applied our Bi-LSTM deep-learning model to fMRI data collected during decision-making on both experiential and monetary gains. For comparison, we extracted data from the ventral striatum (including the nucleus accumbens) based on seminal research that identified this region as a key predictor of monetary risk-seeking behavior (1, 2). We extracted functional neuroimaging data from the ventral striatum (refer to the section titled *Voxel Selection and Definition of Volumes of Interest* in the *SI Appendix* for details on how the location of the ventral striatum was defined). Our results support the earlier work, demonstrating that monetary choices under risk are best predicted using data from the ventral striatum (61.3% prediction accuracy). However, for experiential choices, and in support of our hypothesis, we found that experiential choices are most accurately predicted using data from the hippocampus (71.3% prediction accuracy). Table 1 shows that hippocampal data predict experiential choices with approximately 8% greater accuracy than ventral striatal data—whereas for monetary choices, ventral striatal activity yields a superior prediction accuracy compared to the hippocampus. This pattern supports our hypothesis that the hippocampus (vs. the ventral striatum) contributes differently to predicting risk preferences depending on whether choices are experiential or monetary in nature.

Neurophysiological Hypothesis Test 2: Posterior Hippocampal Contributions in Experiential Choices. Next, to further scrutinize our hypothesis that activation in the hippocampus selectively predicts experiential choices, we refined our analysis by separating the hippocampal data into its posterior and anterior regions (by splitting the dataset along the mediolateral axis) to assess their individual contributions to predicting experiential choices. We had further hypothesized that the posterior hippocampus would be a stronger predictor of experiential choices due to its well-documented role in processing specific episodic memories, which are crucial for recalling detailed personal experiences (37). Conversely, we expected the anterior hippocampus, which is more involved in processing broader, context-dependent memories (37, 38), to be less accurate in predicting these choices. Results from our Bi-LSTM model lend support to our hypothesis: The posterior hippocampus exhibited a notably higher prediction accuracy for experiential choices, achieving an approximately 12% improvement in prediction accuracy over the anterior part (see results in Table 2). This suggests that participants relied heavily on the retrieval of specific episodic memories when making decisions about experiential options, further substantiating our claim that the hippocampus, particularly its posterior region, plays a pivotal role in these types of decisions. Of note, predicting monetary choices from these data was close to chance, as expected. In contrast, the anterior hippocampus showed a lower accuracy in predicting experiential choices than its posterior counterpart (though still higher than for monetary choices), paralleling its association with more generalized memory processing. These findings reinforce the distinct neurophysiological mechanisms underlying experiential versus monetary choices, with the posterior hippocampus being particularly crucial in scenarios where detailed personal memories influence decision-making.

Robustness Check 1: Hippocampal Predictions Compared to the Insula and Amygdala. Because previous research has implicated two other subcortical brain circuits in monetary choices under risk, specifically the insula for risk aversion (1, 3) and the amygdala for risk framing (39) and risk tracking of the expected values of monetary prospects (20), we also compared the predictive performance of the hippocampus and ventral striatum to these two brain circuits (refer to the section titled *Voxel Selection and Definition of Volumes of Interest* in the *SI Appendix* for details on how the locations of the insula and amygdala were defined). Results of our Bi-LSTM model confirmed the hippocampus' superior role in predicting experiential choices when compared to the insula and amygdala (Table 3).

Robustness check 2: Hippocampal Predictions Versus Behavioral Data. We established a behavioral benchmark (called BB1) to compare with the neuroimaging data. This was done by calculating the predictive performance of participants' actual behavior to forecast held-out behavioral data. We included behavior as comparison to test whether data from the hippocampus can better predict future behavior than past behavior can predict future behavior, addressing the commonly held assumption that people's past behavior is the best predictor of their future behavior (40, 41) and contributing to a long-standing debate in neuroeconomics and consumer neuroscience (42): To what extent is fMRI data better at predicting people's future behavior than their past behavior is? Results revealed that compared to all other brain areas previously implicated in choices under risk, experiential choices are still most accurately predicted using data from the hippocampus (68.3% prediction accuracy), whereas monetary choices are most accurately predicted using data from the ventral striatum (58.6% prediction accuracy). Results also showed that data from the hippocampus predict experiential choices better than behavioral data on past experiential choices (58.0 % prediction accuracy from behavioral data) and that data from the ventral striatum predict monetary choices better than behavioral data from past monetary choices (49.7% prediction accuracy from behavioral data). Table 3 summarizes these findings. To enhance robustness, the *SI Appendix* reports two additional behavioral benchmarks for comparison (BB2 and BB3; *SI Appendix*, Tables S2 and S3).

Robustness Check 3: Hippocampal Predictions Compared to the Visual Cortex. To further clarify the unique contribution of the hippocampus in guiding experiential choices, we extracted functional neuroimaging data from the visual cortex as a control region. Unlike the hippocampus—which is implicated in memory—the visual cortex is primarily involved in processing visual information (43) and has not been distinctly associated with either experiential or monetary choices in previous research. Its functional profile makes the visual cortex an ideal benchmark to test whether the predictive power for experiential choices is specific to hippocampal activity (refer to the section titled *Voxel Selection and Definition of Volumes of Interest* in the *SI Appendix* for details on how the location of the visual cortex was defined). In further support of our hypothesis, results revealed that experiential choices are more accurately predicted using data from the hippocampus than using data from the visual cortex, with a 20% improvement in prediction accuracy (Table 4).

Methodological Evaluation 1: Performance Comparison Between Models. Our results were examined using multiple machine- and deep-learning models. Because the nature of our behavioral task was sequential (i.e., it employed a repeated-measures experimental design), we attempted to capture this sequential information in our models. We did so in two ways: First, we built a deep-learning model that captures the sequential information by jointly modeling all the choices made by an individual (i.e., Bi-LSTM with sequential choices). Second, we integrated a so-called Conditional Random Field (CRF)—a technique from natural language processing research—in our deep-learning architectures, which captures the choice transitions between the ten choices participants made as well as the likelihood of a choice happening in a particular trial (i.e., 4D-CNN-CRF and Bi-LSTM-CRF). Results revealed substantial improvements over those models that do not incorporate such sequential information (*SI Appendix*, Table S3). Refer to the *SI Appendix* with the same heading name for a detailed description of our approach and results.

Methodological Evaluation 2: Model Validation using Independently Collected Data. We were also curious whether our best-predicting models would yield substantial performance improvements in secondary fMRI data on decision-making under risk collected by an independent author team. This helped us to ensure model robustness and to further scrutinize the validity of our findings. As a result, we applied our best-performing models to publicly available fMRI data on decision-making under risk generated by an independent research team (34). Results demonstrated the robustness of our models by being able to show substantial performance improvements across different models (*SI Appendix*, Table S4). Refer to the *SI Appendix* with the same heading name for a detailed description of our approach and results.

Methodological Evaluation 3: Cross-Subject Validation. To advance the generalizability of neuroimaging findings to the broader population, we conducted cross-subject validation. This analysis revealed that using fMRI data from a new, unseen individual, our best-performing model can predict with 61.7% accuracy whether the person made any choice under risk, without prior knowledge of their actual behavior (*SI Appendix*, Table S5). This represents a substantial improvement over pure chance and traditional machine-learning approaches. Refer to the *SI Appendix* with the same heading name for a detailed description of our approach and results.

Methodological Evaluation 4: Reverse-Inference Meta-Analyses. Although our study followed the deductive-reasoning approach of fMRI studies (44) and was guided by established psychological interpretations of brain function, we further validated our hypothesis by conducting reverse-inference meta-analyses using Neurosynth (45, 46), which revealed robust associations between hippocampal activation and autobiographical memory processing (left hippocampus: $z = 8.76$, posterior probability = 0.86; right hippocampus: $z = 7.29$, posterior probability = 0.70) and, thus, reinforced the long-standing evidence linking the hippocampus with autobiographical memory (11–14). Refer to the *SI Appendix* with the same heading name for a detailed description of our approach and the results in *SI Appendix*, Table S6.

Discussion

This research makes contributions to our understanding of the neurophysiology of people's choices under risk, especially in the context of everyday experiences. By integrating behavioral and fMRI data, we reveal that experiential choices fundamentally differ from monetary ones. Specifically, we found that people rely on the hippocampus—a region crucial for autobiographical memories—to make experiential decisions. While prior research has long recognized that risk preferences are context-dependent (8, 10, 47), our findings extend this perspective by providing neurophysiological evidence that memory retrieval processes can shape experiential choices differently compared to monetary ones. In particular, hippocampal activation may reflect the retrieval of salient memories that function as personalized reference points, which highlights how underlying neurophysiological mechanisms of risk preferences can vary depending on the nature of the choice.

Furthermore, our findings associate with the broader understanding of hippocampal involvement in memory retrieval, particularly in differentiating posterior from anterior functions. Although our task required participants to interpret textual and numerical information, we did not explicitly measure personal autobiographical recall, nor did we isolate semantic from episodic memory processes. Rather, the contrast between posterior and anterior hippocampal activation in our data resonates with findings suggesting that the posterior hippocampus is more strongly associated with detailed, episodic-like retrieval, whereas the anterior portion underpins broader, context-dependent processing (37). We acknowledge that these results do not resolve debates about whether semantic and episodic memory rely on the same or different neurophysiological substrates, but they contribute to a more nuanced view of hippocampal subregions during experiential decision-making.

A methodological contribution of this research is to offer techniques for assessing how well machine- and deep-learning models predict and whether the information that these models learn is actually meaningful. This contribution is important because psychologists, neuroeconomists, and consumer neuroscientists have asked how to establish benchmarks to evaluate their models' performance (42). In other words, against what threshold are we comparing our neuroimaging results? In the present work, we compared our models' prediction accuracy against three behavioral benchmarks. First, by comparing model prediction accuracy to that of predicting the most probable choice every time (here, the choice of the relatively riskier option), we address the potential bias that participants may be more likely to make a specific choice. Second, by comparing model performance to the sequence obtained by choosing the most probable choice at a particular stage in the experiment, we account for task-related biases, such as the fatigue participants experienced toward the end of our task as a result of having made several choices in sequence. Third, we account for another potential bias that stems from the deep-learning models' knowledge of the sequence of stimuli presented to participants by comparing our model prediction accuracies with the sequence computed using CRF. In summary, we offer three comparison standards for neuroimaging data vis-á-vis behavioral data. These comparison standards contribute to the long-standing database about how well fMRI data predicts future behavior compared to past behavior (42).

Another methodological contribution is how we validate our results. One approach used in prior research is that of single-subject validation, in which results are validated using reserved data from the *same subject* (48–50). Herein, we have developed a cross-subject validation approach in which results are validated using data from *another subject*. Even though cross-subject validation allows for greater applicability and generalizability than single-subject validation (33, 51, 52), there have been few systematic attempts to make use of it in prior work. This study uses cross-subject validation in this context, with our models trained by excluding the data of a certain participant and then predicting their choices.

Conclusion

To conclude, by integrating behavioral and fMRI data, this study underscores that experiential risk-taking engages the hippocampus—crucial for autobiographical memory—whereas monetary choices rely more on the ventral striatum. These findings reinforce that risk preferences are not one-size-fits-all but depend on whether decisions hinge on recalling past experiences or evaluating immediate rewards. Beyond supporting literature on hippocampal involvement in memory, our results therefore highlight its active role in guiding everyday consumer choices and point to the importance of context-specific neurophysiological mechanisms. Notably, this suggests that the hippocampus does more than merely retrieve memories; it can help shape future-oriented experiential decision-making and thus signal a rich interplay between memory processes, experiential consumption, and risk behavior.

Materials and Methods

Fifty-two participants (University of Arizona students) performed a behavioral choice task while their BOLD responses were measured using functional MRI (fMRI). All provided informed consent (University of Arizona IRB), were screened for MRI eligibility, and had normal or corrected-to-normal vision. A within-subject, repeated-measures experimental design manipulated decision domain (experiential, monetary), with high-variance (riskier) versus low-variance (safer) histogram options. Participants practiced the task before scanning on a Siemens 3 T Skyra, then made five experiential and five monetary choices in pseudorandom order. Experiential choices involved rating outcomes (−5 to +5) for songs; monetary choices involved monetary outcomes (−\$5 to +\$5) from games of chance. Each trial displayed two histograms representing past consumers' ratings or, respectively, monetary outcomes. BOLD responses were measured at designated regions of interest, with the outcome being selection of the riskier or safer option.

Data, Materials, and Software Availability. Original materials, including the study package and the behavioral choice task stimuli, as well as data and code for obtaining the reported prediction accuracies have been deposited in Open Science Framework (https://doi.org/10.17605/OSF.IO/PKBV2) (53). The *SI Appendix* provides additional detail and specifies the model architectures.

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1. C. M. Kuhnen, B. Knutson, The neural basis of financial risk taking. *Neuron* **47**, 763–770 (2005).
2. B. Knutson, G. E. Wimmer, C. M. Kuhnen, P. Winkielman, Nucleus accumbens activation mediates the influence of reward cues on financial risk taking. *Neuroreport* **19**, 509–513 (2008).
3. G. R. Samanez-Larkin, N. G. Hollon, L. L. Carstensen, B. Knutson, Individual differences in insular sensitivity during loss anticipation predict avoidance learning. *Psychol. Sci.* **19**, 320–323 (2008).
4. B. Knutson, P. Bossaerts, Neural antecedents of financial decisions. *J. Neurosci.* **27**, 8174–8177 (2007).
5. G. Zauberman, R. K. Ratner, B. K. Kim, Memories as assets: Strategic memory protection in choice over time. *J. Consum. Res.* **35**, 715–728 (2009).
6. D. Clewett, S. DuBrow, L. Davachi, Transcending time in the brain: How event memories are constructed from experience. *Hippocampus* **29**, 162–183 (2019).
7. R. J. Kwortnik Jr., W. T. Ross Jr., The role of positive emotions in experiential decisions. *Int. J. Res. Mark.* **24**, 324–335 (2007).
8. D. Kahneman, A. Tversky, Prospect theory: An analysis of decision under risk. *Econometrica* **47**, 263–291 (1979).
9. A. Tversky, D. Kahneman, Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertainty* **5**, 297–323 (1992).
10. J. Martin, M. Reimann, M. Norton, Experience theory, or how desserts are like losses. *J. Exp. Psychol. Gen.* **145**, 1460–1472 (2016).
11. L. R. Squire, S. Zola-Morgan, The medial temporal lobe memory system. *Science* **253**, 1380–1386 (1991).
12. E. R. Kandel, The molecular biology of memory storage: A dialogue between genes and synapses. *Science* **294**, 1030–1038 (2001).
13. E. R. Kandel, Nobel lecture: The molecular biology of memory storage: A dialog between genes and synapses. *Biosci. Rep.* **21**, 565–611 (2001).
14. E. R. Kandel, *In Search of Memory: The Emergence of a New Science of Mind* (W.W. Norton & Company, New York, NY, 2007).
15. M. Moscovitch, R. Cabeza, G. Winocur, L. Nadel, Episodic memory and beyond: The hippocampus and neocortex in transformation. *Annu. Rev. Psychol.* **67**, 105–134 (2016).
16. C. K. Morewedge, D. T. Gilbert, T. D. Wilson, The least likely of times: How remembering the past biases forecasts of the future. *Psychol. Sci.* **16**, 626–630 (2005).
17. M. Friedman, L. J. Savage, The utility analysis of choices involving risk. *J. Polit. Econ.* **56**, 279–304 (1948).
18. C. Basavaraj, *Predicting Decisions and Disorders from Brain Images* (The University of Arizona, Tucson, Arizona, 2022).
19. D. Kahneman, A. Tversky, Choices, values, and frames. *Am. Psychol.* **39**, 341 (1984).
20. H. C. Breiter, I. Aharon, D. Kahneman, A. Dale, P. Shizgal, Functional imaging of neural responses to expectancy and experience of monetary gains and losses. *Neuron* **30**, 619–639 (2001).
21. K. L. Wiggin, M. Reimann, S. P. Jain, Curiosity tempts indulgence. *J. Consum. Res.* **45**, 1194–1212 (2019).
22. M. Reimann, J. Zaichkowsky, C. Neuhaus, T. Bender, B. Weber, Aesthetic package design: A behavioral, neural, and psychological investigation. *J. Consum. Psychol.* **20**, 431–441 (2010).
23. M. Reimann, R. Castaño, J. Zaichkowsky, A. Bechara, How we relate to brands: Psychological and neurophysiological insights into consumer–brand relationships. *J. Consum. Psychol.* **22**, 128–142 (2012).
24. M. Reimann, D. MacInnis, A. Bechara, Can smaller meals make you happy? Behavioral, neurophysiological, and psychological insights into motivating smaller portion choice *J. Assoc. Consum. Res.* **1**, 71–91 (2016).
25. M. Reimann, D. J. MacInnis, V. S. Folkes, A. Uhalde, G. Pol, Insights into the experience of brand betrayal: From what people say and what the brain reveals. *J. Assoc. Consum. Res.* **3**, 240–254 (2018).
26. C. Warren, M. Reimann, Crazy-funny-cool theory: Divergent reactions to unusual product designs. *J. Assoc. Consum. Res.* **4**, 409–421 (2019).
27. W. Hedgcock, A. R. Rao, Trade-off aversion as an explanation for the attraction effect: A functional magnetic resonance imaging study. *J. Mark. Res.* **46**, 1–13 (2009).
28. A. Waegeman, C. H. Declerck, C. Boone, R. Seurinck, P. M. Parizel, Individual differences in behavioral flexibility in a probabilistic reversal learning task: An fMRI study. *J. Neurosci. Psychol. Econ.* **7**, 203–218 (2014).
29. L. Pauwels, C. H. Declerck, C. Boone, P. Diaz-Gutiérrez, B. Lambert, Does power corrupt? An fMRI study on the effect of power and social value orientation on inequity aversion *J. Neurosci. Psychol. Econ.* **15**, 222–240 (2022).
30. H. Markowitz, Portfolio selection. *J. Finance* **7**, 77 (1952).
31. K. A. Norman, S. M. Polyn, G. J. Detre, J. V. Haxby, Beyond mind-reading: Multi-voxel pattern analysis of fMRI data. *Trends Cogn. Sci.* **10**, 424–430 (2006).
32. T. M. Mitchell *et al.*, Learning to decode cognitive states from brain images. *Mach. Learn.* **57**, 145–175 (2004).
33. S. V. Shinkareva *et al.*, Using fMRI brain activation to identify cognitive states associated with perception of tools and dwellings. *PLoS One* **3**, 1–9 (2008).
34. S. M. Tom, C. R. Fox, C. Trepel, R. A. Poldrack, The neural basis of loss aversion in decision-making under risk. *Science* **315**, 515–518 (2007).
35. S. Rabe-Hesketh, A. Skrondal, *Multilevel and Longitudinal Modeling using Stata* (Stata Press Publication, College Station, TX, ed. 3, 2012).
36. H.-C. Cho, S. Abe, Is two-tailed testing for directional research hypotheses tests legitimate? *J. Bus. Res.* **66**, 1261–1266 (2013).
37. S. M. Hoscheidt, L. Nadel, J. Payne, L. Ryan, Hippocampal activation during retrieval of spatial context from episodic and semantic memory. *Behav. Brain Res.* **212**, 121–132 (2010).
38. L. Nadel, S. Hoscheidt, L. R. Ryan, Spatial cognition and the hippocampus: The anterior–posterior axis. *J. Cogn. Neurosci.* **25**, 22–28 (2013).
39. B. De Martino, D. Kumaran, B. Seymour, R. J. Dolan, Frames, biases, and rational decision-making in the human brain. *Science* **313**, 684–687 (2006).
40. M. F. Ji, W. Wood, Purchase and consumption habits: Not necessarily what you intend. *J. Consum. Psychol.* **17**, 261–276 (2007).
41. J. A. Ouellette, W. Wood, Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychol. Bull.* **124**, 54–74 (1998).
42. A. Smidts *et al.*, Advancing consumer neuroscience. *Market. Lett.* **25**, 257–267 (2014).
43. S. A. Engel *et al.*, fMRI of human visual cortex. *Nature* **369**, 525 (1994).
44. J. W. Hutchinson, M. Reimann, B. Knutson, J. Huber, Commentaries on "Reconsidering the path for neural and physiological methods in consumer psychology". *J. Consum. Psychol.* **34**, 214–221 (2024).
45. R. A. Poldrack, Can cognitive processes be inferred from neuroimaging data? *Trends Cogn. Sci.* **10**, 59–63 (2006).
46. T. Yarkoni, R. A. Poldrack, T. E. Nichols, D. C. Van Essen, T. D. Wager, Large-scale automated synthesis of human functional neuroimaging data. *Nat. Methods* **8**, 665–670 (2011).
47. A.-R. Blais, E. U. Weber, A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgm. Decis. Mak.* **1**, 33–47 (2006).
48. Y.-P. Chen, L. D. Nelson, M. Hsu, From "where" to "what": Distributed representations of brand associations in the human brain. *J. Mark. Res.* **52**, 453–466 (2015).
49. H.-Y. Chan, M. Boksem, A. Smidts, Neural profiling of brands: Mapping brand image in consumers' brains with visual templates. *J. Mark. Res.* **55**, 600–615 (2018).
50. A. Tusche, S. Bode, J.-D. Haynes, Neural responses to unattended products predict later consumer choices. *J. Neurosci.* **30**, 8024–8031 (2010).
51. A. Dehghani, T. Glatard, E. Shihab, Subject cross validation in human activity recognition. arXiv [Preprint] (2019), https://doi.org/10.48550/arXiv.1904.02666 (Accessed on 10 July 2020).
52. J. V. Haxby *et al.*, Distributed and overlapping representations of faces and objects in ventral temporal cortex. *Science* **293**, 2425–2430 (2001).
53. C. Basavaraj, M. Reimann, Hippocampal blood oxygenation predicts choices about everyday consumer experiences: A deep-learning approach. Open Science Framework. https://doi.org/10.17605/OSF.IO/PKBV2. Deposited 1 April 2025.