Value signals in the orbitofrontal cortex incorporate reference-dependent news utility

Abstract

We combine fMRI with a carefully designed task to test reference-dependent news utility with pleasant primary rewards. We hypothesize that value signals in the orbitofrontal cortex will incorporate both contemporaneous and prospective news utility, providing a biological foundation for reference-dependence models and information preferences. We also hypothesize that surprise and anticipation utility are separately identifiable psychological processes encoded in the orbitofrontal cortex. Our results may suggest news utility is experienced as a hedonic response and identify a target region in the brain for potential treatment of gambling and social media addiction.

Introduction

Everyday we are faced with experiences that yield hedonic responses, which can be pleasant (like enjoying a tasty meal) or aversive (like receiving an electric shock). The brain encodes these responses as experienced utility signals, which can be found in the orbitofrontal cortex (OFC) [1–5]. These signals are important because they are used in a variety of psychological processes, like learning the value of actions and stimuli [6], affecting memory encoding and retrieval [7, 8], and directly impacting subjective well-being [9]. A key question in neuroeconomics and behavioral economics is what affects experienced utility. For example, is it influenced only by outcomes, or also by beliefs?

Previous survey evidence has shown that anticipation of future outcomes directly affects current experienced utility [10]. The anticipation of future reward is itself attractive and has been shown to elicit value signals in the ventromedial prefrontal cortex (vmPFC) [11, 12]. Even in the case of aversive outcomes, individuals can become so averse to anticipation of an electric shock (i.e. dread), that they prefer a larger immediate electric shock instead of waiting in anticipation [13]. Therefore it seems that experienced utility is indeed influenced by beliefs, and that people are capable of expressing preferences for information.

The study of information preferences can have beneficial impacts for real-world applications, like finance and health. For instance, household investors are inattentive to their portfolios and exhibit greater trading inactivity during stock market downswings compared to upswings [14]. If investors' utility is affected by incoming information and the utility of this information is loss-averse, then investors may prefer to ignore their portfolio if they expect bad news [15]. This prevents investors from perfect consumption smoothing and generates a willingness-to-pay for expensive portfolio managers. Low-income households that may want to save but cannot afford expensive portfolio managers may actively avoid investing if they anticipate future bad news that negatively impacts their experienced utility.

This type of information avoidance also has negative implications for the early diagnosis of children with autism spectrum disorder. Children of parents who self-report a preference for information avoidance are diagnosed roughly 3 months later, on average, than other children [16]. Clearly, preferences for information pervade our everyday lives, and a deeper understanding could prove instrumental for remedying harmful information avoidance behavior.

Behavioral economists have proposed expectations-based models of reference dependence that incorporate beliefs into experienced utility [17–21]. Under these models, experienced utility is represented as a weighted combination of consumption utility (i.e. the direct pleasure derived solely from consumption) and gain-loss utility (i.e. the pleasure derived from deviations from ex ante expectations). This class of models have become quite influential in behavioral economics, and are capable of explaining some puzzling phenomena.

News utility preferences, developed by Kőszegi and Rabin [20], are particularly well suited for the study of information preferences. In this model, experienced utility has three components: the aforementioned consumption utility, contemporaneous news utility, and prospective news utility. Contemporaneous news utility is experienced when a consumer compares current consumption with previously held beliefs about consumption. Prospective news utility is experienced when a consumer compares future expectations about consumption with previously held expectations about consumption. With these three components, the model is able to explain preferences over information structures while also nesting expectations-based reference-dependence.

Recent experimental evidence using electrical shocks has demonstrated that individuals exhibit preferences over different information structures in a manner consistent with news utility preferences [22]. However, the study did not test news utility preferences with positive primary rewards (e.g. juice or food), nor did it test if news utility is affected by context, a crucial aspect of reference-dependence models. It also did not distinguish between different psychological phenomena (surprise and anticipation). The distinction between surprise and anticipation is important, as surprise (i.e. feelings about good or bad news) is a transient experience that deals with preferences over information structures, while anticipation (i.e. savouring or dread) affects well-being both before and after information has been acquired.

Here, I propose to combine fMRI with a carefully designed task to test reference-dependent news utility with positive primary rewards. The goal of this paper is to show that experienced utility both at the time of news and at the time of consumption is modulated by consumption and surprise. We hypothesize that value signals in the OFC will incorporate both contemporaneous and prospective news utility, in addition to consumption utility. Lastly, we will distinguish between experienced utility derived from surprise and from anticipation.

Methods

Model

News utility preferences [20] are modeled as:

$$U_t = m(c_t) + \sum_{\tau=t}^{T} \delta_{t,\tau} \cdot N(B_{t,\tau}|B_{t-1,\tau}) \quad (1)$$

where $m(c_t)$ is a function of consumption at time t, T is the time horizon for utility, $\delta_{t,\tau}$ is the discount factor at time t associated with consumption at time τ, $N(\cdot)$ is a universal gain-loss utility function [23], and $B_{t,\tau}$ is the belief at time t about consumption at time τ.

The first term can be interpreted as consumption experienced utility (cEU), and the second as surprise experienced utility (sEU). Note that when $\tau \in (t, T]$, this utility function implies a preference for good news at time t about consumption in the future. Furthermore, gain-loss utility is also applicable at the time of consumption ($\tau = t$), therefore nesting previous models of reference-dependence [19].

Subjects

Subjects will be heterosexual males under the age of 50. An initial study will collect 50 online subjects using Prolific. Afterwards, data from 60 additional subjects will be collected from the community surrounding Caltech (Pasadena, CA).

Stimulus Set

Our stimulus set will consist of 72 images of real women in lingerie. This stimulus set has been used in three previous studies [11, 12, 24] and has been shown to strongly activate OFC and vmPFC. A meta-analysis of 87 studies using primary and secondary rewards also reports that stimulus sets similar to ours activate prefrontal and orbitofrontal cortex [5]. Furthermore, this stimulus set allows us to circumvent issues with rapid satiety that affect other primary rewards, like juice or food [5].

Tasks

The experiment will unfold in a sequence of 3 tasks. First is a viewing task depicted in Fig. 1A. Subjects view an information screen, which sets their expectations of reward, followed by an outcome screen, which reveals the either a rewarding or non-rewarding stimulus. The viewing task will have 144 trials split into 2 blocks with two different treatments ("contexts"). See Table 1 for a breakdown of trial conditions in the viewing task. In the high block ("H context"), the probabilities presented (p) will be drawn from $\{1, 2/3, 1/3\}$ and the subjects will be made aware of the possible probabilities at the start of the block. This means the expected probability in H context is 2/3, and $p = 1$ will be considered good news and $p = 1/3$ will be considered bad news with respect to expectations. In the low block ("L context"), $p \in \{2/3, 1/3, 0\}$ and subjects are again made aware of this at the start of the block. The expected probability in L context is 1/3, and $p = 2/3$ will be considered good news and $p = 0$ will be considered bad news.

		Probability (p)			
		1	2/3	1/3	0
Block H	Reward	24	16	8	-
E[p]=2/3	No Reward	-	8	16	-
Block L	Reward	-	16	8	-
E[p]=1/3	No Reward	-	8	16	24

* Numbers in the table represent the number of trials in that condition.

Table 1: Viewing task conditions.

Under certain conditions, fractals will be shown on the information and/or outcome screens. For the outcome screen, let F(R,1) represent a fractal when the subject was rewarded ("nR" meaning no reward) and the probability of reward was 1. A fractal will appear when: F(R,1); F(nR,0); F(R,1/3); and F(nR,1/3). For the information screen, let F(H,1) represent a fractal in the H context when the probability of reward was 1. A fractal will appear when: F(H,1); F(H,1/3); and F(L,1/3). These fractals will inherit value from either the information or from the outcome via Pavlovian learning. Before running the fMRI task, we will ensure that the fractals inherit value using an online pilot study. Once these fractals have inherited value from their respective associations, choices between these fractals enable us to test predictions of news utility preferences.

The second of three tasks will be a fractal choice task, depicted in Fig. 1B. Subjects are asked to make a choice between two fractals which they have seen in the previous task. The subject will face 6 unique choices, each repeated 4 times in random order, for a total of 24 trials. 2 of these choices are designed to test for the existence of contemporaneous news utility: (1) F(R,1/3) vs. F(R,1); (2) F(nR,0) vs. F(nR,1/3). 2 are designed to test for the existence of prospective news utility: (3) F(H,1) vs. F(H,1/3); (4) F(L,1/3) vs. F(H,1/3). The final 2 are designed to compare news utility with consumption utility: (5) F(L,1/3) vs. F(nR,0); (6) F(H,1/3) vs. F(nR,1/3).

Finally, the last of three tasks will be a liking rating task, depicted in Fig. 1C. Subjects will be asked to rate how much they like each rewarding stimulus on a discrete scale from -1 (dislike) to 3 (really like) with free response time. Collecting these ratings gives us an independent measure of value associated with each reward, which we can use to control for reward valence during fMRI analysis.

Inference Strategy

We will first calibrate the experiment using an online study with 50 subjects on Prolific. Next, we will collect data from 60 subjects in-person, and the viewing task will be conducted in an fMRI scanner. The first 30 subjects will be allocated to the exploratory sample. We will use this to explore the data and pin down our analyses. The later 30 subjects will be allocated to the confirmatory sample, where we will attempt to replicate the results from the exploratory sample. If the results in the exploratory and confirmatory sample are similar, we will combine the two samples into a joint data set in the spirit of meta-analysis and report on those results.

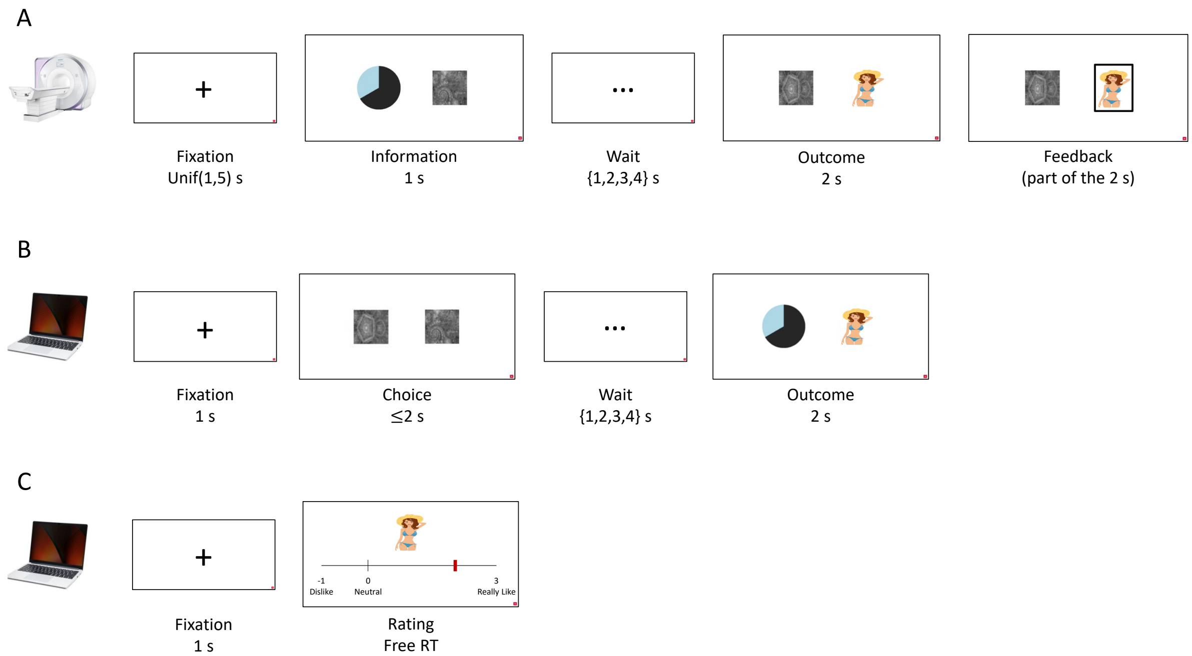

Fig. 1: Tasks. Each subject will complete a sequence of three tasks. (A) Viewing task in the fMRI scanner. A trial begins with a fixation cross for 1 to 5 seconds. An information screen is then presented for 1 second with the probability of receiving a reward in blue and the probability of seeing a no-reward black rectangle in black. The probability is represented in the form of a pie chart, which will be displayed on the left or right side of the screen with 50% probability. The information screen is followed by a waiting screen for 1 to 4 seconds. After, the outcome screen is shown for 2 seconds, with either the rewarding stimulus or no-reward stimulus displayed on the left or right side of the screen with 50% probability. Subjects are asked to press left or right depending on what side of the screen the outcome stimulus is presented. A feedback box will appear during the 2 second outcome screen duration depending on the subject's choice. On certain trials, fractals will be displayed on the information and/or outcome screens on the opposite side of the stimuli. (B) Behavioral fractal choice task. A trial begins with a 1 second fixation cross. After, two fractals are presented on the left and right sides of the screen. Subjects are asked to make a choice between the two fractals within 2 seconds. Upon making a choice, a waiting screen appears for 1 to 4 seconds. After waiting, the outcome screen appears for 2 seconds, displaying either the outcome associated with the fractal (in the case of fractals associated with outcomes) or both the pie chart and outcome associated with the fractal (in the case of fractals associated with information). (C) Behavioral rating task. A trial begins with a 1 second fixation cross. After, subjects are given free response time to rate each of the 72 stimuli on a scale from -1 (dislike) to 3 (really like).

fMRI Data Acquisition

Imaging data will be collected at the Caltech Brain Imaging Center (Pasadena, CA) using a 3T Siemens Magneto TrioTim scanner using a 32-channel radio frequency coil.

Hypotheses

Behavioral

If experienced utility only consists of cEU, then for all 6 unique choices in the fractal choice task, subjects should choose either fractal with equal probability. However if experienced utility consists of cEU and sEU, then subjects should exhibit a preference for F(R,1/3) in choice (1), F(nR,0) in choice (2), F(H,1) in choice (3), and F(L,1/3) in choice (4). See Table 2 (rows cEU and cEU+sEU) and Table 3 for model predictions.

Context	H			L		
Probability	1	2/3	1/3	2/3	1/3	0
cEU	0	0	0	0	0	0
cEU + sEU	$0+1/3$	$0+0$	$0-1/3$	$0+1/3$	$0+0$	$0-1/3$
cEU + aEU	$0+.6$	$0+.4$	$0+.2$	$0+.4$	$0+.2$	$0+0$

Table 2: Model predictions for utility at the time of news.

Outcome	Reward			No Reward		
Probability	1	2/3	1/3	2/3	1/3	0
cEU	1	1	1	0	0	0
cEU + sEU	$1+0$	$1+1/3$	$1+2/3$	$0-2/3$	$0-1/3$	$0+0$

Table 3: Model predictions for utility at the time of consumption.

fMRI

During the viewing task, if experienced utility signals in the OFC are independent of contemporaneous news utility, then we expect neural signals of value to be at baseline when no rewarding stimulus is presented and to be high when the rewarding stimulus is presented, regardless of the initial probability of reward. See Fig. 2A for predictions of experienced utility signals independent of surprise.

In contrast, if experienced utility signals are dependent on contemporaneous news utility, then we expect neural signals of value to scale with the amount of surprise that the outcome induces. For instance, if the outcome is no reward, then we expect a lower signal if the reward was likely ($p = 2/3$) than if it was unlikely ($p = 1/3$). Similarly, we expect neural signal to be monotone decreasing in the probability of reward. See Fig. 2B for predictions of experienced utility signals modulated by contemporaneous news utility. A comparison of the BOLD responses in the OFC at the time of outcome (see Fig. 2C) will provide the key test of the hypotheses.

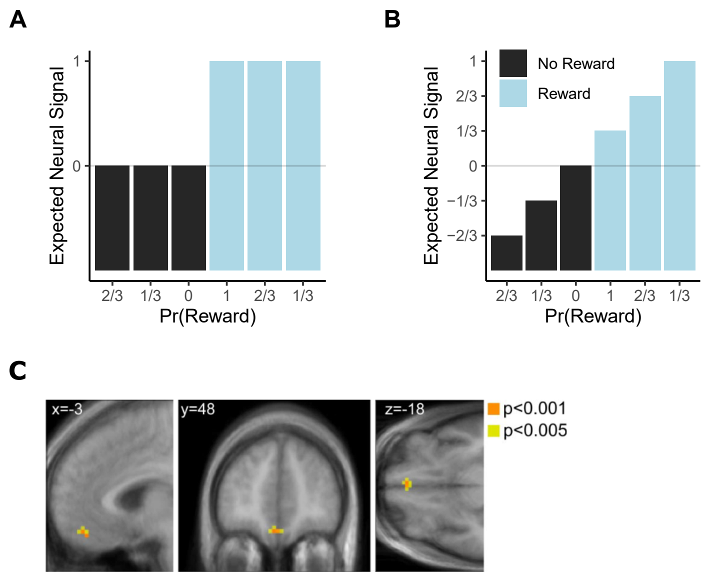

Fig. 2: Predictions of BOLD activity in OFC. (A) Expected neural signal at the time of consumption as a function of the probability of reward if OFC does *not* encode contemporaneous news utility. (B) Expected neural signal if OFC does encode contemporaneous news utility. (C) From Plassmann et al. [4]. Activity in OFC correlates with reported pleasantness of liquids at time of consumption. We hypothesize that news utility signals are encoded in the same region.

News Utility Vs. Anticipation Utility

To clarify the distinction between sEU and anticipation experienced utility (aEU), we look at neural signals at the news and waiting stages of the viewing task. Specifically, sEU occurs at the information and outcome screens (Fig. 3A), whereas aEU occurs during the waiting period between information and outcome (Fig. 3B). According to previous models of anticipation utility [11, 12], aEU only depends on the probability of receiving a reward, not on the context. Given that our experiment manipulates the context in which information is presented, models incorporating either sEU or aEU make different predictions about neural signal at the time of news (see Table 2 and Fig. 3C-D). Choice (4) from the fractal choice task also allows us to differentiate surprise and anticipation utility at the time of news since news utility implies a preference for F(L,1/3), whereas anticipation utility implies indifference between the alternatives.

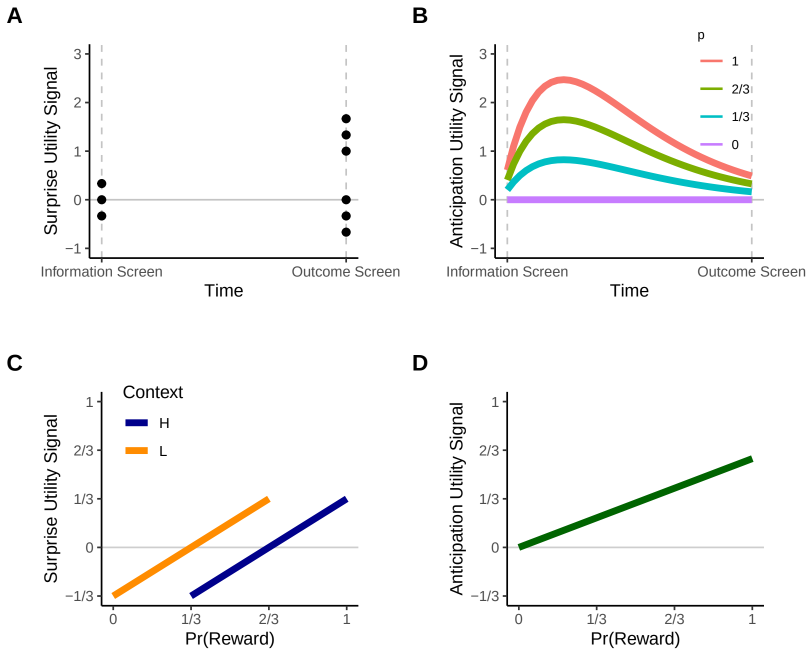

Fig. 3: Surprise utility versus anticipation utility signals. (A) News utility signal throughout the entire trial, starting at the time of news and ending at the time of consumption. Note that expected neural signal for news utility is transient, and depends on context at the time of news and on outcome at the time of consumption. (B) Anticipation utility signal throughout the entire trial. (C) Expected neural signal for news utility at the time of news as a function of the probability of reward. (D) Expected neural signal for anticipation utility at the time of news as a function of the probability of reward.

Conclusion

Beliefs, not just outcomes, directly impact our experienced utility. We hypothesize that the orbitofrontal cortex encodes not only consumption utility, but also contemporaneous and prospective news utility. We also hypothesize that news utility is encoded in a reference-dependent manner, providing a biological foundation expectations-based reference dependence models, especially news utility preferences [20].

To test this, we will run an experiment with a sequence of three tasks: (1) a viewing task where we manipulate expectations about rewards, (2) a fractal choice task where we test the predictions of news utility preferences, and (3) a rating task where we collect independent measures of value to control for reward valence in our fMRI signal. We hypothesize that subjects will exhibit a preference for good news and enjoy pleasant surprises more than certain outcomes, ceteris paribus. Furthermore, we hypothesize that surprise and anticipation signals are encoded in the OFC and are separable signals.

Our results may have important implications for a variety of real-world applications. First, it demonstrates a rigorous methodology for measuring information preferences, which can be beneficial for developing targeted policy to encourage low-income households to save and invest, as well as, to encourage individuals to seek out early diagnosis of health disorders. Second, it provides a deeper understanding of the addictive nature of gambling and social media. For instance, those who abnormally overweight news utility over consumption utility may find risky gambles more appealing since their utility for low probability, high reward payoffs is exaggerated by the element of surprise. Furthermore, the constant urge to check social media may be partially driven by positive news utility every time one checks their feed. A social media influencer might post an advertisement for clothing, which you may become interested in buying. Or a friend posts a video of a travel destination that you suddenly dream of visiting. Previous studies have argued that social rewards (e.g. likes or reposts) act as a reinforcer for social media addiction [25, 26]. News utility offers a different source of reinforcement that may also contribute to social media addiction.

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