Neural precursors of decisions that matter—an ERP study of deliberate and arbitrary choice

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Abstract

The onset of the readiness potential (RP)—a key neural correlate of upcoming action—was repeatedly found to precede subjects' reports of having made an internal decision. This is famously taken as evidence against a causal role for consciousness in human decisions making and thus as a denial of free-will. Yet those studies focused on purposeless, unreasoned, arbitrary decisions, bereft of consequences. It remains unknown to what degree these neural precursors of action generalize to deliberate decisions, which are more ecological and relevant to real life. We therefore directly compared the neural correlates of deliberate and arbitrary decision-making during a $1000-donation task to non-profit organizations. While we found the expected RPs for arbitrary decisions, they were strikingly absent for deliberate ones. Our results are congruent with the RP representing the accumulation of noisy, random fluctuations, which drive arbitrary—but not deliberate—decisions. The absence of RPs in deliberate decisions challenges the generalizability of studies that argue for no causal role for consciousness in decision making from arbitrary to deliberate, real-life decisions.

Introduction

Humans typically experience freely selecting between alternative courses of action, say, ordering a particular item off a restaurant menu. Yet a series of human studies using EEG[1-3], fMRI[4-7], intracranial[8], and single-cell recordings[9] challenged the validity of this common experience, finding neural correlates of decision processes hundreds of milliseconds and even seconds prior to the time that subjects reported having consciously decided. These findings have been captivating scholars from many disciplines in and outside of academia[10-15], with the prospect that the subjective human experience of freely deciding is but an illusion, because human actions might be unconsciously initiated before the conscious decision to act[1,15].

However, in the above studies, subjects were only asked to either decide when to move their hand or flex their wrist, and sometimes also to decide whether to move the right or left hand.[12,16] That is, their decisions were unreasoned, purposeless, and bereft of any real consequence. This stands in sharp contrast to most real-life decisions that are reasoned, purposeful, and bear consequences[17]—from which clothes to wear to what route to take to work, to more formative decisions about life partners, career choices, and so on. Such deliberate decisions are also at the center of the philosophical debate on free will[18,19]. They typically involve more conscious and lengthy deliberation, and could thus be more tightly bound to conscious processes.

Interestingly, though deliberate decisions have been widely studied in the field of neuroeconomics[20,21] or in perceptual tasks[22], little has been done to assess the relation between decision-related activity and subjects' conscious experience of deciding. Here, we combine the two fields of research by comparing neural precursors of deliberate and arbitrary decisions in an EEG experiment. Our experiment utilized a donation-preference paradigm, in which a pair of non-profit organizations (NPOs) were presented in each trial. In deliberate-decision trials, subjects' chose to which NPO they would like to donate $1000, while in arbitrary-decision trials both NPOs received an equal donation of $500, irrespective of

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subjects' key presses (Figure 1). Notably, while the visual inputs and motor outputs were identical between deliberate and arbitrary decisions, the decisions' meaning was radically different: in deliberate blocks, the decisions were meaningful and consequential reminiscent of important, real-life decisions—while in arbitrary blocks, the decisions were meaningless and bereft of consequences—mimicking previous studies of volition.

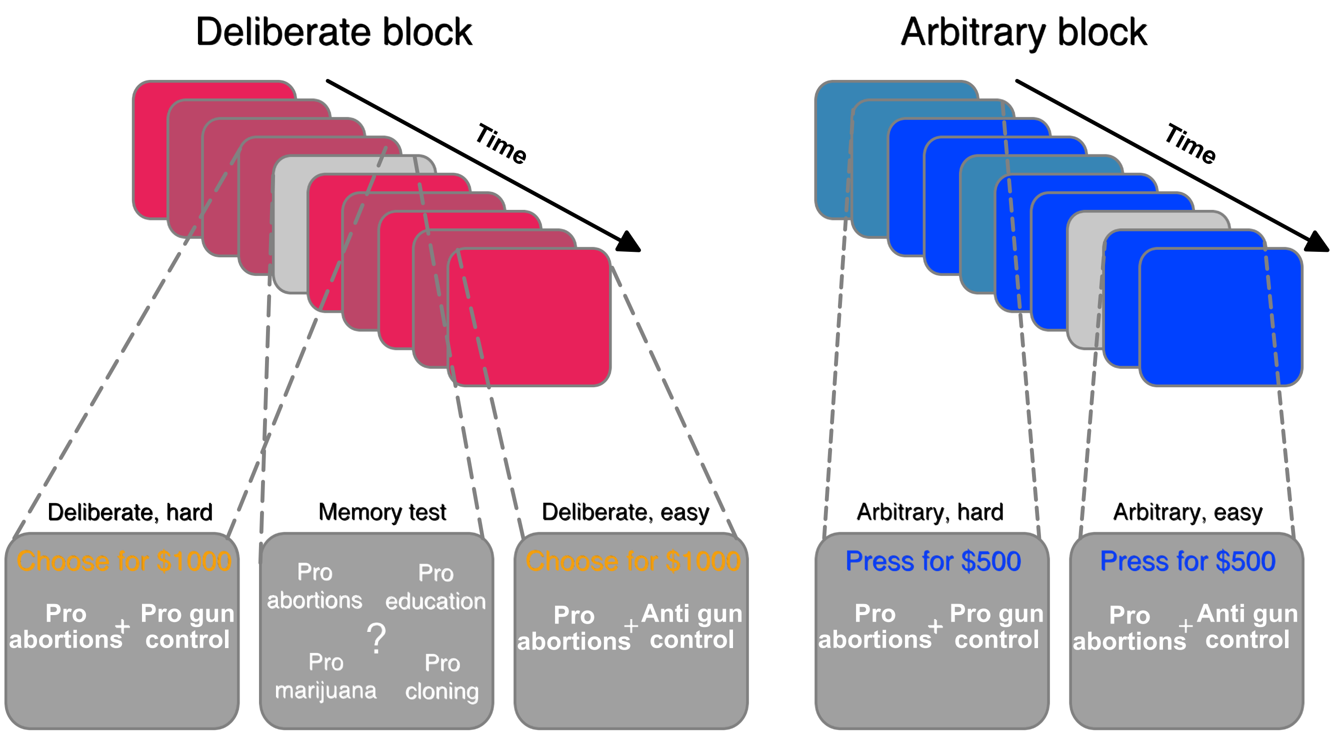

Figure 1: Experimental paradigm. The experiment included deliberate (red, left) and arbitrary (blue, right) blocks, each containing nine trials. In each trial, two NPO names were presented, and subjects were asked to either choose to which NPO they would like to donate (deliberate), or to simply press either right or left, as both NPOs would receive an equal donation (arbitrary). Within each block, some of the trials were easy (lighter colors) decisions, where the subject's preferences for the two NPOs substantially differed (based on a previous rating session), and some were hard decisions (darker colors), where the preferences were more similar (easy and hard trials were intermixed within each block). To make sure subjects were paying attention to the NPO names even in arbitrary trials, memory tests (in grey) were randomly introduced, where subjects were asked to determine which of four NPO names appeared in the immediately previous trial.

Results

Behavioral Results

To validate the experimental paradigm, we manipulated decision difficulty as well as decision type (Fig. 1). We reasoned that this should affect only deliberate decisions, and not arbitrary ones. Subjects' behavior confirmed that the experimental manipulation was successful. Subjects' reaction times (RTs) were substantially slower for deliberate than for arbitrary decisions (Figure 2, left; $F(1,17)=126.11$, $p<0.0001$ for the main effect of decision type, as revealed by a 2-way ANOVA. The ANOVA also showed a main effect of decision difficulty, $F(1,17)=18.76$, $p=0.0004$; all analyses were performed on log-transformed data, because the raw RTs violated the normality assumption ($W=0.94$, $p=0.001$)). Moreover, in deliberate decisions subjects were slower for hard vs. easy decisions ($F(1,17)=20.12$, $p=0.0003$ for the interaction between decision type and decision difficulty; hard vs. easy deliberate decisions: $t(17)=4.78$, $p=0.0002$, and not significantly different between hard vs. easy arbitrary decisions: $t(17)=1.01$, $p=0.325$). This further demonstrates that in deliberate decisions, subjects were making meaningful decisions, affected by the different values of the two NPOs, while in arbitrary decisions they were not.

The consistency between subjects' choices throughout the main experiment and the NPO ratings they gave prior to the main session was also analyzed (see methods). As expected, subjects were highly consistent with their own, previous ratings when making deliberate decisions, but not when making arbitrary ones (Figure 2, right; $F(1,17)=946.55$, $p<0.0001$ for the main effect of decision type. A main effect of decision difficulty was also found: $F(1,17)=57.39$, $p<0.0001$. Again, decision type and decision difficulty interacted ($F(1,17)=25.96$, $p<0.0001$: subjects were much more consistent with their choices in easy vs. hard deliberate decisions ($t(17)=11.15$, $p<0.0001$), than they were in easy vs. hard arbitrary decisions ($t(17)=2.50$, $p=0.028$); though subjects were around chance in their consistency in arbitrary decisions (ranging between 0.39 to 0.64; it seems some subjects were slightly influenced by their preferences in arbitrary, easy decisions trials). Finally, no differences were found between subjects' tendency to press the right vs. left button in the different conditions (both main effects and interaction: F<1).

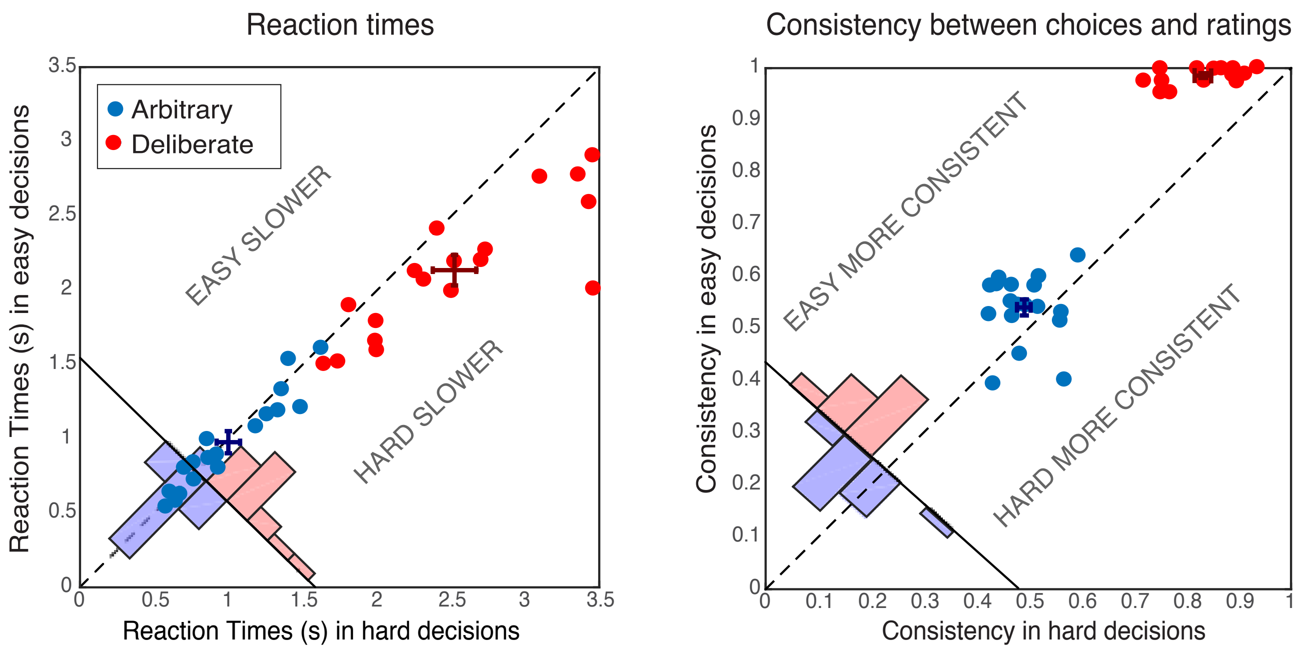

Figure 2: Behavioral results. Response Times (RTs; left) and Consistency Grades (CG; right) in arbitrary (blue) and deliberate (red) decisions. Each dot represents the average RT/CG for easy and hard decisions for an individual subject (hard decisions: x-coordinate; easy decisions: y-coordinate). Group means and SEs are represented in dark red and blue crosses. The histograms at the bottom-left corner of each plot sum the number of dots with respect to the solid diagonal line. The dashed diagonal line represents equal times/consistency for easy and hard decisions; data points below that diagonal indicate longer RTs or higher CGs for hard decisions. In both measures, arbitrary decisions are more centered around the diagonal than deliberate decisions, showing no or substantially reduced differences between easy and hard decisions.

EEG Results

Readiness Potential (RP)

The RP, generally held to index unconscious readiness for upcoming movement[1,12,23,24] (though see [25-27]), was measured over electrode Cz in the different conditions by averaging the activity in the 2 s prior to subjects' movement. Focusing on the last 500 ms before movement onset for our statistical tests, we found a clear RP in arbitrary decisions, yet the RP was completely absent in deliberate decisions (Figure 3; ANOVA $F(1,17)=11.86$, $p=0.003$ for the main effect of decision type; in t-tests against zero, corrected for multiple comparisons, an effect was only found for deliberate decisions (hard: $t(17)=5.75$, $p<0.0001$; easy: $t(17)=5.09$, $p=0.0004$) and not for arbitrary ones (hard: $t(17)=1.24$, $p>0.5$; easy: $t(17)=1.84$, $p=0.336$). Similarly, regressing voltage against time for the last 1000 ms before movement onset, the downward trend was significant for arbitrary decisions ($p<0.0001$, for both easy and hard) but not for deliberate decisions (hard: $p>0.5$, easy: $p=0.35$; all Bonferroni corrected for multiple comparisons)). Notably, this pattern of results was also manifested for single-subject analysis (Fig. S1; 14 of the 18 subjects had significant downward slopes for arbitrary decisions—i.e., $p<0.05$, Bonferroni corrected for multiple comparisons—when regressing voltage against time for every trial over the last 1000 ms before movement onset; but only 5 of the 18 subjects had significant downward slopes for the same regression analysis for deliberate decisions; see methods. In addition, the average slope for deliberate and arbitrary decisions were -0.43 ± 0.31 and -2.30 ± 0.44 (mean±SE), respectively, a significant difference: $t(17)=3.51$, $p=0.001$). The pattern of results seen in Fig. 3A also persisted when separating left-hand button presses from right-hand ones (Figure S2), suggesting that it was not affected by the hand that executed the movement.

RTs in deliberate decisions were typically more than twice as long as RTs in arbitrary decisions. We therefore wanted to rule out the possibility that the absence of RP in deliberate decisions stems from the difference in RTs between the conditions. We carried out two analyses for this purpose. First, we divided the subjects into two groups based on their RT—lower and higher than the median for deliberate and arbitrary trials, respectively—and ran the same analysis using only the faster subjects in the deliberate condition (M=1.91s, SD=0.25) and the slower subjects in the arbitrary condition (M=1.25s, SD=0.23) (Fig. S3A). If RT length affects RP amplitudes, we would expect the RP amplitudes to be more similar between these two groups. However, though there were only half the data points, a similar pattern of results was observed (Figure S3; $F(1,32)=5.11$, $p=0.031$), with significant RP found in arbitrary (easy: $t(8)=4.57$, $p=0.0018$; hard: $t(8)=4.09$, $p=0.0035$), but not deliberate (easy: $t(8)=1.92$, $p=0.09$; hard: $t(8)=0.63$, $p=0.54$) decisions.

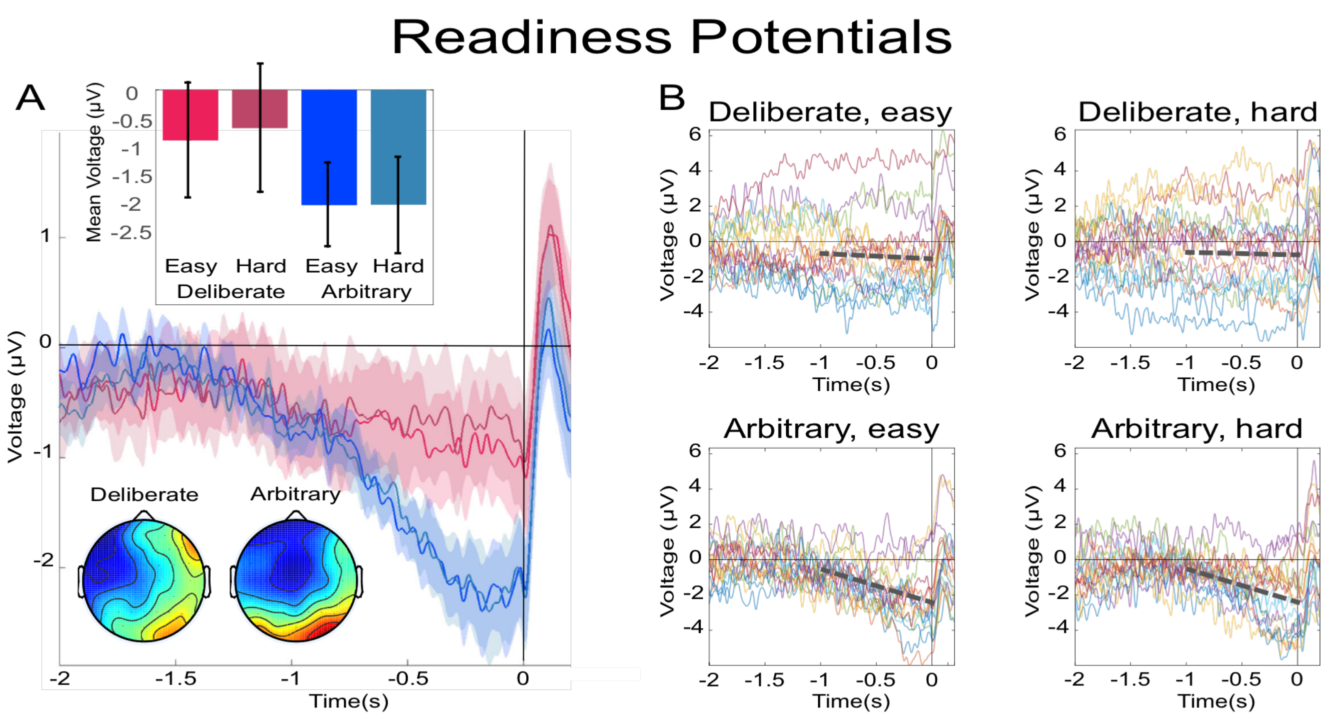

Figure 3: (A) Mean and SE of the Readiness Potential (RP) in deliberate (red shades) and arbitrary (blue shades) easy and hard decisions in electrode Cz, as well as scalp distributions. Zero refers to time of right/left response made by the subject. Notably, the RP significantly differs from zero and displays a typical scalp distribution for arbitrary decisions only. The scalp distribution was calculated over the averaged activity during the last 500 ms before response, across subjects. The inset shows the mean amplitude of the RP, with 95% confidence intervals over the same time window. (B) Individual subjects' Cz activity in the four conditions (n=18). The linear-regression line for voltage against time over the last 1000 ms before movement onset is designated by a dashed, dark-grey line. Note that the waveforms converge to an RP only in arbitrary decisions.

Second, we regressed the difference between RPs (averaged over the last 500 ms before movement onset) in deliberate and arbitrary decisions against the difference between the RTs in these two conditions for each subject (Fig. S3B). Again, if RT length affects RP amplitudes, we would expect differences between RTs in deliberate and arbitrary conditions to correlate with differences between RPs in the two conditions. But no correlation was found between the two measures. Taken together, these results provide strong evidence against the claim that the difference in RPs stems from or is affected by the difference in RTs between the conditions.

Lateralized Readiness Potential (LRP)

The LRP, which reflects activation processes within the motor cortex for action preparation after response selection,[28,29] was measured by subtracting the difference potentials (C3-C4) in right-hand response trials from this difference in left-hand responses trials and averaging the activity over the same time window.[2,28] In this purely motor component, no difference was found between the two decision types (Fig S4; all Fs<1).

Drift Diffusion Model (DDM)

The main finding of this study—the absence of RP in deliberate decisions – is in line with a recent work that used a Drift-diffusion model (DDM) to claim that the RP is a mere artifact of time-locking neural activity to movement onset [25]. DDMs of decision-making typically feature a process that rises toward a threshold. The crossing of that threshold reflects the onset of the decision in the model, possibly leading to action. Schurger and colleagues[25] modelled arbitrary decisions, and suggested that there the threshold crossing leading to movement onset is largely determined by spontaneous subthreshold fluctuations of the neural activity. This challenged the common view of the RP as a neural correlate of unconscious preparation for upcoming action[24]. Instead, Schurger and colleagues claimed, time-locking to movement onset ensures that these spontaneous fluctuations appear, when averaged over many trials, as a gradual increase in neural activity.

To further assess this interpretation of the RP, we expanded the model developed by Schurger and colleagues[25] to a DDM that was composed of a *value-assessment* component and a *noise-generation* component. Under this assumption, Cz-electrode activity mainly reflects the noise-generation component. Each trial was further modeled as a race to threshold between two alternatives: one where the subject chose the NPO that was rated higher in the earlier rating session (the *congruent* option) and the other where the subject preferred the lower-rated NPO (the *incongruent* option). Each race was represented as a leaky stochastic accumulator (see Methods for details and model parameters).

We fit our DDM to our average empirical reaction-times, which were 2.13, 2.52, 0.98 and 1.00 s for the different conditions (henceforth, magnitudes are given for deliberate easy, deliberate hard, arbitrary easy, and arbitrary hard, respectively). The model's mean RTs were 2.04, 2.46, 0.94, and 0.96 s for these conditions (Fig. 4A, B). The model was further fit to the empirical congruency ratios (the proportions of congruent decisions), which were 0.99, 0.83, 0.54 and 0.49. The model's congruency ratios were 1.00, 0.84, 0.53 and 0.53. The model then predicted the shape of the ERP in its noise component (assumed to reflected by Cz-electrode activity) for each decision type: a continuing, RP-like decrease in activity for arbitrary decisions, but only a very slight decrease in activity for deliberate decisions (Fig. 4C; see also Fig S5), which was well in line with our empirical results (Fig. 3A).

Discussion

Since the publication of Libet's seminal work claiming that neural precursors of action, in the form of the RP, precede subjects' reports of having consciously decided to act[1], a vigorous discussion has been ranging between neuroscientists, philosophers, and other scholars about the meaning of these findings for the debate on free will (recent collections include [30-32]). Some claim that these results have removed conscious will from the causal chain leading to action[15,3312,33]. Others are unconvinced that these results are decisive for, or even applicable to, the free-will debate [18,19,34]. At the heart of much of this debate lies the RP, thought to represent unconscious decision/planning mechanisms that initiate subjects' decisions prior to their conscious experience of deciding[1,23].

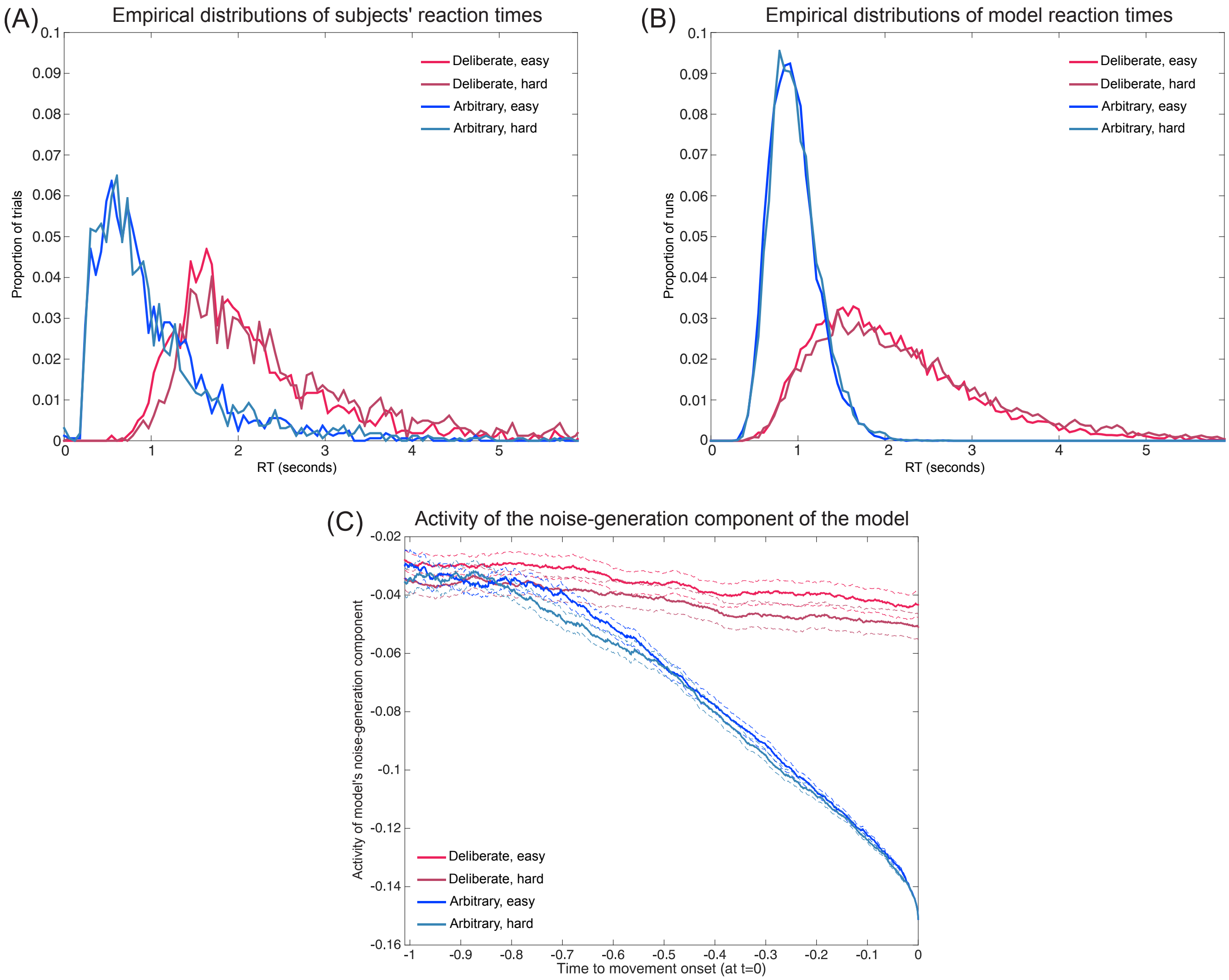

Figure 4: (A) The empirical distributions of subjects' RTs across the four decision types. (B) The equivalent distributions of RTs for the model. (C) The model's prediction for the ERP activity in electrode Cz across all four decision types.

Notably, the RP and similar findings showing neural activations preceding the conscious decision to act have typically been based on arbitrary decisions of different types[1,2,4,5,13,35,36]. This, among other reasons, rested on the notion that for an action to be completely free, it should not be determined in any way by external factors[37]—which is the case for arbitrary, but not deliberate, decisions (where each decision alternative is associated with a value, and the value of alternatives typically guide one's decision). But this notion of freedom faces several obstacles. First, most discussions of free will focus on deliberate decisions, asking when and whether these are free[38-40]. This might be because everyday decisions to which we associate freedom of will—like choosing a more expensive but more environmentally friendly car, helping a friend instead of studying more for a test, donating to charity, and so on—are generally deliberate, in the sense of being reasoned, purposeful, and bearing consequences (although see[41]). In particular , the free will debate is often considered in the context of moral responsibility (e.g., was the decision to harm another person free or not)[12,42-46], and free will is even sometimes defined as the capacity that allows one to be morally responsible[34,47]. In contrast, it seems meaningless to assign blame or praise to arbitrary decisions. Thus, though the scientific operationalization of free will has typically focused on arbitrary decisions, the common interpretations of these studies—in neuroscience and across the free will debate—have often alluded to deliberate ones. Here, we show that this type of inference may not be justified, as the neural precursors of arbitrary decisions do not generalize to meaningful ones[18,19]. Interestingly, while the RP was present in deliberate decisions but absent in arbitrary ones, the LRP—a central, more-motor ERP component—was indistinguishable between the different decision types. This provides evidence that, at the motor level, the neural representation of the deliberate and arbitrary decisions that our subjects made may have been indistinguishable, as was our intention when designing the task.

Our finding and the model thus suggests that two different mechanisms may be involved in arbitrary and deliberate decisions. Earlier literature demonstrated that deliberate, reasoned decision-making—which was mostly studied in the field of neuroeconomics[20] or using perceptual decisions[22]—elicited activity in the prefrontal cortex (PFC; mainly the dorsolateral (DLPFC) part[48,49] and ventromedial (VMPFC) part/orbitofrontal cortex (OFC)[50,51] and the anterior cingulate cortex (ACC)[52,53]. Arbitrary, meaningless decisions, in contrast, were mainly probed using variants of the Libet paradigm, showing activations in the Supplementary Motor Area (SMA), alongside other frontal areas like the frontomedian cortex[54,55] or the frontopolar cortex, as well as the posterior cingulate cortex[4,9] (though see[56], which suggests that a common mechanism may underlie both decision types). Possibly then, arbitrary and deliberate decisions may differ not only in respect to the RP, but may be subserved by different underlying neural circuits, which makes generalization from one class of decisions to the other more difficult. Future studies need to explore the relations between deliberate decision-making and subjects' conscious experience of reaching a decision.

Aside from highlighting the differences between arbitrary and deliberate decisions, this study also challenges a common interpretation of the function of the RP. If the RP is not present before deliberate action, it does not seem to be a necessary link in the general causal chain leading to action. Schurger and colleagues[25] suggested that the RP reflects stochastic fluctuations in neural activity that lead to action following a threshold crossing when humans arbitrarily decide to move. Our results and our model are in line with that interpretation and expand upon it, suggesting that the RP represents the accumulation of noisy, random fluctuations that drive arbitrary decisions, while deliberate decisions are mainly driven by the values associated with the decision alternatives[57]. Our DDM was based on the assumption that every decision is driven by a component based on the values of the decision alternatives (the subject's support for the two NPOs in our case) and by another component representing noise—random fluctuations in neural activity. The value component plays little to no role in arbitrary decisions, so action selection and timing depend on when the accumulation of noise crosses the decision threshold for the congruent and incongruent decision alternatives. In deliberate decisions, in contrast, the value component drives the decisions, while the noise has a smaller effect. Thus, in arbitrary decisions, action onset closely tracks threshold crossings of the noise accumulation. But, in deliberate decisions, the noise component is at more random levels at movement onset. Hence, locking the ERP to movement onset and averaging over trials to obtain the RP, leads to a relatively flat signal for deliberate decisions but to the expected RP shape in arbitrary decisions. This provides strong evidence that the RP is an artificial signal, induced by threshold crossing of random fluctuations in arbitrary decisions and absent in deliberate ones. Further studies of the causal role of consciousness in deliberate versus arbitrary decisions are required to test this claim.

Methods

Subjects

Eighteen healthy subjects participated in the study. They were California Institute of Technology (Caltech) students as well as members of the Pasadena community. All subjects had reported normal or corrected-to-normal sight and no psychiatric or neurological history. They volunteered to participate in the study for payment ($20 per hour). Subjects were prescreened to include only participants who were socially involved and active in the community (based on strength of their support of social causes, past volunteer work, past donations to social causes, and tendency to vote). Two additional subjects were excluded, one due to highly noisy recording and the other due to extremely long RTs, which deviated from the mean by more than two standard deviations. The experiment was approved by Caltech's Institutional Review Board, and informed consent was obtained from all participants after the experimental procedures were explained to the subjects.

Stimuli and apparatus

Subjects sat in a dimly lit room. The stimuli were presented on a 21" Viewsonic G225f (20" viewable) CRT monitor with a 60-Hz refresh rate and a 1024×768 resolution using Psychtoolbox version 3 and Mathworks Matlab 2014b[58,59]. They appeared with a gray background (RGB values: [128, 128,128]). The screen was located 60 cm away from subjects' eyes. Stimuli included names of 50 real non-profit organizations (NPOs). Twenty organizations were consensual (e.g., the Cancer Research Institute, or the Hunger project), and thirty were more controversial: we chose 15 causes that are widely debated (e.g., pro/anti guns, pro/anti abortions), and selected one NPO that supports each of the two sides of the debate. This was done to achieve variability in subjects' willingness to donate to the different NPOs. In the main part of the experiment, succinct descriptions of the causes (e.g., pro-marijuana legalization, pro-child protection; for a full list of NPOs and acronyms, see Table S1) were presented in black Comic Sans MS.

Procedure & Experimental Design

In the first part of the experiment, subjects were presented with each NPO separately. They were instructed to rate how much they would like to support that NPO with a $1000 donation on a scale of 1 ("I would not like to support this NPO at all) to 7 ("I would very much like to support this NPO"). No time pressure was put on the subjects, and they were given access to the website of each NPO to give them the opportunity to learn more about the NPO and the cause it supports.

After the subjects finished rating all NPOs, the main experiment began. It included 360 trials, divided into 40 blocks of 9 trials each. In each block, subjects made either deliberate or arbitrary decisions. Two succinct causes descriptions. representing two actual NPOs, were presented in each trial (Fig. 1). In deliberate blocks, subjects were instructed to choose the NPO to which they would like to donate $1000 by pressing the <Q> or <P> key on the keyboard, for the NPO on the left or right, respectively, as soon as they decided. Subjects were informed that at the end of each block one of the NPOs they chose would be randomly selected to advance to a lottery. Then, at the end of the experiment, the lottery will take place and the winning NPO will receive a $20 donation. In addition, that NPO will advance to the final, inter-subject lottery, where one subject's NPO will be picked randomly and will be given a $1000 donation. It was stressed that the donations were real and that no deception was used in the experiment. To persuade the subjects that the donations are real, we presented a signed commitment to donate the money, and promised to send them the donation receipts after the experiment. Thus, subjects knew that in deliberate trials, every choice they made was not hypothetical, and could potentially lead to an actual $1020 donation to their chosen NPO.

Arbitrary trials were identical to deliberate trials except for the following crucial differences. Subjects were told that, at the end of each block, the pair of NPOs in one randomly selected trial would advance to the lottery together. And, if that pair wins the lottery, both NPOs would receive $10 each. Further, the NPO pair that would win the inter-subject lottery would receive a $500 donation each. Hence it was stressed to the subjects that there was no reason for them to prefer one NPO over the other in arbitrary blocks, as both NPOs would receive the same donation regardless of their button press. Subjects were told to therefore simply press either <Q> or <P> when they felt the urge to do so.

Thus, while subjects' decisions in the deliberate blocks were meaningful and consequential, their decisions in the arbitrary blocks had no impact on the final donations that were made. In these trials, subjects were further urged not to let their preferred NPO dictate their response. Note that we did not ask subjects to report their "W-time" (time of consciously reaching a decision), because this measure was shown to rely on neural processes occurring after movement onset[60] and to potentially be backward inferred from movement time[61]. Even more importantly, clock monitoring was demonstrated to have an effect on RP size[62], so it could potentially confound our results[63].

In addition, we manipulated decision difficulty (Easy/Hard) throughout the experiment, randomly intermixed within each block. Decision difficulty was determined based on the rating difference between the two presented NPOs. NPO pairs with 1 or 4 or more rating point difference were designated hard or easy, respectively. Based on each subject's ratings, we created a list of NPO pairs, half of each were easy choices and the other half hard choices.

Each block started with an instruction written either in dark orange (Deliberate: "In this block choose the cause to which you want to donate $1000") or in blue (Arbitrary: "In this block both causes may each get a $500 donation regardless of the choice"). Short-hand instructions appeared at the top of the screen throughout the block in the same colors as that block's initial instructions; Deliberate: "Choose for $1000" or Arbitrary: "Press for $500 each" (Fig. 1). Each trial started with a fixation cross, with a duration drawn from a uniform distribution between 1 and 1.5s. Then, the two cause descriptions appeared on the left and right side of the fixation cross (left/right assignments were randomly counterbalanced), and remained on the screen until the subjects responded with a key press. The cause corresponding to the pressed button then turned white, and a new trial started. If subjects did not respond within 20s, they received an error message and were informed that if this trial would be selected for the lottery, no NPO would receive a donation. However, this did not happen for any subject on any trial.

To assess the consistency of subjects' decisions during the main experiment with their ratings in the first part of the experiment, subjects' choices were coded in the following way: each binary choice in the main experiment was given a consistency grade of 1, if subjects chose the NPO that was rated higher in the rating session, and 0 if not. Then a consistency grade was calculated as the mean over all the choices. A consistency grade of 1 indicates perfect consistency with one's ratings, 0 – perfect inconsistency, and 0.5 – chance performance.

To better equate memory load, attention, and other cognitive aspects between deliberate and arbitrary decisions—except those aspects directly associated with the decision type, which was the focus of our investigation—we wanted to make sure subjects were carefully reading and remembering the causes also during the arbitrary trials. We therefore randomly interspersed 36 memory catch-trials throughout the experiment (thus more than one catch trial could occur per block). On such trials, four succinct descriptions of causes were presented and subjects had to select the one that appeared in the previous trial. A correct or incorrect response added or subtracted 50 cents from their total, respectively. (Subjects were informed that if they reached a negative balance, no money will be deducted off their payment for participation in the experiment.) Thus, subjects could earn $18 more for the experiment, if they answered all memory test questions correctly. Subjects typically did well on these memory questions, on average erring in 2.5 out of 36 memory catch trials (7% error) and gaining an additional $16.75 (SD=3.19).

ERP recording methods

The EEG was recorded using an Active 2 system (BioSemi, the Netherlands) from 64 electrodes distributed based on the extended 10–20 system and connected to a cap, and seven external electrodes. Four of the external electrodes recorded the EOG: two located at the outer canthi of the right and left eyes and two above and below the center of the right eye. Two external electrodes were located on the mastoids, and one electrode was placed on the tip of the nose. All electrodes were referenced during recording to a common-mode signal (CMS) electrode between POz and PO3. The EEG was continuously sampled at 512 Hz and stored for offline analysis.

ERP analysis

ERP analysis was conducted using the "Brain Vision Analyzer" software (Brain Products, Germany) and in-house Mathworks Matlab scripts. Data from all channels were referenced offline to the average of all channels. The data were then digitally high-pass filtered at 0.1 Hz using a Finite Impulse Response (FIR) filter to remove slow drifts. A notch filter at 59-61 Hz was applied to the data to remove 60-Hz electrical noise. The signal was then cleaned of blink artifacts using Independent Component Analysis (ICA)[64]. Signal artifacts were detected as amplitudes exceeding ±100 μV, differences beyond 100 μV within a 200 ms interval, or activity below 0.5 mV for over 100 ms (the last condition was never found). Sections of EEG data that included such artifacts in any channel were removed (150ms prior and after the artifact), leaving an average number of 70.38 trials with a range of 36-86 out of 90 trials per condition. Channels that consistently had artifacts were replaced using interpolation (4.2 channels per subject, on average).

The EEG was segmented by locking the waveforms to subjects' decision onset, starting 2s prior to the decision and ending 0.2s afterwards, with the segments averaged separately for each decision type (Deliberate/Arbitrary x Easy/Hard) and decision content (right/left). The baseline period was defined as the time window between -1000ms and -500ms prior to the beginning of the trial. Baseline adjustment included subtracting the mean amplitude of the activity during the baseline period from all the data points in the segment.

Differences greater than expected by chance were assessed using two-way ANOVAs with decision type (deliberate, arbitrary) and decision difficulty (easy, hard), using IBM SPSS statistics, version 24. For both RP and LRP signals, the mean amplitude from 500 ms before to button-press onset were used for the ANOVAs. Greenhouse–Geisser correction was never required as sphericity was never violated[65].

Trend analysis on all subjects' data (Fig. 3B) was carried out by regressing the voltage for every subject against time for the last 1000 ms before movement onset using first-order polynomial linear regression. We used every 10th time sample for the regression (i.e., the 1st, 11th, 21st, 31st samples, and so on) to conform with the individual-subject analysis (see below). For the individual-subject analysis, the voltage on all trials was regressed against time in the same manner (i.e., for the last 1000 ms before movement onset and using first-order polynomial linear regression). As individual-trial data is much noisier than the mean over all trials in each subjects, we opted for standard robust-regression using iteratively reweighted least squares (implemented using the *robustfit()* function in Mathworks Matlab). The iterative robust-regression procedure is time consuming. So, we used every 10th time sample instead of every sample to make the procedure's run time manageable.

Model and Simulations

All simulations were performed using Mathworks Matlab 2014b. The model was devised off the one proposed by Schurger and colleagues[25]. They built a drift-diffusion model[66,67] for arbitrary decisions only, which included a leaky stochastic accumulator (with a threshold on its output) and a time-locking/epoching procedure. Their model amounted to iterative numerical integration of the differential equation

$$\delta x_i = (I - kx_i)\Delta t + c\xi_i\sqrt{\Delta t}$$

where I is the drift rate, k is the leak (exponential decay in x), ξ is Gaussian noise, and c is a noise-scaling factor (we used $c = 0.05$). Δt is the discrete time step used in the simulation (we used $\Delta t = 0.001$, similar to our EEG sampling rate). Here I represents a constant urgency to respond that is inherent in the demand characteristics of the task, evidenced by the fact that no subject took more than 20 s to decide on any trial. The leak term, k, ensures that the model would not be too linear; i.e., it prevents the urgency from setting up a linear trajectory for the accumulator toward the threshold. Hence, due to the leak term, doubling the magnitude of the threshold would make the accumulator rarely reach the threshold, instead of reaching it in roughly twice the amount of time (up to the noise term) without a leak term.

Our model accounted for both arbitrary and deliberate decisions and was built to fit our empirical results, based on with two Schurger-like components. The first one accumulated activity that drove arbitrary decisions (i.e., random fluctuations[25]). The second component drove deliberate decisions based on subjects' values associated with the decision alternatives. Henceforth we term these *Noise* and *Value* components for ease of description. Our model used its Noise component for arbitrary decisions and its Value one for deliberate decisions.

Schurger and colleagues modeled only the decision when to move. But our subjects decided both when and which hand to move. So, we had to extend the Schurger model in that respect as well. We did this using a race-to-threshold mechanism between the two decision alternatives. In our paradigm, the difference in rating was either 1 (hard decisions) or 4-6 (easy decisions; see "Procedure &

Experimental Design" in Methods), so there was always an alternative that was ranked higher than the other. Choosing the higher or lower alternative was termed a congruent or incongruent choice with the initial ratings, respectively.

Using a parameter sweep, we found the values of the thresholds, urgency, and leak that best fit our average empirical reaction times for {easy, hard} x {deliberate, arbitrary} decisions as well as our empirical consistency ratios for those 4 decision types. The model's reaction time was defined as the overall time (where each step took $\Delta t = 0.001$ s) that it took until the first threshold crossing in the race-to-threshold pair. We used the same threshold value of 0.15 and leak value of k=0.5 for all model types. The only parameter that was modulated across {deliberate, arbitrary} x {easy, hard} decisions x {congruent, incongruent} decision alternatives was the urgency, I (Table 1). These parameters were then fixed when fitting the simulated Cz activity across all conditions.

Urgency (I) values	Congruent		Incongruent	
	Easy	Hard	Easy	Hard
Deliberate	0.0400	0.1010	0.0228	0.0000
Arbitrary	0.1650	0.1648	0.1650	0.1566

Table 1: Values of the urgency parameter, I, in our model across {deliberate, arbitrary} x {easy, hard} decisions x {congruent, incongruent} decision alternatives.

Each simulation consisted of either 120 runs of the model, the same as the number of empirical trials per condition (Fig. 4C), or 10000 runs of the model for a smoother reaction-time distribution for the model (Fig. 4B). For each run of the model, we identified the first threshold crossing point and extracted the last second (1000 steps) before the crossing in each run. If the first crossing was earlier than sample no. 1,000 by $n > 0$ samples, we padded the beginning of the epoch with n null values (NaN or "not-a-number" in Matlab). These values did not contribute to the average across simulated trials, so the simulated average RP became noisier at earlier time points in the epoch. Our model was therefore similarly limited to the Schurger model in its inability to account for activity earlier than the beginning of the trial. (Fig. 3C).

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References

1 Libet, B., Gleason, C. A., Wright, E. W. & Pearl, D. K. Time of conscious intention to act in relation to onset of cerebral activity (readiness-potential). The unconscious initiation of a freely voluntary act. *Brain* **106 (Pt 3)**, 623-642 (1983).

2 Haggard, P. & Eimer, M. On the relation between brain potentials and the awareness of voluntary movements. *Experimental Brain Research* **126**, 128-133 (1999).

3 Salvaris, M. & Haggard, P. Decoding Intention at Sensorimotor Timescales. *PloS one* **9**, e85100 (2014).

4 Soon, C. S., Brass, M., Heinze, H. J. & Haynes, J. D. Unconscious determinants of free decisions in the human brain. *International Journal of Psychology* **43**, 238-238 (2008).

5 Soon, C. S., He, A. H., Bode, S. & Haynes, J. D. Predicting free choices for abstract intentions. *Proceedings of the National Academy of Sciences* **110**, 6217-6222 (2013).

6 Bode, S., Bogler, C. & Haynes, J. D. Similar neural mechanisms for perceptual guesses and free decisions. *Neuroimage* **65**, 456–465 (2012).

7 Bode, S. *et al.* Predicting perceptual decision biases from early brain activity. *The Journal of Neuroscience* **32**, 12488-12498 (2012).

8 Perez, O. *et al.* Preconscious prediction of a driver's decision using intracranial recordings. *Journal of cognitive neuroscience* (2015).

9 Fried, I., Mukamel, R. & Kreiman, G. Internally generated preactivation of single neurons in human medial frontal cortex predicts volition. *Neuron* **69**, 548-562 (2011).

10 Frith, C. D. & Wolpert, D. M. Abnormalities in the awareness and control of action. *Philosophical Transactions of the Royal Society B: Biological Sciences* **355**, 1771-1788 (2000).

11 Jeannerod, M. *Motor cognition: What actions tell the self*. Vol. 42 (Oxford University Press, 2006).

12 Haggard, P. Human volition: towards a neuroscience of will. *Nature Reviews Neuroscience* **9**, 934-946 (2008).

13 Lau, H., Rogers, R., Haggard, P. & Passingham, R. E. Attention to intention. *Science* **303**, 1208-1210 (2004).

14 Mele, A. R. *Free will and luck*. (Oxford University Press, 2006).

15 Wegner, D. M. *The Illusion of Conscious Will*. (MIT Press, 2002).

16 Roskies, A. L. How does neuroscience affect our conception of volition? *Annual Review of Neuroscience* **33**, 109-130 (2010).

17 Ullman-Margalit, E. & Morgenbesser, S. Picking and choosing. *Social Research* **44**, 757-785 (1977).

18 Roskies, A. How Does Neuroscience Affect Our Conception of Volition? *Annual Review of Neuroscience* **33**, 109-130 (2010).

19 Breitmeyer, B. G. Problems with the psychophysics of intention. *Behavioral and brain sciences* **8**, 539-540 (1985).

20 Glimcher, P. W., Camerer, C., Fehr, E. & Poldrack, R. A. (Academic Press, London, 2009).

21 Sanfey, A. G., Loewenstein, G., McClure, S. M. & Cohen, J. D. Neuroeconomics: cross-currents in research on decision-making. *Trends in Cognitive Sciences* **10**, 108-116 (2006).

22 Gold, J. I. & Shadlen, M. N. The neural basis of decision making. *Annu. Rev. Neurosci.* **30**, 535-574 (2007).

23 Kornhuber, H. H. & Deecke, L. Readiness for movement—the Bereitschafts potential-story. *Current Contents Life Sciences* **33**, 14 (1990).

24 Shibasaki, H. & Hallett, M. What is the Bereitschaftspotential? *Clinical Neurophysiology* **117**, 2341-2356 (2006).

25 Schurger, A., Sitt, J. D. & Dehaene, S. An accumulator model for spontaneous neural activity prior to self-initiated movement. *Proceedings of the National Academy of Sciences* **109**, E2904-E2913 (2012).

26 Trevena, J. & Miller, J. Brain preparation before a voluntary action: Evidence against unconscious movement initiation. *Consciousness and cognition* **19**, 447-456 (2010).

27 Miller, J., Shepherdson, P. & Trevena, J. Effects of clock monitoring on electroencephalographic activity is unconscious movement initiation an artifact of the clock? *Psychological Science* **22**, 103-109 (2011).

28 Eimer, M. The lateralized readiness potential as an on-line measure of central response activation processes. *Behavior Research Methods, Instruments, & Computers* **30**, 146-156 (1998).

29 Masaki, H., Wild - wall, N., Sangals, J. & Sommer, W. The functional locus of the lateralized readiness potential. *Psychophysiology* **41**, 220-230 (2004).
30 Mele, A. R. (Oxford University Press, Oxford, 2015).
31 Sinnott-Armstrong, W. & Nadel, L. in *Oxford Series in Neuroscience, Law and Responsibility* (Oxford University Press, 2011).
32 Pockett, S., Banks, W. P. & Gallagher, S. *Does consciousness cause behavior?* , (Mit Press, 2009).
33 Haggard, P. Conscious intention and motor cognition. *Trends in Cognitive Sciences* **9**, 290-295 (2005).
34 Mele, A. *Effective intentions: the power of conscious will*. (Oxford University Press, USA, 2009).
35 Libet, B. Subjective antedating of a sensory experience and mind-brain theories: reply to Honderich (1984). *J Theor Biol* **114**, 563-570 (1985).
36 Sirigu, A. *et al.* Altered awareness of voluntary action after damage to the parietal cortex. *Nature Neuroscience* **7**, 80-84 (2003).
37 Libet, B. Unconscious cerebral initiative and the role of conscious will in voluntary action. *Behavioral and brain sciences* **8**, 529-539 (1985).
38 Frankfurt, H. G. Freedom of the Will and the Concept of a Person. *The Journal of Philosophy* **68**, 5-20 (1971).
39 Hobbes, T. in *Leviathan, with selected variants from the Latin edition of 1668* (ed E Curley) (Hackett, 1994).
40 Wolf, S. *Freedom Within Reason*. (Oxford University Press, 1990).
41 Deutschländer, R., Pauen, M. & Haynes, J.-D. Probing folk-psychology: Do Libet-style experiments reflect folk intuitions about free action? *Consciousness and Cognition* **48**, 232-245 (2017).
42 Strawson, G. The impossibility of moral responsibility. *Philosophical Studies* **75**, 5-24 (1994).
43 Fischer, J. M. Recent Work on Moral Responsibility*. *Ethics* **110**, 93-139 (1999).
44 Sinnott-Armstrong, W. *Moral psychology: Free will and moral responsibility*. (MIT Press, 2014).
45 Roskies, A. L. How does the neuroscience of decision making bear on our understanding of moral responsibility and free will? *Current opinion in neurobiology* **22**, 1022-1026 (2012).
46 Maoz, U. & Yaffe, G. What does recent neuroscience tell us about criminal responsibility? *Journal of Law and the Biosciences* **3**, 120-139 (2016).
47 Mele, A. *Free will and luck*. (Oxford University Press, 2006).
48 Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E. & Cohen, J. D. The neural basis of economic decision-making in the ultimatum game. *Science* **300**, 1755-1758 (2003).
49 Wallis, J. D. & Miller, E. K. Neuronal activity in primate dorsolateral and orbital prefrontal cortex during performance of a reward preference task. *European Journal of Neuroscience* **18**, 2069-2081 (2003).
50 Ramnani, N. & Owen, A. M. Anterior prefrontal cortex: insights into function from anatomy and neuroimaging. *Nature Reviews Neuroscience* **5**, 184-194 (2004).
51 Wallis, J. D. Orbitofrontal cortex and its contribution to decision-making. *Annu. Rev. Neurosci.* **30**, 31-56 (2007).
52 Bush, G., Luu, P. & Posner, M. I. Cognitive and emotional influences in anterior cingulate cortex. *Trends in Cognitive Sciences* **4**, 215-222 (2000).
53 Carter, C. S. *et al.* Anterior cingulate cortex, error detection, and the online monitoring of performance. *Science* **280**, 747-749 (1998).

54 Krieghoff, V., Waszak, F., Prinz, W. & Brass, M. Neural and behavioral correlates of intentional actions. *Neuropsychologia* **49**, 767-776 (2011).
55 Brass, M. & Haggard, P. The what, when, whether model of intentional action. *The Neuroscientist* **14**, 319-325 (2008).
56 Hughes, G., Schütz-Bosbach, S. & Waszak, F. One action system or two? Evidence for common central preparatory mechanisms in voluntary and stimulus-driven actions. *The Journal of Neuroscience* **31**, 16692-16699 (2011).
57 Maoz, U. *et al.* Predeliberation activity in prefrontal cortex and striatum and the prediction of subsequent value judgment. *Front Neurosci* **7**, 225 (2013).
58 Brainard, D. The psychophysics toolbox. *Spatial Vision* **10**, 433-436, doi:http://booksandjournals.brillonline.com/content/journals/10.1163/156856897x00357 (1997).
59 Pelli, D. G. The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision* **10**, 437-442 (1997).
60 Lau, H., Rogers, R. & Passingham, R. Manipulating the experienced onset of intention after action execution. *Journal of cognitive neuroscience* **19**, 81-90 (2007).
61 Banks, W. P. & Isham, E. A. We infer rather than perceive the moment we decided to act. *Psychological Science* **20**, 17 (2009).
62 Miller, J., Shepherdson, P. & Trevena, J. Effects of Clock Monitoring on Electroencephalographic Activity. *Psychological Science* **22**, 103-109 (2011).
63 Maoz, U. *et al.* in *Surrounding Free Will* (ed Alfred R Mele) (Oxford University Press, 2015).
64 Jung, T. P. *et al.* Removing electroencephalographic artifacts by blind source separation. *Psychophysiology* **37**, 163-178 (2000).
65 Picton, T. W. *et al.* Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria. *Psychophysiology* **37**, 127-152 (2000).
66 Ratcliff, R. A theory of memory retrieval. *Psychological Review* **85**, 59-108 (1978).
67 Usher, M. & McClelland, J. L. The time course of perceptual choice: the leaky, competing accumulator model. *Psychological review* **108**, 550 (2001).