Confidence in value-based choice

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Decisions are never perfect, with confidence in one's choices fluctuating over time. How subjective confidence and valuation of choice options interact at the level of brain and behavior is unknown. Using a dynamic model of the decision process, we show that confidence reflects the evolution of a decision variable over time, explaining the observed relation between confidence, value, accuracy and reaction time. As predicted by our dynamic model, we show that a functional magnetic resonance imaging signal in human ventromedial prefrontal cortex (vmPFC) reflects both value comparison and confidence in the value comparison process. Crucially, individuals varied in how they related confidence to accuracy, allowing us to show that this introspective ability is predicted by a measure of functional connectivity between vmPFC and rostrolateral prefrontal cortex. Our findings provide a mechanistic link between noise in value comparison and metacognitive awareness of choice, enabling us both to want and to express knowledge of what we want.

The subjective confidence we have in our decision-making, and that of others, has far-reaching consequences. For example, the recommendations of a financial advisor who expresses high confidence in a particular investment option will carry more weight than one who is ambivalent. An expression of doubt in or caution concerning a particular course of action can lead one to question or revisit a previous decision. Previous work has established that the vmPFC has a central role in computing the value of potential choice options[1–5], with activity in this region reflecting the dynamic evolution of a value comparison[6]. However, this work has focused exclusively on the choice process, without considering the subject's level of confidence in the decision. Consequently, it is unknown how a process of value comparison, instantiated in vmPFC, relates to subjective confidence.

Previous studies have reported neural correlates of decision confidence in brain regions associated with a value representation. For example, firing rates in rat orbitofrontal cortex[7] and functional magnetic resonance imaging (fMRI) signal in human vmPFC[8] show graded changes as perceptual decisions become more difficult. However, as these studies delineate confidence in terms of factors governing choice, they are unable to tease apart the relationship between trial-to-trial subjective confidence and decision value. In contrast, the field of perceptual decision-making has noted that confidence can be measured independently of the choice process itself[9,10], where it is conceptualized as reflecting a 'second-order' metacognitive evaluation. Critically, dissociating confidence from other features of the decision process requires acquisition of separate measures of choice and confidence[11].

Here we implement such an approach to dissociate value and confidence during decision-making and to identify their respective neural substrates. We collected trial-by-trial estimates of decision confidence while healthy volunteers chose between pairs of snack items. We also measured the subjective value of each snack item by means of a standard incentive-compatible bidding procedure. This allowed us to dissociate

confidence from value, and in so doing provide evidence that confidence reflects an assessment of choice accuracy.

To explore systematic relationships between confidence, accuracy, choice and reaction time, we modeled our data using a variant of a race model[7,12] (one of a larger class of dynamic models of decision-making[13]). This model predicts that subjective confidence reflects the stochastic accumulation of evidence during the value comparison process. As is consistent with this prediction, we show that the same anatomical region in ventromedial prefrontal cortex (vmPFC) not only reflects a difference in value between available options, but also the confidence associated with a value comparison process. Finally, we show that individual differences in participants' abilities to relate confidence to decision performance is linked to increased functional connectivity between vmPFC and rostrolateral prefrontal cortex (RLPFC), a region previously shown to function in metacognitive appraisal[14].

RESULTS

We scanned twenty hungry participants while they made choices between food items that they could consume later (**Fig. 1a**). After making each choice, participants reported the degree of confidence in their decision (choice confidence). Note that confidence, or certainty, in the present study is conceptually distinct from risk, in that each choice determined a known outcome. Confidence here reflects the degree of subjective certainty in having made the best choice, which equates to choosing the higher valued item. To establish value for individual items, we asked participants at the end of the scanning session to place a bid for each food item using a standard incentive-compatible procedure, the Becker-DeGroot-Marschak (BDM) mechanism[15]. BDM is widely used in behavioral economics and neuroeconomics to elicit nonstrategic reservation prices, also known as willingness-to-pay. In this phase subjects were required to state their maximum willingness-to-pay for each food item (see Online Methods). Several studies have shown that this mechanism reliably elicits goal values

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Figure 1 Task and behavioral results. (**a**) fMRI task (top): subjects were presented with a choice between two snacks and were then required to choose (2.5 s) one item to consume at the end of the experiment. After each choice, subjects indicated their level of confidence in having made a correct decision (choice confidence). Post-scanning task (bottom): subjects were presented with each item individually and had to submit a bid to buy each item. After each bid, they were asked to rate their level of confidence in having provided a correct bid price (bid confidence). (**b**) Probability of choosing the item on the right as a function of DV (that is, bid price) between the two items (logistic fit) for an exemplar subject (see **Supplementary Fig. 2** for all individual subjects). Dashed line, all choices; black line, low-confidence choices; gray line, high-confidence choices. The red double-headed arrow indicates the increase in choice accuracy (change in slope) for high- versus low-confidence trials used in the between-subjects analyses (**Figs. 4b** and **5b**). (**c**) The slope of the logistic fit is systematically higher (sharper) in high-confidence compared to low-confidence trials (**P < 0.005; ***P < 0.0001). (**d**) Average RT as a function of confidence and |DV|. (**e**) Heat map showing mean z-scored confidence (color bar) across subjects, as a function of subject-specific |DV| and RT quantiles. Error bars represent s.e.m.
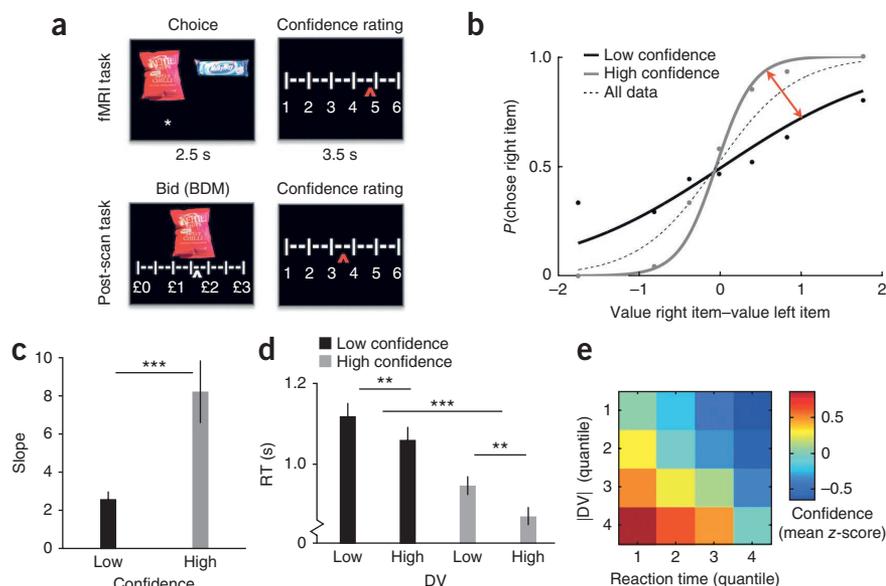
that are used by the decision maker to guide choice[16–18]. Participants also provided a rating of their confidence in each bid (bid confidence). Participants' bids for the leftmost items were then subtracted from bids for the rightmost items to calculate a signed difference in value (DV) between each pair of items, which was then entered into a logistic regression to predict the probability that the subject chose the rightmost item on each trial (**Fig. 1b**). In line with previous studies[2,19], we found that DV was a reliable predictor of participants' choices, with the slope of the logistic regression being a measure of choice accuracy, or noise in the choice process[20].

Choice, confidence and reaction time

Unsigned |DV| only accounted for an average of 17.7% of the variance in participants' confidence ratings ($r = 0.42 \pm 0.19$, s.d.). This partial independence between confidence and |DV| allowed us to ask whether confidence reflects changes in choice accuracy (the selection of items with higher subjective value). By splitting our logistic regression fit into high- and low-confidence trials, we showed that higher confidence was consistently associated with increased choice accuracy (**Fig. 1b,c** and **Supplementary Fig. 1**). This effect of confidence on choice was also reflected in reaction time (RT), with main effects of both |DV| and confidence (both $P < 0.001$) but no interaction (**Fig. 1d**). The three-way relationship between |DV|, confidence and RT is plotted in **Figure 1e**. We recognize that other factors (internal and external) besides |DV| and RT are likely to affect subjective confidence. We report a limited set of these factors (**Supplementary Table 1**) for which we could exercise good experimental control.
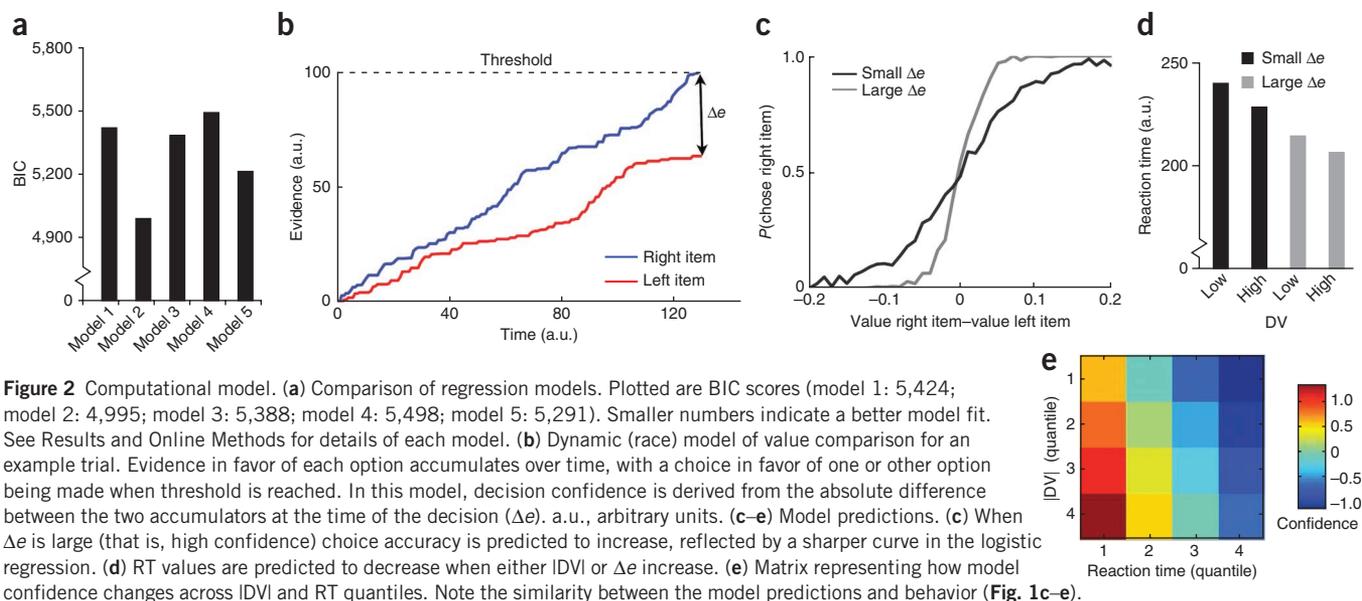
Using logistic regression, we next compared models of the interaction between confidence and value comparison. Choice confidence, unlike DV, is in itself not a predictor of choice (right or left item) but instead refers to accuracy of the decision. We thus expected choice confidence to modulate the link between DV and choice. Model 1 predicted choice using DV alone; model 2 included choice confidence (that is, confidence at the decision time) as a modulator of DV (DV × confidence); models 3–5 examined whether bid confidence (that is, confidence at the bid time) could explain additional variance in the link between DV and choice (see Online Methods). In accordance with our predictions,

model 2 provided a better account (that is, lower Bayesian information criterion (BIC)) of participants' choices than the other four models (**Fig. 2a**), as shown by the difference in BIC relative to model 2: model 1, 214.6; model 3, 196.2; model 4, 251.7; model 5, 111.9. Furthermore, model 2 was a better fit than the canonical model 1 in 19 of 20 participants as assessed by a likelihood ratio test ($\alpha = 0.05$). This analysis confirms that a critical modulator of choice accuracy is second-order confidence arising in the context of the comparison process (model 2) as opposed to first-order confidence in the item values (models 3–5).

Stability of confidence over time

We next examined whether the relationship between confidence and choice was stable over time. Splitting the logistic regression analysis into separate sessions revealed a robust main effect of confidence ($F_{1,19} = 39.75$; $P < 0.0001$) but a nonsignificant main effect of session ($F_{3,57} = 0.3$; $P = 0.7$) and a lack of interaction between session and confidence ($F_{3,57} = 0.13$; $P = 0.9$; **Supplementary Fig. 2**). To examine whether local fluctuations in attention affected confidence, we constructed a serial autocorrelation regression model that predicted the current confidence rating from the confidence ratings given on the immediately preceding five trials, in addition to |DV|. None of the autocorrelation coefficients reached group-level significance (all $t < 1.2$, $P > 0.27$). Together these results indicate that confidence is a stable predictor of choice accuracy and that it does not reflect local changes in attention.

As each item pairing was presented twice (once in each spatial configuration), it was also possible to examine the relationship between confidence ratings given for identical choice pairs. As confidence is partly determined by absolute difference in value (|DV|, which does not vary across choice pairs), we expected some stability purely driven by DV. Thus, to address this question, we computed the partial correlation between first and second confidence ratings, controlling for DV. There was no significant difference between mean confidence ratings for the first and second presentations of the same item pairs ($t_{19} = -0.64$, $P = 0.53$). For 19 of 20 subjects, there was a significant partial correlation ($P < 0.05$) between confidence ratings for repeated item pairs after controlling for the influence of |DV|, indicating stability in confidence for judgments of particular item pairs that cannot be accounted for by |DV| alone.

Figure 2 Computational model. (**a**) Comparison of regression models. Plotted are BIC scores (model 1: 5,424; model 2: 4,995; model 3: 5,388; model 4: 5,498; model 5: 5,291). Smaller numbers indicate a better model fit. See Results and Online Methods for details of each model. (**b**) Dynamic (race) model of value comparison for an example trial. Evidence in favor of each option accumulates over time, with a choice of one or other option being made when threshold is reached. In this model, decision confidence is derived from the absolute difference between the two accumulators at the time of the decision (Δe). a.u., arbitrary units. (**c**–**e**) Model predictions. (**c**) When Δe is large (that is, high confidence) choice accuracy is predicted to increase, reflected by a sharper curve in the logistic regression. (**d**) RT values are predicted to decrease when either |DV| or Δe increase. (**e**) Matrix representing how model confidence changes across |DV| and RT quantiles. Note the similarity between the model predictions and behavior (**Fig. 1c–e**).

We then examined whether choices were stable over time. On average, 14.7% of choices ($\pm 5.7\%$ s.d.) were reversed on the second presentation. Choices that would be subsequently reversed were associated with significantly lower initial confidence than those that would subsequently be repeated (in arbitrary units: reversal confidence = 3.11 $\pm$ 0.72 (s.d.); repetition confidence = 4.40 $\pm$ 0.54 (s.d.); $t_{19} = 12.1$, $P < 10^{-10}$). In a logistic regression model predicting subsequent reversal from both |DV| and initial confidence, initial confidence was a significant negative predictor of choice reversal (mean standardized regression coefficient -0.99 ± 0.40 (s.d.); one-sample t-test $t_{19} = -11.2$, $P < 10^{-9}$). These data support a hypothesis that low confidence is associated with subsequent changes of mind.

Race model

Our best-fitting regression model suggested that confidence reflects accuracy in a value comparison. This led us to explore in more detail the precise mechanism by which confidence and value interact during the decision process. We adapted a race model[12,21] wherein evidence in favor of each of the options (the snacks presented on the left and right sides of the screen) is accumulated over time and the decision is made on the basis of the first option to reach a threshold (**Fig. 2b**). In this model, confidence is defined as the absolute difference between the two accumulators at decision time (Δe). Such a model predicts that when Δe is large, then choice accuracy is increased, reflected by a sharper slope in the logistic regression (**Fig. 2c**). Thus, the race model neatly accounts for an increase in choice accuracy we observed behaviorally in the high-confidence condition (**Fig. 1b** and **Supplementary Table 2**). Furthermore this model predicts a decrease in RT when either |DV| or Δe are increased (**Fig. 2d**), as seen in the behavioral data (**Fig. 1d**). The intuition is that, even within a particular level of initial DV,
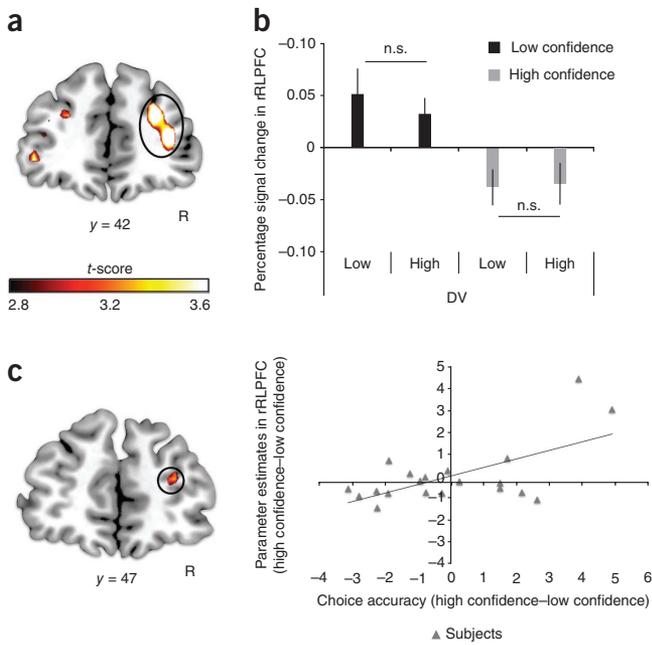
inter-trial noise in the value comparison process results in some trials having greater final DV values (higher confidence) than others. Such decisions will tend to be made more quickly, be more accurate and be associated with higher confidence (**Fig. 2e**). Indeed, this predicted relationship among RT, |DV| and confidence closely matched the behavioral data (**Fig. 1e**). Finally, since the model predicts that confidence reflects the stochastic evolution of a value comparison process, it will only be weakly related to initial DV. This feature of the model provides a parsimonious explanation for why DV and confidence are dissociable in our behavioral data.

Confidence and value in vmPFC

We next hypothesized that if choice confidence is an emergent property of a value comparison process, the same brain regions involved
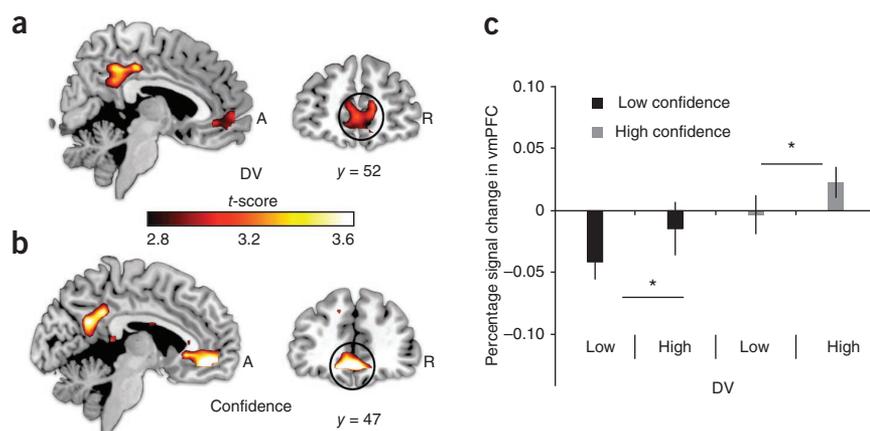
Figure 3 vmPFC. (**a**) Brain activity in precuneus and vmPFC. vmPFC (Montreal Neurological Institute (MNI) space coordinates (x, y, z) = (12, 56, 4); circled) correlating with increases in DV between the two items presented ($P < 0.05$, FWE corrected at cluster level). Left image, sagittal section; right image, coronal. (**b**) Brain activity in precuneus and vmPFC (12, 47, −11) correlating with increases in subjective confidence ($P < 0.05$ FWE corrected at the cluster level). (**c**) Signal in vmPFC (6-mm sphere centered at the peak of the DV main effect (12, 56, 4)), showing main effects of DV and degree of confidence in the absence of an interaction. The plot (extracted from GLM 2; see Online Methods) is shown only to clarify the signal pattern in vmPFC (that is, lack of interaction between confidence and DV) and to confirm statistical inference (from GLM 1) regarding the main effects of DV and confidence. *$P < 0.01$. Error bars represent s.e.m.

a

$y = 42$ R

t-score

2.8   3.2   3.6

b

n.s.

■ Low confidence
■ High confidence

n.s.

Low | High   Low | High

DV

Percentage signal change in rRLPFC

c

$y = 47$ R

Parameter estimates in rRLPFC (high confidence–low confidence)

Choice accuracy (high confidence–low confidence)

▲ Subjects

Figure 4 RLPFC. (**a**) Brain activity in rRLPFC correlating with decreases in subjective confidence ($P < 0.005$, small-volume FWE corrected). Coronal section; R, right. (**b**) Signal in rRLPFC (6-mm sphere MNI space coordinates (x, y, z) = (39, 41, 16)) showing a main effect of confidence but not DV. The plot (extracted from GLM 2; see Online Methods) is shown only to clarify the signal pattern in rRLPFC (that is, absence of main effect of DV). n.s., not significant. (**c**) Between-subjects regression analysis considering the change in choice accuracy (slope of the logistic fit) between low- and high-confidence trials (see red double-headed arrow in **Fig. 1b**) as a covariate for confidence-related activity in rRLPFC (peak (x, y, z) = (27, 44, 16); $P < 0.05$, small-volume FWE corrected). The scatter plot is not used for statistical inference (which was carried out in the SPM framework); it is shown solely for illustrative purposes. Error bars represent s.e.m.

of |DV| and confidence in vmPFC but no interaction between them (2×2 ANOVA with factors value, confidence: main effect of value $F_{1,19} = 5.1$, $P < 0.05$; main effect of confidence $F_{1,19} = 7.6$, $P < 0.05$; interaction $F_{1,19} = 0.7$, $P > 0.5$) (**Fig. 3c**). The absence of an interaction at the neural level is consistent with a theoretical independence between value and noise in the choice process, such that one can have high confidence in a low-value choice and vice versa. Furthermore, the pattern across conditions closely resembles that seen for RT values (**Fig. 1d**) providing convergent evidence that vmPFC activity is tightly linked to behavior. We also confirmed that the response to confidence was not driven by a categorical response to errors[8] (**Supplementary Fig. 3**).

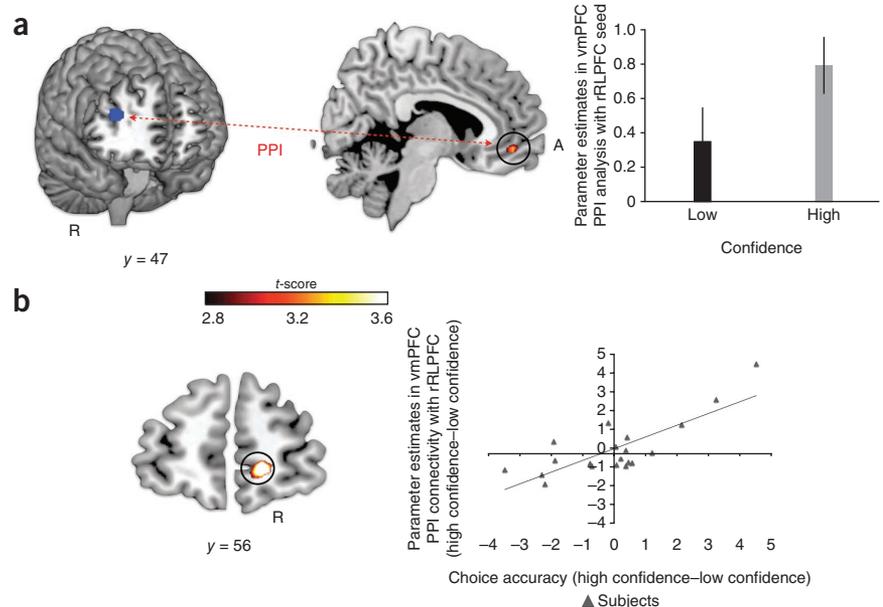## Confidence in right rostrolateral prefrontal cortex

A key question is how confidence-related information represented in vmPFC becomes available for self-report. One computationally plausible hypothesis is a hierarchical model wherein confidence in a comparison process is 'read out' by an anatomically distinct second-order network[22–24]. Right rostrolateral prefrontal cortex (rRLPFC) is a likely candidate, as this region is implicated in metacognitive assessments of perceptual decisions[9,14,25]. Consequently, we tested whether this region acts more generally in metacognitive appraisal by enabling explicit report of confidence in a value comparison.

We first established that rRLPFC tracked changes in reported confidence but did not code for DV (**Fig. 4a,b**, **Supplementary Fig. 4** and **Supplementary Table 3**; $P < 0.005$, small-volume corrected (SVC)), as expected for a region providing a readout of decision confidence.

in value-based decision-making should also represent subjective confidence in a value estimate. In other words, if a brain region involved in value comparison is implementing a process akin to a race model[6], then activity in that region should be modulated by both initial |DV| and noise (confidence) on that trial. To test this hypothesis, we constructed a general linear model (GLM) of our fMRI data in which each trial was modulated by two parametric regressors: |DV| and confidence orthogonalized with respect to |DV|. We show that activity in vmPFC was indeed modulated by both value and confidence (**Fig. 3a,b** and **Supplementary Table 3**; $P < 0.05$ family-wise error (FWE) corrected at cluster level). This pattern is consistent with the established function of this region in encoding goal-values[1,2] and with our hypothesis that this region also represents the confidence associated with a value comparison.

We next investigated whether |DV| and confidence interacted in vmPFC by splitting the model into high- and low-confidence trials, both parametrically modulated by |DV| (**Fig. 2c**). This analysis showed main effects

Figure 5 Connectivity analysis. (**a**) PPI analysis. Left: three-dimensional rendering, radiological orientation. Right: sagittal section. vmPFC (circled in black in right panel) shows increases in connectivity with a region of rRLPFC (6-mm sphere (x, y, z) = (39, 41, 16); blue, left panel) previously identified as being modulated by confidence (vmPFC peak (x, y, z) = (9, 50, −11); R, right; A, anterior. $P < 0.05$, small-volume FWE corrected). 3D rendering made in mricron (radiological orientation). R, right. A, anterior. (**b**) Between-subjects regression analysis considering the increase in choice accuracy (see red double-headed arrow in **Fig. 1b**) between high-confidence and low-confidence conditions as a covariate for the modulation of connectivity (vmPFC peak (x, y, z) = (15, 56, −5); $P < 0.05$, small-volume FWE corrected). Coronal section. The scatter plot was not used for statistical inference (which was carried out in the SPM framework); it is shown solely for illustrative purposes. Error bars represent s.e.m.

a

R $y = 47$ PPI   A

t-score

2.8   3.2   3.6

Parameter estimates in vmPFC PPI analysis with rRLPFC seed

Low   High

Confidence

b

$y = 56$ R

Parameter estimates in vmPFC PPI connectivity with rRLPFC (high confidence–low confidence)

Choice accuracy (high confidence–low confidence)

▲ Subjects

Figure 6 Schematic of network relating confidence to subjective report. Summary of the relationship between our computational model and neuroimaging analyses. (**a**) Confidence in the decision (Δe) emerges from the value comparison process instantiated in vmPFC. (**b**) To reach metacognitive awareness (and be reported by the participant), this information is transferred to rRLPFC. The parameter σ_{conf} governs the noise in the readout of Δe (that is, decision confidence). If σ_{conf} is zero, the information about confidence (Δe) is uncorrupted, resulting in a pronounced shift in the choice accuracy between high-confidence and low-confidence trials (red double-headed arrows). As the level of metacognitive noise increases (higher values of σ_{conf}) the shift between the two curves (low and high confidence) diminishes. Differences in σ_{conf} account for the inter-subject variability in metacognitive reportability we observed behaviorally. a.u., arbitrary units.
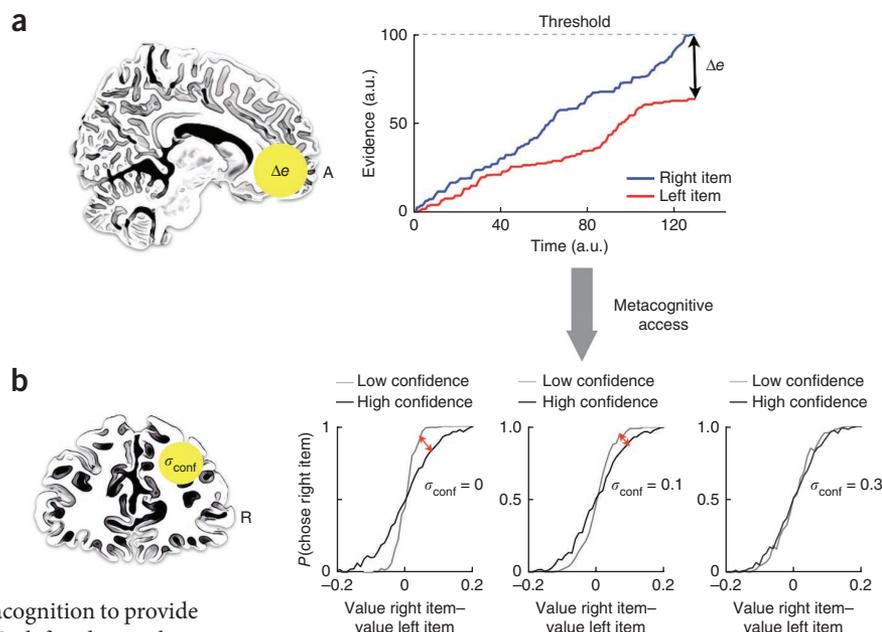
We next harnessed individual differences in metacognition to provide a more stringent test for the role of rRLPFC. We defined an individual's metacognitive accuracy as the change in choice accuracy (slope of the logistic fit) between low- and high-confidence trials (**Fig. 1b**). We reasoned that if rRLPFC acts in the metacognitive appraisal of confidence, activity in this region and/or its coupling with vmPFC should predict this change in slope across individuals. To test our first prediction, we entered change in slope as a between-subjects covariate in the whole-brain analysis of confidence-related activity, finding that this parameter significantly modulated the response to confidence in rRLPFC ($P < 0.05$; SVC for multiple comparisons). In other words, participants manifested a neurometric-psychometric match between their behavioral and neural responses to change in confidence level (**Fig. 4c**).

Metacognitive access: interaction between vmPFC and rRLPFC
To test our second prediction, that these two regions are part of the same functional network (in the context of our task), we performed a psychophysiological interaction (PPI) analysis using rRLPFC as a seed (**Fig. 5a**). This analysis revealed a robust modulation of connectivity between rRLPFC and vmPFC ($P < 0.05$ small-volume FWE corrected) by confidence level (**Fig. 5a,b**). Furthermore, the strength of connectivity between these two regions also predicted metacognitive accuracy across subjects (vmPFC; $P < 0.05$; SVC for multiple comparisons) (**Fig. 5b**). Thus, both activity in rRLPFC itself and its coupling strength with vmPFC influenced the degree to which confidence was effectively read out for metacognitive report.

How might this readout process relate to our computational model of confidence? Intuitively, if reported confidence is a noisy facsimile of the confidence inherent in a decision process, the relationship between confidence and behavior will weaken and metacognitive accuracy will decrease[26]. We were able to modify the race model, introduced previously, to account for the inter-subject variability in metacognitive reports observed experimentally. We introduced an additional parameter (σ_{conf}) governing the noise in the read-out of Δe (that is, decision confidence) computed during the value comparison. Variation in this parameter captured variability in the change in slope between high- and low-confidence conditions, despite overall choice accuracy remaining equal (**Fig. 6**). Together with our imaging results, this analysis suggests that rRLPFC may indeed mediate variability in reported confidence (see **Fig. 6** and Discussion).

DISCUSSION
Here we show that decision confidence emerges from a value comparison process in vmPFC and that this region is in turn accessed by rRLPFC to enable a subjective assessment of confidence. Our neural findings are consistent with previous evidence showing that choice difficulty is coded by vmPFC in humans and analogous OFC neurons in rodents[7,8]. There is also an established body of work showing that this brain area represents the expected value of an outcome[1–6]. However, as previous studies defined confidence in terms of factors governing choice, they were unable to tease apart the relationship between value and confidence. Our results go beyond these studies by dissociating subjective confidence from DV. In so doing, we demonstrate that neural activity in the same anatomical region represents both variables, suggesting that confidence and DV are separate behavioral manifestations of the same underlying decision variable.

Choice confidence can be seen to emerge from the dynamics of noisy accumulators in the race model[7,12,21], leading to dual effects of DV and RT on confidence[27]. The race model has previously been proposed to account for decision confidence in perceptual decision-making. In keeping with recent research efforts that have incorporated dynamic models into the field of economic decision-making[28], we find that this model captures several features of the relationship between choice, RT and confidence in a value-based choice model. The separation between confidence and BDM values in the present study provides a new perspective on how an underlying decision variable can be fractionated into distinct behavioral components. Given that DV and confidence had independent effects on vmPFC activity, this result provides convergent support for the idea that vmPFC acts as a dynamic accumulator of choice values[6]. Our findings also accord with a theoretical Bayesian scheme in which uncertainty, or precision, is an inherent property of the neural code[29–31].

A central problem for computational models of metacognition is how confidence information is read out for appraisal and communication to others. It has been proposed[22,24] that such a computation can be achieved by a two-layer neural network architecture, in which the second-order network receives information about the performance of the first-order network and uses this information to generate reports of confidence. Our fMRI data can be interpreted in this framework

and suggests that rRLPFC is a plausible locus for this second-order network. First, rRLPFC represented confidence but not DV, as predicted for a brain region that has access to information about confidence but is not directly involved in value comparison. Second, both confidence-related activity in rRLPFC and coupling between rRLPFC and vmPFC predicted the relationship between confidence and accuracy across individuals. This result can be explained if the coupling between vmPFC and rRLPFC reflects the fidelity with which reported confidence tracks the evolution of a putative accumulator process in vmPFC (**Figs. 2b** and **6**). Notably, confidence-related activity in rRLPFC is also seen in perceptual decision-making[14], together with a modulation of connectivity with visual cortex. This pattern of findings suggests that rRLPFC might have a domain-general role in metacognitive evaluation of decision-making, supporting the notion of a segregated neural process governing metacognitive access[22,24,26].

An alternative interpretation of our data is that information about choice confidence is coded elsewhere, perhaps in parallel to the construction of choice values, and is then communicated to vmPFC (possibly via rRLPFC), where it is incorporated into the choice process. This mechanism would be analogous to a modulation of the vmPFC value signal during self-control by dorsolateral PFC[32]. Resolving this possibility is beyond the design of the current study and will require techniques with high temporal resolution, such as magnetoencephalography, that can track the evolution of confidence and valuation in the brain.

Our data show that humans have metacognitive access to noise in a value comparison and that increased choice accuracy is associated with high subjective confidence. In other words, although choices often appear noisy from the point of view of the experimenter[20,33], subjective confidence ratings reveal systematic changes in this noise, reflected by changes in choice accuracy. Metacognitive access to confidence in a value comparison is likely to be useful for revisiting a choice that did not turn out as expected. Alternatively, but not mutually exclusively, metacognitive access may facilitate communication of confidence to others[34], as when a financial advisor directs a client toward one stock option over another.

By integrating computational modeling with neural analysis, we provide evidence that subjective confidence is integral to the brain's representation of value in the vmPFC. Our work outlines a neural schema for how confidence-related information is computed and transferred to a distinct brain region (rRLPFC), supporting metacognitive report. Far from being a blind process of selection corrupted by noise, it would appear that value-based choices are accompanied by fluctuations in subjective confidence. A metacognitive access to value computation enables us not only to want but also to know what we want.

METHODS

Methods and any associated references are available in the online version of the paper.

Note: Supplementary information is available in the online version of the paper.

AUTHOR CONTRIBUTIONS
B.D.M. and S.M.F. conceived and designed the study. B.D.M., N.G. and S.M.F. developed stimuli and gathered and analyzed behavioral and fMRI data. B.D.M., S.M.F. and R.J.D. interpreted the data and wrote the paper.

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ONLINE METHODS

Participants. Twenty-eight participants (mean age 24.24) took part in the study. Four participants were excluded because of excessive head motion. Three participants were excluded for erratic choice patterns that prevented reliable estimation of a logistic fit (an inverse temperature parameter five or more times larger than the average of the group). Participants were only included if they used a sufficient range of confidence ratings (s.d. > 0.8) to allow estimation of metacognitive ability. This criterion led to the exclusion of one more subject. Twenty participants were included in the final analysis.

Scanning task. Participants were required to fast for 4 h before the study. During scanning they were required to make a series of binary choices between 19 common snack items (2,000 ms) to consume later (see **Supplementary Table 4** for a list of items). Participants were asked to choose between each combination of items ($n = 170$) twice, counterbalanced across left-right spatial configurations (total number of choices = 340) and divided into four sessions. After each choice, participants were asked to indicate their confidence in their decision (that is, "How confident are you that the choice you made was the right one for you?") on a continuous sliding scale between 1 (low confidence) and 6 (high confidence). Participants had 3,500 ms to move the pointer to the position that accurately reflected their confidence in the previous decision.

Post-scanning BDM task. Participants were presented each item on a computer screen and asked to submit a bid (from £0 to £3, using a sliding scale) to buy the item (unlimited time). After each bid, participants were asked to indicate their confidence in the bid they had just submitted (that is, "How confident are you that the bid you made was the right one for you?"; bid confidence) on a continuous sliding scale between 1 (low confidence) and 6 (high confidence). At the end of the experiment, one choice from the scanning phase was played out and the subject had the opportunity to buy the chosen item by means of an auction administered according to the Becker-DeGroot-Marschak (BDM) procedure[15]. More specifically, the experimenter randomly extracted a price from a uniform distribution (£0 to £3)—the 'market price' of that item. If the participant's bidding price (willingness-to-pay) was above the market price, no transaction occurred. If the subject's bidding price was below the market price, the participant bought the snack item at the market price. At the end of the experiment, participants had to remain in the lab for an additional hour. During this hour, the only food they were allowed to consume was the item purchased in the auction, if any. This procedure encouraged subjects to choose preferred snacks during the scanning phase[16,18]. Participants were compensated £40 for participation in the study. The price of any item purchased by a subject was deducted from this £40 participation fee.

Behavioral analysis and model. To examine the effect of value and confidence on choice we compared five candidate logistic regression models. All had the form

$$P(c = R | X) = \Lambda(X\beta)$$

where $\Lambda(x)$ is the logistic cumulative distribution function:

$$\Lambda(x; u, s) = \frac{1}{1 + e^{-\frac{x-u}{s}}}$$

$$P(c = R | X) = \frac{1}{1 + e^{-a + b_1 x_1 + b_2 x_2 + \ldots b_n x_n}}$$

$$\log \frac{P(c = R)}{1 - P(c = R)} = a + b_1 x_1 + b_2 x_2 + \ldots b_n x_n$$

The simplest candidate model predicts the probability of choosing the rightmost option from the signed difference in value (DV), defined as $V_R - V_L$:

$$\text{Model 1}: X = \text{DV}$$

The slope of this function is assumed to result from randomness in choice[20]. If, on the other hand, subjects have metacognitive access to the noise in their decision process, we might expect choice confidence to modulate the impact of DV on choice:

$$\text{Model 2}: X = [\text{DV} \ (\text{DV} \times \text{conf}_{\text{choice}})]$$

A second set of models examined whether confidence in the item price (bid confidence) modulates the link between DV and choice. On each trial there were two bid confidences (one for each item). Model 3 modulated DV by the mean bid confidence to enable direct comparison with model 2; model 4 split the DV predictor by bid confidence (low, high and mixed low/high, based on a subject-specific median split); model 5 extended model 4 by including additional regressors for the modulation of choice confidence (that is, model 2 split by different bid confidences):

$$\text{Model 3}: X = [\text{DV} \ (\text{DV} \times \overline{\text{conf}}_{\text{BDM}})]$$

$$\text{Model 4}: X = [\text{DV}_{\text{low}} \ \text{DV}_{\text{mixed}} \ \text{DV}_{\text{high}}]$$

$$\text{Model 5}: X = [\text{DV}_{\text{low}} (\text{DV}_{\text{low}} \times \text{conf}_{\text{choice}}) \\ \text{DV}_{\text{mixed}} (\text{DV}_{\text{mixed}} \times \text{conf}_{\text{choice}}) \\ \text{DV}_{\text{high}} (\text{DV}_{\text{high}} \times \text{conf}_{\text{choice}})]$$

Models were compared via BIC scores using a fixed-effects analysis, where a difference in BIC of 5 indicates strong evidence for one model over another[35]. Two subjects were excluded from the analysis in models 4 and model 5 owing to a low variability in item confidence, precluding a median split. In addition, we assessed the improvement in model fit obtained for model 2 over nested model 1 for each subject individually using a likelihood ratio test (χ^2, 1 d.f.).

Dynamic model of value comparison (race model). To predict how value, confidence and reaction time interact during decision-making, we harnessed a dynamic model of the value comparison process[7,21]. In the race model, separate decision variables accumulate evidence for distinct options, with the final decision determined by which accumulator reaches threshold first. On each time step during accumulation, a new evidence sample is drawn from a normally distributed random variable $s_t = N(u_{\text{stim}}, \sigma_{\text{stim}})$. u_{stim} is positive if the correct choice (higher value item) is the righthand item, negative if the correct choice is the left item. Because s_t is drawn from a normal distribution, the actual value of s_t at each time step may be positive or negative. The accumulators evolve according to the following equations:

$$R_{t+1} = \begin{cases} R_t + S_t, & S_t > 0 \\ R_t, & S_t \leq 0 \end{cases}$$

$$L_{t+1} = \begin{cases} L_t, & S_t \geq 0 \\ L_t - S_t, & S_t < 0 \end{cases}$$

The race terminates when either R_t or L_t reach a predetermined threshold, θ, with the decision being determined by which accumulator reaches threshold first. Therefore at decision time, $t(\theta)$, either R_t or $L_t = \theta$. The finishing point of the losing accumulator depends on the values of u_{stim} and σ_{stim}.

An estimate of decision confidence, Δe, can be recovered from the race model as the distance between the two accumulators R_t and L_t at the time the race is terminated (**Fig. 2b**; refs. 7,12).

We simulated the model using the same parameters as in ref. 7. We simulated 1,000 trials at each level of u_{stim} and recorded mean choice, confidence and reaction time. We display the simulation output in an identical manner to the behavioral data (**Fig. 2c–e**).

Even for identical levels of decision performance, it is known that the relationship between subjective confidence and decision-making varies between tasks and individuals[9,36]. We sought to account for this variability by introducing an additional parameter relating model confidence to subjective confidence, σ_{conf}. On each trial, reported confidence was drawn from a Gaussian distribution centered on Δe: conf = $N(\Delta e, \sigma_{\text{conf}})$. This feature of our model is consistent with the notion that reported confidence is derived from a higher-order stage of decision-making corrupted by noise[26]. We note that other functional forms for the link between model confidence and reported confidence are possible, but we do not investigate these here. We repeated the simulation three times with three levels of σ_{conf}, for a fixed σ_{stim}. Examination of psychometric function plots (**Fig. 6b**) shows that σ_{conf} can account for the variability in change in slope observed across individuals.

Image acquisition and analysis. Scanning acquisition was performed using a Siemens 3.0 T Allegra MRI Scanner (Erlangen, Germany). Gradient echo T2*-weighted EPI (echoplanar) functional images with BOLD-sensitive contrast were acquired (imaging parameters: 48 transverse slices; TR, 2.88 s; TE, 30 ms; 3 × 3 in-plane resolution; 2-mm slice thickness; 1-mm gap between adjacent slices; z-shim -0.4 mT/m; positive phase encoding direction; slice tilt $-30°$), optimized to detect changes in orbitofrontal cortex. For each subject, 228 volumes per session were collected (total number of volumes over four sessions = 912), followed by a whole brain high-resolution T1-weighted anatomical structural scan and local field maps. Image analysis was performed using SPM8 (http://www.fil.ion.ucl.ac.uk/spm/). The first five volumes from each session were discarded to allow for T1 equilibration. Raw functional, structural and field map files were reconstructed using TBR. Field maps were reconstructed into a single phase file. This field map file was then used to realign and unwarp EPI functional images. Structural images were reregistered to mean EPI images and segmented into gray and white matter. These segmentation parameters were then used to normalize and bias correct the functional images. Normalized images were smoothed using a Gaussian kernel of 8 mm full-width at half-maximum.

General linear model 1 (parametric). Onset regressors beginning at the presentation of the two items were modulated by two parametric regressors: (i) unsigned difference in value ($|DV|$), defined as the absolute difference in value between the item presented on the right (V_R) and the item presented on the left (V_L), with values V_R and V_L ascertained from subjects' bids in the post-scanning phase ($|DV| = |V_R - V_L|$); and (ii) post-choice confidence ratings, which ranged from 0 to 500 on an arbitrary scale. In this model, confidence is orthogonalized with respect to $|DV|$ by the SPM8 software. Second, for each subject we constructed a separate GLM using a factorial design.

General linear model 2 (factorial). Events were split into regressors based on confidence level (that is, low and high confidence) using a median split for each individual subject. Each of these regressors was modulated by a $|DV|$ parametric regressor (defined above).

Statistical inference. Second-level group contrasts from GLM 1 were calculated as one-sample t-tests against zero for each first-level linear contrast. Activations were reported as significant if they survived family-wise error correction (FWE) for multiple comparisons across the whole brain at the cluster level. For rRLPFC, we employed small-volume correction using an 8-mm sphere centered on the coordinates (36, 44, 28) taken from ref. 14. For GLM 2, rfxplot[37] (http://rfxplot.sourceforge.net/) was used to extract percentage signal change at each region of interest defined by 6-mm spheres around the vmPFC and rRLPFC peak voxels from GLM 1. These values were entered into 2 × 2 ANOVAs (factors value, confidence) to further clarify the pattern of activity seen in GLM 1. In analysis of individual differences we employed small-volume correction (SVC) using 8-mm spheres centered on the peak activations in vmPFC and rRLPFC taken from GLM 1.

Psychophysiological interaction analysis. To assess changes in connectivity between rRLPFC and vmPFC as a function of confidence, we carried out a psychophysiological interaction (PPI) analysis. PPI is a measure of context-dependent connectivity, explaining the regional activity of other brain regions (here, vmPFC) in terms of the interaction between responses in a seed region (here, rRLPFC) and a cognitive or sensory process. We used the second GLM (factorial) to run our PPI analysis (for details, see paragraph above). We carried out PPI analysis using the Generalised PPI toolbox for SPM (gPPI; http://www.nitrc.org/projects/gppi/). gPPI creates a new GLM in which the deconvolved activity of the seed region is assigned to separate regressors dependent on the status of the original psychological variable (high or low confidence), and reconvolved with the hemodynamic response function. Average time courses were extracted from all voxels in a 6-mm sphere surrounding the rRLPFC peak coordinate (39, 41, 16). The main effects of high and low confidence, the seed-region time course and motion parameters were included as regressors of no interest. The PPI contrast compares high_conf * rRLPFC ($+1$) with low_conf * rRLPFC (-1). This analysis showed a significant activation in vmPFC (9, 50, -11) that reflects the increased connectivity between vmPFC and rRLPFC during high compared to low confidence trials.

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