Deciding about courses of action involves minimizing costs and maximizing benefits. Decision neuroscience studies have implicated both the ventral and dorsal medial PFC (vmPFC and dmPFC) in signaling goal value and action cost, but the precise functional role of these regions is still a matter of debate. Here, we suggest a more general functional partition that applies not only to decisions but also to judgments about goal value (expected reward) and action cost (expected effort). In this conceptual framework, cognitive representations related to options (reward value and effort cost) are dissociated from metacognitive representations (confidence and deliberation) related to solving the task (providing a judgment or making a choice). We used an original approach aimed at identifying consistencies across several preference tasks, from likeability ratings to binary decisions involving both attribute integration and option comparison. fMRI results in human male and female participants confirmed the vmPFC as a generic valuation system, its activity increasing with reward value and decreasing with effort cost. In contrast, more dorsal regions were not concerned with the valuation of options but with metacognitive variables, confidence being reflected in mPFC activity and deliberation time in dmPFC activity. Thus, there was a dissociation between the effort attached to choice options (represented in the vmPFC) and the effort invested in deliberation (represented in the dmPFC), the latter being expressed in pupil dilation. More generally, assessing commonalities across preference tasks might help in reaching a unified view of the neural mechanisms underlying the cost/benefit tradeoffs that drive human behavior.

Key words: effort; reward; metacognition; decision-making; pupillometry; fMRI

Significance Statement

Decision neuroscience studies have implicated the medial PFC in forming the cognitive representations that drive human choice behavior. However, different studies using different tasks have suggested somewhat inconsistent links between precise computational variables and specific brain regions. Here, we use fMRI to demonstrate a robust functional partition of the medial PFC that generalizes across tasks involving an estimation of goal value and/or action cost to provide a judgment or make a choice. This general functional partition makes a critical dissociation between neural representations of decisional factors (the expected costs and benefits attached to a given option) and metacognitive estimates (confidence in the judgment or choice, and effort invested in the deliberation process).
vmPFC would estimate the expected reward while the dmPFC would estimate the expected effort (Bartra et al., 2013; Kurniawan et al., 2013; Clithero and Rangel, 2014; Skvortsova et al., 2014). However, this view has been challenged by representations of effort cost found in vmPFC activity and reward value in dmPFC activity (Gläscher et al., 2009; Fouragnan et al., 2015; Klein-Flugge et al., 2016; Pisauro et al., 2017; Arulpragasam et al., 2018; Seaman et al., 2018; Aridan et al., 2019; Hogan et al., 2019; Westbrook et al., 2019; Lopez-Gamundi et al., 2021). Other accounts insist on the comparison between options that occurs during choice and suggest that the two regions estimate decision values in opposite fashion (Boorman et al., 2009; Wunderlich et al., 2009; Hunt et al., 2012; Jocham et al., 2012): the vmPFC would activate while the dmPFC would deactivate with value difference (chosen minus unchosen option value). Yet this other view has been questioned because the correlation with chosen and unchosen option values is not always observed in these regions, and because the value difference may be confounded with other constructs, such as default preference, choice confidence, and decision time (Lim et al., 2011; Qin et al., 2011; De Martino et al., 2013; Jocham et al., 2014; Massar et al., 2015; Lopez-Persem et al., 2016; Bobadilla-Suarez et al., 2020). Thus, both types of accounts have received empirical support but also contradictory evidence, such that their validity is still debated.

Here, we intend to take a step aside from these debates and propose a functional partition that would generalize beyond choice tasks. Indeed, contrary to the view that there is no value representation outside of choice contexts (Hayden and Niv, 2021), neural correlates of values in the medial PFC have been found in many tasks that do not involve any choice between the items presented, including likeability rating and distractive tasks or even passive viewing, during which covert likeability ratings are spontaneously generated (Lebreton et al., 2009; Plassmann et al., 2010; Harvey et al., 2010; I. Levy et al., 2011; Abitbol et al., 2015; De Martino et al., 2017; Shenhav and Karmarkar, 2019; Lopez-Persem et al., 2020). We therefore reasoned that a general account for the role of the medial PFC in expressing preference should explain the pattern of activity observed during both rating and choice.

The new functional partition that we propose here is based on a metacognitive account (Lee and Daunizeau, 2021): the idea is that, whatever the task, the brain invests effort in deliberation until it reaches a satisfactory level of confidence in the intended response. Thus, a second cost/benefit trade-off would govern the metadecision about when to make a response, the cost being the amount of time spent in deliberation and the benefit being the level of confidence attained. During this double cost/benefit arbitration, the brain would represent two sorts of variables: (1) at the decisional level, the reward and effort values associated to options proposed for rating or choice; and (2) at the metacognitive level, the expected confidence in the response and the required amount of deliberation. The aim of the present study is to test whether this functional partition can account for the pattern of activity observed in medial prefrontal regions across rating and choice tasks.

Materials and Methods

General overview. To this aim, we reversed the typical logic of standard functional neuroimaging approach, which specifies the roles of brain regions with contrasts that isolate minimal differences between conditions. The idea is to move from the variants that are characterized by various conditions and tasks, with the aim to reach more robust conclusions. Thus, we used a series of preference tasks (also called "value-based" tasks) that enable the investigation of (1) the assignment of reward value or effort cost to a single option, with likeability rating tasks; (2) the comparison between two reward or two effort options with A/B choice tasks; and (3) the integration of reward and effort attributes for one option to accept or reject, with Yes/No choice tasks. In all these tasks, we defined the same key variables of interest as the global stimulus value (Val), which increases with more appetitive reward and/or less aversive effort, the confidence in the response (Conf), which is higher for more extreme ratings and more likely choices, and deliberation time (DT), meaning duration of the effort invested in the valuation process so as to reach a satisfactory response. We then explored the relationships between these three variables at the behavioral level, and their representations in the medial PFC at the neural level.

Subjects. In total, 40 right-handed volunteers participated in this fMRI study, which was approved by the Pitié-Salpêtrière Hospital ethics committee. Participants were recruited through the Relais d’Information en Sciences de la Cognition online platform (https://www.risc.cnrs.fr/) and signed informal consent before participation in the study. All participants were screened for the use of psychotropic medications and drugs, history of psychiatric and neurologic disorders, and traumatic brain injury. One participant was excluded from all analyses because of a clear misunderstanding about task instructions, leaving n = 39 participants for behavioral data analysis (22 females/17 males, aged 25.4 ± 4.1 years). Another participant was excluded from the fMRI analysis because of excessive movement inside the scanner (>3 mm within-session per direction). Eleven additional participants were excluded from pupil size analysis because of poor signal detection in at least one of the sessions (leaving a total of n = 27 participants for pupil analysis).

All participants gave informed consent and were paid a fixed amount for their participation. The 15 first subjects were paid 60€, and the 25 other subjects were paid 75€. The difference in payoffs corresponds to a difference in scanning protocols, although all participants performed the same tasks. The pilot protocol (n = 15) aimed at comparing fMRI data acquisition sequences: regular EPI, EPI with multiband acceleration, EPI with multiband acceleration + multi-echo acquisition. The main protocol (n = 25) aimed at addressing the neurocognitive question of interest with the best acquisition sequence. For this main protocol, we kept the regular EPI sequence for all sessions, as we saw no clear advantage for multiband acceleration or multiecho acquisition in basic contrast images. Therefore, the analyses only include fMRI data using regular EPI acquisition (three sessions for the pilot protocol, all nine sessions for the main protocol).

Behavioral tasks. All tasks were programmed using the Psychotoolbox (Brainard, 1997) Psychotoolbox-3 running in MATLAB (The MathWorks, version 2012). Participants were given a 4-button box (FORP 932, Current Designs) placed under their right hand to provide their responses. Stimuli were projected on a computer screen, their luminance being estimated using standard function of red-green-blue composition (0.299 × red + 0.587 × green + 0.114 × blue; see http://www.w3.org/TR/AERT#color-contrast). Stimuli comprised 144 reward items (72 food and 72 goods) and 72 effort items (36 mental and 36 physical). Half the reward items were presented with text only (Rew_t), and the other half were presented with both text and image (Rew_i). All effort items were only described with text (Eff_t). For each task, fMRI sessions were preceded by a short training (not included in the analysis), for participants to familiarize with the sort of items they would have to valuate and with the button pad they would use to express their preferences.

Participants all started with a (dis-)likeability rating task (see Fig. 1A), performed during the first three fMRI sessions, each divided into three 24-trial blocks corresponding to the three stimulus type (Rew_t, Rew_i, Eff_t). The order of blocks within a session was counterbalanced across participants. The items were presented one by one, and participants rated them by moving a cursor along a visual analog scale. They used their index and middle fingers to press buttons corresponding to left and right movements, and validated the final position of the cursor by pressing a third button, which triggered the new trial. The initial
position of the cursor, at the beginning of each trial, was randomly placed between 25% and 75% of the 0-100 rating scale. There was no mark on the scale, giving the impression of a continuous rating, although it was in practice discretized into 100 steps. The left and right extremes of the scale were labeled “I would not care” and “I would like it enormously” for reward items, “I would not mind” and “I would dislike it enormously” for effort items. Both reward and effort scales included indifference at one extremity, such that the two scales could form a continuum of increasing likeability from very aversive effort to very appetitive reward. In any case, the situations to be rated were hypothetical: the question was about how much they would like the reward (should it be given to them at the end of the experiment) and how much they would dislike the effort (should it be imposed to them at the end of the experiment). Should the timeout (10 s in rating tasks and 5 s in choice tasks) be reached, the message “too slow” would have been displayed on screen and the trial repeated later, but this remained exceptional.

After the three rating sessions, participants performed a series of binary choices. The A/B choice task (see Fig. 1B) involved expressing a preference between two options of a same dimension, presented on the left and right of the screen. The two options were items presented in the rating task, drawn from the same category, regarding both the presentation mode (Rewt vs Rewi, Rew vs Rewi, Eff vs Eff) and type of stimulus (food vs goods, goods vs goods, mental vs mental, physical vs physical). Each item was presented twice, following two intermixed pairing schedules: one varied the mean rating (i.e., stimulus value) while controlling for distance (i.e., decision value or choice difficulty), whereas the other varied the distance in rating while controlling the mean. Participants selected the reward they would most like to obtain, or the effort they would least dislike to exert, by pressing the left or right button with their index or middle finger. The chosen option was then highlighted in red, and subjects proceed to the next trial.

The A/B choice task included three 24-trial blocks presenting the three types of options (Rewi, Rewt, Eff), the order of blocks being counterbalanced across participants. Participants selected the reward they would most like to obtain, or the effort they would least dislike to exert, by pressing the left or right button with their index or middle finger. The chosen option was then highlighted in red, and subjects proceed to the next trial.

The fMRI sessions devoted to the A/B choice task included three 24-trial blocks presenting the three types of options (Rewi, Rewt, Eff), the order of blocks being counterbalanced across participants.

Then, participants performed the Yes/No choice task (see Fig. 1C), which involved deciding whether to accept exerting a given effort to get a given reward. Thus, every trial proposed one option combining two dimensions (one Rew and one Eff, item). Each item was presented twice, following two intermixed pairing schedules: one associating more pleasant reward with more painful effort (thus controlling for decision value or choice difficulty), the other associating more pleasant reward with less painful effort (thus varying choice difficulty). The mean net value was also balanced across fMRI sessions. Participants selected their response by pressing the button corresponding to “Yes” or “No,” positions counterbalanced across trials by pressing the left or right button, with their index or middle finger.
encountered in everyday life but are difficult to implement in the lab (e.g., walking a 1 km distance). Another reason was to allow for a distinction between the estimation of effort cost and motor preparation processes that are triggered when efforts are implemented (Hogan et al., 2019).

*Behavioral data analysis.* All data were analyzed using MATLAB 2017a (The MathWorks).

Choices were fitted with logistic regression models of decision value, with intercept and slope parameters.

For A/B choices, the model was as follows:

\[
P_{\text{left}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot V) + \beta_2 \cdot Jitter}}
\]

Where \(P_{\text{left}}\) is the probability of choosing the left option, \(V\) is the decision value, i.e., the difference in likeability rating between left and right options (\(V_{\text{left}} - V_{\text{right}}\)), while \(\beta_0\) and \(\beta_1\) are the intercept and slope parameters capturing potential bias and choice consistency (inverse temperature).

For Yes/No choices, the model was as follows:

\[
P_{\text{accept}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot V_{\text{Rew}} + \beta_2 \cdot V_{\text{Eff}})}}
\]

Where \(P_{\text{accept}}\) is the probability of accepting the offer (make the effort to get the reward), \(V_{\text{Rew}}\) and \(V_{\text{Eff}}\) are the likeability ratings provided for the reward and effort items. Thus, the decision value (or net value) here is a weighted sum of reward and effort likeability (one being positive and the other negative), the parameter weights \(\beta_{\text{Rew}}\) and \(\beta_{\text{Eff}}\) serving as both scaling factors and inverse temperature.

The stimulus value (Val) and response confidence (Conf) regressors used in the analysis of DT and fMRI data were defined as the addition of likeability ratings assigned to the items on screen and the squared distance from the mean response, respectively. They were adapted to each task, as shown in Table 1.

In each case, \(V\) is either the reward or effort likeability provided by \(z\)-scored individual rating of the item presented in a given trial, and \(P\) is the probability generated for each trial using the logistic model fitted to choices. By construction (before \(z\)-scoring), \(V\) is positive for reward items (which are liked) and negative for effort items (which are disliked). The mean response used in confidence estimation is simply the mean rating over trials, the mean frequency of left choice and the mean frequency of accept choice, depending on the task. The validity of our confidence proxy had been previously assessed and confirmed in two independent datasets (see Fig. 3).

DT was defined across tasks as the time between stimulus onset and first button press. Trial-wise variations in DT were fitted with linear regression models, including a session-specific intercept, factors of no interest (fixation cross, display duration (litter), stimulus luminance (Lum), text length in number of words (Length)) and factors of interest [stimulus value (Val), response confidence (Conf)]. Thus, the model was as follows:

\[
DT = \beta_0 + \beta_1 + \beta_2 \cdot \text{litter} + \beta_3 \cdot \text{Lum} + \beta_4 \cdot \text{Length} + \beta_5 \cdot \text{Val} + \beta_6 \cdot \text{Conf}
\]

*fMRI data acquisition.* Functional and structural brain imaging data were collected using a Siemens Magnetom Prisma 3-T scanner equipped with a Siemens 64 channel Head/Neck coil. Structural T1-weighted images were coregistered to the mean EPI, segmented and normalized to the standard T1 template and then averaged across subjects for anatomic localization of group-level functional activation. Functional T2*-weighted EPIs were acquired with BOLD contrast using the following parameters: TR = 2.01 s, TE = 25 ms, flip angle = 78°, number of slices = 57, slice thickness = 2.5 mm, FOV = 200 mm. A tilted-plane acquisition sequence was used to optimize sensitivity to BOLD signal in the orbitofrontal cortex (Deichmann et al., 2003; Weiskopf et al., 2007). The number of volumes per session was not predefined because all responses were self-paced. Volume acquisition was just stopped when the task was completed.

Most subjects (\(n = 25\)) performed nine fMRI sessions (three per task) using this standard EPI sequence. The pilot subgroup (\(n = 15\)) also performed nine fMRI sessions, but the fMRI data acquisition sequences were alternated between standard EPI, EPI with multiband acceleration factor (TR = 1.20 s; TE = 25 ms; flip angle = 66°; number of slices = 44; slice thickness = 2.5 mm; acceleration factor = 2) and EPI with multiband acceleration factor + multiecho (TR = 1.28 s; TE = 11.00 ms and 29.89 ms; flip angle = 69°; number of slices = 44; slice thickness = 2.5 mm; acceleration factor = 2). The order of fMRI sequences was counterbalanced across participants. Preliminary analyses of basic contrast images were done using the pilot dataset to select the best acquisition sequence. As there was no clear benefit with the multiband and multiecho add-ons, we retained the standard EPI for the main experiment.

Table 1. Definition of Val and Conf in each task

<table>
<thead>
<tr>
<th>Rating task</th>
<th>A/B choice task</th>
<th>Yes/No choice task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Val</td>
<td>([V \cdot \text{mean}(V)]^2)</td>
<td>([P_{\text{left}} - \text{mean}(P_{\text{left}})]^2)</td>
</tr>
<tr>
<td>Conf</td>
<td>([V \cdot \text{mean}(V)]^2)</td>
<td>([P_{\text{accept}} - \text{mean}(P_{\text{accept}})]^2)</td>
</tr>
</tbody>
</table>
correction for multiple comparisons at the voxel level. To avoid double dipping (Kriegeskorte et al., 2009) in statistical tests, regression estimates were extracted from ROIs redefined for each participant through a leave-one-out procedure. Regarding Bayesian model selection, to avoid biasing the comparison in favor of one or the other GLM, an independent ROI was defined as the conjunction between the positive minus negative value contrast in a published meta-analysis (Bartra et al., 2013) and the bilateral medial OFC region from the AAL atlas (Zouzou-Mazoyer et al., 2002). Additionally, we defined twelve 8 mm radius spherical ROIs in the medial wall to illustrate the distribution of regression estimates for Val, Conf, and DT. Parameter estimates were extracted from each voxel within these ROIs and then averaged across voxels.

**Meta-analysis of fMRI studies.** The meta-analytic maps were extracted from the online platform Neurosynth (https://www.neurosynth.org/), using the key words “value” (470 studies), “confidence” (79 studies) and “effort” (204 studies) for “uniformity test,” which displays brain regions that are consistently activated across papers mentioning the target key word. Each map was binarized to visualize clusters surviving a significance threshold of \( p < 0.01 \) after false discovery rate correction for multiple comparisons.

**Pupil size.** Pupil diameter was recorded at a sampling rate of 1000 Hz, using an EyeLink 1000 plus (SR Research) eye-tracker. The eye-tracker was calibrated before the start of fMRI sessions, once the subject was positioned inside the scanner. A cubical interpoleation was performed to compensate for any period of time when the pupil signal was lost because of blinking. The pupil size time series were subsequently bandpass filtered (1/128-1 Hz) and \( z \)-scored per session.

Within-trial variations in pupil size was baseline-corrected (by removing the mean signal over the 200 ms preceding stimulus onset) and time-locked either to stimulus onset or button press. Then trial-wise variations in pupil size were fitted with a linear regression model that included factors of no interest (an intercept per block, jitter duration, stimulus luminance, and text length), variables of interest (Val, Conf, and DT defined as in the Behavioral data analysis) and neural activity (extracted from vmPFC, mPFC, and dmPFC ROI clusters). Within-trial individual time series of regression estimates were then smoothed using a 100 ms kernel. Group-level significant time clusters were identified after correction for multiple comparisons estimated according to random field theory, using the RFT GLM_contrast.m function of the VBA toolbox (available at http://mmb-team.github.io/VBA-toolbox/).

**Results**

**Behavior**

Participants (\( n = 39 \) in total, 22 females) first performed a series of ratings, divided into three fMRI sessions (Fig. 1A). Each session presented 72 items to be evaluated one by one. Within a session, items were grouped into three blocks: one block with 24 reward items presented by text + image (Rewti), one block with 24 reward items presented by text only (Rewt), and one block with 24 effort items presented by text only (Eff). The reason for varying the mode of presentation was to assess the generality of the neural valuation process across different inputs that require more or less imagination, according to a previous study (Lebreton et al., 2013). For reward, participants were asked to rate how much they would like it, should they be given the item immediately after the experiment. Symmetrically, the instruction for effort was to rate how much they would dislike it, should they be requested to exert it immediately after the experiment. We included both food and nonfood (goodies) reward items, and both mental and physical effort items. There was no number on the scale, just labels on endpoints, and ratings were pseudo-continuous, from “I would not care/mind” to “I would like/dislike it enormously.” Thus, the left endpoint corresponded to indifference and the right endpoint to extreme attraction or extreme aversion (Fig. 1A).

The \( z \)-scored rating was taken as a proxy for stimulus value (Val) in this task, while the square of \( z \)-score rating was taken as a proxy for response confidence (Conf). The quadratic relationship between confidence and rating has been validated empirically and accounted for by a Bayes optimal model mapping a probabilistic distribution (over likeability) onto a bounded visual scale (Lebreton et al., 2015; Lopez-Persem et al., 2020). Under this model, confidence is inversely proportional to the variance of the underlying probability distribution, hence to the variability in likeability rating across presentations of the same item when they are repeated (which was not the case in the present design).

The confidence proxy used here is not to be confounded with motivational salience, which would be maximal for very appetitive reward and very aversive effort. Instead, confidence is maximal at the extremes of the rating scale, meaning for both very appetitive and null reward or for both very aversive and null effort (Fig. 2A). Also, Val and Conf were orthogonal variables by construction (Conf being a U-shaped function of Val for both reward and effort).

DT was defined as the time between item onset and the first button press used to move the cursor along the scale. DT was regressed against a linear model that included Val and Conf proxies (Fig. 2B), in addition to factors of no interest (e.g., jitter duration, stimulus luminance, text length, and trial index; see Materials and Methods). Irrespective of stimulus type, we found a significant effect of both value (Rewti: \( \beta_{\text{Val}} = -0.21 \pm 0.02, p = 4 \times 10^{-11} \); Rewt: \( \beta_{\text{Val}} = -0.17 \pm 0.02, p = 6 \times 10^{-11} \); Eff: \( \beta_{\text{Val}} = 0.26 \pm 0.03, p = 2 \times 10^{-11} \)) and confidence (Rewti: \( \beta_{\text{Conf}} = -0.17 \pm 0.03, p = 3 \times 10^{-8} \); Rewt: \( \beta_{\text{Conf}} = -0.19 \pm 0.03, p = 7 \times 10^{-8} \); Eff: \( \beta_{\text{Conf}} = -0.13 \pm 0.04; p = 0.0024 \)). Thus, participants were faster to provide their rating when the item was more appetitive (or less aversive) and when they were more confident (going toward the extremes of the rating scale). Among the factors of no interest, we observed effects of jitter duration, stimulus luminance, and text length, which were therefore included as regressors in subsequent analyses. However, there was no significant effect of trial index, which discards a possible contamination of DT by habituation or fatigue.

Then, participants performed a series of binary choices, either A/B choices or Yes/No choices. The choice tasks were always performed after the rating tasks because the ratings were used to control the difficulty of choices (i.e., the difference in value between the two options). In the A/B choice task (Fig. 1B), participants were asked to select the reward they would prefer to receive at the end of the experiment, if they were offered one of two options, or the effort they would prefer to exert if they were forced to implement one of two options. Thus, the two options always pertained to the same dimension (reward or effort), and even to the same subcategory (food or good for reward; mental or physical for effort), to avoid shortcut of deliberation by general preference. The mode of presentation (text or image) was also the same for the two options, to avoid biasing the choice by a difference in salience. To obtain a same number of trials as in the rating task, each item was presented twice, for a total of 72 choices per stimulus type (Rewti, Rewt, Eff) distributed over three fMRI sessions. Within a session, items were grouped into three blocks: one block with 24 choices between reward items presented with text + image (Rewti), one block with 24 choices between reward items presented with text only (Rewt) and one block with 24 choices between effort items presented with text only (Eff). In the Yes/No choice task (Fig. 1C), participants were asked whether they would be willing to exert an effort to obtain a...
reward, at the end of the experiment. Only items described with
text were retained for this task (since there was no picture for
effort items), each item again appearing twice, for a total of 144
choices divided into three fMRI sessions of 48 trials each.

The A/B choice task was meant to assess value comparison
between the two options, within a same dimension. The decision
value (\(D_V\)) in this task was defined as the difference in
(dis-)likeability rating between the two options. We checked
with a logistic regression (\(Fig. 2\)) that \(D_V\) was a significant
predictor of choices, regardless of stimulus type (Rew: \(\beta_{AV} =
3.28 \pm 0.27, p = 7 \times 10^{-13}; \beta_{SW} = 3.28 \pm 0.27, p =
7 \times 10^{-13}; \beta_{EF} = -2.87 \pm 0.16, p = 4 \times 10^{-17}\)). The Yes/No
choice task was meant to assess value integration across two
dimensions, for a single option. The decision value (or net
value) in this task was defined as a linear combination of
reward and effort ratings. It would make no sense to fit an
effort discounting function here because such function is
meant to capture the mapping from objective effort levels
to subjective effort estimates, which we directly collected (with
dislikeability ratings). We checked with a logistic regression
that both reward and effort ratings were significant predictors
of choice in this task (Rew: \(\beta_{AV} = 1.50 \pm 0.09, p = 6 \times 10^{-20}; \beta_{SW} =
-1.12 \pm 0.08, p = 1 \times 10^{-16}\)).

To analyze DT (time between stimulus onset and button
press) in choice tasks, we defined proxies for stimulus value
and response confidence, as we did for the rating task. Stimulus value
(Val) was defined as the addition of the likeability ratings
assigned to the two stimuli on screen. In the A/B choice
task, this is simply the sum of the two item ratings. In the
Yes/No choice task, this is the frequency of left option being selected. In the Yes/No choice task, decision
value is the addition of weighted reward and effort likeability ratings (\(\beta_{AV} = V_{left} \times V_{right}/2\)), which is equivalent to both stimulus value (Val) and to the value difference between yes
and no options (net value minus zero). Continuous lines indicate logistic regression fits of choice rate. Dashed lines indicate variations in the confidence proxy (Conf). B, DT as a function of confidence proxy (Conf), defined as the square of centered likeability rating (\(P^2\)) for rating tasks and the square of centered choice likelihood (\(P^2\)) for choice tasks. The Conf proxy was validated in
two different datasets where confidence in rating or choice was directly asked to participants (see \(Fig. 3\)). Dots represent mean across participants. x and y error bars indicate interparticipant SS, continuous lines indicate regression fits.
that DT decreased with value in the A/B choice task (Rew\textsubscript{A}: $\beta_{\text{Val}} = -0.06 \pm 0.01$, $p = 3 \times 10^{-2}$; Rew\textsubscript{B}: $\beta_{\text{Val}} = -0.06 \pm 0.01$, $p = 3 \times 10^{-2}$;Eff.: $\beta_{\text{Val}} = 0.05 \pm 0.01$, $p = 8 \times 10^{-4}$), albeit not in the Yes/No choice task ($\beta_{\text{Val}} = 0.033 \pm 0.024$, $p = 0.172$). DT also decreased with confidence (Fig. 2B) in both the A/B choice task (Rew\textsubscript{A}: $\beta_{\text{Conf}} = 0.741 \pm 0.20$, $p = 2 \times 10^{-10}$; Rew\textsubscript{B}: $\beta_{\text{Conf}} = -1.98 \pm 0.18$, $p = 4 \times 10^{-13}$; Eff.: $\beta_{\text{Conf}} = -1.73 \pm 0.22$, $p = 2 \times 10^{-9}$) and the Yes/No choice task ($\beta_{\text{Conf}} = -1.15 \pm 0.15$, $p = 1 \times 10^{-9}$).

Thus, the relationship between DT and confidence was similar in rating and choice tasks: participants were faster when they were more confident (because of a strong preference for one response or the other). They also tended to be faster when the options were more appetitive (or less aversive), but this trend was not significant in all tasks.

Because we did not measure confidence in the present study, we verified that our proxy could predict confidence ratings in separate datasets. This proxy has already been validated for likeability rating tasks used in previous studies (Lébreton et al., 2015; De Martino et al., 2017; Lopez-Persem et al., 2020), a result that we reproduced here (Fig. 3). To test whether the same proxy could also predict confidence in choice tasks, we used another dataset from a published study (Lee and Daunizeau, 2020). In this study, participants provided confidence ratings about having selected the best option in binary A/B choices (between food items presented 2 by 2). Our confidence proxy could significantly predict confidence judgments not only in the likeability rating task but also in the A/B choice task, even when including Val and DT as competitors (without orthogonalization) in the same regression model (rating: $\beta_{\text{Conf}} = 0.49 \pm 0.09$; $p = 8 \times 10^{-2}$; choice: $\beta_{\text{Conf}} = 0.21 \pm 0.02$; $p = 2 \times 10^{-11}$).

**Neural activity**

The aim of fMRI data analysis was to dissociate the first-level variables related to option attributes (reward and effort estimates) from the second-level variables related to metacognition (confidence and deliberation) across value-based tasks (rating and choice). To assess whether these variables can be dissociated on the basis of existing literature, we conducted a meta-analysis of fMRI studies using Neurosynth platform (Fig. 4A) with value, confidence, and effort as key words. Results show that the three key words are associated to similar activation patterns, with clusters in both vmPFC and dmPFC. To better dissociate the neural correlates of these constructs in our dataset, we built a GLM where stimulus onset events were modulated by our three variables of interest: Val, Conf, and DT (defined as in Behavioral data analysis). Factors of no interest that were found to influence DT (jitter duration, stimulus luminance, text length) were also included as modulators of stimulus onset events, before the variables of interest. By construction, the correlation between regressors of interest was low (between $-0.084$ and $-0.204$). Nevertheless, to avoid any confound in the interpretation, we used serial orthogonalization. Thus, the variables of interest were orthogonalized with respect to factors of no interest, and DT was made orthogonal to all other regressors, including Val and Conf.

After correction for multiple comparisons at the voxel level, we found only three significant clusters in the PFC (Fig. 4B): Val was signaled in vmPFC activity (Extended Data Fig. 4-1), Conf in mPFC activity (Extended Data Fig. 4-2), and DT in dmPFC activity (Extended Data Fig. 4-3). All three correlations were positive, there was no significantly negative correlation in any brain region when correcting for multiple comparisons. With a more

**Figure 3.** Validation of the confidence proxy (Conf). Our proxy for confidence (Conf = square of centered likeability rating or choice likelihood) was tested against confidence ratings collected in independent datasets. Left, In the likeability rating task (Lopez-Persem et al., 2020), participants first rated the likeability of food, face, and painting items and then provided a confidence rating about their own likeability judgment. Right, In the A/B binary choice task (Lee and Daunizeau, 2020), participants selected their preferred item between options shown in pairs, and then provided a confidence rating about having made the best choice. Graphs represent confidence rating as a function of binned Conf. Dots represent means over participants. Error bars indicate interparticipant SEs. Dotted lines indicate linear regression fits.

**Figure 4.** Neural mapping of value, confidence, and deliberation. A, Meta-analysis of fMRI studies. Statistical maps (sagittal slices) were extracted from the Neurosynth platform with the “value,” “confidence,” and “effort” key words. Significant clusters in the medial PFC are similar across key words, being located in both ventral and dorsal regions. B, Neural correlates of confidence, value, and deliberation constructs in the present dataset (in red, blue, and green, respectively). Statistical maps were obtained with a GLM, including the different variables as parametric modulators of stimulus onset, across rating and choice tasks. Sagittal slice was taken at the same coordinates as the Neurosynth output, and superimposed on the average anatomic scan normalized to canonical (MNI) template. Coronal slices show the extent of the different medial prefrontal clusters. Statistical threshold was set at $p < 0.05$ after family-wise error for multiple comparisons at the voxel level. For clusters outside the medial PFC, see activations in Extended Data Figures 4-1, 4-2, and 4-3. For clusters obtained using the same GLM without orthogonalization of regressors and using the same GLM with events modeled as boxcar instead of stick functions, see Figure 5 and Extended Data Figures 5-1, 5-2, and 5-3.
Neural mappings of value, confidence, and deliberation obtained with alternative GLM. The maps display significant correlates of Val (red), Conf (blue) and DT (green) in the medial PFC. A, Statistical map (same as in Fig. 4B) obtained with the main GLM is shown for comparison. B, Statistical map obtained with the same GLM when events were modeled with a boxcar function encompassing the period from trial onset to first button press. For all maps, sagittal slices were taken at the same coordinates as the Neurosynth output (shown in Fig. 4A), and superimposed on the average anatomic scan normalized to canonical (MNI) template. Maps were thresholded at $p < 0.05$ after voxel-wise family-wise error correction for multiple comparisons. For all maps, only the main clusters of interest located in the medial PFC are shown. For clusters outside the medial PFC, please refer to Extended Data Figures 4-1, 4-2, 4-3, 5-1, 5-2 and 5-3.

Figure 5. Neural mappings of value, confidence, and deliberation obtained with alternative GLM. The maps display significant correlates of Val (red), Conf (blue) and DT (green) in the medial PFC. A, Statistical map (same as in Fig. 4B) obtained with the main GLM is shown for comparison. B, Statistical map obtained with the same GLM when events were modeled with a boxcar function encompassing the period from trial onset to first button press. For all maps, sagittal slices were taken at the same coordinates as the Neurosynth output (shown in Fig. 4A), and superimposed on the average anatomic scan normalized to canonical (MNI) template. Maps were thresholded at $p < 0.05$ after voxel-wise family-wise error correction for multiple comparisons. For all maps, only the main clusters of interest located in the medial PFC are shown. For clusters outside the medial PFC, please refer to Extended Data Figures 4-1, 4-2, 4-3, 5-1, 5-2 and 5-3.

We further analyzed the relationship between computational variables and activity in the three medial prefrontal ROI with post hoc $t$ tests on regression estimates. To avoid any double-dipping issue, we used a leave-one-out procedure, such that clusters were defined from group-level analyses including all subjects but the one in whom regression estimates were extracted. We first verified that the three main associations were not driven by any particular task (Fig. 6B,C). Indeed, regression estimates were significant in both rating and choice tasks, more specifically for Val in vmPFC activity (rating: $\beta_{Val} = 0.69 \pm 0.13$, $p = 6 \times 10^{-6}$; choice: $\beta_{Val} = 0.47 \pm 0.10$, $p = 3 \times 10^{-5}$), for Conf in mPFC activity (rating: $\beta_{Conf} = 0.75 \pm 0.11$, $p = 8 \times 10^{-6}$; choice: $\beta_{Conf} = 0.31 \pm 0.10$, $p = 0.004$), and for DT in dmPFC activity (rating: $\beta_{DT} = 0.39 \pm 0.11$, $p = 9 \times 10^{-4}$; choice: $\beta_{DT} = 0.74 \pm 0.11$, $p = 7 \times 10^{-4}$). Our point was to generalize the associations across different tasks; comparing between tasks would be meaningless because tasks were not designed to be comparable (any possible significant contrast could be because of many differences of no interest).

We also investigated whether each cluster of interest was better associated with the corresponding variable (across tasks), again using a leave-one-out procedure to avoid double dipping (Fig. 6B): Val was better reflected in vmPFC activity ($\beta_{Val/vmPFC} > \beta_{Val/mPFC}$; $p = 9 \times 10^{-3}$; $\beta_{Val/vmPFC} > \beta_{Val/dmPFC}$; $p = 4 \times 10^{-7}$), Conf in mPFC activity ($\beta_{Conf/mPFC} > \beta_{Conf/vmPFC}$; $p = 0.0043$; $\beta_{Conf/mPFC} > \beta_{Conf/dmPFC}$; $p = 3 \times 10^{-7}$), and DT in dmPFC activity ($\beta_{DT/dmPFC} > \beta_{DT/vmPFC}$; $p = 0.066$; $\beta_{DT/dmPFC} > \beta_{DT/mPFC}$; $p = 7 \times 10^{-4}$). However, the fact that vmPFC, mPFC, and dmPFC better reflected Val, Conf, and DT, respectively, does not imply that these regions were not
affected by the other variables. In particular, vmPFC activity was also associated with Conf and DT ($\beta_{\text{Conf}} = 0.26 \pm 0.10, p = 0.012$; $\beta_{\text{DT}} = 0.40 \pm 0.11, p = 0.001$), even if it was dominated by Val-related activity. Nevertheless, all crossovers between interactions and regions were significant: from vmPFC to mPFC, the relative encoding of Val and Conf ($\beta_{\text{Val} - \text{Conf}}$) significantly reversed ($0.29 \pm 0.11 \text{ vs } -0.30 \pm 0.10, p = 2 \times 10^{-5}$) and similarly, from mPFC to dmPFC, the relative encoding of Conf and DT ($\beta_{\text{Conf} - \text{DT}}$) significantly reversed ($0.27 \pm 0.13 \text{ vs } -0.72 \pm 0.14, p = 9 \times 10^{-9}$). The distant crossover interaction between vmPFC and dmPFC ($\beta_{\text{Val} - \text{DT}}$) was also significant ($0.15 \pm 0.15 \text{ vs } -0.30 \pm 0.10, p = 10^{-5}$).

We next looked for further generalization of the valuation signal, not solely across tasks but also across stimuli. In the main analysis, fMRI time series were regressed against a GLM that separated stimulus types (Rew$\text{left}$, Rew$\text{right}$, and Eff$\text{left}$) into different onset regressors, each modulated by corresponding ratings. Instead of testing the average regression estimates across stimulus categories, we tested regression estimates obtained for each category, separately (Fig. 6D). Regression estimates (extracted using leave-one-out procedure across rating and choice tasks) show that vmPFC activity was positively related to the subjective value of reward items, whether or not they are presented with an image (Rew$\text{left}: \beta_{\text{Val}} = 0.49 \pm 0.13, p = 8 \times 10^{-3}$; Rew$\text{right}: \beta_{\text{Val}} = 0.61 \pm 0.13, p = 5 \times 10^{-5}$), and negatively correlated to the subjective cost of effort items (Eff$\text{left}: \beta_{\text{Val}} = -0.35 \pm 0.13, p = 0.017$). Thus, the association between Val and vmPFC activity was independent of the presentation mode, and integrated costs as well as benefits.

On a different note, we questioned the validity of our Val proxy to capture value-related activity in choice tasks. Again, the reason for summing stimulus values in choice tasks instead of taking the difference between chosen and unchosen option values, as is often done, was that we wanted a proxy that could generalize to rating tasks, in which there is no notion of difference, since there is only one stimulus on screen. The value difference regressor (chosen minus unchosen option value) is related to all three variables that we intend to dissociate here as capturing different concepts (stimulus value, response confidence, deliberation effort). Nevertheless, we wondered whether vmPFC activity in choice tasks would

**Figure 6.** Neural representations of value, confidence, and deliberation across behavioral tasks. A. Distribution of regression estimates (intersubject means ± SEs) obtained for Val, Conf, and DT variables along a ventro-dorsal line within the medial PFC (sampled in each 8 mm radius shown on the average anatomic map). Colored circles represent sampled spheres in which correlation with the corresponding variable was maximal. B. Decomposition of regression estimates obtained for each variable of interest, plotted separately for rating and choice tasks (noted R and C) and for the different ROI (vmPFC, mPFC, dmPFC). C. Decomposition of regression estimates obtained for each variable of interest (Val, Conf, and DT), plotted separately for each choice task (noted A/B and Y/N) in the different ROIs (vmPFC, mPFC, dmPFC). For the three region–variable associations, there was no significant difference between regression estimates obtained in the A/B and Yes/No choice tasks. D. Regression estimates were extracted across rating and choice tasks, separately for rewards presented as text (Rewt) or image (Rewi) and separately for reward (Rew) and effort (Eff) values. The vmPFC ROI was based on group-level cluster activated with Val using GLM1, following a leave-one-out procedure to avoid double dipping. E. Regression estimates were extracted from the vmPFC (group-level cluster activated to Val), using a GLM where Val, Conf, and DT were replaced by the chosen and unchosen option values ($V_c$ and $V_u$) across the two choice tasks. In more details, $V_c/\text{left}$ were $V_{\text{left}}/\text{right}$ for a left choice in the A/B task, and $\beta_{\text{Rew}} \times V_{\text{left}} + \beta_{\text{DT}} \times V_{\text{right}}$ for a yes choice in the Yes/No task (and vice-versa for opposite choices). F. Results of a Bayesian model comparison between the main GLM (GLM1) where Val is the sum, and an alternative GLM (GLM4) where Val is the difference between option values ($V_c - V_u$), for explaining vmPFC activity across the two choice tasks. The vmPFC was defined by a conjunction between the correlates of positive minus negative value from a published meta-analysis (Bartra et al., 2013) and the medial PFC region from the AAL atlas (Tzourio-Mazoyer et al., 2002) to avoid biasing the comparison in favor of the first GLM. Exceedance probability estimates were averaged across all voxels within the vmPFC ROI. Similar results were obtained when restricting the comparison to the A/B choice task. In all plots, bars represent means across participants; error bars indicate interparticipant SEs. Significance of t test against zero: ***p < 0.005; **p < 0.01; *p < 0.05; (*) p < 0.10.
be better captured by the difference \( V_c - V_{uc} \) than by the sum \( V_c + V_{uc} \). To test this, we simply replaced our partition (Val/Conf/DT) by \( V_c \) and \( V_{uc} \) regressors, and fitted the GLM to fMRI activity recorded during choice tasks only (Fig. 6E). The two regression estimates, extracted from the Val cluster in the main analysis, were significantly positive (\( \beta_{V_c} = 0.42 \pm 0.12, \ p = 9 \times 10^{-4}; \beta_{V_{uc}} = 0.29 \pm 0.07, \ p = 2 \times 10^{-4} \)), with no significant difference between the two (\( p = 0.36 \)), therefore showing no evidence for a representation of the difference. We completed this simple analysis by a comparison using Bayesian model selection at the group level, between two variants of the main GLM where Val was replaced by either the sum \( V_c + V_{uc} \) or the difference \( V_c - V_{uc} \), competing to explain choice-related activity in a vmPFC ROI defined from the literature (to avoid nonindependence issues). Although not formally conclusive, the comparison showed that exceedance probability was in favor of the sum model (Fig. 6F), thus validating our Val proxy as most relevant to capture vmPFC activity, even during choices. Another advantage of this Val proxy is being orthogonal to confidence, whereas the difference between option values is not. The consequence is that the neural correlates of Conf were unaffected by introducing the Val regressor, or by serial orthogonalization (Fig. 5).

Importantly, no consistent association with reward value or effort cost was observed in putative opponent brain regions, such as the dmPFC, which was instead systematically reflecting DT. Thus, it appeared that dmPFC activity reflected the metacognitive effort cost invested in the ongoing task (deliberation about the response) rather than the effort cost attached to the option on valuation. Importantly, the association with DT was observed despite the fact that DT was orthogonalized to both value and confidence, suggesting that the dmPFC represents the effort invested above and beyond that induced by the difficulty of value-based judgment or decision.

The parametric modulation by DT was also obtained when dmPFC activation was fitted with a boxcar function extending from stimulus response (Fig. 5), suggesting a modulation in amplitude beyond prolonged activity.

However, DT is a very indirect proxy for the effort invested in solving the task, and could be affected by many other factors (e.g., distraction or mind-wandering). We therefore investigated the relationship between brain activity and another proxy that has been repeatedly related to effort: pupil size. Neural activity was extracted in each ROI by fitting a GLM containing one event (stimulus onset) per trial. Then pupil size at each time point was regressed across trials against a GLM that contained factors of no interest (luminance, jitter duration, text length), variables of interest (Val, Conf, DT), and neural activity (vmPFC, mPFC, dmPFC).

A positive association between pupil size and dmPFC activity was observed in both rating and choice tasks (Fig. 7), \( \sim 1 \) s before the response. This association was not an artifact of the trial being prolonged (and therefore of the response to luminance being cut at different durations), since it was observed both when locking time courses on stimulus onset and on motor response (button press). Finally, it was specific to the dmPFC ROI, and observed even if dmPFC was made independent (through serial orthogonalization) to all other variables (notably Val, Conf, and DT). Thus, the association between dmPFC and pupil size was observed above and beyond DT and factors that could affect DT. In contrast, there was no consistent association between vmPFC and pupil size before the response, suggesting that the correlates of DT observed in vmPFC were not related to effort but to some other factors affecting DT, such as mind-wandering.

Discussion

Exploring the neural correlates of variables that are common to rating and choice tasks, we observed a functional partition within the medial PFC: stimulus value, response confidence, and DT were best reflected in vmPFC, mPFC, and dmPFC activity, respectively.

Our results confirm the role attributed to the vmPFC as a generic valuation system (D. J. Levy and Glimcher, 2012; Bartra et al., 2013). The subjective value of reward items was reflected in vmPFC activity regardless of the category (food vs goods), as was reported in many studies (Chib et al., 2009; Lebreton et al., 2009; Abitbol et al., 2015; Lopez-Perssem et al., 2020). Also, vmPFC value signals were observed whether or not reward items were presented with images, suggesting that they can be extracted from both direct perceptual input or from text-based imagination, which was shown to recruit episodic memory systems (Lebreton et al., 2013). Critically, our results show that the vmPFC also reflects the effort cost (whether mental or physical) attached to potential courses of actions. Therefore, they challenge previous suggestions that the vmPFC is involved in stimulus valuation, independently of action costs (Rangel and Hare, 2010; Clairis and Pessiglione).
Pessiglione et al., 2018). They rather suggest that the vmPFC might compute a net value, its activity increasing with reward benefit and decreasing with effort cost, so as to prescribe whether or not an action is worth engaging. This idea is in line with recent mounting evidence that vmPFC activity decreases with effort demand (Aridan et al., 2019; Hogan et al., 2019; Westbrook et al., 2019; Lopez-Gamundi et al., 2021).

The mPFC was not affected by reward value or effort cost, but the confidence in the response. Our notion of confidence (defined as the squared distance from the mean response) was orthogonal to stimulus value (defined as the addition of reward and/or effort values). This confidence proxy was previously shown to correlate with confidence ratings and to elicit similar neural correlates (De Martino et al., 2017; Lopez-Persem et al., 2020). The value proxy is related to the representation of overall value (or “set liking”) assigned to choice options, which was previously observed in vmPFC activity (Blair et al., 2006; Palminteri et al., 2009; Hare et al., 2011; Jocham et al., 2014; Gluth et al., 2015; Shenhav and Karmarkar, 2019). The two notions are close to the sum and difference signals that may emerge from an attractor network model in which two neuronal populations compete for their favorite option through mutual inhibition (Hunt et al., 2012). Our results suggest a partial dissociation of value and confidence signals (as in Shenhav and Karmarkar, 2019) that is consistent with a previously described ventro-dorsal gradient from value to confidence (De Martino et al., 2017). The same dissociation applied to the rating task, where there is no comparison between unrelated options. There could be a covert comparison between current and previous items, but with the purpose to adjust the rating, not to select an option and discard the other. We also acknowledge that, in a sense, a likeability rating can be conceived as a choice, since one position on the rating scale must be selected. However, this would be choosing between a large number (virtually infinite) of possible responses ordered along a single dimension (likeability). It is highly unlikely that the brain would solve the rating task through a competition mechanism in which each neuronal population would vote for one position on the scale. Thus, observing the same pattern of medial PFC activity across rating and choice tasks suggests that the functional role of this region cannot be reduced to models narrowly applied to the classical case of comparison between two options. It is more compatible with a neural network model (Pessiglione and Daunizeau, 2021) whose function is to generate values (from stimulus features), not to compare them for option selection. As rating and choice tasks both involve valuating the stimuli and selecting the response in which confidence is maximal, it may not be surprising that they share a common representation of stimulus value and response confidence, in the vmPFC and mPFC, respectively. Confidence was the only variable significantly associated to mPFC activity but was also positively reflected in vmPFC activity, as previously reported (Chua et al., 2006; De Martino et al., 2013; Gherman and Philiaistides, 2018). Indeed, the addition of value and confidence signals in the vmPFC is a pattern that has been already observed in both fMRI and iEEG activity (Lebreton et al., 2015; Lopez-Persem et al., 2020). On the contrary, dmPFC activity tended to decrease with confidence, but this trend did not survive significance threshold.

The variable that was robustly associated with dmPFC activity was DT. This variable was not orthogonal to the others, since it decreased with both stimulus value and response confidence. In some of our analyses, DT was post hoc orthogonalized with respect to the other variables, meaning that the association with dmPFC activity was observed above and beyond the variance explained by stimulus value and response confidence. This association alone would not yield a clear-cut interpretation, since many factors may affect response time. However, the systematic link observed between trial-wise dmPFC activation and the increase in pupil size just before the response hints that this association might reflect the cognitive effort invested in the task. Indeed, pupil size has been associated to the intensity of not only physical effort, such as handgrip squeeze (Zénon et al., 2014), but also mental effort, such as focusing attention to resolve conflict or overcome task difficulty (Kahneman and Beatty, 1966; Alnaes et al., 2014; van der Wel and van Steenbergen, 2018). By contrast, we did not observe this systematic link with pupil size during deliberation with vmPFC activity. The link between vmPFC and DT might therefore reflect other sources of variance, such as mind-wandering (being slower because of some off-task periods), in accordance with a previous report that elevated baseline vmPFC activity predicts prolonged response time (Hinds et al., 2013). Regarding dmPFC, our ROI overlaps with clusters that have been labeled dACC, or sometimes pre-SMA, in previous studies (Shenhav et al., 2013; Kolling et al., 2016; Kaminski et al., 2017). The association with DT is compatible with a role attributed to this region in the exertion of both physical effort (Kurniawan et al., 2013; Skvortsova et al., 2014; Chong et al., 2017) and cognitive control (Botvinick et al., 2001; Kerns et al., 2004; Sohn et al., 2007). Importantly, this dmPFC region differs from clusters located with the cingulate gyrus that have been more specifically related to physical effort (Prevost et al., 2010; Klein-Flugge et al., 2016).

To recapitulate, we have teased apart the neural correlates of likeability, confidence, and deliberation in the medial PFC, which have been confused in previous fMRI studies, as shown by meta-analytic maps. The key distinction operated here is perhaps between effort as an attribute of choice option and effort as a resource allocated to solving the task, or in other words, between valuation applied to effort (implicating the vmPFC) and effort invested in valuation (implicating the dmPFC). This dissociation is consistent with the idea that the vmPFC anticipates the aversive value of a potential effort, whereas the dmPFC represents the intensity of effort when it must be exerted. It could be related to efforts being hypothetical in our design, but previous studies have observed similar effort representation in the vmPFC (not the dmPFC) when efforts were not hypothetical but only implemented later, at the end of the experiment (Aridan et al., 2019; Hogan et al., 2019; Westbrook et al., 2019). At a metacognitive level, our results could be interpreted in the frame of a resource allocation model, where the effort or time invested in deliberation is meant to increase confidence in the response, whether a rating or a choice (Lee and Daunizeau, 2021). Yet our results cannot tell whether the dmPFC signals the need for deliberation effort, monitors the time invested in deliberation, or generates an aversive feeling related to the prolongation of deliberation.

Even if showing robust associations across tasks between brain regions and cognitive variables, our approach also bears limitations. Notably, our design would not allow comparing between conditions, as is traditionally done in neuroimaging studies. One may want, for instance, to compare between tasks and test whether brain regions are more involved in one or the other, but this would be confounded by several factors, such as the order (choice tasks being performed after rating tasks). A significant contrast would not be interpretable anyway because there is more than one minimal difference between tasks. Thus, the aim to generalize the role of brain regions across tasks carries the inherent drawback of a limited specificity, but also the
promises of a more robust understanding of anatomo-functional relationships. We hope this study will pave the way to further investigations following a similar approach, assessing a same concept across several tasks in a single study, instead of splitting tasks over separate reports, with likely inconsistent conclusions.

References


