Neurocomputational mechanisms underlying effort-based value integration

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1 Summary

In everyday life, we encounter many decisions requiring the consideration of prospective effort, such as taking exercise and altruistic behaviors. Therefore, the ability to accurately weigh effort costs against potential rewards is critical for optimal goal-directed behavior. The common currency theory proposes that values of different options are mapped to a common scale by a neural network to ensure efficient decision-making across different cost types. This theory provides a general framework to explain how rewards and costs are integrated and has gained popularity in decision-making associated with other types of cost, such as risk and delay. Although a few studies have examined the computational and neural mechanisms underlying effort-based value integration, it remains unclear if effort discounts prospective outcomes in a similar way to other costs, and, at the neural level, it is still under debate if effort-based value integration engages a general valuation neural network as suggested by the common currency theory, or instead relies on a specific network compared with other cost domains.

In this dissertation, I address these questions across a meta-analytic study and two empirical studies. In study 1 (Lopez-Gamundi et al., 2021) of this dissertation, we conducted two separate meta-analyses to examine consistent neural correlates of effort-reward integration or raw effort requirement in related fMRI studies. We found that the vmPFC activity scaled positively with net value but negatively with raw effort. On the other hand, the dmPFC was also identified in both analyses, but its activity scaled negatively with net value and positively with raw effort. These findings are generally consistent with previous findings in other cost domains.

In study 2 (Yao et al., 2022), to directly test if the common currency theory could be applied to value integration during effort-based decision-making, we reanalyzed the choice behavior and fMRI data of an open-access dataset, which included both effort-based and risky (one-option) decision-making tasks. Using computational modeling, we found that effort and risk showed distinct discounting effects on prospective

outcomes. At the neural level, we conducted multivariate decoding analyses and found that a large cluster including both the vmPFC and dmPFC represented subjective value independent of cost types.

In study 3 (Yao et al., 2022), we examined the replicability of the findings of Study 2 in an independent sample of participants. Moreover, to maintain similar overall acceptance rates between tasks, we estimated participant-specific indifference points for all combinations of rewards and costs (effort or risk) before scanning and manipulated the amounts of smaller rewards around these indifference points during scanning. We confirmed that effort and risk distinctively devalued rewards. At the neural level, we found that the dmPFC represented subjective value in a task-independent manner.

Taken together, these findings highlight the role of the dmPFC in subjective value computation across effort-based and risky decision-making. Finally, I discuss how these results may reconcile the ongoing debates on the neural mechanisms underlying effort-reward integration and outline potential implications for the common currency theory.

2 Glossary

common currency theory A theory positing that the values of different options are converted to a single scale at the neural level, which allows efficient value comparison across different categories and contexts. 1, 9, 11, 12, 16, 36, 45, 51, 56

dACC Dorsal anterior cingulate cortex. 11, 50

dmPFC Dorsomedial prefrontal cortex. A section of the prefrontal cortex that is overlapping with multiple anatomical regions including the dorsal anterior cingulate cortex and some parts of the pre-supplementary motor area (Kolling et al., 2012). 1, 2, 11–13, 15, 22, 31–33, 35, 36, 39, 43, 46, 48–52, 54, 55

hierarchical Bayesian analysis A computational modeling method that specifies a statistical model in multiple levels (e.g., individual and group level) and estimates the posterior distributions of the parameters using the Bayesian method (Huys et al., 2011). The use of the prior group-level distribution over the parameters allows it to move outlier fits closer to the group mean after multiple iterations and to generate more stable estimates. As a Bayesian approach, it finds the posterior distributions of the parameters instead of point estimates, thus providing more information about the parameters (Ahn et al., 2013). 28

LOOIC Leave-one-out information criterion. A Bayesian criterion to compare the out-of-sample predictive accuracy between models (Vehtari et al., 2017). A lower value indicates a better fit between the model and data. 28

MNI space A widely used 3-dimensional coordinate system of the human brain that originated from the Montreal Neurological Institute. 19, 21, 30

MVC Maximum voluntary contraction. An index of maximum physical effort measured from the effort calibration task. It can be used as a reference to quantify effort requirements across participants. 23, 49

MVPA Multivariate pattern analysis. A method that uses a combination of multiple variables measuring neural activity (blood-oxygen-level-dependent (BOLD) signals from multiple voxels during fMRI scanning in this dissertation) to characterize cognitive processes (Haynes, 2015). 14, 16, 37, 46, 48, 49, 51, 52

pre-SMA The most anterior portion of the supplementary motor area. 22, 35

ROI Region of interest. 22, 35, 36

searchlight analysis An MVPA method mainly used for fMRI data. It measures the information in small spherical clusters (i.e., searchlights) of voxels. The value (e.g., decoding accuracy) for each searchlight is assigned to its centered voxel (Etzel et al., 2013). This approach can be used to identify locally informative brain regions. 32

subjective value The net value of a prospective outcome discounted by some costs. It is inherently subjective and thus different across participants. Subjective values of options can be estimated by a computational model using a decision-making task, as options with higher subjective values would be selected more often. 2, 7, 9, 11–13, 17, 27, 28, 31, 32, 39, 41, 43, 48, 50, 51, 55

univariate analysis A widely used fMRI data analysis method, in which statistical analyses are conducted separately for each voxel using a general linear model. 14, 16, 37, 46, 48–52

utility A subjective measure reflecting how much people like or dislike an outcome (Kahneman & Tversky, 1979). The utility function is typically concave for positive outcomes and convex for negative outcomes. 27

vmPFC ventromedial prefrontal cortex. A region that is located in the ventromedial section of the prefrontal cortex. It has often been included in the common currency theory as a hub region in subjective value calculation across different tasks (D. J. Levy & Glimcher, 2012). 1, 2, 10–12, 15, 22, 31–33, 35, 36, 39, 43, 45, 46, 48–52, 54, 55

3 Introduction

Many decisions in real life require people to consider potential rewards and costs at the same time (Basten et al., 2010; Burke et al., 2013). One typical type of cost is effort (see Box 1). We often need to decide if it is worth exerting effort to obtain some rewards. For example, one may think about whether to have dinner in a good restaurant that is far away from home, whether to go to the gym to do exercise, and whether to help a friend move to a new flat. Therefore, the ability to weigh effort costs against prospective outcomes is critical for our personal happiness and social relationships with other people.

On the other hand, maladaptive effort-based decision-making has been observed across a range of psychiatric and neurological disorders, such as schizophrenia (Gold et al., 2015), Parkinson's disease (Chong et al., 2015), major depression (Treadway et al., 2012), and addictions (Brassard & Balodis, 2021). Moreover, a diminished willingness to exert effort is closely associated with behavioral apathy in general (Bonnelle et al., 2016). Hence, elucidating the mechanisms underlying effort-based decision-making may shed light on the development of effective treatments or interventions for related disorders (Westbrook et al., 2020).

A key component that influences people's effort-based decision-making is the net value of an option, which is based on how much a prospective outcome is devalued by related effort requirement (Chong et al., 2017). Individuals are more likely to select options with higher net values during decision-making. Since the computation of net value is inherently highly subjective for different people (Figure 1), it has been referred to as subjective value by researchers (Kable & Glimcher, 2007; Peters & Büchel, 2009).

However, despite considerable advances, there is still an ongoing debate on how the brain integrates potential rewards and effort costs to generate subjective value. Moreover, a broader question is whether effort-reward integration relies on a similar neural network compared to decisions associated with other cost types. This dissertation aims to address these questions and advance our understanding of the neural and computational mechanisms underlying effort-based subjective valuation.

Box 1| Three common types of costs in decision-making

Rewards are rarely obtained without incurring costs. Thus, we often need to weigh the benefits of an option (e.g., potential monetary rewards) against accompanying costs when making decisions (Basten et al., 2010).

One of the most well-studied types of cost is ***risk*** (Kahneman & Tversky, 1979; Mohr et al., 2010), which has been usually defined as the probabilities associated with possible outcomes of each option (Brand et al., 2006; Kahneman & Tversky, 1979). Since the uncertainty induced by probabilities decreases individuals' willingness to select a risky option, such a phenomenon is also called probabilistic discounting (L. Green & Myerson, 2004). Please note that risk is different from ambiguity, another situation in which the outcome of a choice is uncertain (I. Levy et al., 2010). For risky decision-making, the probability of each option is known, whereas for ambiguous decision-making even these probabilities are unclear (Brand et al., 2006; I. Levy et al., 2010).

Delay is another type of cost that is commonly involved in our everyday decisions. A typical scenario for this decision situation is to select a smaller reward immediately or a larger reward after waiting a period of time. Therefore, it is also called intertemporal decision-making by some researchers (Kable & Glimcher, 2007; Peters & Büchel, 2009). Since delay discounting is an important index of self-control, a great number of studies have also examined its development throughout the lifespan (L. Green et al., 1994; Steinberg et al., 2009) and related deficits in mental disorders (Amlung et al., 2019; Bickel & Marsch, 2001).

Similar to the effects of risk and delay, ***effort*** requirements can also decrease the net value of an option. Therefore, effort is regarded as another typical type of cost. Moreover, effort can be experienced in different domains (Chong et al., 2017; Schmidt et al., 2012). For example, this dissertation focuses on decision-making tasks requiring physical effort. Some other tasks including working memory or task switching components are more cognitively effortful (Chong et al., 2017; Sayalı & Badre, 2019).

3.1 Common currency theory

A fundamental question in decision-making research is how humans make choices between options with different attributes. The common currency theory provides a plausible perspective to address this question (D. J. Levy & Glimcher, 2012). As shown in Figure 1, this theory posits that people need to take different attributes of an option into account and calculate a (subjective) net value for each option based on a combination of these attributes. This allows us to efficiently compare options of different kinds because the subjective value is represented on a single common scale.

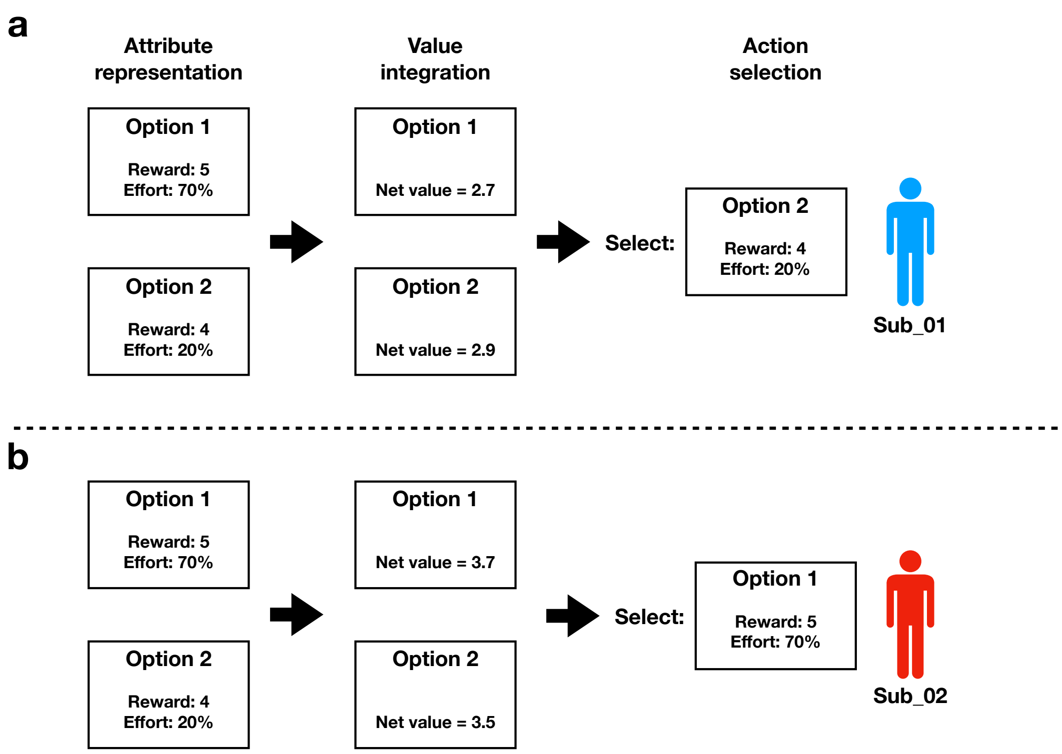

Figure 1. A graphical illustration of three basic processes during effort-based decision-making. First, a decision maker needs to form representations of the decision problem, such as the attributes (e.g., effort demands, potential rewards) associated with each option; second, as suggested by the common currency theory, they calculate the net value of each option based on associated attributes; and finally, they can compare available options based on their net values and make a selection. The net value calculation is highly subjective, so different people **(a, b)** may generate a different subjective value for the same option. This schematic is based on the framework proposed by Rangel et al. (2008).

The idea of the common currency representation is not new, because many other classic theories of decision-making (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) are also implicitly or explicitly based on a similar assumption. However, apart from these classic theories, the common currency theory has also been inspired by the findings from neuroscience studies and assumes that a common neural network is involved in subjective value computation across different decision-making tasks (Bartra et al., 2013; D. J. Levy & Glimcher, 2012; Padoa-Schioppa, 2011). Hence, it has also been directly called the neural common currency theory by some researchers (Kobayashi & Hsu, 2019; Sescousse et al., 2015).

Accumulating evidence suggests a small group of brain regions, which mainly includes the vmPFC and, arguably to a lesser degree, ventral striatum, play a critical role in value integration across different tasks (Clithero & Rangel, 2013; D. J. Levy & Glimcher, 2012). For example, previous work showed the vmPFC activity correlated with values of primary and secondary rewards (Chib et al., 2009; McNamee et al., 2013; Sescousse et al., 2013). Such effects have been observed in both anticipation and receipt periods during decision-making (Bartra et al., 2013) and can be extended to social contexts (Cutler & Campbell-Meiklejohn, 2019).

This valuation network has also often been identified during cost-reward decision-making (Box 1). For example, in one of the earliest studies in this field, Kable and Glimcher (2009) found that neural activity in several brain regions, including the vmPFC and ventral striatum, positively scaled with the subjective value of the delayed options. These findings were replicated by a great number of follow-up studies examining value integration during risky and intertemporal decision-making (I. Levy et al., 2010; Park et al., 2011; Peters & Büchel, 2009, 2010).

3.2 Effort-based value integration

In addition to risk and delay, another common type of cost in our everyday decisions is effort (Box 1). Due to its ubiquitous presence, there has been a surge of interest in the neural basis of effort-based value integration. Building upon the common currency theory and evidence from risky and intertemporal decision-making studies (Kable & Glimcher, 2007; I. Levy et al., 2010; Peters & Büchel, 2009), a common assumption is that effort-based value integration relies on a similar neural network including the vmPFC and ventral striatum.

This view has indeed received some supportive evidence. For example, in one study by Arulpragasam et al. (2018), participants were asked if they were willing to exert some physical effort to obtain a certain amount of reward during fMRI scanning. They found that the vmPFC activity was positively associated with subjective value. This finding was replicated in another study using a two-option decision-making paradigm, in which participants had to choose between a sure option (i.e., 100%) with a low physical effort requirement and an alternative with 50% to exert a higher amount of physical effort (Hogan et al., 2019). Except for decision-making associated with physical effort, one study found that a neural network including the vmPFC also tracked the subjective value of cognitive effort (Westbrook et al., 2019). These findings all implicate that the vmPFC also plays a critical role in subjective value computation during effort-based decision-making.

On the other hand, however, some studies observed subjective value signals beyond the abovementioned classic valuation network during effort-based decision-making. For example, an early fMRI study found value signals in the dmPFC (and some parts of the striatum) during a one-option effort-based decision-making task (Croxson et al., 2009). The association between the dmPFC activity and subjective value has also been identified by some follow-up studies using physical or cognitive effort-based decision-making tasks (Chong et al., 2017; Klein-Flügge et al., 2016), although the cluster location and direction of the effect varied between studies. These results are also in line with rat studies, in which lesions to the dmPFC (specifically the dACC) diminished the willingness to exert effort to obtain large rewards (Walton et al., 2003). Taken together, these findings raise the possibility that another neural network centered around the dmPFC is specifically involved in effort-based value integration.

3.3 Effort-based vs. other decision-making

Although the studies mentioned above examined if the domain-general valuation network suggested by the common currency theory could play a similar role in effort-based value integration, they only used a single decision-making task and thus can only provide circumstantial evidence. To directly test this question, a few studies went one step further by comparing the neural correlates of subjective value between decisions associated with effort and other types of costs (e.g., risk, see Box 1), yet yielding mixed results.

For example, Prévost et al. (2010) conducted one of the first studies that compared effort-based and intertemporal decision-making. In this study, participants were asked if they would like to exert some physical effort or wait for a period of time to view erotic stimuli afterward. They found that the vmPFC and ventral striatum activity positively correlated with the subjective value of delayed rewards, whereas a distinct network, including the dmPFC and anterior insula, showed negative neural correlates of subjective value during effort-based decision-making. A follow-up study (Massar et al., 2015) using monetary rewards showed that subjective value calculation during effort-based and intertemporal decision-making seemed to rely on a common network including the inferior frontal gyrus and some temporal and parietal regions. Moreover, similar to the study by Prévost et al. (2010), this study also showed that the dmPFC was uniquely recruited to encode rewards discounted by cognitive effort. In a similar vein, another study compared effort-based and risky decision-making. The results, however, showed that vmPFC activity increased with subjective value in both tasks (Aridan et al., 2019). Finally, a study included decision-making tasks associated with three common types of cost, namely effort, risk, and delay (Box 1). The main finding was that both the vmPFC and dmPFC seemed to be involved in subjective value computation across these three tasks (Seaman et al., 2018).

3.4 Potential issues related to the inconsistency across previous studies

In summary, there is still an ongoing debate on the neural basis underlying effort-based value integration. The inconsistency between previous studies may be related to several issues:

First, some studies may be statistically underpowered because of small sample sizes, which can reduce the probability of detecting effects related to value integration in some brain regions. The findings from these studies are also less reliable because they are more easily influenced by outliers (Poldrack et al., 2017). Except for conducting independent confirmatory studies with sufficient sample sizes, another approach to addressing this issue is to conduct a meta-analysis to quantitatively synthesize evidence across multiple previous studies (Müller et al., 2018).

Second, different paradigms have been used in previous studies. Thus, some results from individual studies could be related to specific task features rather than subjective value. Moreover, even in a similar paradigm, researchers may focus on different cognitive processes. For example, some studies only examined the neural correlates of raw effort requirement instead of value integration (Hauser et al., 2017; Vassena et al., 2014). Although subjective value is calculated directly based on effort requirement, the neural substrates of these two processes could be different.

Third, some studies required participants to exert chosen effort during decision-making, while the other studies did not, making it difficult to disentangle the effects of motor components from value integration at the neural level. This is important because some regions identified in previous studies, such as the dmPFC, are anatomically adjacent to motor-related brain areas and may be activated by motor preparation (Chong et al., 2017). A solution used in some studies is to ask participants to execute effort at the end of the experiment after completing all decisions (Aridan et al., 2019; Chong et al., 2017; Westbrook et al., 2019).

Fourth, many of the abovementioned effort-based decision-making studies used a model-based fMRI analysis (Arulpragasam et al., 2018; Chong et al., 2017; Klein-Flügge et al., 2016; Prévost et al., 2010), in which the latent variable of interest (trial-wise subjective value in this case) was estimated by a computational model. However, various discounting models were used in these studies. For example, Prévost et al. (2010) used a hyperbolic model to describe effort discounting, whereas Chong et al. (2017) found that the parabolic model showed the best fit. Thus, there has been no consensus yet on the computational mechanisms underlying effort-based value integration.

Finally, previous studies mainly relied on the univariate analysis for fMRI data, in which general linear models were conducted separately for each voxel and the dependencies between voxels were largely ignored (Haynes, 2015). Another approach rarely used in effort-based decision-making studies is multivariate pattern analysis (MVPA). Because it exploits the interrelationship between multiple brain voxels, it may be more sensitive to detecting subjective value information in heterogeneous regions (Haynes & Rees, 2006; Norman et al., 2006), such as the medial prefrontal cortex (Nee et al., 2011).

4 Research questions and hypotheses

This thesis aims to address the abovementioned limitations and to advance our understanding of (1) which brain regions are consistently involved in effort-based value integration, and (2) whether value integration during effort-based and risky decision-making relies on similar neurocomputational mechanisms.

Specifically, in study 1, I aim to answer the questions:
Question 1. *Is the classic valuation network involved in effort-based value integration?*
Question 2. *What is the role of the dmPFC in effort-based value integration and raw effort processing?*

A great number of studies have shown neural correlates of subjective value in an overlapping network, mainly including the vmPFC and ventral striatum, across different reward categories and decision situations. These findings have been identified in some but not all studies examining effort-based value integration. We hypothesized that the insignificant results in some studies could be due to the lack of statistical power or specific task settings. To test this hypothesis, we conducted a meta-analysis to examine the consistent neural basis of effort-based valuation integration across studies using different paradigms. Importantly, to improve statistical power, we used full statistical images of the original studies (i.e., image-based meta-analysis) instead of the significant peak coordinates reported in the respective studies (i.e., coordinate-based meta-analysis) whenever possible (Luijten et al., 2017; Müller et al., 2018).

Moreover, some regions outside the classic valuation network, especially the dmPFC, were also often identified in previous work. Since some of these studies only examined the neural correlates of raw effort requirement instead of value integration, it is unclear if the relationship between the dmPFC activity and value integration remained significant after isolating these two types of studies. Thus, we conducted a separate meta-analysis of studies that examined the neural correlates of raw effort.

In study 2, I aim to examine the questions:

Question 3. *Do effort and risk have similar discounting effects on prospective outcomes?*

Question 4. *Can MVPA provide new evidence related to value integration?*

The meta-analysis focused on the neural basis of effort-based value integration. In study 2, to provide more direct evidence on whether the common currency theory could be applied to effort-based decision-making, we reanalyzed the choice and fMRI data from an existing dataset (Aridan et al., 2019) to comprehensively compare effort-based and risky decision-making using a combination of behavioral modeling and univariate and multivariate fMRI analyses.

At the behavioral level, we examined a wide range of discounting functions used in previous studies (Arulpragasam et al., 2018; Chong et al., 2017; Klein-Flügge et al., 2015; Prévost et al., 2010). Although it is still under debate which computational model can best describe effort-based value integration, a general consensus is that the discounting effects are negligible for small effort demands when they are easy to execute (Chong et al., 2017; Klein-Flügge et al., 2015; Seaman et al., 2018), whereas participants appear to be sensitive to small risks (Pachur et al., 2017; Seaman et al., 2018). Therefore, we hypothesized that effort and risk have different discounting effects on prospective outcomes.

At the neural level, in addition to the univariate analysis used in previous studies, we also applied a multivariate decoding analysis. This MVPA method may be more sensitive to detecting subjective value information if it is encoded in a distributed manner (Jimura & Poldrack, 2012; Kahnt, 2018). Moreover, the multivariate cross-task decoding analysis also allowed us to more directly test if value integration in these two tasks relied on similar neural mechanisms (Kahnt, 2018).

In study 3, I aim to examine the questions:

Question 5. *Are the findings of study 2 reliable and replicable?*

Question 6. *Can brain regions identified from study 2 represent subjective value after controlling decision difficulty?*

Since study 2 was based on a one-option decision-making paradigm, we conducted an independent empirical study to examine if the findings could be replicated and extended to two-option decision-making. Notably, in study 3, we further divided each choice into evaluation and selection periods to isolate the effects of motor selection on value integration. Moreover, participants accepted more effortful options relative to risky options in study 2, which may reflect different decision difficulties in these two tasks. To experimentally control the impacts of decision difficulty on value processing to maintain similar overall acceptance rates between tasks, in study 3, we increased the overall effort requirements and conducted a pre-scanning task to estimate indifference points for all combinations of larger rewards and effort/risk levels using a stepwise titration procedure (Westbrook et al. 2013; Westbrook et al. 2019; see Methods for details). We hypothesized that some regions identified in study 2 can still represent subjective value information after controlling decision difficulty.

5 General methodology

In this chapter, I will give a general overview of the methods used in the meta-analytic study (Lopez-Gamundi et al., 2021) and two empirical studies (Yao et al., 2022). These include the literature search, data extraction, and quantitative synthesis procedures for the meta-analytic study, and participant samples, experimental tasks, behavioral modeling, neuroimaging data acquisition, preprocessing, and analysis for the empirical studies.

5.1 Study 1: Meta-analyses

5.1.1 Exhaustive literature search

We conducted a systematic literature search to identify fMRI studies examining effort-related value integration or raw effort processing in three databases: PubMed, Web of Science, and ProQuest. The searching terms were: ("fMRI" OR "functional magnetic resonance imaging") AND ("effort discounting" OR "effort-based decision-making" OR"effort valuation" OR "effort anticipation" OR "cost-benefit valuation" OR "effort expenditure" OR "effort allocation" OR "cognitive effort" OR "physical effort" OR "reward related motivation" OR "reward related effort" OR "effortful goal directed action").

Studies were included in the meta-analysis if they: (1) were original articles based on healthy human participants; (2) used a task with clear effort (or combined effort and other attributes, such as reward) cues during the anticipation phase; (3) conducted the task during fMRI scanning; (4) reported whole-brain results in a standard brain template (e.g., MNI space).

Two researchers first reviewed the title and abstract of all identified studies to limit the scope of the candidate papers. A full-text review was independently performed by both researchers for the remaining studies. Finally, 25 studies were included in the final corpus (Figure 2). Among these studies, two and ten examined value integration and raw effort processing, respectively, and 13 studies examined both processes. It should be noted that, although most studies examining value integration calculated subjective value using computational modeling, a few studies used simplified methods to approximate net value (e.g., log(reward/effort)). We also included these studies to ensure that we had a sufficient number of studies for a meta-analysis (Müller et al., 2018).

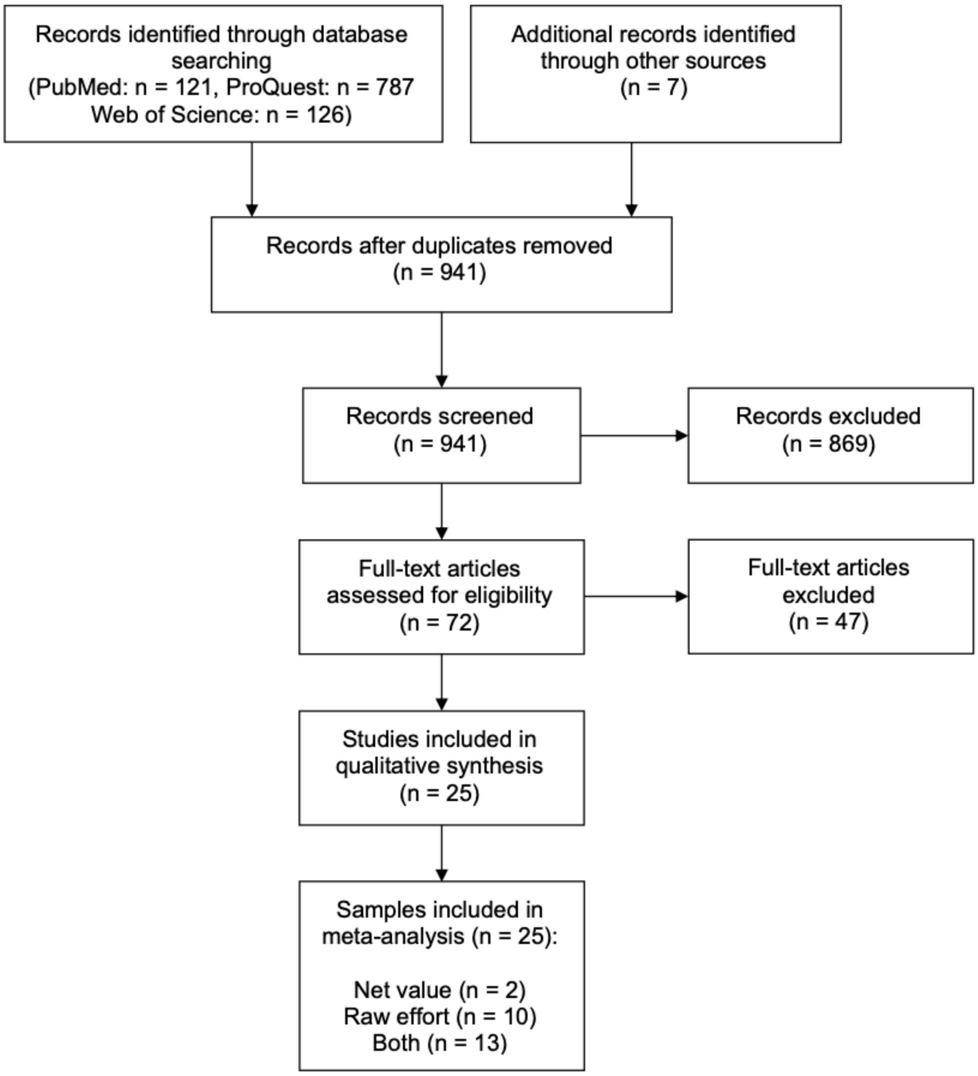

Figure 2. Literature selection flow diagram. A total of 15 (11 statistical images and 4 whole-brain coordinates) and 23 (15 statistical images and 8 whole-brain coordinates) studies were included in meta-analyses for effort-based value integration and raw effort processing, respectively. This process followed the guideline of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The flow diagram was adapted from Lopez-Gamundi et al. (2021)

5.1.2 Data extraction

Since the statistical images contain more information compared with the significant peak coordinates, we contacted the authors of these 25 studies to request whole-brain statistical maps. If statistical maps were not available, we extracted the peak coordinates of the significant clusters reported in original studies and converted all these coordinates to the MNI space.

The net value meta-analysis (15 studies, with a total of 428 participants) included 11 statistical images (73%) and 4 whole-brain coordinates. The raw effort analysis (23 studies, with a total of 549 participants) included 15 statistical images (65%) and 8 whole-brain coordinates.

5.1.3 Quantitative synthesis

We performed two hybrid (i.e., a combination of image- and coordinate-based approaches) meta-analyses using Seed-based d Mapping with Permutation of Subject Images (SDM-PSI, version 6.21; http://www.sdmproject.com). For preprocessing, it recreated voxel-wise whole-brain maps of standardized effect sizes (i.e., Hedge's g) and their variances for each study (Albajes-Eizagirre et al., 2019; Radua et al., 2012). When original statistical maps were unavailable, SDM-PSI used anisotropic kernels to estimate the boundary of voxel-wise effect sizes based on the coordinates and their respective t-values (Radua et al., 2014).

After preprocessing, SDM-PSI estimated the voxel-wise mean effect and variances using maximum likelihood estimation. Random-effect models were used to calculate the mean effect size across studies, and SDM z-maps were calculated by dividing the voxel-wise effect sizes by their standard errors. Finally, a null distribution was estimated for each meta-analysis from 50 whole-brain permutations, since z-values may deviate from a normal distribution.

According to an independent meta-analysis (Bartra et al., 2013) that investigated the valuation network in general, in our two analyses for net value and raw effort, we focused on seven *apriori* ROIs: the vmPFC, right and left ventral striatum, anterior and posterior dmPFC (ACC and pre-SMA in the original meta-analysis), and right and left anterior insula. A 6-mm radius spherical mask was created for each ROI centered on the peak coordinates from Bartra et al. (2013). Effect sizes and variances were extracted from those ROIs for each study, and were quantitatively synthesized using the metafor package (Viechtbauer, 2010) in R (version 4.1.2; http://cran.r-project.org).

To complement the ROI analyses, we also conducted two whole-brain analyses for net value and raw effort, respectively. To address the multiple comparisons problem, we used a familywise error (FWE) correction with 1000 subject-based permutations and a threshold-free cluster enhancement (TFCE) corrected $p < 0.025$, following SDM-PSI's recommendations (Albajes-Eizagirre et al., 2019).

5.2 Study 2-3: Empirical studies

5.2.1 Participants

Study 2 was based on an existing dataset from prior work (Aridan et al., 2019). The experiment was conducted at the University of Texas at Austin and included 40 participants. One participant was excluded from the effortful task because they showed significant gain-aversive and loss-seeking behavior. Two participants were excluded from the risky task because of extreme choice behaviors (accepted or rejected $> 90\%$ of gambles). Therefore, we analyzed the data from 39 and 38 participants for effort-based and risky decision-making, respectively.

Study 3 was conducted at Beijing Normal University. We recruited 36 participants. Five participants were excluded from the fMRI tasks because of extreme choice behaviors (accepted or rejected $> 90\%$ of high-cost options) during the pre-scanning tests. Another participant was excluded from the effortful task during scanning because they showed significant gain-aversive and loss-seeking behavior.

Thus, we analyzed the data from 30 and 31 participants for effort-based and risky decision-making, respectively.

5.2.2 Experimental tasks

Study 2

Two one-option decision-making tasks, with effort and risk as costs, respectively, were conducted during fMRI scanning. Before the effort-based decision-making task, participants were asked to complete an effort calibration task to measure their MVC (Figure 3a), and a cue-effort training task (Figure 3b) to get familiar with the relationship between cues and required effort levels.

For effort-based decision-making, as shown in Figure 3c, each option is associated with three components: a gain ($2, 4, 6, 8, 10, 12), a loss ($1, 2, 3, 4, 5, 6), and a physical effort requirement (30, 40, 50, 60, 70% MVC). The combination of all levels of these three components yielded a total of 180 trials, which were split into five runs. In each trial, participants were asked whether they would like to strongly accept, weakly accept, weakly reject, or strongly reject an option. These four responses were collapsed into accept and reject categories in subsequent analyses (Aridan et al., 2019). Participants did not need to execute effort during decision-making. At the end of the experiment, a trial was randomly selected. If participants accepted this option during decision-making, they had to exert the required effort by squeezing a dynamometer. The outcome (gain or loss) was determined by their successful effort performance. If they rejected the selected option, they would not gain or lose any rewards from this task.

The risky decision-making task was based on a similar task structure (Figure 3d), except that the effort requirement was replaced by the loss probability (10, 30, 50, 70, 90%). At the end of the experiment, a trial was randomly selected. The outcome (gain or loss) was based on participants' choice (accept or reject) and losing probability.

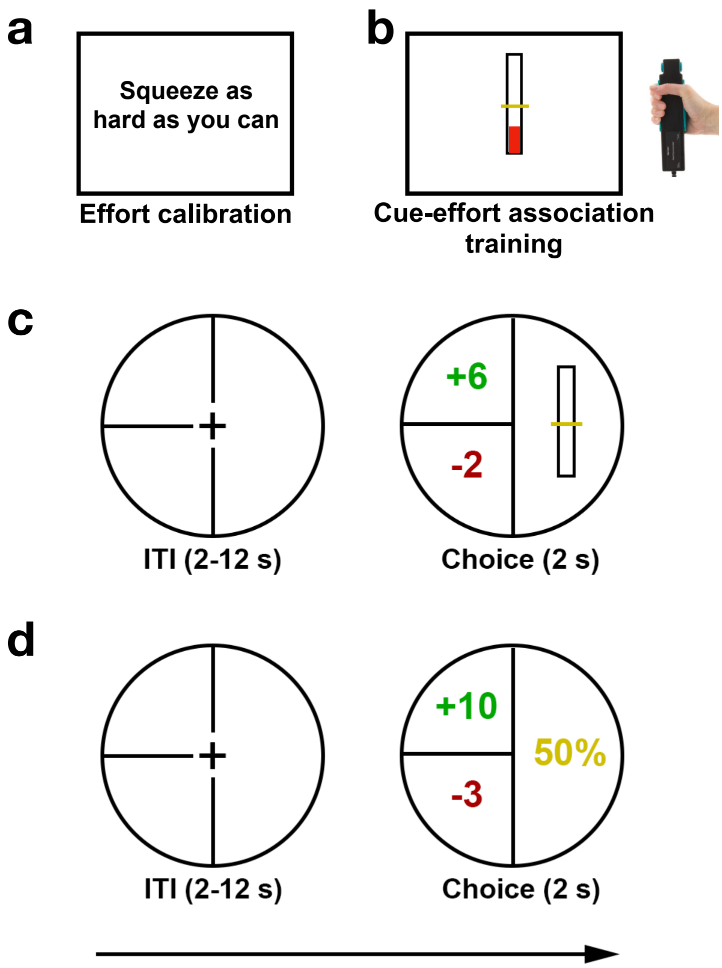

Figure 3. Experimental design of study 2. Each participant completed **(a)** an effort calibration task to estimate their MVC and **(b)** a cue-effort association training task before decision-making tasks. An example trial of the **(c)** effort-based and **(d)** risky decision-making tasks. Adapted from Aridan et al. (2019).

Study 3

This study used a two-option decision-making paradigm. For effort-based decision-making, similar to study 2, participants were asked to complete an effort calibration task and a cue-effort training task at the beginning. A difference is that participants had to complete an additional task to estimate indifference points for all combinations of effort costs (level 1-4) and rewards (2, 3, or 4) based on a previously validated procedure (Westbrook et al., 2013). Specifically, participants were presented with two options in each trial, one with a larger reward and an effort requirement and another with a smaller reward but no effort requirement. As shown in Figure 4a, the amount of the smaller reward was changed in a stepwise titration manner. After five iterations, the amount of the smaller reward was close to the subjective value of the larger-reward option, and the two options were indifferent to participants.

After these pre-scanning tasks, participants were asked to complete a similar two-option decision-making task within the scanner (Figure 4b). We manipulated the amount of the smaller reward around the indifference point of the corresponding larger-reward option (Westbrook et al., 2019):

$$SR = IDP \cdot (1 + prox) \tag{5.1}$$

where SR is the small reward, and IDP is the indifference point. $prox$ is a proximity parameter that controlled the difference between the high-effort and effortless options. A positive $prox$ value indicated that the effortless option was favored, and vice versa. This setting allowed us to explicitly manipulate the decision difficulty of each trial and control the overall acceptance rate of effortful options.

This task included three runs and a total of 168 trials. Each run of the task included 48 slightly biased trials (unique combinations of $prox$ values from {-0.4, -0.1, 0.2, 0.5}, 4 effort levels, and 3 larger rewards) and eight strongly biased trials (unique combination of $prox$ values from {-0.8, 0.8} and 4 effort levels, randomly paired with a large reward). Please note that the amount of the smaller reward would not exceed that of the larger reward. As shown in Figure 4b, in each trial, participants were presented with two options (evaluation, 2s) before getting the notice to make a choice (action, within 2s), followed by a 2-4s intertrial interval (ITI). At the end of the experiment, ten trials were randomly selected outside of the scanner. If participants chose the effortful option, they had to exert the required effort to obtain the reward.

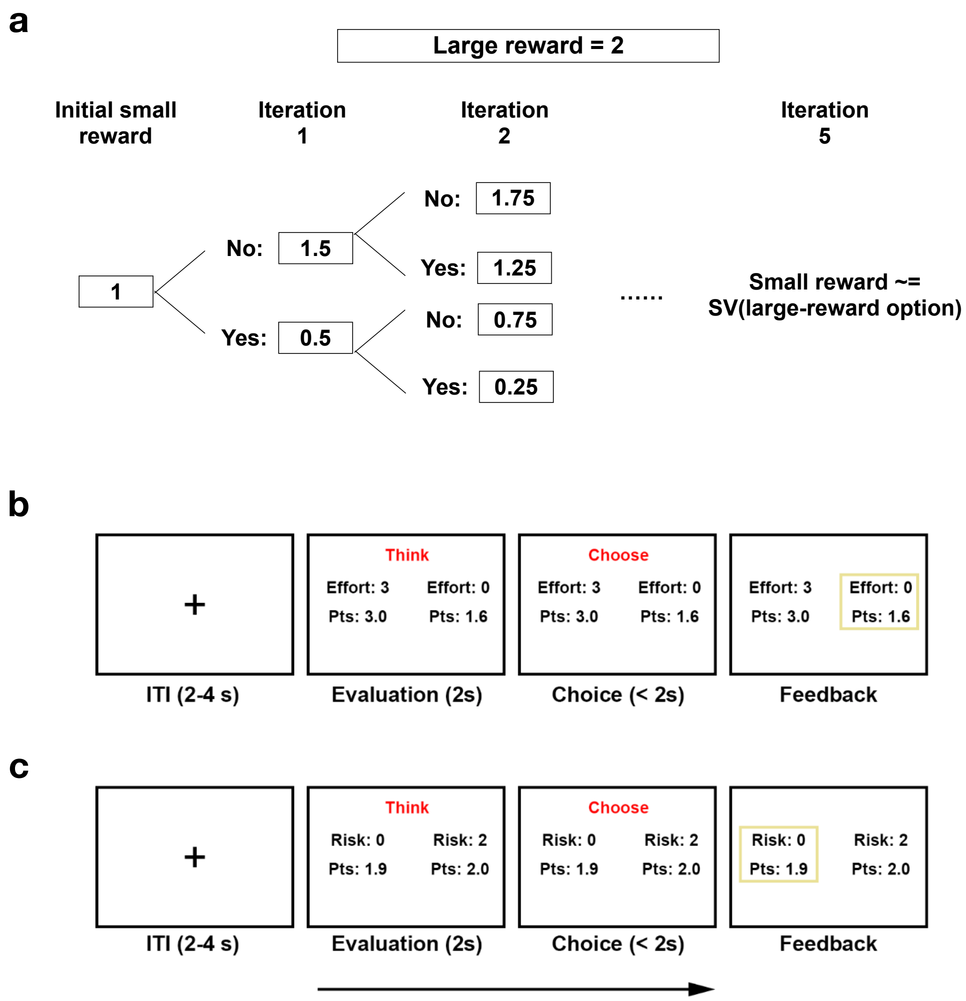

Figure 4. Experimental design of study 3. (a) Each participant completed a task to estimate their indifference points for all unique combinations of effort levels and rewards prior to scanning. This task followed a stepwise titration procedure used in Westbrook et al. (2013). During scanning, we manipulated the amount of the smaller-reward option based on the indifference point of the larger-reward option and a proximity parameter. An example trial of the **(b)** effort-based and **(c)** risky decision-making task. Adapted from Yao et al. (2022)

The risky decision-making part was based on a similar procedure (Figure 4c). Two pre-scanning tasks were conducted to establish the associations between risk level cues and loss probability and to estimate indifference points, respectively. Finally, a risky decision-making task with 168 trials (3 runs) was conducted during scanning. Ten trials were randomly selected outside the scanner at the end of the experiment. The outcome was based on participants' choice and loss probability of the chosen option. The order of the effortful and risky tasks was counterbalanced across participants.

5.2.3 Behavioral modeling

We used five discounting functions (i.e., linear, hyperbolic, parabolic, two-parameter power, and sigmoidal functions; Figure 5) used in previous studies (Arulpragasam et al., 2018; Chong et al., 2017; Klein-Flügge et al., 2015; Prévost et al., 2010) to describe the way that a prospective outcome is discounted by a cost:

$$\text{Linear:} \quad SV = OC - k \cdot Cost \tag{5.2}$$

$$\text{Hyperbolic:} \quad SV = OC \cdot \frac{1}{1 + k \cdot Cost} \tag{5.3}$$

$$\text{Parabolic:} \quad SV = OC - k \cdot Cost^2 \tag{5.4}$$

$$\text{2-Power:} \quad SV = OC - k \cdot Cost^p \tag{5.5}$$

$$\text{Sigmoidal:} \quad SV = OC \cdot (1 - (\frac{1}{1 + e^{-k \cdot Cost - tp}} - \frac{1}{1 + e^{k \cdot tp}})(1 + \frac{1}{e^{k \cdot tp}})) \tag{5.6}$$

where SV is subjective value, and OC is the prospective outcome of an option. k is a free parameter that reflects the discounting rate and is included in all models. The two-parameter power function includes another free parameter p, which reflects the cost sensitivity (i.e., effort or risk). The sigmoidal function also includes an additional free parameter tp, which is the turning point of the curve (Klein-Flügge et al., 2015). $Cost$ denotes the objective effort requirement or loss probability.

We calculated OC based on the utility function (Kahneman & Tversky, 1979):

$$OC = Gain^{\alpha} - \lambda \cdot Loss^{\alpha} \tag{5.7}$$

where parameter α is used to yield a concave utility function for gains and a convex utility function for losses. Parameter λ reflects the relative weighting of losses and gains.

Since no potential losses were used in study 3, OC is only based on potential gains and parameter α:

$$OC = Gain^{\alpha} \tag{5.8}$$

For risky decision-making, in addition to the ten candidate models mentioned above, we included an additional model based on cumulative prospect theory (Nilsson et al., 2011; Tversky & Kahneman, 1992) in the model space.

After computing subjective values of options, we used the softmax function to calculate the probability of choosing the effortful or risky option in each trial. Models were fitted using a hierarchical Bayesian analysis by following the procedure used in the hBayesDM package (Ahn et al., 2017). We compared models using the leave-one-out information criterion (LOOIC), a Bayesian index to evaluate the out-of-sample predictive performance of a model (Vehtari et al., 2017).

In addition to this relative type of model comparison, we also conducted posterior predictive checks to examine if the posterior prediction simulated by the winning model could capture key features of the behavioral data (Zhang et al., 2020). Finally, we examined if the parameters of the winning model could be accurately identified using parameter recovery analyses (Lockwood & Klein-Flügge, 2021; Palminteri et al., 2017; Wilson & Collins, 2019).

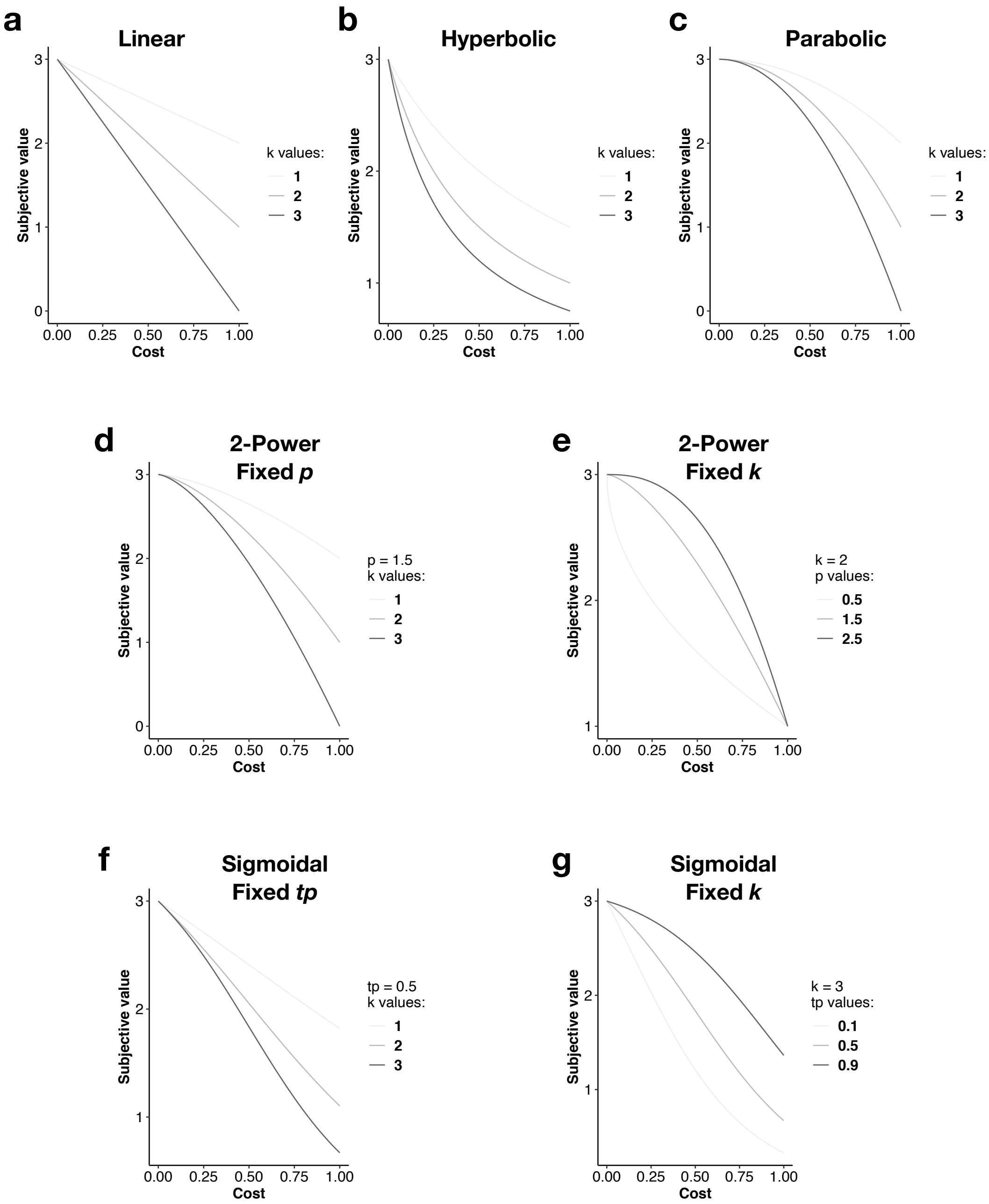

Figure 5. Discounting functions examined in this dissertation We compared models based on **(a)** linear, **(b)** hyperbolic, **(c)** parabolic, **(d-e)** two-parameter power, and **(f-g)** sigmoidal discounting functions. All functions include a discounting rate parameter k. The two-parameter power includes another free parameter p, which controls the shape of the curve together with k. The sigmoidal function also includes an additional free parameter tp, which is the turning point of the curve.

5.2.4 MRI data acquisition and preprocessing

Data acquisition

In study 2, structural and functional MRI data were collected on a 3T Siemens Skyra MRI scanner. High-resolution structural images were collected using a T1-weighted MPRAGE pulse sequence. Functional images were collected with a T2∗-weighted multiband echo-planar imaging (EPI) pulse sequence. Slice orientation was tilted 30° backward relative to the anterior commissure-posterior commissure (AC-PC) line to reduce signal dropout in the orbitofrontal region (Deichmann et al., 2003). Detailed scanning parameters were reported in Aridan et al. (2019).

In study 3, structural and functional MRI data were collected on a 3T Siemens Trio scanner. High-resolution structural images were collected using a T1-weighted MPRAGE pulse sequence. Functional images were collected with a T2∗-weighted EPI pulse sequence. Detailed scanning parameters were reported in Yao et al. (2022).

Preprocessing

fMRI data were preprocessed using SPM12 (version 7177; http://www.fil.ion.ucl.ac.uk/spm/software/spm12) and the DPABI toolbox (Yan et al., 2016) in MATLAB 2019b (http://www.mathworks.com). The preprocessing followed standard procedures and included: spatial realignment, co-registration of anatomical and functional images, segmentation of structural images, normalization to MNI space, and smoothing with a 6-mm full-width-half-maximum Gaussian kernel. Participants who showed excessive head motion (i.e., $>$ 3 mm of displacement or 3° of rotation in any of the six motion parameters in more than two runs of a task) were excluded from subsequent analyses.

5.2.5 fMRI analysis

Univariate analysis

For study 2, we conducted two general linear models (GLMs) to replicate findings reported in Aridan et al. (2019). Specifically, we split trials of each decision-making task into high- and low-value trials based on the median subjective value, derived from the winning model. Both GLMs include two regressors for the choice period of high- and low-value trials. The contrast of high vs. low-value trials was estimated for each participant (i.e., first-level analysis) and taken to group-level random-effect analyses.

For study 3, we conducted another two GLMs to examine the neural correlates of subjective value during effort-based and risky decision-making, respectively. Because each trial included two options, we used the median subjective value of the chosen options to split the trials for each decision-making task (Arulpragasam et al., 2018; Hogan et al., 2019). Therefore, both GLMs include two regressors for the evaluation period of high- and low-value of the chosen options. We computed the contrast of high vs. low-chosen-value for each participant and used these contrast images to perform one-sample t tests for second-level group analyses.

Trials without responses and six motion parameters were included as regressors of no interest in all GLMs. We conducted voxelwise analyses in a frontostriatal mask, including Brodmann area (BA) 9, 10, 11, 23, 32, and bilateral striatum (nucleus accumbens, caudate, and putamen) from the Harvard-Oxford structural atlas (http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/Atlases). This mask covered most related brain regions in the valuation network (Bartra et al., 2013; Clithero & Rangel, 2013; Lopez-Gamundi et al., 2021) and excluded most sensory and motor regions. Results were corrected using a voxel-level uncorrected threshold of $p < 0.001$ and FWE cluster-level corrected $p < 0.05$ based on Gaussian Random Field Theory (GRFT). Because of the findings from study 1, we were particularly interested in the roles of the vmPFC and dmPFC in value integration. Thus, we extracted the mean effect sizes from spherical masks (radius = 6 mm) centered at the peak coordinates around these two regions. When there was no significant cluster, we used the peak coordinates (vmPFC: 0, 40, -4; dmPFC: 0, 22, 38) from a previous study (Piva et al., 2019) to extract effects for illustration.

MVPA

Multivariate decoding analyses were performed using a linear support vector machine (SVM) approach implemented in The Decoding Toolbox (TDT, v 3.999E; Hebart et al. 2015). In study 2, we repeated the two GLMs used in the univariate analysis on unsmoothed data. The beta images from the choice period were used to decode the subjective value magnitude for each task. Specifically, a five-fold leave-one-run-out cross validation was used to estimate the decoding accuracy, in which the SVM was trained on all but one run and tested on the left-out run.

For study 3, we divided each run into two halves to increase the number of datasets (Jimura & Poldrack, 2012). Again, GLMs were conducted on unsmoothed data, and beta images from the evaluation period were used for the within-task decoding analyses. Since we manipulated decision difficulty in study 3, to ensure that the within-task decoding results on chosen subjective value were not completely driven by decision difficulty, we did the decoding analyses for high- ($|prox| <= 0.2$) and low-difficulty ($|prox| > 0.2$) trials separately in each task.

Moreover, to more directly test whether a brain region encodes subjective value using similar patterns across effort-based and risky decision-making, we performed a cross-task multivariate decoding for each study. The SVM was trained on all but one run of one task (e.g., run 1-4 of the risky task in study 2) and tested on one run of the other task (e.g., run 5 of the effortful task in study 2), and a leave-one-run-out cross validation (10-fold for study 2 and 12-fold for study 3) was used to examine the decoding accuracy.

For all multivariate decoding analyses, we used a searchlight analysis (radius =

3 voxels) within the frontostriatal mask. Within-task decoding results were corrected using a voxel-level uncorrected threshold of $p < 0.001$ and FWE cluster-level corrected threshold of $p < 0.05$. For exploratory purposes, we used a more lenient threshold of voxel-level $p < 0.005$ and FWE cluster-level corrected $p < 0.05$ for the cross-task decoding results. Mean effects from the vmPFC and dmPFC were extracted for illustration.

6 Summary of the dissertation studies

In this chapter, I summarize the findings from the meta-analytic study and two empirical studies included in the dissertation.

6.1 Study 1: Meta-analyses

In study 1 (Lopez-Gamundi et al., 2021), we used a meta-analytic approach to quantitatively summarize evidence from studies examining value integration (15 studies, including 11 statistical maps and 4 whole-brain coordinates) or/and raw effort processing (22 studies, including 15 statistical maps and 7 whole-brain coordinates). Except for a small number of studies using a valuation task without decision-making (e.g., effort incentive delay task in Croxson et al. (2009) and Kurniawan et al. (2013)), most of the included studies were based on a decision-making paradigm. To increase the statistical power of the meta-analysis, we used statistical maps from the original studies whenever possible.

We first examined the averaged neural correlates of net value and raw effort in seven *a priori* ROIs (vmPFC, right and left ventral striatum, anterior and posterior dmPFC, and right and left anterior insula), which were identified in a general valuation network from another meta-analysis (Bartra et al., 2013). We found that the vmPFC and the posterior dmPFC (pre-SMA in the original study) were the only regions that showed significant associations with both net value and raw effort magnitude. Specifically, the vmPFC activity correlated positively with net value and negatively with raw effort, whereas the posterior dmPFC showed an opposite activity pattern (Figure 6 and 7). In addition to these two regions, we found that the activity of the bilateral ventral striatum was positively associated with net value. The averaged effects in other ROIs were negligible.

Next, to complement the ROI analyses, we also conducted two whole-brain meta-analyses on the neural basis of effort-based value integration and raw effort

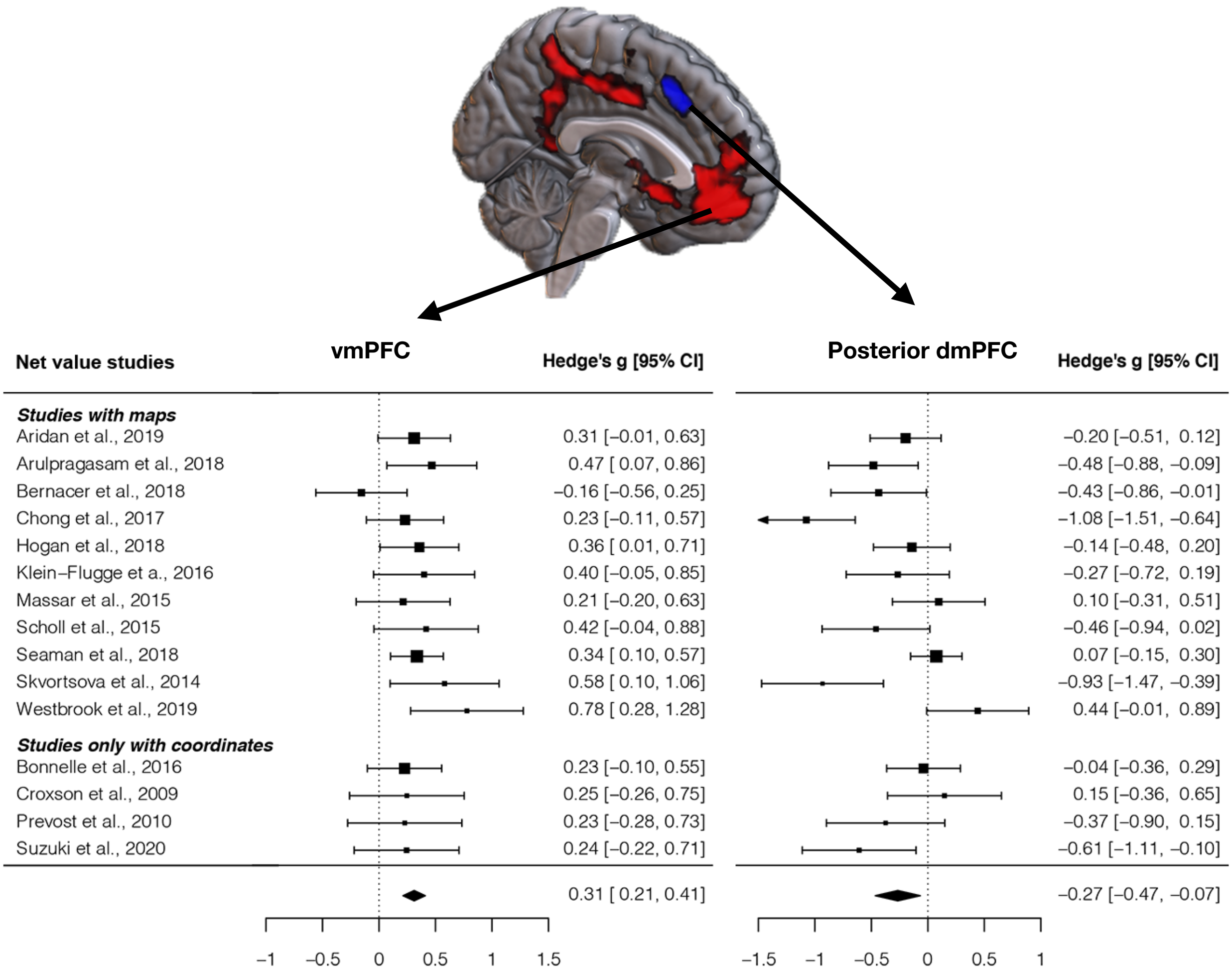

Figure 6. Net value meta-analysis results Whole-brain results (top) and forest plots for effects extracted from the vmPFC (bottom left; MNI coordinates: 2, 46, -8) and posterior dmPFC (bottom right; MNI coordinates: -2, 16, 46) ROIs.

processing, respectively. Again, we identified significant clusters around the vmPFC and dmPFC in both analyses, with similar patterns as found in the ROI analyses (Figure 6 and 7). Moreover, in the net value analysis, we also observed significant positive effects in the dorsal striatum, and some other prefrontal and limbic regions.

In summary, this study provides supportive evidence to the common currency theory by showing positive neural correlates of effort-related net value in a network including the vmPFC and ventral striatum. The vmPFC and posterior dmPFC appear to be sensitive to both net value and raw effort. However, since conventional univariate analysis focuses on positive effects, the negative association between the dmPFC activity and net value was often neglected in previous studies. Therefore, I will address this issue using MVPA, which takes both positive and negative neural signals into account and generates unsigned results (Haynes & Rees, 2006; Norman et al., 2006), in the next two studies.

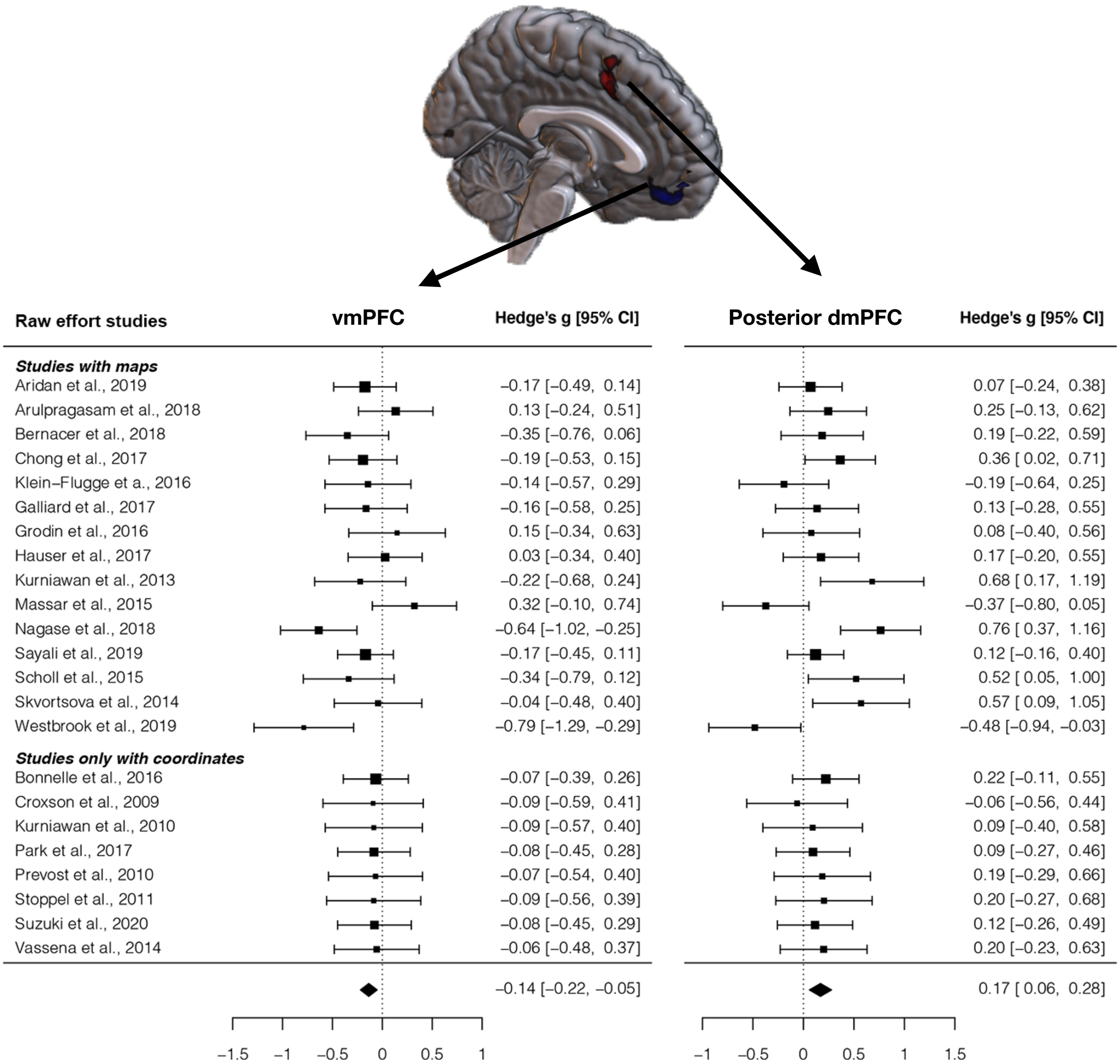

Figure 7. Raw effort meta-analysis results Whole-brain results (top) and forest plots for effects extracted from the vmPFC (bottom left; MNI coordinates: 2, 46, -8) and posterior dmPFC (bottom right; MNI coordinates: -2, 16, 46) ROIs.

6.2 Study 2: Comparing effort-based and risky decision-making

In study 2 (Yao et al., 2022), we reanalyzed the choice and fMRI data of an existing dataset (Aridan et al., 2019) to directly compare the neurocomputational mechanisms underlying value integration during effort-based and risky decision-making. One issue of previous work is that behavioral models were insufficiently compared and neural data were mainly analyzed using univariate approaches. In this study, we therefore tested a wide range of models used in previous studies under a hierarchical Bayesian framework (Ahn et al., 2017) and used both univariate and multivariate approaches to analyzing the fMRI data.

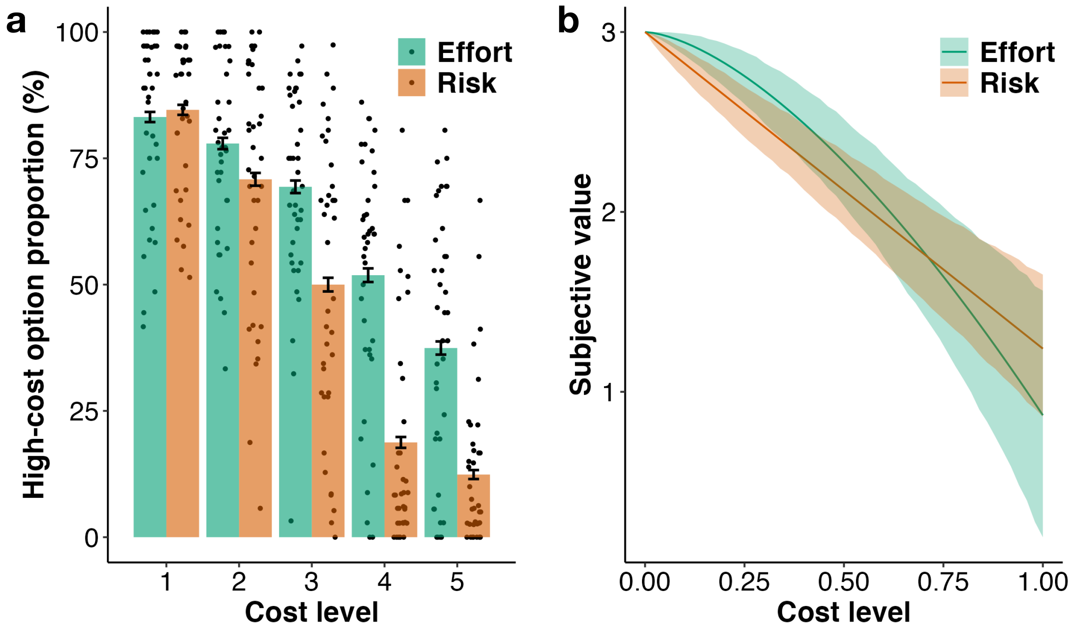

Figure 8. Behavioral results of study 2. (a) Participants accepted less effort and risky options when cost levels increased. **(b)** Average fits of the two-parameter power function for effort and risk. Shaded regions represent 95% highest density interval (HDI) of the mean fitted line.

Regarding the choice behavior, we found that participants showed a significantly higher acceptance rate (of costly options) during effort-based decision-making, compared with the risky decision-making task (Figure 8a). Using a computational modeling approach to more precisely examine the choice behavior on a trial-by-trial basis, we found that both effort-based and risky decision-making were best described by a two-parameter power model. Posterior predictive checks and parameter recovery analyses suggest that the winning model is reliable and can capture the general pattern of the choice behaviors. Our analysis strategy thus allowed us to compare these two types of decision-making under a common computational framework.

We next focused on the two parameters (k and p) of the power function that control the discounting curve (Figure 5d-e), and compared four variants of this model with either the same or separate values on these two parameters for the effort-based and risky decision-making tasks. We found that the model with separate values on both parameters showed the best fit, suggesting that effort and risk had different discounting effects on prospective outcomes. As shown in Figure 8b, compared with risk, effort discounted outcomes to a smaller extent when costs were low but showed larger devaluations when costs were high.

At the neural level, we first conducted the univariate analyses to replicate findings reported in Aridan et al. (2019). As expected, for effort-based decision-making, we found that the vmPFC activity was positively associated subjective value, whereas the dmPFC showed a negative association (Figure 9a). For risky decision-making, the vmPFC activity also positively correlated with subjective value, but the effect in the dmPFC was not detectable (Figure 9b).

Next, we conducted within-task multivariate decoding analyses on subjective value for each task. We found that a large cluster including the vmPFC, dmPFC, and broader frontal regions represented subjective value information in both the effortful and risky tasks (Figure 9c-d). Finally, we conducted a cross-task multivariate decoding analysis to directly test if these value neural codes could be generated across effort-based and risky decision-making. Indeed, we found that the vmPFC and dmPFC represented subjective value in a task-independent manner.

In summary, study 2 shows that effort and risk have different discounting effects on prospective outcomes. Although univariate analyses mainly highlight the role of the vmPFC in value integration during both effort-based and risky decision-making, multivariate analyses suggest that the dmPFC can also represent subjective value information regardless of cost types.

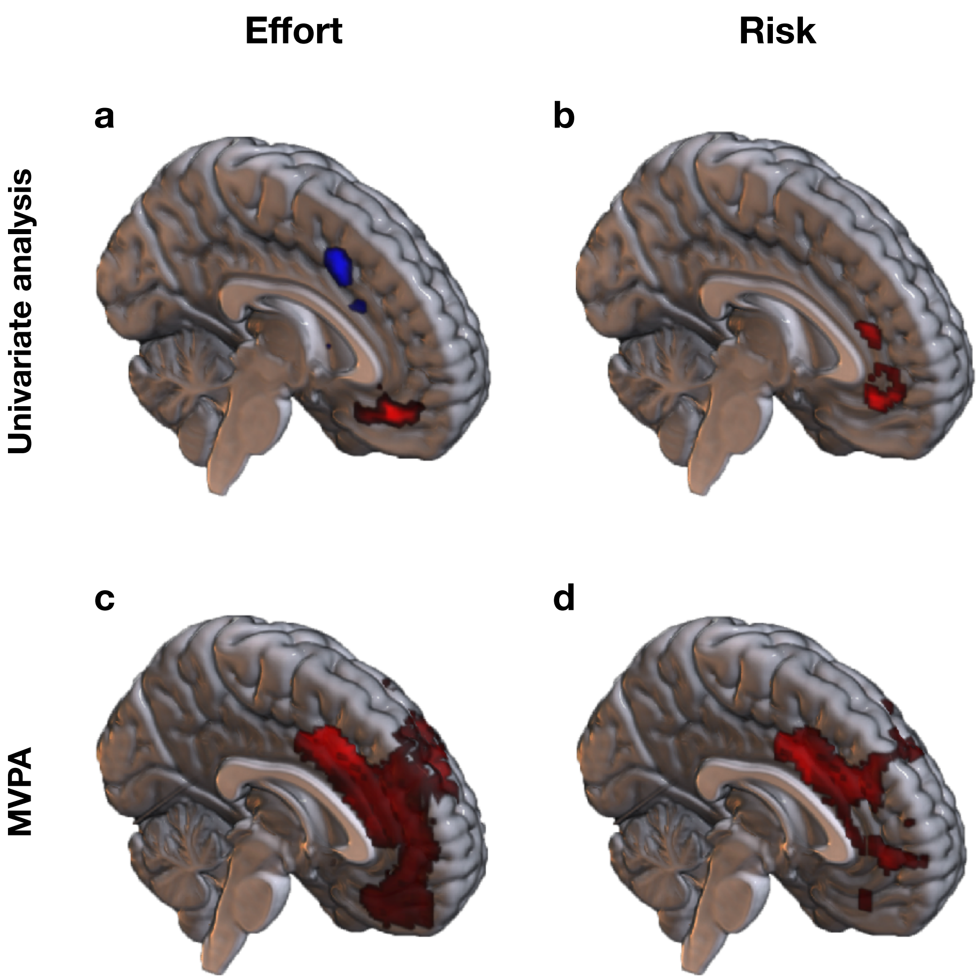

Figure 9. fMRI results of study 2. Univariate analyses showed that the vmPFC activity was positively associated with subjective value during **(a)** effort-based and **(b)** risky decision-making. Moreover, the dmPFC activity was negatively associated with subjective value during effort-based decision-making. MVPA results showed that both the vmPFC and dmPFC represented subjective value during **(c, d)** both decision-making tasks

6.3 Study 3: Value signals after controlling decision difficulty

In study 3 (Yao et al., 2022), we aimed to replicate the findings of study 2 in a two-option decision-making paradigm and to experimentally control the effects of motor action and decision difficulty on value integration. To this end, we divided each choice into evaluation and selection periods. Moreover, we estimated the indifference points of all large-reward-high-cost options outside the scanner and manipulated the decision difficulty (i.e., subjective value differences between options) of each trial based on these indifference points and a proximity parameter during scanning.

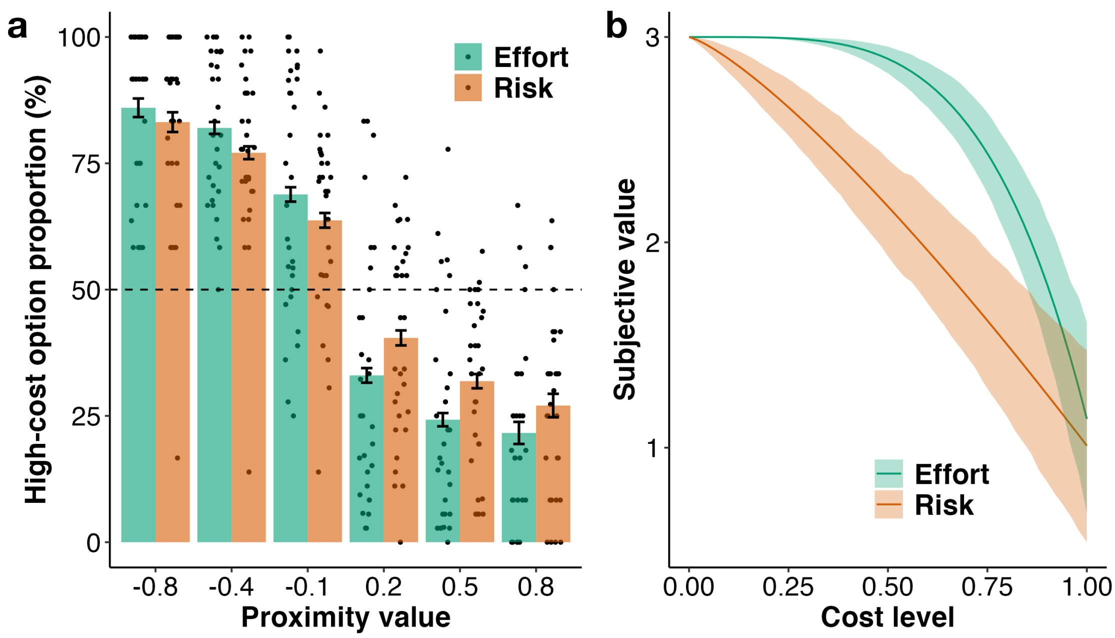

Figure 10. Behavioral results of study 3. (a) Participants' choices were influenced by the proximity values. **(b)** Average fits of the two-parameter power function for effort and risk. Shaded regions represent 95% highest density interval (HDI) of mean fits.

In the pre-scanning task that we used to estimate indifference points (Figure 4a), we found that participants selected more high-cost options in the effortful compared with the risky task. Importantly, participants showed comparable rates of high-cost options in two tasks during scanning, and their choice behaviors changed as a function of the proximity parameter values (Figure 10a). These results suggest that our manipulations were effective in matching choice patterns across tasks during scanning.

Regarding the behavioral modeling results, consistent with study 2, we found the two-parameter power model was the best for both tasks. Again, when combining the data from the effortful and risky tasks of study 3 together, the model with separate k and p for effort and risk showed the best fit, because the effort discounting curve has a more concave shape compared with that of the risk (Figure 10b).

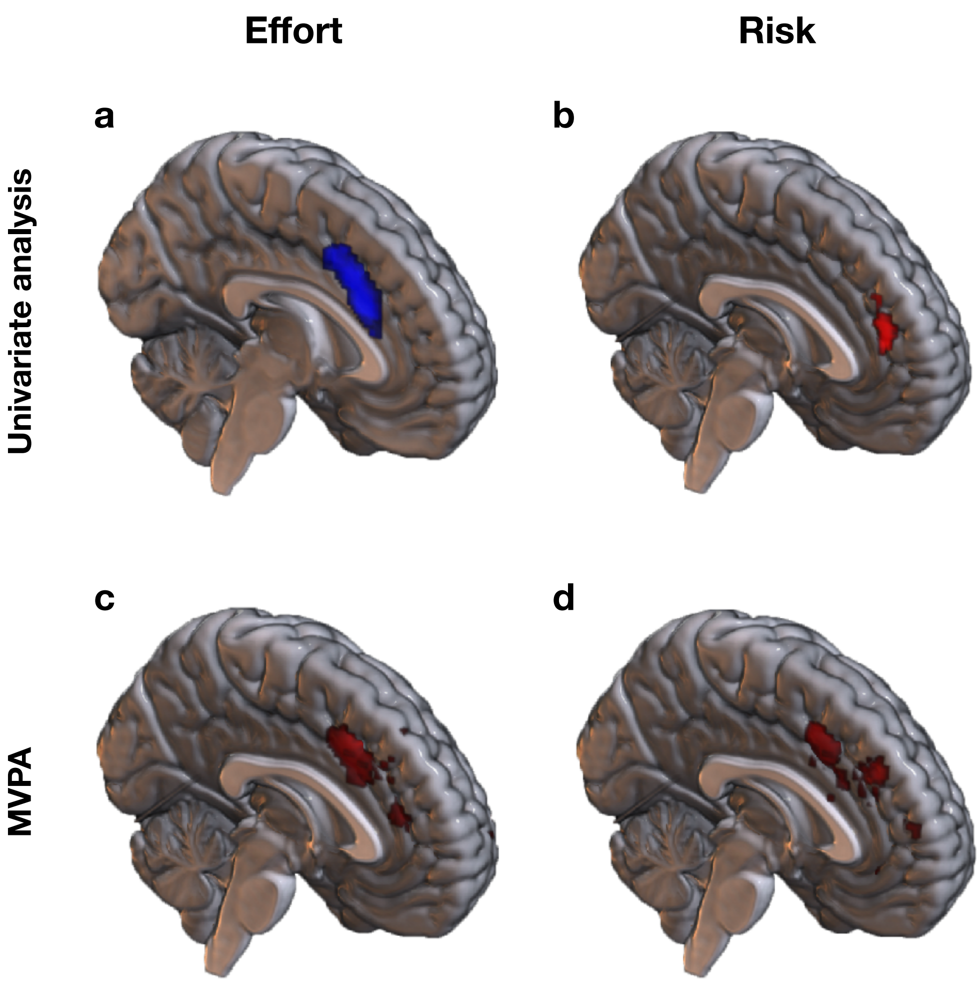

Figure 11. fMRI results of study 3. Univariate analyses showed that **(a)** the dmPFC activity was negatively associated with subjective value during effort-based decision-making. **(b)** Activity of the rostral ACC positively correlated with subjective value during risky decision-making. MVPA results showed that **(c)** the dmPFC represented subjective value during effort-based decision-making. **(d)** For risky decision-making, value information could be decoded from both the vmPFC and dmPFC.

Univariate analyses showed that the dmPFC activity was negatively associated with chosen subjective value during effort-based decision-making (Figure 11a), and a region around the intersection of the vmPFC and dmPFC scaled positively with subjective value during risky decision-making (Figure 11b). Unexpectedly, we did not observe significant effects in the vmPFC in both tasks in study 3.

Despite inconsistent univariate results between tasks, both within-task multivariate decoding analyses showed that the dmPFC represented subjective value (Figure 11c-d). Our control analyses in high- and low-difficulty trials all identified subjective value codes in the dmPFC, suggesting that the results were not merely driven by decision difficulty. Finally, the cross-task multivariate decoding analysis confirmed that the dmPFC encoded subjective value via a task-independent manner, and this cluster partly overlapped with the region that we identified in study 2.

In summary, study 3 confirms that effort and risk have different effects on prospective outcomes. Moreover, multivariate analyses consistently decode subjective value information in the dmPFC, and such neural codes are detectable in trials with different decision difficulties and could be generalized across tasks.

7 General discussion and future directions

In this final chapter, I will begin by discussing the six research questions of my dissertation. After this, I will broadly discuss the implications of these results for the common currency theory and why these findings are useful for a better understanding of mental disorders with motivational deficits. Finally, I will end this chapter by discussing a few promising directions for future research based on this dissertation.

7.1 Discussion of the research questions

Question 1. *Is the classic valuation network involved in effort-based value integration?*

In study 1, we conducted a meta-analysis of previous fMRI studies to examine the consistent neural basis of effort-based value integration. The results showed that neural activity of the vmPFC and ventral striatum, two key components of the classic valuation network, positively correlated with effort-based net value.

The vmPFC and ventral striatum have often been regarded to play a critical role in value integration across multiple reward types (e.g., primary and secondary rewards; Sescousse et al. 2013), valuation phases (e.g., anticipation and receipt; Bartra et al. 2013; Kahnt et al. 2010), and cost types (e.g., risk and delay; Kable and Glimcher 2009; Peters and Büchel 2009). Our findings are in line with these previous studies and suggest that the classic valuation network is also involved in effort-based value integration.

As mentioned in Introduction, some previous studies did not observe significant value signals in this network (Chong et al., 2017; Klein-Flügge et al., 2016; Massar et al., 2015; Prévost et al., 2010). After extracting effects from the vmPFC and ventral striatum from these studies, we found that most of these neural correlation effects are positive. Considering the fact that a majority of included studies were based on relatively limited sample sizes ($N < 30$), some of them may be statistically underpowered to detect neural correlates of effort-related net value in the classic valuation network.

The lack of statistical power has been a major problem in fMRI studies for a long time, and the small sample size is a critical cause of this issue (Button et al., 2013; Poldrack et al., 2017). This study demonstrates that the image-based meta-analysis can partly address this issue by quantitatively synthesizing evidence across multiple studies. Importantly, the use of unthresholded statistical images allowed us to exploit more information other than significant coordinates (Luijten et al., 2017; Salimi-Khorshidi et al., 2009). Therefore, even if an effect is not significant in some individual studies, it may still be identified in an image-based meta-analysis if its activity pattern is consistent across included studies.

Question 2. *What is the role of the dmPFC in effort-based value integration and raw effort processing?*

Some researchers have argued that the dmPFC and some other regions are specifically involved in effort-based valuation (Bonnelle et al., 2016; Burke et al., 2013; Chong et al., 2017; Klein-Flügge et al., 2016; Kurniawan et al., 2013). Since a few studies only identified the association between the dmPFC activity and raw effort rather than net value, in study 1, we conducted a separate meta-analysis to examine neural correlates of raw effort.

Interestingly, we found that the vmPFC and the posterior dmPFC were the only regions that appeared to be sensitive to both net value and raw effort, although the vmPFC activity scaled positively with net value and negatively with raw effort, whereas the dmPFC showed the opposite activity pattern. A potential limitation of univariate analysis is that this approach focuses on positive effects (or neural activations). Therefore, the involvement of the dmPFC in effort-based value integration may be often neglected in this context (Lopez-Gamundi et al., 2021).

Unlike univariate analysis, MVPA takes both positive and negative effects into account and yields unsigned decoding accuracy (Haynes, 2015; Norman et al., 2006).

Moreover, because this approach examines neural activity patterns across voxels, it may be able to detect distributed coding of value in the medial prefrontal cortex beyond the assumption of univariate analysis (Jimura & Poldrack, 2012; Kahnt, 2018). Therefore, in addition to univariate analysis, we also used multivariate decoding analyses to examine neural correlates of subjective value in the next 2 empirical studies.

Question 3. *Do effort and risk have similar discounting effects on prospective outcomes?*

In study 2, we reanalyzed choice and fMRI data from an open-access dataset (Aridan et al., 2019). We first compared a wide range of discounting models used in previous work (Figure 5; Arulpragasam et al. 2018; Chong et al. 2017; Klein-Flügge et al. 2015; Prévost et al. 2010), and found that the model based on the two-parameter showed the best fit for effort-based decision-making. In addition to the discounting rate k included in all other candidate models, this model includes an additional parameter p that reflects effort sensitivity (Arulpragasam et al., 2018; Suzuki et al., 2021). These two parameters together control the shape of the discounting curve (Figure 5d-e). Therefore, compared with linear and parabolic models, two nested versions from the same family, the free parameter p allows for higher flexibility in the shape of the discounting curve to account for individual differences in effort-based valuation (Arulpragasam et al., 2018).

Surprisingly, the two-parameter power discounting model also showed the best fit for risky decision-making. Since different types of costs can still exhibit different discounting effects under the same computational framework (Lockwood et al., 2017), we did another model comparison with a focus on the two parameters that control the discounting curve. In line with previous work, effort showed an obvious concave discounting pattern, with negligible devaluations for lower cost levels but much pronounced devaluations for higher cost levels (Arulpragasam et al., 2018; Klein-Flügge et al., 2015). On the other hand, risk showed more linear discounting effects.

Therefore, effort may devalue outcomes to a less extent compared with risk unless cost levels are high (e.g., > 70% of the upper threshold). Since most decision-making tasks used in previous work evenly cover a wide range of cost levels, our finding also explains the fact that participants often accepted more effortful, relative to risky, options (Aridan et al., 2019; Seaman et al., 2018).

Question 4. *Can MVPA provide new evidence related to value integration?*

At the neural level, we used both univariate and multivariate approaches to analyze the fMRI data in study 2. Consistent with previous work (Kable & Glimcher, 2009; Lopez-Gamundi et al., 2021; Peters & Büchel, 2009) and the original study of this dataset (Aridan et al., 2019), our univariate analyses showed that the vmPFC activity was positively correlated with subjective value in both tasks. Notably, we also observed the negative association between the dmPFC activity and subjective value during effort-based decision-making, as shown in the meta-analysis in study 1.

Compared with the univariate analyses, the within-task multivariate decoding analyses showed that a larger cluster including both the vmPFC and dmPFC represented subjective value during effort-based and risky decision-making. Strikingly, the cross-task multivariate decoding analysis also identified significant results in the dmPFC and a small portion of the vmPFC, suggesting that these regions can represent subjective value in a task-independent manner. In contrast to the univariate analysis that examines univariate changes (particularly increases) in the voxel-wise intensity of local regions (Friston et al., 1994), MVPA, including the multivariate decoding used in study 2, evaluates patterns of neural signal across multiple voxels (Haynes, 2015; Kahnt et al., 2014). In MVPA, a brain region would be regarded to represent a cognitive process (e.g., value integration) if its neural activity patterns could accurately distinguish different conditions (e.g., high and low values) related to this process. Therefore, value signals in a brain region could be detected by MVPA even if it showed negative or insignificant activations in a univariate analysis (Jimura & Poldrack, 2012).

Although relatively fewer fMRI studies in this field utilized MVPA, some of them have shown value signals in the dmPFC across different tasks (Gross et al., 2014; Piva et al., 2019; Pogoda et al., 2016; Wang et al., 2014). These findings together suggest that MVPA may provide more information regarding the neural basis of value integration compared with univariate analysis. Thus, it can be used as a complementary approach to conventional univariate analysis in analyzing fMRI data.

Question 5. *Are the findings of study 2 reliable and replicable?*

In study 3, we examined if the behavioral modeling and neural findings of study 2 could be replicated in an independent study based on two-option decision-making. Similar to study 2, we found that both tasks can best be described by a two-parameter power discounting model, and the discounting curve of the effort is more concave than that of the risk (Figure 10b). Since we increased the overall effort requirement (50-95% MVC) in study 3, it allowed us to more accurately estimate the discounting effects of high effort levels.

Regarding the neural data, the univariate results showed that the dmPFC activity negatively scaled with subjective value during effort-based decision-making. A cluster at the intersection of the vmPFC and dmPFC showed positive correlates of subjective value during risky decision-making. Despite inconsistent univariate results between the effortful and risky tasks, multivariate decoding analyses showed that the dmPFC represented subjective value in both tasks, and such subjective value neural codes appear to be cost-independent as found in study 2.

Multivariate decoding analyses of both study 2 and study 3 highlight the role of the dmPFC in value integration regardless of cost types, suggesting that this result is reliable and robust across studies (Piva et al., 2019). Notably, in line with previous work on intertemporal decision-making (Wang et al., 2014), multivariate analyses can accurately decode subjective value based on neural activity patterns of the dmPFC even in the absence of significant univariate effects. Therefore, the dmPFC may represent subjective value using a distributed activity pattern that may be beyond the detectability of conventional univariate analysis. These findings again highlight the advantage of using both univariate and multivariate approaches for fMRI data analysis.

Surprisingly, the subjective value signals in the vmPFC were less significant in most analyses of study 3 (Figure 11), compared with the findings of study 2 (Figure 9). As discussed above, the role of the vmPFC in value integration has been established in a large number of studies (Bartra et al., 2013; Clithero & Rangel, 2013; Kahnt et al., 2014; I. Levy et al., 2010; Peters & Büchel, 2009). Moreover, our meta-analysis of effort-based valuation studies and multivariate decoding analyses of study 2 all highlighted its critical involvement in value integration. One possible explanation is the BOLD signal around this region is likely to be influenced by susceptibility gradients. In study 2, an optimized orientation (Deichmann et al., 2003) was used to reduce these influences in the vmPFC. However, this optimized orientation was not used when collecting fMRI data in study 3. Future research is needed to test the effects of different orientations on neural correlates of subjective value in the vmPFC.

Question 6. *Can brain regions identified from study 2 represent subjective value after controlling decision difficulty?*

In study 3, another major modification is that we estimated indifference points of all combinations of cost levels and large rewards before scanning (Figure 4a), and manipulated the decision difficulty of each trial based on its indifference point and a proximity parameter (Equation 5.1). We repeated the abovementioned multivariate decoding separately on high- and low-difficulty trials for each task. Importantly, we can still decode subjective value information in the dmPFC in both difficulty conditions of each task.

In effort-based decision-making, there is still an ongoing debate on the dmPFC (especially the dACC) in value integration (Chong et al., 2017; Hogan et al., 2019;

Klein-Flügge et al., 2016; Massar et al., 2015; Westbrook et al., 2019). Some previous studies showed that the dmPFC activity was mainly associated with decision difficulty but not subjective value (Hogan et al., 2019; Westbrook et al., 2019), whereas the other studies identified subjective value signals after controlling decision difficulty (Chong et al., 2017; Klein-Flügge et al., 2016). Because the dmPFC as a whole is a highly heterogeneous region (Neubert et al., 2015), some effects related to subjective value may be undetectable by univariate analysis that treats voxels in this region as homogenous (Kahnt, 2018). Our MVPA results in high- and low-difficulty conditions suggest that the subjective value codes found in the dmPFC are not driven by decision difficulty. These analyses also provide more supportive evidence of its direct involvement in value integration.

7.2 Beyond the common currency theory

A broader question that all studies included in this dissertation aim to answer is whether the common currency theory could be applied to effort-based value integration. This theory has gained popularity in decision neuroscience literature in general, because it provides a testable framework and related neural basis to explain how humans make decisions between different types of options (D. J. Levy & Glimcher, 2012).

As mentioned in Introduction, a classic valuation network, mainly including the vmPFC and ventral striatum, has been believed to play a critical role in value integration across different tasks. In study 1, we found that, although some individual effects were small, the association between the classic valuation network and effort-based value integration was robust and consistent across studies. Supporting this view, in study 2, we found that subjective value could be accurately decoded based on neural activity patterns of the vmPFC. In study 3, we also found significant value signals in the vmPFC during risky decision-making using MVPA, although the multivariate effects of this region during effort-based decision-making were smaller

(Cohen's $d = 0.26$). Taken together, although more research using MVPA is needed to confirm our results, these findings generally confirm that the vmPFC, a central node of the classic valuation network, is also critically involved in effort-based value integration.

In addition to the vmPFC, the three studies included in the dissertation consistently highlight the role of the dmPFC in value integration. As discussed above, there is considerable debate over the exact role of this region. One possibility is that, as shown in our net value meta-analysis in study 1, it often negatively correlates with net value magnitude in conventional univariate analysis, making this association overlooked by some researchers. Moreover, the dmPFC is a heterogeneous region and appears to be related to multiple cognitive processes (Ebitz & Hayden, 2016; Shenhav et al., 2013; Shenhav et al., 2016; Vassena et al., 2020). Using multivariate decoding analyses in study 2 and study 3, we found that subjective value information could be accurately decoded based on activity patterns of the dmPFC across effort-based and risky decision-making, and the results remained detectable after controlling decision difficulty. These findings agree with previous MVPA studies examining risky and intertemporal decision-making (Piva et al., 2019; Wang et al., 2014) and thus extend the scope of the valuation network suggested by the common currency theory (Figure 12).

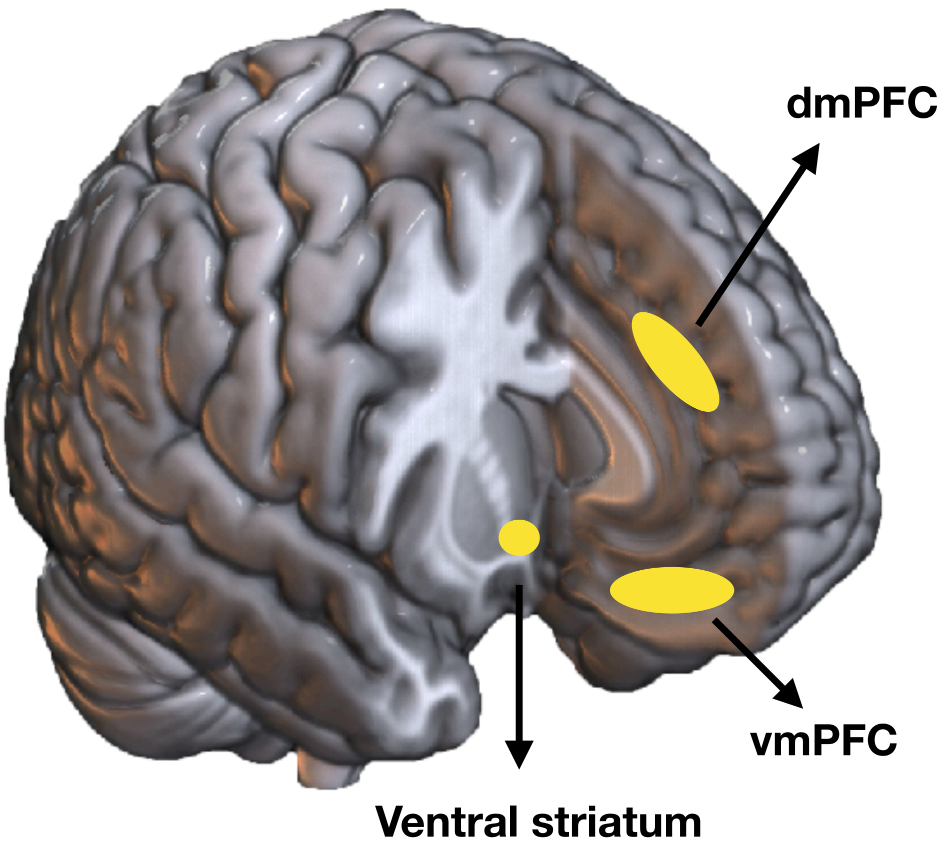

Figure 12. An updated valuation network. The common currency theory suggests that a neural network, mainly including the vmPFC and ventral striatum, is involved in task-independent value integration. The multivariate decoding results of this dissertation and findings from other MVPA studies suggest that the dmPFC also plays a critical role in value integration across different tasks. Therefore, the dmPFC may serve as another possible hub in the valuation network.

7.3 Implications for disorders with motivational deficits

The three studies included in this dissertation focused on healthy populations. However, the findings and methods may be useful for studies examining the neural and computational alterations related to effort-based value integration in multiple mental disorders (Chong et al., 2016).

First, effort-based value integration is central to understanding motivation, which is the desire to achieve a goal by overcoming the cost of required actions. Motivational deficits have been observed in multiple psychiatric disorders. For example, the lack of motivation is a core feature of major depressive disorder (Cooper et al., 2018). Moreover, overestimation of the cost of effort involved in goal-directed behaviors is closely related to Schizophrenia (Gold et al., 2015). Previous work has mainly relied on self-report tools or questionnaires to measure motivation. However, these methods provide a general description rather than a mechanistic explanation of the processes underlying motivational deficits (Chong et al., 2016). Effort-based decision-making paradigms included in this dissertation allow us to objectively quantify motivation and related processes, such as effort and reward sensitivity (Chong et al., 2016; M. F. Green et al., 2015), thus providing a complementary approach to examining motivational deficits in addition to self-report measures and questionnaires.

Another contribution of this dissertation is that we tested several computational models commonly used in effort-based decision-making studies and found that the two-parameter power discounting model showed the best fit. There has been considerable interest in using computational modeling approaches to advance our understanding of psychiatric disorders in recent years (Friston et al., 2014; Huys et al., 2016). Although some studies have used effort-based decision-making tasks to explore motivational deficits, many of them still relied on a model-free approach to analyzing behavioral data (Brassard & Balodis, 2021; Treadway et al., 2012; Yang et al., 2014). Our findings thus provide a suitable computational framework that can be used in future research to examine alterations related to effort-based value integration.

Finally, our neural findings may also help elucidate the neural mechanisms underlying disorders with motivational deficits. Previous work has shown neuroanatomical abnormalities (e.g., gray matter reduction) in the vmPFC, dmPFC, and some subcortical regions in patients with major depressive disorder and psychosis (Bora et al., 2012; Fusar-Poli et al., 2011). Importantly, an fMRI study showed that individuals with higher behavioral apathy showed increased dmPFC activity during effort-based decision-making (Bonnelle et al., 2016). Although more direct evidence is still needed, the vmPFC and dmPFC dysfunctions appear to be closely related to motivational deficits. Moreover, considering the critical roles of the vmPFC and dmPFC in value integration across different decision-making situations, these regions may also serve as candidate intervention targets for disorders with altered cost-benefit integration in general (Eppinger et al., 2013; Frank et al., 2004; D. J. Levy & Glimcher, 2012).

7.4 Future directions

All studies of this dissertation are based on evidence from fMRI data. While these studies consistently highlight the association between some potential hub regions and effort-based value integration, it is unable to establish causal relationships solely based on this correlational evidence (Lieberman et al., 2019). Future work may overcome this limitation by examining effort-based decision-making in patients with the vmPFC or dmPFC lesions (Camille et al., 2011; Gläscher et al., 2012). Another approach to address this issue is to use non-invasive brain stimulation approaches (Soutschek et al., 2018; Wittkuhn et al., 2018; Yao et al., 2021). Although most available methods can mainly influence the neural activity in superficial cortical regions, some newly emerging techniques are able to reach deeper areas (Carmi et al., 2018; Pasquinelli et al., 2019).

Moreover, the two empirical studies of this dissertation focused on physical effort as measured by a hand dynamometer. Although this setting has been widely used in previous work, as shown in our meta-analysis (Lopez-Gamundi et al., 2021), these findings should be treated cautiously when generalizing to other types of effort (e.g., cognitive effort). Therefore, another promising direction for future research is to compare the neural correlates of subjective value in different effort domains (Chong et al., 2017; Schmidt et al., 2012).

7.5 Conclusion

To conclude, this dissertation elucidates the neural and computational mechanisms underlying effort-based value integration using multiple methods. Our studies have provided supportive evidence to the common currency theory and extended the scope of the classic valuation network.

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9 Appendix

9.1 Deutsche Zusammenfassung

Im Alltag sind wir mit vielen Entscheidungen konfrontiert, die eine Abwägung des voraussichtlichen Aufwands erfordern, wie z. B. sportliche Aktivitäten und altruistisches Verhalten. Daher ist die Fähigkeit, die Kosten des Aufwands mit den potenziellen Belohnungen genau abzuwägen, entscheidend für optimales zielgerichtetes Verhalten. Die Theorie der gemeinsamen Währung besagt, dass die Werte verschiedener Optionen auf einer gemeinsamen Skala abgebildet werden, um eine effiziente Entscheidungsfindung über verschiedene Kostenarten hinweg zu gewährleisten. Diese Theorie bietet einen allgemeinen Rahmen, um zu erklären, wie Belohnungen und Kosten integriert werden, und hat bei der Entscheidungsfindung im Zusammenhang mit anderen Kostenarten wie Risiko und Verzögerung an Popularität gewonnen. Obwohl einige Studien die komputationalen und neuronalen Mechanismen untersucht haben, die der aufwandsbasierten Integration subjektiver Werte zugrunde liegen, bleibt unklar, ob Aufwand erwartete Ereignisse in ähnlicher Weise wie andere Kosten diskontiert. Weiterhin wird auf neuronaler Ebene diskutiert, ob die aufwandsbasierte Wertintegration auf ein allgemeines neuronales Bewertungsnetzwerk zurückzuführen ist, wie es die Theorie der gemeinsamen Währung nahelegt oder stattdessen auf ein spezifisches Netzwerk im Vergleich zu anderen Arten von Kosten zurückgreift.

In dieser Dissertation befasse ich mich mit diesen Fragen im Rahmen einer Meta-Analyse früherer Studien und zweier empirischer Studien. In der ersten Dissertationsstudie (Lopez-Gamundi et al., 2021) haben wir zwei separate Meta-Analysen durchgeführt, um neuronale Korrelate der Anstrengungs-Belohnungs-Integration bzw. reiner Anstrengungsanforderung in verwandten fMRI-Studien zu untersuchen. Wir fanden heraus, dass die Aktivität des ventromedialen präfrontalen Kortex (vmPFC) positiv mit subjektiven Werten, aber negativ mit reinen Aufwandsanforderungen skaliert. Andererseits wurde der dorsomediale präfrontale Kortex (dmPFC) in beiden

Analysen identifiziert, zeigte aber ein entgegengesetztes Aktivitätsmuster. Diese Ergebnisse stimmen im Allgemeinen mit früheren Erkenntnissen bei anderen Arten von Kosten überein.

In Studie 2 (Yao et al., 2022) haben wir das Wahlverhalten und die Daten eines frei zugänglichen Datensatzes mittels funktioneller Magnetresonanztomografie (fMRT), der sowohl anstrengungsbasierte als auch riskante (eine Option) Entscheidungsaufgaben enthielt, erneut analysiert, um direkt zu prüfen, ob die Theorie der gemeinsamen Währung auf die Wertintegration bei anstrengungsbasierten Entscheidungen angewendet werden kann. Mithilfe von Computermodellen fanden wir heraus, dass Anstrengung und Risiko unterschiedliche Diskontierungseffekte auf prospektive Ergebnisse haben. Auf neuronaler Ebene führten wir multivariate Dekodierungsanalysen durch und fanden heraus, dass ein großes Cluster, das sowohl den vmPFC als auch den dmPFC umfasst, den subjektiven Wert unabhängig von der Art der Kosten repräsentiert.

In Studie 3 (Yao et al., 2022) untersuchten wir die Replizierbarkeit der Ergebnisse aus Studie 2 mit einer unabhängigen Stichprobe von Versuchspersonen. Um ein ähnliches Entscheidungsverhalten zwischen den Aufgaben sicherzustellen, haben wir vor dem Scannen teilnehmerspezifische Indifferenzpunkte für alle Kombinationen von Belohnungen und Kosten (Aufwand oder Risiko) geschätzt. Zudem haben wir während des Scannens die Beträge kleinerer Belohnungen um diese Indifferenzpunkte manipuliert. Hierdurch konnten wir bestätigten, dass Aufwand und Risiko die Belohnungen deutlich abwerteten. Auf neuronaler Ebene stellten wir fest, dass der dmPFC den subjektiven Wert aufgabenunabhängig repräsentiert.

Zusammengenommen betonen die Ergebnisse die Rolle des dmPFC bei der subjektiven Wertberechnung unter Anstrengung und Risiko. Abschließend erörtere ich, wie diese Ergebnisse die laufenden Debatten über die neuronalen Mechanismen der Integration von Aufwand und Belohnung in Einklang bringen können und skizziere mögliche Implikationen für die Theorie der gemeinsamen Währung.

9.2 List of publications

1. Yao, Y.-W., Song, K.-R., Schuck, N. W., Li, X., Fang, X.-Y., Zhang, J.-T., Heekeren, H. R., & Bruckner, R. (2022). The dorsomedial prefrontal cortex represents subjective value across effort-based and risky decision-making. *PsyArXiv*. https://doi.org/10.31234/osf.io/6rpy5

2. Lopez-Gamundi, P., Yao, Y.-W., Chong, T. T. J., Heekeren, H. R., Mas-Herrero, E., & Marco-Pallarés, J. (2021). The neural basis of effort valuation: A meta-analysis of functional magnetic resonance imaging studies. *Neuroscience & Biobehavioral Reviews*, *131*, 1275–1287

3. Yao, Y.-W., Chopurian, V., Zhang, L., Lamm, C., & Heekeren, H. R. (2021). Effects of non-invasive brain stimulation on visual perspective taking: A meta-analytic study. *NeuroImage*, *242*, 118462

4. Song, K.-R., Potenza, M. N., Fang, X.-Y., Gong, G.-L., Yao, Y.-W., Wang, Z.-L., Liu, L., Ma, S.-S., Xia, C.-C., Lan, J., Deng, L.-Y., Wu, L.-L., & Zhang, J.-T. (2021). Resting-state connectome-based support-vector-machine predictive modeling of internet gaming disorder. *Addiction Biology*, *26*, e12969

5. Yao, Y.-W., Liu, L., Worhunsky, P. D., Lichenstein, S., Ma, S.-S., Zhu, L., Shi, X.-H., Yang, S., Zhang, J.-T., & Yip, S. W. (2020). Is monetary reward processing altered in drug-naive youth with a behavioral addiction? findings from internet gaming disorder. *NeuroImage: Clinical*, *26*, 102202

9.3 Eigenanteil

Erklärung gemäß § 7 Abs. 3 Satz 4 der Promotionsordnung über den Eigenanteil an den veröffentlichten oder zur Veröffentlichung vorgesehenen eingereichten wissenschaftlichen Schriften im Rahmen meiner publikationsbasierten Arbeit

I. Name, Vorname: Yao, Yuanwei
Institut: Fachbereich Erziehungswissenschaft und Psychologie
Promotionsfach: Psychologie
Titel: Master of Science

II. Nummerierte Aufstellung der eingereichten Schriften (Titel, Autoren, wo und wann veröffentlicht bzw. eingereicht):

1. Lopez-Gamundi, P[1]., Yao, Y.-W[1]., Chong, T. T. J., Heekeren, H. R., Mas-Herrero, E., & Marco-Pallarés, J. (2021). The neural basis of effort valuation: A meta-analysis of functional magnetic resonance imaging studies. *Neuroscience & Biobehavioral Reviews, 131*, 1275-1287.
   [1] Shared first authorship with equal contribution.

2. Yao, Y.-W., Song, K.-R., Schuck, N. W., Li, X., Fang, X.-Y., Zhang, J.-T., Heekeren, H. R., & Bruckner, R. (2022). The dorsomedial prefrontal cortex represents subjective value across effort-based and risky decision-making. *PsyArXiv*. https://doi.org/10.31234/osf.io/6rpy5.

III. Darlegung des eigenen Anteils an diesen Schriften:

Die Bewertung des Eigenanteils erfolgt auf der Skala: “vollständig – überwiegend – mehrheitlich – in Teilen”.

Zu II. 1.: Konzeption (mehrheitlich), Datenerhebung (mehrheitlich), Datenanalyse (überwiegend), Ergebnisdiskussion (mehrheitlich), Erstellen des Manuskriptes (mehrheitlich).

Zu II. 2.: Konzeption (überwiegend), Versuchsdesign (überwiegend), Programmierung (in Teilen), Datenerhebung (in Teilen), Datenanalyse (überwiegend), Ergebnisdiskussion (mehrheitlich), Erstellen des Manuskriptes (überwiegend).

9.4 Eidesstattliche Erklärung

Hiermit erkläre ich an Eides statt,

- dass ich die vorliegende Arbeit selbstständig und ohne unerlaubte Hilfe verfasst habe,
- dass ich mich nicht bereits anderwärts um einen Doktorgrad beworben habe und keinen Doktorgrad in dem Promotionsfach Psychologie besitze und
- dass ich die zugrunde liegende Promotionsordnung vom 08.08.2016 kenne.

Berlin, 19.08.2022

Yuanwei Yao

9.5 Research articles

Lopez-Gamundi, P[1]., Yao, Y.-W[1]., Chong, T. T. J., Heekeren, H. R., Mas-Herrero, E., & Marco-Pallarés, J. (2021). The neural basis of effort valuation: A meta-analysis of functional magnetic resonance imaging studies. *Neuroscience & Biobehavioral Reviews, 131*, 1275-1287. https://doi.org/10.1016/j.neubiorev.2021.10.024.

[1] Shared first authorship with equal contribution.

Yao, Y.-W., Song, K.-R., Schuck, N. W., Li, X., Fang, X.-Y., Zhang, J.-T., Heekeren, H. R., & Bruckner, R. (2022). The dorsomedial prefrontal cortex represents subjective value across effort-based and risky decision-making. *PsyArXiv*. https://doi.org/10.31234/osf.io/6rpy5.