ChinaRxiv 中X

AI translation · View original & related papers at
chinarxiv.org/items/chinaxiv-202409.00130

Physical or Cognitive Effort Impairment? Assessing Effort-Reward Motivation in Depression Using Computational Models

Authors: Wen Xiujuan, Yujing Ma, Siqi Tan, Li Yun, Liu Wenhua, Liu Wenhua

Date: 2024-09-10T00:00:00+00:00

Abstract

Motivational impairment is a common feature of depression, with patients frequently displaying abnormal reward evaluation or experience. Understanding the specific type of effort that patients with depression are unwilling to exert in effort-reward motivation tasks—whether physical or cognitive effort—is essential for facilitating the restoration of social functioning. However, there is currently a dearth of research examining how effort type (physical or cognitive effort) influences scientific understanding. Moreover, computational modeling methods, which possess the advantage of finely assessing motivation-related variables, have not been widely adopted in this field. Utilizing experimental methods to differentially evaluate depressed patients' decision-making between 'cognitive effort' and 'physical effort,' combined with computational model-based data analysis, to investigate motivational impairment behaviors in depression from an effort-reward motivation perspective, can promote the elucidation of the underlying cognitive-neural basis of this impairment.

Full Text

Preamble

Motivation Deficits in Physical Effort or Cognitive Effort Expenditure? Evaluation of Effort-Based Reward Motivation and Application of Computational Modeling in Depression

WEN Xiujuan[1,2], MA Yujing[1,2], TAN Siqi[2], LI Yun[2], LIU Wenhua[1,2]
(1 The Affiliated Brain Hospital, Guangzhou Medical University, Guangzhou 510370, China)
(2 School of Health Management, Guangzhou Medical University, Guangzhou 511436, China)

Abstract

Motivation deficits are a common feature of depression, with patients frequently exhibiting abnormal reward assessment or experience. Understanding the specific type of effort that individuals with depression are unwilling to expend—whether physical or cognitive—is crucial for helping patients restore social functional activities. However, current research lacks investigation into how effort type (physical vs. cognitive) influences study conclusions. Meanwhile, computational modeling offers the advantage of finely assessing motivation-related variables, yet this approach remains underutilized in this field. By experimentally distinguishing and evaluating "cognitive effort" and "physical effort" decision-making in depressed patients and integrating computational modeling for data analysis, we can explore motivational deficits from an effort-reward perspective and illuminate their underlying cognitive-neural mechanisms.

Keywords: Depression, anhedonia, motivation deficits, physical effort, cognitive effort, computational modeling

As a common mental disorder, depression has reached a global prevalence of 5% and is projected to become the leading cause of disease burden worldwide (WHO, 2023). Clinically, patients with depression typically exhibit low mood, loss of interest in previously enjoyable activities, sleep disturbances, appetite changes, fatigue or low energy, difficulty concentrating, and suicidal ideation (American Psychiatric Association, 2013). Additionally, a large-scale domestic survey revealed that nearly two-thirds of patients with depression experience impaired social functioning, including inability to study, work, or participate in social activities normally (Lu et al., 2021).

Anhedonia—a core symptom of depression—may be a primary factor affecting social functional activities in depressed patients. Individuals with anhedonia often lose interest in attractive stimuli and lack motivation to obtain rewards, creating difficulties in daily life (American Psychiatric Association, 2013). Researchers commonly distinguish between anticipatory and consummatory anhedonia: the former refers to lack of interest in anticipated pleasurable activities, while the latter refers to reduced pleasure during ongoing activities (Gard et al., 2006). Both types influence an individual's willingness to expend effort for further action. Specifically, individuals with high anticipatory anhedonia show disinterest in anticipated rewards and are thus unwilling to expend effort to engage in reward-seeking activities. Those with high consummatory anhedonia experience little pleasure when obtaining rewards, reducing their future willingness to expend effort for similar activities. This willingness to expend effort for rewards is considered a motivational behavior known as effort-based reward motivation (Chong et al., 2016).

Although research shows that deficits in effort-based reward motivation can affect depression treatment and progression, existing findings on the nature and strength of the association between depression and effort-reward motivation remain ambiguous (Horne et al., 2021). Some studies measure physical effort as a motivational indicator, such as the number of button presses within a time limit (Giustiniani et al., 2020; Racine et al., 2019; Wilhelm et al., 2021), while others use cognitive effort, such as performance on short-term letter or number memory tasks (Clay et al., 2022; Soutschek & Tobler, 2020; Xie & Zhang, 2023). Understanding whether depressed patients are unwilling to expend physical effort, cognitive effort, or both is important because it indicates which functional activities in daily life—such as work and family—may be impaired. For instance, individuals who prefer staying home versus those who feel mentally empty and sluggish may correspond to physical and cognitive effort deficits, respectively. However, few studies have examined how methodological features, such as different effort types (physical vs. cognitive) or task instructions, might influence research conclusions.

Computational modeling, an emerging and promising research method, has seen preliminary application in mental illness research. Compared to subjective scales and traditional experimental measurements that use average values to estimate overall states, computational modeling employs trial-by-trial analysis, using mathematical parameters to quantify changes in effort willingness during experimental tasks, enabling more refined and objective assessment of motivational behavior in depressed individuals (Huys et al., 2021). Moreover, computational models contain many free parameters derived from observed data through mathematical functions, allowing quantitative assessment of complex cognitive processes that cannot be directly measured. This offers significant advantages for understanding complex, multi-component psychological constructs like reward and motivation. Currently, few studies combine computational modeling with laboratory-based effort-reward motivation assessment, making it necessary to evaluate the characteristics and limitations of common computational modeling approaches to promote broader application in depression research.

To advance understanding of the relationship between depression and reward motivation—including how effort type (physical vs. cognitive) may differentially impact the disease—this paper reviews laboratory assessment methods for effort-reward motivation in depression, computational modeling approaches, and preliminary applications combining these methods. Based on this foundation, we discuss potential issues in computational modeling research paradigms and identify important future research directions.

1. Experimental Measurement Methods for "Physical Effort" and "Cognitive Effort" in Depression

Previous laboratory studies assessing effort-based reward acquisition have typically categorized effort into "physical effort" and "cognitive effort" based on its source—whether somatic or mental (Steele, 2020). A few studies have distinguished between subjective and objective effort (Kurzban et al., 2013; Rewitz et al., 2023), but this approach is rarely used and will be omitted here for brevity. Research comparing whether physical and cognitive effort differentially impact motivational goal attainment is currently lacking. Below, we briefly introduce common paradigms for measuring physical and cognitive effort to clarify their differences.

For physical effort measurement, studies commonly use brief keyboard button-pressing tasks (hereafter "button-press tasks") or hand dynamometers to assess grip strength (hereafter "handgrip tasks") to quantify willingness to expend physical effort. For cognitive effort, researchers typically use working memory, digit judgment, task-switching, and conflict inhibition tasks to measure willingness to expend mental effort.

1.1 Physical Effort Measurement Methods

The most common physical effort assessment is the Effort-Expenditure for Rewards Task (EEfRT) developed by Treadway et al. (2009, 2012). In this task, participants choose between a "difficult task" (pressing a button 100 times with the pinky finger within 21 seconds) and an "easy task" (pressing a button 30 times with the index finger within 7 seconds). They are informed that the difficult task yields higher, variable rewards, while the easy task provides fixed, low rewards. To enhance ecological validity, rewards are probabilistic (low, medium, or high probability, e.g., 12%, 50%, 88%) rather than guaranteed upon task completion. This task has been widely used in depression motivation research (Berwian et al., 2020; Bi et al., 2022; Park et al., 2017; Yang et al., 2014, 2016).

Subsequent variations include the Effort-Cost Computation Task (Berwian et al., 2020), Modified Effort-Expenditure for Rewards Task (Bi et al., 2022), and Effort-Based Reinforcement Task (Park et al., 2017). The Effort-Cost Computation Task adjusted button-press requirements and high-reward settings. The Modified Effort-Expenditure for Rewards Task altered difficulty levels by adding multiple difficult task options. The Effort-Based Reinforcement Task differs by assessing effort to avoid reward loss rather than to obtain rewards (Park et al., 2017).

Another common method is the handgrip task, which uses a dynamometer (e.g., BIOPAC hardware modules, www.biopac.com) to record grip strength as a measure of physical effort. Common paradigms in depression research include simple handgrip tasks requiring brief maximal squeezing for reward (Cléry-Melin et al., 2011; Vinckier et al., 2022) and reward-decision handgrip tasks that first measure each participant's Maximum Voluntary Contraction (MVC—the average or maximum grip force over a short period), then require choosing between high-effort options (squeezing at 40%-100% MVC) and low-effort options (no squeezing, 0% MVC) (Cathomas et al., 2021).

Other physical effort tasks include the Progressive Ratio Task, Effort-Reward Picture Task, and Effort Doors Task (Bowyer et al., 2023; Klawohn et al., 2022; Sherdell et al., 2012).

1.2 Cognitive Effort Measurement Methods

Common cognitive effort tasks are adapted from the N-back working memory task. The N-back task presents a series of letters or numbers on a computer screen, requiring participants to recall the item presented N trials back (e.g., 1, 2, 3). Larger N values indicate greater memory difficulty. Westbrook et al. (2020) adapted this into the Cognitive Effort Discount Task for assessing cognitive effort in depression. In this task, participants choose between difficult and easy N-back tasks, with difficult tasks offering higher rewards.

The Cognitive Effort Motivation Task, developed more recently by Ang et al. (2022), presents participants with high-effort options (accurately recalling positions of multiple squares) and low-effort options (recalling position of a single square). High-effort choices yield variable, high rewards, while low-effort choices provide fixed, low rewards.

Additional cognitive effort tasks include the Cognitive Effort Deck Choice Task, Cognitive Performance Task, Computerized Cognitive Task, and Progressive Ratio Task, which use task-switching or number comparison to assess cognitive effort (Bowyer et al., 2023; Klawohn et al., 2022; Sherdell et al., 2012).

1.3 Relevant Behavioral Studies

Studies using physical effort tasks typically measure the probability of choosing "high-reward, high-effort" options to assess effort expenditure for rewards. Two studies using the EEfRT task found that depressed patients were less willing than healthy individuals to expend physical effort for rewards (Treadway et al., 2009; Yang et al., 2014). Similar findings were reported using simple handgrip tasks (Vinckier et al., 2022). However, studies using other physical effort paradigms (e.g., Effort-Reward Picture Task, Progressive Ratio Task) found no differences between depressed patients (Klawohn et al., 2022; Sherdell et al., 2012; Cléry-Melin et al., 2011), remitted patients (Yang et al., 2014), or college students with high depressive symptoms (Bi et al., 2022) and healthy controls.

Studies using cognitive effort tasks measure selection of high-effort cognitive activities. Hershenberg et al. (2016) and Wood-Ross et al. (2021) found that while healthy individuals willingly attempted cognitively demanding tasks, depressed patients preferred easier tasks, indicating reduced willingness to expend cognitive effort for rewards (Hammar et al., 2011; Wood-Ross et al., 2021). However, two other studies using different cognitive effort tasks found no such differences (Barch et al., 2023; Hershenberg et al., 2016). Notably, conventional cognitive effort tasks (e.g., N-back, Computerized Cognitive Task) primarily assess memory capacity, whereas Hammar et al. assessed executive function and Barch et al. assessed response capacity, which may contribute to divergent findings.

Some studies simultaneously assessed both physical and cognitive effort to examine relationships with depressive symptoms (Tran et al., 2021; Vinckier et al., 2022). Higher anhedonia severity correlated with lower motivation for physical activity, but no association was found with cognitive activity motivation (Tran et al., 2021). Compared to healthy individuals, depressed patients showed greater sensitivity to physical than cognitive effort, suggesting stronger aversion to physical effort expenditure (Vinckier et al., 2022).

2. Computational Modeling Methods for Motivation Deficits in Depression

Computational modeling is an emerging assessment method in mental illness research (Huys et al., 2021). Its advantages include: (1) Unlike traditional methods that use mean reaction times or accuracy as behavioral measures, computational modeling can weigh trial-by-trial variations through free parameters (Adams et al., 2015) and quantify inter-trial behavioral adjustments, dynamically capturing behavioral changes during task performance (Clairis & Pessiglione, 2024); (2) It provides a more comprehensive understanding of behavioral characteristics (Robinson & Chase, 2017). While traditional analyses examine single dimensions (e.g., reaction time or choice behavior), computational models like the drift-diffusion model integrate choice and reaction time data for deeper insights (Ratcliff et al., 2016); (3) Combining computational modeling with neuroimaging can reveal the cognitive-neural basis of behavioral changes (Husain & Roiser, 2018). Traditional methods correlate neural and behavioral measures at the individual level, whereas computational modeling can link model parameters representing specific cognitive processes to neural measures at both individual and trial-by-trial levels, explaining dynamic neural activity changes.

Given the interdisciplinary nature of computational modeling, different fields employ varying approaches. Below, we focus on models applicable to depression motivation research and their measurement content, while also reviewing compatible effort-reward experimental paradigms to guide future research.

2.1 Theoretical Foundations of Computational Models

Models for assessing motivation deficits in depression include conventional function models (linear, hyperbolic, parabolic, exponential), net value and effort-cost-benefit optimization models, drift-diffusion models, and reinforcement learning models. Function and optimization models are based on cost-benefit framework theory, where behavior aims to obtain rewards (benefits) requiring effort (costs), with net value equaling reward minus effort cost (Pessiglione et al., 2018). Drift-diffusion theory posits that decision-making involves information accumulation until a threshold is reached (Ratcliff et al., 2016). Reinforcement learning theory suggests individuals learn from environmental feedback to adjust behavior for maximal reward (Chen et al., 2015; Pike & Robinson, 2022).

Function models are most widely applicable to the physical and cognitive effort tasks described above. Net value models have narrower application, currently used in only a few depression studies examining physical effort (e.g., Vinckier et al., 2022). Drift-diffusion models offer flexibility for exploring cognitive decision-making. Reinforcement learning models can be applied to most physical and cognitive effort tasks to examine how past feedback influences reward learning. These complementary models facilitate comprehensive understanding of effort-reward processes from different perspectives.

Computational models contain free parameters derived from observed data that represent specific cognitive processes and behavioral characteristics (Husain & Roiser, 2018). Below, we introduce key parameters relevant to depression research to guide model selection.

2.2 Conventional Function Models

Depression research often examines how much individuals care about effort expenditure (Berwian et al., 2020; Vinckier et al., 2022). Generally, individuals evaluate target activities; greater concern about required effort reduces willingness to engage (Müller et al., 2022). In function models, the free parameter k represents effort sensitivity, weighting effort's impact on behavior and termed "effort discounting" (Aridan et al., 2019; Arulpragasam et al., 2018). This parameter is a key focus in depression effort-reward motivation research. Larger k values indicate lower subjective value of the target task, greater value devaluation (discounting), and higher effort sensitivity (Aridan et al., 2019; Arulpragasam et al., 2018). Common models include linear, hyperbolic, parabolic, and exponential functions:

Linear function: SV(t) = R(t) * (1 - k * E(t))
Hyperbolic function: SV(t) = R(t) / (1 + k * E(t))
Parabolic function: SV(t) = R(t) - k * E(t)
Exponential function: SV(t) = R(t) * e^(-k * E(t))

Where SV(t) represents subjective value per trial t, R(t) represents reward value, E(t) represents effort level, k is the free parameter representing effort's impact, and e is Euler's number (~2.718281828).

Studies also examine reward value (R), effort level (E), and subjective value (SV) (Ang et al., 2022; Chong et al., 2017). Reward and effort levels are predetermined by experimenters, representing potential rewards (typically monetary amounts) and required effort (typically graded effort levels). Subjective value represents the individual's valuation of the reward.

2.3 Net Value and Effort-Cost-Benefit Optimization Model

This model includes additional free parameters beyond effort sensitivity, enabling examination of broader factors like fatigue state impact on behavior (Le Bouc et al., 2016; Vinckier et al., 2022).

The model posits that individuals evaluate effort costs and benefits (rewards), calculating net value as benefit minus cost (Le Bouc et al., 2016; Vinckier et al., 2022). Positive net value indicates willingness to expend effort for reward; negative net value indicates unwillingness. The formula is:

Net value: V(Fi) = (1 + kr * R) * Fi - (kc * Fi / (1 - Fi)) * (1 + kf * T)

Benefit value is proportional to reward (R) and reward sensitivity (free parameter *kr*). Larger *kr* indicates higher assessed benefit value. Effort sensitivity is represented by free parameter *kc*; larger values indicate higher sensitivity. Fatigue impact on effort cost is weighted by free parameter *kf*; larger values indicate greater fatigue sensitivity (Le Bouc et al., 2016; Vinckier et al., 2022).

2.4 Drift-Diffusion Model

The drift-diffusion model, commonly used in economic decision-making research, offers richer parameters than conventional function models (Cataldo et al., 2023; Grange, 2022). Recent studies have applied it to abnormal motivation in depression to deepen understanding of cognitive decision-making deficits (Berwian et al., 2020).

This model views decision-making as an information accumulation process that triggers when accumulated evidence reaches a decision boundary (Ratcliff et al., 2016). Key parameters include starting point, boundary threshold, and drift rate. In depression research, the starting point represents baseline preference for "high-effort, high-reward" options; boundary threshold represents required information accumulation for different options; drift rate represents information accumulation speed. Higher drift rates indicate faster accumulation of information favoring high-effort, high-reward options and greater preference for them (Berwian et al., 2020).

The model estimates reward sensitivity (free parameter βrew) and effort sensitivity (free parameter βeff) by linking drift rate (v) to reward (R) and effort (E):

Drift rate: v = βrew * R - βeff * E

Larger βrew indicates greater reward sensitivity; larger βeff indicates greater effort sensitivity.

2.5 Reinforcement Learning Model

Unlike previous models focusing on individual-level parameters, reinforcement learning models consider inter-trial variability, flexibly describing how individuals learn from past feedback and plan future actions. Key parameters include prediction error (PE) and learning rate. PE reflects whether current information (reward or effort) is better or worse than expected (Chen et al., 2015). Learning rate reflects the magnitude of adjustment when updating value functions using PE.

The most commonly used model-free reinforcement learning approach is the Rescorla-Wagner model, which assumes current trial value equals previous trial value plus the product of learning rate and PE. PE is determined by the difference between received and expected reward. For more details, see Sutton and Barto (2018).

3. Application of Computational Models in Depression "Physical Effort" and "Cognitive Effort" Research

Few studies have applied computational modeling to depression effort-reward research. Recent preliminary studies have primarily focused on characterizing physical or cognitive effort sensitivity in depressed patients, with rare examination of other factors like reward information or fatigue. These studies reveal interesting findings and unresolved issues warranting further exploration.

Two 2020 and 2022 studies using computational paradigms showed elevated physical effort sensitivity in depression (Berwian et al., 2020; Vinckier et al., 2022) . Vinckier et al. used the net value and effort-cost-benefit optimization model to assess physical effort sensitivity during a simple handgrip task. Compared to healthy individuals, depressed patients showed higher physical effort sensitivity (parameter kc), which correlated significantly with subjectively reported apathy symptoms. Remitted patients also showed elevated physical effort sensitivity. Berwian et al. used the drift-diffusion model to assess physical effort sensitivity in remitted patients performing an effort-cost computation task, finding significantly higher effort sensitivity (parameter βeff) than in healthy controls (Berwian et al., 2020).

Two 2022 studies using function models to assess cognitive effort sensitivity showed similar results (Ang et al., 2022; Westbrook et al., 2022). Ang et al. used function models with a cognitive effort motivation task, finding higher cognitive effort sensitivity (parameter k) in patients versus healthy controls. Westbrook et al. used the N-back cognitive effort task with function model fitting, also showing higher effort sensitivity (parameter k) in depressed patients. These findings indicate that depressed patients are less willing than healthy individuals to expend both physical and cognitive effort for rewards.

One 2021 study using function models and a handgrip task found no difference in physical effort sensitivity between depressed patients and healthy controls (Cathomas et al., 2021). However, this study included only medicated, stable patients with long illness duration (average 3 episodes) and a small healthy control sample (n=18), making it difficult to rule out medication effects or sample size limitations.

Notably, the studies by Vinckier et al. and Berwian et al. are distinctive for analyzing additional factors like reward and fatigue impacts. While Vinckier et al. found higher effort sensitivity in patients, they observed no group differences in reward or fatigue sensitivity (parameters kr and kf). Similarly, Berwian et al. found group differences in effort sensitivity but not reward sensitivity. These results suggest effort sensitivity may have greater influence than reward information or fatigue on goal-directed behavior. However, since all three factors affect real-world behavior and are interrelated, future research should use computational modeling with appropriate measures to verify these findings.

Notably, depression effort-reward computational modeling studies have focused on individual-level parameters, with limited attention to trial-level parameters. However, reinforcement learning studies in healthy populations offer directions for future depression research. Two studies using reinforcement learning models with physical effort tasks found that positive PE increased learning rates while negative PE decreased them (Jarvis et al., 2022), and that reward information was learned faster than effort information, suggesting greater sensitivity to rewards (Skvortsova et al., 2014). Studies of cognitive effort in healthy populations found that individuals adjust PE and learning rates to influence updating of cognitive effort cost expectations, affecting effort learning processes (Sayalı & Badre, 2021; Silva et al., 2023).

4. Cognitive Neuroscience Studies of "Physical Effort" and "Cognitive Effort" in Depression

In contrast to the limited computational modeling studies, numerous traditional experimental studies have examined cognitive-neural correlates of motivation deficits in depression. While many have assessed physical and cognitive effort-related performance, findings are often inconsistent. Neurophysiological studies have focused more on physical than cognitive effort. Below, we review traditional studies exploring physical and cognitive effort in depression, as well as studies combining computational modeling with cognitive neuroscience techniques.

4.1 Neural Activity Studies of Physical and Cognitive Effort in Depression

Imaging studies show abnormal brain activity during physical effort decision-making in depression, primarily involving prefrontal cortex, striatum, cingulate cortex, and insula (Bi et al., 2022; Park et al., 2017; Rzepa et al., 2017; Rzepa & McCabe, 2019; Yang et al., 2016). For example, Yang et al. (2016) found reduced responses in left caudate, left superior temporal gyrus, and right caudate, plus frontal and cingulate abnormalities during a button-press effort-reward task. Park et al. (2017) found abnormal ventral tegmental area-substantia nigra connectivity and reduced striatal-orbitofrontal cortex connectivity during an effort-based reinforcement task. Recent studies also found reduced insula activation in college students with high depressive symptoms and adolescent patients (Bi et al., 2022; Rzepa & McCabe, 2019).

EEG studies show abnormal brain activity during effort-reward processing in depression. Bowyer et al. used the effort-doors task and found reduced P300, Stimulus-Preceding Negativity (SPN), and Reward-Positivity (RewP) in depressed patients. Since SPN relates to outcome anticipation and RewP to reward/punishment responses, this suggests reduced outcome sensitivity. P300, related to attention allocation to effort information, suggests reduced attention to effort cues. In cognitive effort, Wood-Ross et al. found increased EEG alpha power during a computerized cognitive task, which, given alpha's association with reduced attention, suggests attentional deficits during effort-reward motivation (Wood-Ross et al., 2021).

In summary, depressed patients show abnormal physical and cognitive effort behaviors, with physical effort deficits potentially more severe than cognitive ones. However, inconsistent findings may stem from different paradigms, particularly variations in physical vs. cognitive effort assessment. Additionally, motivation deficits likely vary by depression severity, making sample characteristics important factors. Patients also show abnormal neural activity in prefrontal cortex, striatum, anterior cingulate, and insula related to effort motivation deficits. Future research should combine EEG and fMRI to investigate physiological mechanisms of cognitive and physical effort motivation deficits and compare potential differences.

4.2 Studies Combining Computational Modeling with Cognitive Neuroscience

Studies combining computational modeling with neuroimaging to assess physical and cognitive effort have primarily used healthy samples.

Some studies used function-model-based computational approaches to investigate neural substrates. Arulpragasam et al. (2018) with physical effort tasks and Westbrook et al. (2019) with cognitive effort tasks both found ventromedial prefrontal cortex (vmPFC) involvement in integrating effort cost processing and encoding effort-related subjective value. Other studies found anterior cingulate cortex, ventral striatum, and dorsomedial prefrontal cortex (dmPFC) also encode effort-related subjective value during physical effort tasks (Aridan et al., 2019; Bernacer et al., 2019a, 2019b; Goh et al., 2021; Hogan et al., 2019; Lockwood et al., 2022; Suzuki et al., 2021; Yao et al., 2023). One study comparing physical and cognitive effort found both activated similar regions including dmPFC, dorsolateral prefrontal cortex, intraparietal sulcus, and anterior insula, which correlated with reward and effort sensitivity. Notably, amygdala activity correlated only with reward sensitivity during cognitive effort, suggesting a unique role in cognitive reward processing (Chong et al., 2017).

Reinforcement-learning-based computational studies in healthy populations found vmPFC and anterior insula activity correlated with reward and effort prediction errors, respectively, during physical effort tasks (Skvortsova et al., 2014). During cognitive effort, frontoparietal networks encoded effort prediction errors (Sayalı & Badre, 2021). Another recent study using both effort types found similar activation in vmPFC and dmPFC, with vmPFC involved in value encoding and dmPFC in effort control (Clairis & Pessiglione, 2024).

Studies also examined fatigue effects on physical effort. Hogan et al. (2020) used function models to show motor and somatosensory cortex involvement in effort cost valuation during fatigue. Müller et al. (2021) combined reinforcement learning and function models, finding middle frontal gyrus and cingulate activity related to effort cost valuation during fatigue.

Recent notable studies used non-invasive brain stimulation (e.g., transcranial magnetic stimulation, transcranial alternating current stimulation) with computational modeling to assess how brain activity changes affect physical and cognitive effort.

Soutschek & Tobler (2020) used TMS with function models during a cognitive effort task, finding that inhibiting dorsolateral prefrontal cortex (DLPFC) increased effort sensitivity and reduced post-effort fatigue. Soutschek et al. (2022) used tACS with Bayesian drift-diffusion models, finding that theta tACS over dmPFC increased preference for high-reward, high-effort options, enhancing willingness to expend cognitive effort for rewards.

Bi et al. (2024) combined TMS, EEG, and function models in depressed patients performing a physical effort task, finding that activating left DLPFC reduced effort sensitivity and increased P300, Contingent Negative Variation (CNV), and SPN amplitudes. This suggests enhanced left DLPFC activity may improve attention to effort/reward information, motor preparation, and reward anticipation in depression.

Thus, computational modeling of effort-reward neural substrates has focused primarily on healthy populations, with few studies in depressed patients (Bi et al., 2024). Computational modeling's flexible parameters can help distinguish brain activity related to different reward motivation subcomponents, advancing understanding of the neural basis of motivation deficits as a core depressive symptom. Non-invasive brain stimulation is both a research tool and clinical treatment for depression. Future research combining brain stimulation, neuroimaging, electrophysiology, and computational modeling could examine pre- and post-intervention brain changes, benefiting clinical treatment.

5. Current Issues in Research

Existing studies combining computational modeling with physical or cognitive effort paradigms have preliminarily examined behavioral and neural mechanisms of motivation deficits in depression. Computational modeling's advantages in finely assessing motivation variables and dynamic states can illuminate underlying cognitive-neural mechanisms. However, several issues remain.

First, inconsistent experimental paradigms across studies—varying in effort levels, reward magnitudes, and stimulus materials—may lead to inconsistent conclusions. Many designs inadequately consider individual differences in effort capacity. Some physical effort paradigms allow personalized effort level calibration, such as measuring individual MVC for handgrip tasks, accounting for physical strength differences. However, most cognitive effort tasks use objective difficulty standards (e.g., number of digits to remember) without considering baseline cognitive ability or capacity limits. Inappropriate difficulty levels (too easy or too hard) can produce ceiling or floor effects, obscuring group differences. Future research could adopt sophisticated algorithms like Computerized Adaptive Testing (He et al., 2022) to efficiently estimate individual cognitive capacity and assign appropriate difficulty levels, avoiding ceiling/floor effects.

Second, most studies examine only physical or cognitive effort, with few assessing both (Chong et al., 2017; Clairis & Pessiglione, 2024; Matthews et al., 2023; Tran et al., 2021; Vinckier et al., 2022). However, physical and cognitive effort unwillingness may interact throughout reward motivation processes. Future research should assess both effort types in the same sample, using computational modeling to quantify effort-related variables and determine whether different effort types have similar or distinct disease impacts. Additionally, few studies assess how other symptoms affect motivation deficits. Fatigue, another important depressive symptom (American Psychiatric Association, 2013), reduces effort-reward willingness (Hogan et al., 2020; Iodice et al., 2017). Negative self-bias may also affect motivation, as patients may believe they lack ability to obtain rewards despite effort (LeMoult & Gotlib, 2019). Future research should examine how clinical features like fatigue and negative bias influence motivation deficits for a more comprehensive understanding.

Finally, current computational models primarily use cost-benefit frameworks that treat effort as a cost factor, neglecting effort's motivational potential (Inzlicht et al., 2018; Yi et al., 2019). Individuals may view high effort as a challenge worth pursuing for high rewards. The reliance on single theoretical frameworks limits model diversity. While effort sensitivity is a key parameter, motivation is complex and cannot be fully explained by single metrics. Future research should apply diverse computational models (e.g., Bayesian, active inference, reinforcement learning) using additional sensitive measures like reinforcement learning's effort discounting or learning rate parameters (Jarvis et al., 2022) to capture trial-by-trial motivational changes, providing more comprehensive understanding of depression's motivational deficits.

6. Summary

Motivation deficits are a crucial clinical feature of depression, severely impacting treatment, recovery, and social functioning. Laboratory methods distinguishing physical and cognitive effort, combined with computational modeling, enable deeper investigation of motivational deficits. Findings show depressed patients exhibit both physical and cognitive effort impairments compared to healthy individuals, with associated abnormal neural activity in prefrontal cortex, striatum, anterior cingulate, and insula, potentially underlying unwillingness to expend effort for rewards.

Traditional anhedonia research has examined reward anticipation, consumption, and learning (Berridge & Robinson, 2003). However, Treadway and Zald (2011) argue that understanding anhedonia's neurophysiological basis requires examining continuous behavioral responses throughout reward processing, not just single stages. They propose that both anticipatory and consummatory anhedonia may cause decision-making deficits, leading individuals to overestimate costs, underestimate benefits, or fail to integrate cost-benefit information, resulting in abnormal selection behavior. From this perspective, anhedonia can be viewed as impaired "effort-reward decision-making" (Treadway & Zald, 2011). This framework differs from traditional approaches by focusing on the entire reward processing sequence. Whether physical and cognitive effort share common or distinct neural substrates remains uncertain due to limited research (Tran et al., 2021; Vinckier et al., 2022).

Computational modeling offers significant value for exploring effort-reward motivation. Its flexible parameters can assess both traditional measures (reward sensitivity, value assessment, learning) (Chong et al., 2017; Clairis & Pessiglione, 2024) and underexplored factors like fatigue (Matthews et al., 2023; Müller et al., 2021), greatly expanding research scope. Combining this approach with neuroimaging, electrophysiology, and brain stimulation in clinical populations can help understand not only anhedonia's neural basis but also whether related psychopathological features like cognitive impairment and psychomotor retardation have distinct neural patterns (Horne et al., 2021).

Future directions include: (1) Combining computational modeling with neurophysiological or neuroimaging methods to clarify cognitive effort abnormalities, as cognitive effort research remains limited; (2) Investigating effort behavior differences across disease stages (acute vs. remitted) to assess impacts of severity and cognitive impairment; (3) Applying key computational metrics (e.g., effort sensitivity) clinically to precisely assess physical and cognitive effort deficits and guide psychotherapy selection—cognitive behavioral therapy may benefit those with severe cognitive effort deficits, while behavioral activation may help those with physical effort deficits (Huibers et al., 2021; Richards et al., 2016); (4) Developing more computational assessment indicators to examine relationships between effort-reward motivation deficits and treatment outcomes, facilitating development of more effective psychotherapies to restore social functioning.

References

Yi, W., Mei, S., & Zheng, Y. (2019). Effort: Cost or reward? *Advances in Psychological Science*, 27(8), 1439–1450.

Adams, R. A., Huys, Q. J. M., & Roiser, J. P. (2015). Computational psychiatry: Towards a mathematically informed understanding of mental illness. *Journal of Neurology, Neurosurgery & Psychiatry*, 87(1), 53–63. https://doi.org/10/gdvhx4

American Psychiatric Association (Ed.). (2013). *Diagnostic and statistical man-*

ual of mental disorders: DSM-5 (5th ed). American Psychiatric Association.

Ang, Y. S., Gelda, S. E., & Pizzagalli, D. A. (2023). Cognitive effort-based decision-making in major depressive disorder. *Psychological Medicine*, 53(9), https://doi.org/10.1017/S0033291722000964

Aridan, N., Malecek, N. J., Poldrack, R. A., & Schonberg, T. (2019). Neural correlates of effort-based valuation with prospective choices. *NeuroImage*, 185, 446–454. https://doi.org/10/gjjf55

Arulpragasam, A. R., Cooper, J. A., Nuutinen, M. R., & Treadway, M. T. (2018). Corticoinsular circuits encode subjective value expectation and violation for effortful goal-directed behavior. *Proceedings of the National Academy of Sciences*, 115(22), E5233–E5242. https://doi.org/10/gdkz59

Barch, D. M., Culbreth, A. J., Ben Zeev, D., Campbell, A., Nepal, S., & Moran, E. K. (2023). Dissociation of cognitive effort-based decision making and its associations with symptoms, cognition, and everyday life function across schizophrenia, bipolar disorder, and depression. *Biological Psychiatry*, 94(6), 501–510. https://doi.org/10.1016/j.biopsych.2023.04.007

Bernacer, J., Martinez-Valbuena, I., Martinez, M., Pujol, N., Luis, E. O., Ramirez-Castillo, D., & Pastor, M. A. (2019a). An amygdala-cingulate network underpins changes in effort-based decision making after a fitness program. *NeuroImage*, 203, 116181. https://doi.org/10/gmccnh

Bernacer, J., Martinez-Valbuena, I., Martinez, M., Pujol, N., Luis, E., Ramirez-Castillo, D., & Pastor, M. A. (2019b). Neural correlates of effort-based behavioral inconsistency. *Cortex*, 113, 96–110. https://doi.org/10.1016/j.cortex.2018.12.005

Berridge, K. C., & Robinson, T. E. (2003). Parsing reward. *Trends in Neurosciences*, 26(9), 507–513. https://doi.org/10.1016/S0166-2236(03)00233-9

Berwian, I. M., Wenzel, J. G., Collins, A. G. E., Seifritz, E., Stephan, K. E., Walter, H., & Huys, Q. J. M. (2020). Computational mechanisms of effort and reward decisions in patients with depression and their association with relapse after antidepressant discontinuation. *JAMA Psychiatry*, 77(5), 513. https://doi.org/10.1001/jamapsychiatry.2019.4971

Bi, R., Dong, W., Zheng, Z., Li, S., & Zhang, D. (2022). Altered motivation of effortful decision-making for self and others in subthreshold depression. *Depression and Anxiety*, 39(8–9), 633–645. https://doi.org/10.1002/da.23267

Bi, R., Zhao, Y., Li, S., Xu, F., Peng, W., Tan, S., & Zhang, D. (2024). Brain stimulation over the left DLPFC enhances motivation for effortful rewards in patients with major depressive disorder. *Journal of Affective Disorders*, https://doi.org/10.1016/j.jad.2024.04.064

Bowyer, C. B., C.J. Brush, Christopher J. Patrick, & Greg Hajcak. (2023). Effort and appetitive responding in depression: Examining deficits in motivational and consummatory stages of reward processing using the effort-doors task. *Biological Psychiatry Global Open Science*, 3(4), 10773–11082. https://doi.org/10.1016/j.bpsgos.2022.08.002

Cataldo, A. M., Scheuer, L., Maksimovskiy, A. L., Germine, L. T., & Dillon, D. G. (2023). Abnormal evidence accumulation underlies the positive memory deficit in depression. *Journal of Experimental Psychology: General*, 152(1), 139–156. https://doi.org/10.1037/xge0001268

Cathomas, F., Klaus, F., Guetter, K., Seifritz, E., Hartmann-Riemer, M. N., Tobler, P. N., Kaiser, S., & Kaliuzhna, M. (2021). Associations between negative symptoms and effort discounting in patients with schizophrenia and major depressive disorder. *Schizophrenia Bulletin Open*, 2(1), sgab022. https://doi.org/10.1093/schizbullopen/sgab022

Chen, C., Takahashi, T., Nakagawa, S., Inoue, T., & Kusumi, I. (2015). Reinforcement learning in depression: A review of computational research. *Neuroscience & Biobehavioral Reviews*, 55, 247–267. https://doi.org/10/f7j7k6

Chong, T. T.-J., Apps, M., Giehl, K., Sillence, A., Grima, L. L., & Husain, M. (2017). Neurocomputational mechanisms underlying subjective valuation of effort costs. *PLOS Biology*, 15(2), e1002598. https://doi.org/10/f9rgrk

Chong, T.-T.-J., Bonnelle, V., & Husain, M. (2016). Quantifying motivation with effort-based decision-making paradigms in health and disease. *Progress in Brain Research*, 229, 71–100. https://doi.org/10.1016/bs.pbr.2016.05.002

Clairis, N., & Pessiglione, M. (2024). Value estimation versus effort mobilization: A general dissociation between ventromedial and dorsomedial prefrontal cortex. *The Journal of Neuroscience*, e1176232024. https://doi.org/10.1523/JNEUROSCI.1176-23.2024

Clay, G., Mlynski, C., Korb, F. M., Goschke, T., & Job, V. (2022). Rewarding cognitive effort increases the intrinsic value of mental labor. *Proceedings of the National Academy of Sciences*, 119(5), e2111785119. https://doi.org/10.1073/pnas.2111785119

Cléry-Melin, M. L., Schmidt, L., Lafargue, G., Baup, N., Fossati, P., & Pessiglione, M. (2011). Why don't you try harder? An investigation of effort production in major depression. *PloS one*, 6(8), e23178. https://doi.org/10.1371/journal.pone.0023178

Gard, D. E., Gard, M. G., Kring, A. M., & John, O. P. (2006). Anticipatory and consummatory components of the experience of pleasure: A scale development study. *Journal of Research in Personality*, 40(6), 1086–1102. https://doi.org/10.1016/j.jrp.2005.11.001

Giustiniani, J., Nicolier, M., Teti Mayer, J., Chabin, T., Masse, C., Galmès, N., Pazart, L., Trojak, B., Bennabi, D., Vandel, P., Haffen, E., & Gabriel, D. (2020). Event-related potentials (ERP) indices of motivation during the effort expenditure for reward task. *Brain Sciences*, 10(5), 283. https://doi.org/10/gpvxms

Goh, A. X.-A., Bennett, D., Bode, S., & Chong, T. T.-J. (2021). Neurocomputational mechanisms underlying the subjective value of information. *Communications Biology*, 4(1), 1346. https://doi.org/10.1038/s42003-021-02850-3

Grange, J. A. (2022). Computational modelling of the speed–accuracy tradeoff: No evidence for an association with depression symptomatology. *Journal of Psychiatric Research*, 147, 111–125. https://doi.org/10/gpwszf

Hammar, Å., Strand, M., Årdal, G., Schmid, M., Lund, A., & Elliott, R. (2011). Testing the cognitive effort hypothesis of cognitive impairment in major depression. *Nordic Journal of Psychiatry*, 65(1), 74–80. https://doi.org/10.3109/08039488.2010.494311

He, X., Qiu, B., Deng, Y., Liu, T., Chen, Y., & Zhang, W. (2022). Adaptive assessment of the capacity of cognitive control. *Quarterly Journal of Experimental Psychology*, 75(1), 43–52. https://doi.org/10.1177/17470218211030838

Hershenberg, R., Satterthwaite, T. D., Daldal, A., Katchmar, N., Moore, T. M., Kable, J. W., & Wolf, D. H. (2016). Diminished effort on a progressive ratio task in both unipolar and bipolar depression. *Journal of Affective Disorders*, https://doi.org/10.1016/j.jad.2016.02.003

Hogan, P. S., Chen, S. X., Teh, W. W., & Chib, V. S. (2020). Neural mechanisms underlying the effects of physical fatigue on effort-based choice. *Nature Communications*, 11(1), 4026. https://doi.org/10/gg7v3n

Hogan, P. S., Galaro, J. K., & Chib, V. S. (2019). Roles of ventromedial prefrontal cortex and anterior cingulate in subjective valuation of prospective effort. *Cerebral Cortex*, 29(10), 4277–4290. https://doi.org/10/gmnw4h

Horne, S. J., Topp, T. E., & Quigley, L. (2021). Depression and the willingness to expend cognitive and physical effort for rewards: A systematic review. *Clinical Psychology Review*, 88, 102065. https://doi.org/10/gk5373

Huibers, M. J. H., Lorenzo-Luaces, L., Cuijpers, P., & Kazantzis, N. (2021). On the road to personalized psychotherapy: A research agenda based on cognitive behavior therapy for depression. *Frontiers in Psychiatry*, 11, 607508. https://doi.org/10.3389/fpsyt.2020.607508

Husain, M., & Roiser, J. P. (2018). Neuroscience of apathy and anhedonia: A transdiagnostic approach. *Nature Reviews Neuroscience*, 19(8), 470–484. https://doi.org/10.1038/s41583-018-0023-9

Huys, Q. J. M., Browning, M., Paulus, M. P., & Frank, M. J. (2021). Advances in the computational understanding of mental illness. *Neuropsychopharmacology*, 46(1), https://doi.org/10/ghm627

Inzlicht, M., Shenhav, A., & Olivola, C. Y. (2018). The effort paradox: Effort is both costly and valued. *Trends in Cognitive Sciences*, 22(4), 337–349. https://doi.org/10/gc9qnq

Iodice, P., Calluso, C., Barca, L., Bertollo, M., Ripari, P., & Pezzulo, G. (2017). Fatigue increases the perception of future effort during decision making. *Psychology of Sport and Exercise*, 33, 150–160. https://doi.org/10.1016/j.psychsport.2017.08.013

Jarvis, H., Stevenson, I., Huynh, A. Q., Babbage, E., Coxon, J., & Chong, T. T.-J. (2022). Effort reinforces learning. *Journal of Neuroscience*, 42(40), https://doi.org/10.1523/JNEUROSCI.2223-21.2022

Klawohn, J., Joyner, K., Santopetro, N., Brush, C. J., & Hajcak, G. (2022). Depression reduces neural correlates of reward salience with increasing effort over the course of the progressive ratio task. *Journal of Affective Disorders*, https://doi.org/10.1016/j.jad.2022.03.051

Kurzban, R., Duckworth, A., Kable, J. W., & Myers, J. (2013). An opportunity cost model of subjective effort and task performance. *Behavioral and Brain Sciences*, 36(6), 661–679. https://doi.org/10/f5j8tr

Le Bouc, R., Rigoux, L., Schmidt, L., Degos, B., Welter, M.-L., Vidailhet, M., Daunizeau, J., & Pessiglione, M. (2016). Computational dissection of dopamine motor and motivational functions in humans. *The Journal of Neuroscience*, 36(25), 6623–6633. https://doi.org/10.1523/JNEUROSCI.3078-15.2016

LeMoult, J., & Gotlib, I. H. (2019). Depression: A cognitive perspective. *Clinical Psychology Review*, 69, 51–66. https://doi.org/10.1016/j.cpr.2018.06.008

Lockwood, P. L., Wittmann, M. K., Nili, H., Matsumoto-Ryan, M., Abdurahman, A., Cutler, J., … & Apps, M. A. (2022). Distinct neural representations for prosocial and self-benefiting effort. *Current Biology*, 32(19), 4172-4185. https://doi.org/10.1016/j.cub.2022.08.010

Lu, J., Xu, X., Huang, Y., Li, T., Ma, C., Xu, G., Yin, H., Xu, X., Ma, Y., Wang, L., Huang, Z., Yan, Y., Wang, B., Xiao, S., Zhou, L., Li, L., Zhang, Y., Chen, H., Zhang, T., … Zhang, N. (2021). Prevalence of depressive disorders and treatment in China: A cross-sectional epidemiological study. *The Lancet Psychiatry*, 8(11), 981–990. https://doi.org/10.1016/S2215-0366(21)00251-0

Matthews, J., Pisauro, M. A., Jurgelis, M., Müller, T., Vassena, E., Chong, T., & Apps, M. A. J. (2023). Computational mechanisms underlying the dynamics of physical and cognitive fatigue. *Cognition*, 240, 105603. https://doi.org/10.1016/j.cognition.2023.105603

Müller, T., Husain, M., & Apps, M. A. J. (2022). Preferences for seeking effort or reward information bias the willingness to work. *Scientific Reports*, 12(1), 19486. https://doi.org/10.1038/s41598-022-21917-7

Müller, T., Klein-Flügge, M. C., Manohar, S. G., Husain, M., & Apps, M. A. J. (2021). Neural and computational mechanisms of momentary fatigue and persistence in effort-based choice. *Nature Communications*, 12(1), 4593. https://doi.org/10/gmccmr

Park, I. H., Lee, B. C., Kim, J.-J., Kim, J. I., & Koo, M.-S. (2017). Effort-based reinforcement processing and functional connectivity underlying amotivation in medicated patients with depression and schizophrenia. *The Journal of Neuroscience*, 37(16), 4370–4380. https://doi.org/10.1523/JNEUROSCI.2524-16.2017

Pessiglione, M., Vinckier, F., Bouret, S., Daunizeau, J., & Le Bouc, R. (2018). Why not try harder? Computational approach to motivation deficits in neuro-psychiatric diseases. *Brain: A Journal of Neurology*, 141(3), 629–650. https://doi.org/10.1093/brain/awx278

Pike, A. C., & Robinson, O. J. (2022). Reinforcement learning in patients with mood and anxiety disorders vs control individuals: A systematic review and meta-analysis. *JAMA Psychiatry*, 79(4), 312–322. https://doi.org/10.1001/jamapsychiatry.2022.0051

Racine, S. E., Horvath, S. A., Brassard, S. L., & Benning, S. D. (2019). Effort expenditure for rewards task modified for food: A novel behavioral measure of willingness to work for food. *International Journal of Eating Disorders*, 52(1), 71–78. https://doi.org/10/gnf9h8

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, 20(4), https://doi.org/10.1016/j.tics.2016.01.007

Rewitz, K., Schindler, S., & Wolff, W. (2023). Examining the alignment between subjective effort and objective force production. *PsyArXiv*. https://doi.org/10.31234/osf.io/vr2gn

Richards, D. A., Ekers, D., McMillan, D., Taylor, R. S., Byford, S., Warren, F. C., Barrett, B., Farrand, P. A., Gilbody, S., Kuyken, W., O'Mahen, H., Watkins, E. R., Wright, K. A., Hollon, S. D., Reed, N., Rhodes, S., Fletcher, E., & Finning, K. (2016). Cost and Outcome of Behavioural Activation versus Cognitive Behavioural Therapy for Depression (COBRA): a randomised, controlled, non-inferiority trial. *The Lancet*, 388(10047), 871–880. https://doi.org/10.1016/S0140-6736(16)31140-0

Robinson, O. J., & Chase, H. W. (2017). Learning and choice in mood disorders: Searching for the computational parameters of anhedonia. *Computational Psychiatry*, 1(0), 208. https://doi.org/10/ggnx69

Rzepa, E., Fisk, J., & McCabe, C. (2017). Blunted neural response to anticipation, effort and consummation of reward and aversion in adolescents with depression symptomatology. *Journal of Psychopharmacology*, 31(3), 303–311. https://doi.org/10.1177/0269881116681416

Rzepa, E., & McCabe, C. (2019). Dimensional anhedonia and the adolescent brain: Reward and aversion anticipation, effort and consummation. *BJPsych Open*, 5(6), https://doi.org/10.1192/bjo.2019.68

Sayalı, C., & Badre, D. (2021). Neural systems underlying the learning of cognitive effort costs. *Cognitive, Affective, & Behavioral Neuroscience*, 21(4), 698–716. https://doi.org/10/gjwhjt

Sherdell, L., Waugh, C. E., & Gotlib, I. H. (2012). Anticipatory pleasure predicts motivation for reward in major depression. *Journal of Abnormal Psychology*, 121(1), 51–60. https://doi.org/10.1037/a0024945

Silva, C. F. da, Lombardi, G., Edelson, M., & Hare, T. A. (2023). Rethinking model-based and model-free influences on mental effort and striatal prediction errors. *Nature Human Behaviour*, 7(6), 956-969. https://doi.org/10.1038/s41562-023-01573-1

Skvortsova, V., Palminteri, S., & Pessiglione, M. (2014). Learning to minimize efforts versus maximizing rewards: Computational principles and neural correlates. *Journal of Neuroscience*, 34(47), 15621–15630. https://doi.org/10/f6sdhv

Soutschek, A., Nadporozhskaia, L., & Christian, P. (2022). Brain stimulation over dorsomedial prefrontal cortex modulates effort-based decision making. *Cognitive, Affective, & Behavioral Neuroscience*, 22(6), 1264-1274. https://doi.org/10.3758/s13415-022-01021-z

Soutschek, A., & Tobler, P. N. (2020). Causal role of lateral prefrontal cortex in mental effort and fatigue. *Human Brain Mapping*, 41(16), 4630–4640. https://doi.org/10.1002/hbm.25146

Steele, J. (2020). What is (perception of) effort? Objective and subjective effort during attempted task performance. *PsyArXiv*. https://doi.org/10.31234/osf.io/kbyhm

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (Second edition). The MIT Press.

Suzuki, S., Lawlor, V. M., Cooper, J. A., Arulpragasam, A. R., & Treadway, M. T. (2021). Distinct regions of the striatum underlying effort, movement initiation and effort discounting. *Nature Human Behaviour*, 5(3), 378–388. https://doi.org/10.1038/s41562-020-00972-y

Tran, T., Hagen, A. E. F., Hollenstein, T., & Bowie, C. R. (2021). Physical- and cognitive-effort-based decision-making in depression: Relationships to symptoms and functioning. *Clinical Psychological Science*, 9(1), 53–67. https://doi.org/10.1177/2167702620949236

Treadway, M. T., Bossaller, N. A., Shelton, R. C., & Zald, D. H. (2012). Effort-based decision-making in major depressive disorder: A translational model of motivational anhedonia. *Journal of Abnormal Psychology*, 121(3), 553–558. https://doi.org/10/f364bv

Treadway, M. T., Buckholtz, J. W., Schwartzman, A. N., Lambert, W. E., & Zald, D. H. (2009). Worth the 'EEfRT'? The effort expenditure for rewards task as an objective measure of motivation and anhedonia. *PLoS ONE*, 4(8), e6598. https://doi.org/10/dv4nmj

Treadway, M. T., & Zald, D. H. (2011). Reconsidering anhedonia in depression: Lessons from translational neuroscience. *Neuroscience and Biobehavioral Reviews*, 35(3), 537–555. https://doi.org/10.1016/j.neubiorev.2010.06.006

Vinckier, F., Claire Jaffre, Claire Gauthier, Sarah Smajda, Pierre Abdel-Ahad, Raphaël Le Bouc, Jean Daunizeau, Mylène Fefeu, Nicolas Borderies, Marion Plaze, Raphaël Gaillard, & Mathias Pessiglione. (2022). Elevated effort cost identified by computational modeling as a distinctive feature explaining multiple behaviors in patients with depression. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 7(11), https://doi.org/10.1016/j.bpsc.2022.07.011

Westbrook, A., Lamichhane, B., & Braver, T. (2019). The subjective value of cognitive effort is encoded by a domain-general valuation network. *The Journal of Neuroscience*, 39(20), 3934–3947. https://doi.org/10/ggmg4t

Westbrook, A., van den Bosch, R., Määttä, J. I., Hofmans, L., Papadopetraki, D., Cools, R., & Frank, M. J. (2020). Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. *Science*, 367(6484), 1362–1366. https://doi.org/10.1126/science.aaz5891

Westbrook, A., Yang, X., Bylsma, L. M., Daches, S., George, C. J., Seidman, A. J., Jennings, J. R., & Kovacs, M. (2022). Economic choice and heart rate fractal scaling indicate that cognitive effort is reduced by depression and boosted by sad mood. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, 8(7), 687–694. https://doi.org/10.1016/j.bpsc.2022.07.008

WHO. (2023). Depression. https://www.who.int/health-topics/depression

Wilhelm, R. A., Threadgill, A. H., & Gable, P. A. (2021). Motor preparation and execution for performance difficulty: Centroparietal beta activation during the effort expenditure for rewards task as a function of motivation. *Brain Sciences*, 11(11), 1442. https://doi.org/10/gpv59p

Wood-Ross, C., Best, M. W., Milanovic, M., & Bowie, C. R. (2021). Brain of thrones: Cognitive effort and perceived performance during a cognitive task in major depressive disorder. *Cognitive Therapy and Research*, 45(5), 986–999. https://doi.org/10.1007/s10608-020-10145-9

Xie, W., & Zhang, W. (2023). Effortfulness of visual working memory: Gauged by physical exertion. *Journal of Experimental Psychology: General*, 152(7), 2074. https://doi.org/10.1037/xge0001391

Yang, X. H., Huang, J., Zhu, C. Y., Wang, Y. F., Cheung, E. F., Chan, R. C., & Xie, G. R. (2014). Motivational deficits in effort-based decision making in individuals with subsyndromal depression, first-episode and remitted depression patients. *Psychiatry research*, 220(3), 874-882. https://doi.org/10.1016/j.psychres.2014.08.056

Yang, X., Huang, J., Lan, Y., Zhu, C., Liu, X., Wang, Y., Cheung, E. F. C., Xie, G., & Chan, R. C. K. (2016). Diminished caudate and superior temporal gyrus responses to effort-based decision making in patients with first-episode major depressive disorder. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, https://doi.org/10.1016/j.pnpbp.2015.07.006

Yao, Y.-W., Song, K.-R., Schuck, N. W., Li, X., Fang, X.-Y., Zhang, J.-T., Heekeren, H. R., & Bruckner, R. (2023). The dorsomedial prefrontal cortex represents subjective value across effort-based risky decision-making. *NeuroImage*, https://doi.org/10.1016/j.neuroimage.2023.120326

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv — Machine translation. Verify with original.