Measuring Cognitive Effort: Methods, Issues, and Improvements

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Abstract

Cognitive effort constitutes the volitional mental activities that individuals actively invest to overcome existing habits and achieve goals. Constrained by theoretical framework heterogeneity and insufficient methodological standardization, the field of cognitive effort measurement currently lacks methods that can precisely capture its multidimensional characteristics. Broadly speaking, existing measurement approaches can be summarized into scale-based methods (2 types) and experimental methods (11 types). Scale-based methods are vulnerable to interference from factors including their own reliability and validity issues when applied to cognitive effort measurement, metacognition, individual differences, testing environments, and cultural influences; experimental methods are limited by constraints such as the confounding of effort and difficulty, individual differences in cognitive abilities, temporal factors, and variations in theoretical models. Future directions should focus on enhancing the accuracy and reliability of scale applications; integrating interdisciplinary technologies to dissociate cognitive effort from difficulty levels; dynamically calibrating individual differences and employing multimodal verification of cognitive effort; and innovating measurement methods and theories to accommodate diverse research requirements.

Full Text

How to Measure Cognitive Effort: Methods, Problems, and Improvements

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Abstract

Cognitive effort refers to the voluntary, willful mental activity that individuals actively invest to overcome existing habits and achieve goals. Constrained by heterogeneous theoretical frameworks and insufficient methodological standardization, the field of cognitive effort measurement currently lacks methods that can accurately reflect its multidimensional characteristics. Current measurement methods can be summarized into two categories: scale methods (3 types) and experimental methods (20 types). Scale methods are susceptible to interference from reliability and validity issues inherent in their application to cognitive effort measurement, as well as from metacognition, individual differences, testing environment, and cultural factors. Experimental methods are constrained by factors such as confusion between effort and difficulty, individual differences in cognitive ability, time, and variations in theoretical models. Future research should enhance the accuracy and reliability of scale usage, integrate interdisciplinary technologies to separate cognitive effort from difficulty levels, dynamically calibrate individual differences, validate cognitive effort through multimodal approaches, and innovate measurement methods and theories to adapt to different research needs.

Keywords: cognitive effort, measurement methods, improvement suggestions

Introduction

Cognitive effort, also known as mental effort, is the active, voluntary mental activity that individuals invest to overcome existing habits and achieve established goals during information processing, thinking, and decision-making. This effort involves not only the degree of engagement in demanding tasks but is also typically accompanied by an aversive subjective experience. In daily life, people frequently encounter situations requiring cognitive effort: students must invest substantial cognitive resources to obtain satisfactory grades during final examinations; consumers must perform careful calculations to maximize discount benefits during events like "Double Eleven" shopping festivals; workers must maintain high concentration to complete component assembly tasks. Moreover, patients with mental illnesses—including individuals with depression, schizophrenia, Huntington's disease, and bipolar disorder—may utilize psychological interventions such as cognitive restructuring and cognitive training during their rehabilitation process, which similarly require cognitive effort.

Experimental Methods for Measuring Cognitive Effort

Reaction Conflict-Based Experiments

Cognitive Performance Tasks. Cognitive performance tasks are classical paradigms for measuring cognitive effort. In these tasks, participants must overcome interference from conflicting information to make correct responses. For example, in the Stroop task, participants identify the ink color of color words while the semantic meaning of the words may be consistent or inconsistent with the ink color. When inconsistency occurs, participants must overcome interference and invest more cognitive effort to make correct judgments.

Number Judgment Tasks. Number judgment tasks are typical and widely used measures of cognitive effort, essentially representing a form of task switching. Task-switching paradigms impose high cognitive demands, typically manifested as increased reaction time and decreased accuracy, with participants tending to choose experimental tasks with fewer switches. Currently, number judgment tasks and their variants have been widely applied in other experiments to manipulate cognitive effort.

These tasks require participants to make odd-even or magnitude judgments on a series of numbers (1 to 9, excluding 5) presented on screen according to cue signals. During switches between these two types of judgment tasks, participants must shift cognitive strategies and thinking patterns, requiring different levels of cognitive effort due to task differences.

Simon Dot Motion Conflict Tasks. In studies investigating cognitive effort and attention, Simon dot motion conflict tasks are primarily used to examine individuals' responses to stimulus direction. In this experimental task, participants perform keypress responses based on dot matrix colors, where different colors correspond to different key positions on either side of the keyboard. Simultaneously, participants must ignore interfering information regarding the left-right motion direction of the dot matrix. This task creates a situation where key position cues conflict with dot motion direction cues, requiring participants to expend cognitive effort and invest cognitive resources to overcome interference and make correct keypress responses.

The measurement indicators for cognitive effort in these reaction conflict-based experiments, along with manipulations of cognitive effort levels and difficulty levels, are summarized in . See for details.

Reaction Conflict-Based Experiments: Manipulation of cognitive effort levels and difficulty levels

Attention-Based Experiments Attention is also a limited cognitive resource, and its allocation and maintenance are influenced by cognitive effort. Researchers have noted that cognitive effort involves the ability to allocate attention among different tasks, meaning that when performing high cognitive effort tasks, individuals need to mobilize more attentional resources to complete tasks. Consequently, some scholars have adopted attention-based experimental tasks to study cognitive effort. Current attention-based experiments for studying cognitive effort mainly include four types: number switching tasks, rapid serial visual presentation tasks, oddball discrimination tasks, and visual fuzzy search paradigms.

Number Switching Tasks. Researchers developed number switching tasks to measure cognitive effort. These tasks require participants to classify each number in a random sequence from 1 to 9 as odd or even. The task includes multiple effort levels; higher switching probability between odd and even judgments requires higher cognitive effort. Participants must quickly judge the parity of each number and respond via keypress, with only sequences completed within the time limit and with no more than one error marked as "correct." The difference between this task and task-switching paradigms is that in number switching tasks, participants only need to make odd-even judgments on numbers appearing on screen, with consistent task types throughout without involving other task switches.

Rapid Serial Visual Presentation Tasks. To explore the relationship between effort cost and reward, researchers adapted rapid serial visual presentation tasks, which had been applied in cognitive effort studies of Huntington' s disease patients. The adapted task requires participants to monitor rapidly changing letters on screen to find target letters. At trial onset, a pie chart cue indicates cognitive effort level across multiple levels. More colored segments in the pie chart indicate more letters presented subsequently on screen, meaning participants must expend higher cognitive effort. After successfully completing each effort level, participants receive corresponding feedback.

Oddball Discrimination Tasks. In the domain of cognitive effort research, some scholars have employed oddball discrimination tasks as their experimental paradigm. This task requires participants to quickly identify the "different item" among three visual stimuli within limited time. Cognitive effort is manipulated by changing potential reward amounts to affect participants' motivation levels and by providing or hiding progress bar information to influence participants' perception of task progress. When participants can obtain more reward or visually understand their proximity to reward goals through progress bar information, they accelerate response speed and consequently invest more cognitive effort.

Visual Fuzzy Search Paradigm. To study the relationship between cognitive effort and reward, researchers adapted visual fuzzy search paradigms used in time estimation tasks, requiring participants to identify specific targets. At experiment onset, a fixation point appears on screen, followed by search tasks at two cognitive effort levels. At low cognitive effort levels, clear white visual stimuli are presented (with black background); at high cognitive effort levels, visual stimuli are obscured or overlaid by multiple small white squares, requiring participants to overcome visual obstacles to identify cues for correct keypress responses, thereby expending cognitive effort.

The measurement indicators for cognitive effort in these attention-based experiments, along with manipulations of cognitive effort levels and difficulty levels, are summarized in . See for details.

Attention-Based Experiments: Manipulation of cognitive effort levels and difficulty levels

Digital Operation-Based Experiments Individuals expend cognitive effort during numerical operations, and manipulating the difficulty of arithmetic tasks can quantify cognitive effort. In recent years, numerous scholars have utilized mental arithmetic tasks—a type of digital operation-based experiment —to deeply explore relationships and mechanisms between cognitive effort and individuals' subjective experiences, rewards, and decision-making.

Mental arithmetic tasks mainly include two forms. The first form involves continuous addition and subtraction. At task onset, a random number between 1 and 9 appears on screen, followed by successive plus or minus signs and corresponding numbers. Participants must perform continuous addition and subtraction operations on these numbers within a specified time. Finally, two options appear on screen—one correct and one incorrect answer—and participants must select the correct answer to obtain rewards.

The second form requires participants to perform addition operations on each digit in three-digit sequences separately. In formal experiments, participants choose between "add 1" (simple task) and "add 3" (complex task). In the "add 1" task, participants add 1 to each digit and input the result; in the "add 3" task, participants add 3 to each digit and input the result.

The measurement indicators for cognitive effort in these digital operation-based experiments, along with manipulations of cognitive effort levels and difficulty levels, are summarized in . See for details.

Digital Operation-Based Experiments: Manipulation of cognitive effort levels and difficulty levels

In summary, scale methods directly quantify individuals' subjective perception of cognitive resource investment through self-report, enabling researchers to directly obtain participants' subjective experiences of cognitive effort and deeply understand individual subjective feelings during cognitive processes. This directness not only reveals participants' self-awareness of cognitive effort but also provides researchers with a unique perspective to explore individuals' mental states and subjective experiences during cognitive tasks, offering important supplementary understanding for multidimensional comprehension of cognitive effort. Experimental methods, conversely, assess cognitive effort investment by designing specific experimental tasks and observing and recording participants' behavioral performance. The aforementioned experimental tasks have been purposefully combined with cutting-edge technologies such as event-related potentials, functional magnetic resonance imaging, or computational modeling according to their specific research objectives and data characteristics, enabling researchers to infer psychological processes and mechanisms of cognitive effort from different dimensions and significantly enhancing the precision and reliability of experimental results. The development and application of these two method categories provide practical tools for cognitive effort measurement, yet these measurement tools still have certain limitations. The following sections analyze challenges and reflections facing these two measurement methods and propose possible improvement suggestions.

Challenges and Reflections in Cognitive Effort Measurement

Scale Method Challenges and Reflections Although subjective measurement tools such as the Cognitive Demand Scale and NASA Task Load Index have been widely used in cognitive effort research, their reliability and validity for measuring cognitive effort remain to be examined since these scales were not originally developed for this purpose. For example, some researchers found that NASA Task Load Index scores were not stable predictors of the subjective value of effort in experiments.

Additionally, the accuracy and reliability of self-report scales are susceptible to interference from individuals' metacognitive abilities. During scale completion, individuals with higher metacognitive abilities can more accurately evaluate their mental states and behaviors, while those with lower metacognitive abilities may produce deviations from actual conditions due to insensitivity or inaccuracy regarding their own cognitive processes.

Finally, self-report scales are also influenced by individual differences, testing environment, and culture. Individual differences—such as age, education level, and psychiatric history—lead to inconsistent understanding of scale items and subjective costs of cognitive effort. For instance, older or less educated individuals may have difficulty understanding complex scale items; compared to healthy individuals, psychiatric patients may have cognitive impairments leading to biased understanding of scale items due to damaged relevant brain regions. Testing environment also affects individuals' performance when completing self-report scales. For example, when completing subjective assessments of cognitive effort under time constraints, individuals may feel anxious and tense, thereby overestimating the cognitive effort required for tasks; individuals in anxious states may underestimate their cognitive abilities, consequently overestimating required cognitive effort levels. Furthermore, cultural differences affect individuals' understanding of scale items. For example, expressions of cognitive effort in Western cultures may be understood as maintaining focused investment during task completion, while understanding in Eastern cultures may also relate to social responsibility.

Experimental Method Challenges and Reflections First, improper manipulation of cognitive effort and difficulty in experiments can lead to confusion between the two. For example, in cognitive challenge tasks, high-difficulty tasks not only increase cognitive effort demands but also reduce participants' probability of successful completion due to task complexity, making participants' avoidance behaviors influenced by multiple factors including effort cost, success probability, and reward acquisition probability. Similarly, in cognitive effort motivation tasks, although grids used by participants are changed according to their working memory capacity, high effort levels require participants to remember more information, causing effort and task difficulty to change simultaneously and preventing complete separation.

Second, individual differences in cognitive ability affect perception of task difficulty. Individual differences in cognitive ability directly influence subjective assessment of task load. When task difficulty is not standardized, systematic errors such as ceiling or floor effects may occur. In such cases, subjective assessment of cognitive effort reflects more about individuals' perception of task difficulty rather than true sensitivity to cognitive effort. For instance, psychiatric patients have cognitive differences compared to healthy individuals due to damaged relevant brain regions and may perceive tasks as more difficult. Moreover, individual differences exist among healthy individuals; for example, in n-back tasks, individual differences in working memory capacity affect task performance and response accuracy, with higher-capacity individuals completing tasks better while lower-capacity individuals show lower accuracy.

Third, different difficulty levels in experimental tasks can cause time discounting effects. Increased task difficulty requires not only more cognitive effort but also longer completion time, as seen in visual fuzzy search paradigms and mental arithmetic tasks. Higher cognitive effort levels or greater task difficulty require more time for information processing and comparison, potentially causing reward delays. If time factors are not controlled in task design, participants may reduce subjective task value due to longer waiting times for rewards. This time discounting effect may be misinterpreted as increased cognitive effort cost.

Fourth, theoretical heterogeneity of cognitive effort leads to diversified measurement methods, with the validity of each measurement tool requiring examination. Researchers have proposed different theoretical models: the internal cost model suggests cognitive effort carries a subjective cost derived from limited organismic resources; the opportunity cost model states that individuals must evaluate the "opportunity cost" of choosing current tasks—i.e., benefits foregone from not performing other potential tasks; the signal model indicates that expending cognitive effort not only consumes limited cognitive resources but also triggers negative emotions like fatigue and anxiety, which prompt individuals to adjust behavior to avoid resource consumption and effort expenditure. However, positive emotions generated during effort can reduce or even offset inherent negative emotions, thereby promoting effortful behavior. These three theoretical models provide different theoretical references for the aforementioned experimental tasks. When difficulty increases in these experiments, participants need to invest more cognitive resources, making limited cognitive resources an internal cost that aligns with the internal cost model. All these experiments involve outcome feedback, and emotions elicited by outcomes serve as signals prompting individuals to re-evaluate task value and cognitive effort investment, thus aligning with the signal model. Additionally, cognitive effort motivation tasks, number judgment tasks, and the second form of mental arithmetic tasks use task selection willingness across different cognitive effort levels as measurement indicators, aligning with the opportunity cost model' s view that individuals weigh potential task benefits and opportunity costs when choosing high-effort tasks.

The matching relationships between the aforementioned experimental tasks and different theoretical models are summarized in . See for details.

Theoretical Models Matching Experimental Categories

However, due to differences among cognitive effort theories, different measurement methods can match different theoretical models. Based on different theories and research needs, different measurement methods vary in measurement indicators, manipulation of cognitive effort' s core functions, and effort levels, leading to diversified measurement tools for cognitive effort. These tools measure cognitive effort from different dimensions, but whether they can truly measure the intended effects and degrees of cognitive effort requires further verification.

Improvement Suggestions: Constructing Standardized Measurement Methods Matched to Research Objectives

Improving Scale Accuracy and Reliability To enhance the reliability and precision of self-report scales in measuring cognitive effort, multiple optimization approaches can be implemented:

First, combine the Cognitive Demand Scale and NASA Task Load Index. To more accurately capture the immediacy of individuals' cognitive effort evaluations during experiments, researchers can have participants rate each experimental task using the scale during rest intervals between tasks, then complete the scale after all experimental tasks to comprehensively assess individuals' degree of participation in and enjoyment of cognitive effort activities throughout the entire experiment.

Second, future research should develop self-report questionnaires specifically designed to measure cognitive effort based on mature theoretical constructs of cognitive effort. During scale development, rigorous psychometric procedures must be followed, with scale reliability tested in practical applications to ensure reliability indices meet recognized standards in psychological research. To validate scale validity, the Cognitive Demand Scale and NASA Task Load Index can serve as criteria, with empirical research examining associations between newly developed scales and these established measures to provide empirical evidence for criterion-related validity. Ultimately, through rigorous reliability and validity testing procedures, a statistically robust and reliable self-report scale can be formed to provide effective measurement tools for cognitive effort.

Third, future research can implement systematic improvements starting from key aspects of the measurement process to optimize scale method applications in cognitive effort measurement. For example, brief metacognitive ability training can be provided before participants complete scales to help them more intuitively understand and evaluate their own cognitive effort levels, thereby avoiding ceiling or floor effects. To reduce interference from immediate environmental factors during measurement, external environments should remain consistent or stable across different participants when completing scales to control for extraneous variables affecting data results. To reduce individual difference impacts on scale data, researchers can also collect and analyze relevant demographic variables such as age, education level, or mental health status. Additionally, self-report scales can be combined with other measurement methods, such as integrating scale methods with experimental methods or physiological measurement techniques, or utilizing statistics and machine learning technologies to attempt obtaining cognitive effort data from different channels, thereby achieving mutual verification and supplementation across measurement tools to improve comprehensiveness and reliability of measurement results. Furthermore, to maintain high reliability and validity of scales across different cultural environments, they can be applied to groups from different cultural backgrounds, considering differences in language systems and economic development levels, with appropriate revisions made to scale content or structure based on statistical results.

Integrating Interdisciplinary Technologies to Separate Cognitive Effort from Difficulty Future research should further strengthen methodological integration across disciplines, introducing multiple technological approaches to deepen exploration of cognitive effort's internal mechanisms. The current cognitive effort research field has formed a research path combining experimental and scale methods, but future work must continue integrating multidisciplinary research methods, such as introducing technical tools from economics and neuroscience. Behavioral economics provides a new perspective for quantifying cognitive effort—experimental paradigms based on economic decision-making. These paradigms treat cognitive effort as a cost and quantify its subjective value by analyzing individuals' choice behaviors across different task difficulty scenarios. Examples include decision tasks based on cognitive effort developed by some researchers, cognitive effort discounting paradigms, and reward tasks for cognitive effort expenditure.

Beyond traditional behavioral experimental designs, researchers can also adopt different measurement indicators according to research purposes and introduce more diversified technical approaches. Common techniques in current psychological research include neuroimaging technologies such as electroencephalography, functional magnetic resonance imaging, and functional near-infrared spectroscopy. Combining neuroimaging research tools with machine learning algorithms from computer science holds promise for establishing predictive models between cognitive effort and neural signals, thereby distinguishing neural representation differences between task difficulty and cognitive effort investment. Additionally, virtual reality scenario simulation from human-computer interaction technology can be introduced, allowing participants to complete experimental tasks in virtual environments while synchronously collecting behavioral data, interaction data, environmental data, physiological data, and equipment data, thereby monitoring and separating cognitive effort from difficulty levels under near-realistic conditions.

Dynamically Calibrating Individual Differences and Multimodally Validating Cognitive Effort Future research needs to combine individualized experimental design with standardized experimental design to construct experimental tasks with coordinated variation between the two approaches and introduce computational models such as mixed-effects models. Using mathematical concepts and computer technology to describe, simulate, and study individuals' complex behaviors can improve measurement tools' precision and reproducibility, thereby better controlling interference caused by individual cognitive ability differences and time discounting effects in experiments. Individualized experimental design adjusts computer program task parameters dynamically based on participants' real-time cognitive ability performance. For example, when manipulating cognitive effort in n-back tasks, the "n" value in the program can be adjusted dynamically based on participants' working memory capacity to ensure moderate task difficulty and avoid ceiling or floor effects. Standardized experimental design emphasizes ensuring uniform experimental conditions to guarantee comparable results. For example, in oddball discrimination tasks, task presentation methods can be standardized and trial durations at each difficulty level strictly regulated to ensure all participants complete tasks under identical experimental conditions, preventing extraneous variable interference in cognitive effort measurement.

The synergy between individualized and standardized experimental design is not simple addition but requires "dynamic baseline calibration" to achieve flexibility and rigor in experimental program parameter design while maintaining core task structure—allowing key experimental parameters in computer programs (such as cue presentation time and frequency of different difficulty tasks) to be fine-tuned in real-time based on different individuals' task performance. Using number judgment tasks as an example, when participants correctly complete low-difficulty tasks consecutively, pre-written code can increase digital switching frequency in the experimental program to raise cognitive load while maintaining standardized experimental flow design and environmental settings. Furthermore, to explore individual difference effects on cognitive effort mechanisms, researchers can construct new theoretical models based on previous theoretical models, experimental data collection, and computational modeling analyses. For example, opportunity cost models can be combined with reinforcement learning algorithms to dynamically fit participants' cognitive effort discount rates during experimental tasks by analyzing their decision patterns in high versus low cognitive effort options, quantifying individuals' sensitivity to cognitive effort costs. Alternatively, based on internal cost models, computational models can be used during data analysis to construct "cognitive resource-task demand" matching models to explore individuals' cognitive resource allocation strategies.

Additionally, given the existence of multiple cognitive effort measurement paradigms within the same dimension, future researchers can conduct multidimensional validation studies of cognitive effort measurement—focusing on construct validity verification of different measurement paradigms within the same dimension. Using the working memory dimension as an example, researchers can comprehensively apply n-back tasks, cognitive challenge tasks, and cognitive effort motivation tasks through pairwise combinations or three-way integration to systematically examine criterion-related validity among these tasks. Based on this foundation, future researchers should be guided by specific research objectives when selecting cognitive effort measurement experimental tasks, precisely choosing and using tasks that match research goals to improve experimental result validity and reliability. Furthermore, future cognitive effort measurement research should adopt multidimensional measurement paradigms from different dimensions of cognitive effort to systematically examine cognitive effort' s mechanisms across dimensions, constructing multi-task measurement matrices for cross-validation of measurement results from each dimension to comprehensively test construct validity of each dimension for cognitive effort measurement.

Innovating Measurement Theories and Methods to Adapt to Different Research Needs When exploring the nature of cognitive effort, researchers have found it is not merely a cost. Some studies have discovered that cognitive effort invested in tasks can enhance subjective cognitive value assessment of task outcomes—essentially endowing task results with higher value attributes. In this regard, cognitive dissonance and effort justification models suggest that people tend to assign higher value assessments to outcomes requiring more effort, thereby justifying their own effort expenditure. Cognitive demand theory emphasizes that individuals' cognitive demand traits affect their subjective value assessment of cognitive effort, with individuals higher in cognitive demand more willing to engage in challenging tasks and obtain higher intrinsic value from them. Learned industriousness theory posits that through repeated association of high-effort tasks with high-level rewards, effort itself gradually becomes a reinforcer that drives individuals to prefer expending effort. Additionally, some researchers have found that when individuals face choices between "completing a cognitive effort task" and "doing nothing," they do not always avoid cognitive effort tasks and sometimes even prefer them to avoid boredom. This finding challenges the traditional "principle of least effort" and suggests researchers should continue deeper exploration of cognitive effort' s motivational mechanisms.

Therefore, future research can focus on paradoxes of cognitive effort, combining current theoretical models to develop innovative experimental tasks for more comprehensive investigation of cognitive effort' s influencing factors and specific mechanisms under different conditions. In designing experimental paradigms, researchers need not limit themselves to developing or adapting single experimental paradigms but can integrate multiple previous paradigms.

Combining established experimental paradigms with innovative designs offers a promising approach for future research. For instance, researchers could introduce a "boredom avoidance" option into traditional effort-reward trade-off paradigms while employing drift-diffusion models to quantify individual differences in the weighting of effort costs versus boredom aversion, thereby empirically testing the "cognitive effort paradox" hypothesis. At the theoretical level, attempts can be made to integrate existing models by organically combining internal cost models, signaling models, and learned industriousness theory to construct a "motivation-effort-reinforcement" framework. This framework emphasizes that the subjective valuation of cognitive effort is driven not only by cost-benefit considerations but also by individuals' reinforcement history and emotional experiences. Grounded in this theoretical foundation, researchers could develop corresponding experimental tasks and integrate multiple technical approaches to collect diverse experimental data, thereby validating the framework' s validity and practical utility and providing a more comprehensive and innovative theoretical perspective for understanding the mechanisms of cognitive effort.

Furthermore, future measurements of cognitive effort should not be limited to the four dimensions mentioned above—working memory, response conflict, attention, and numerical operations. Researchers should also explore the mechanisms of cognitive effort in other dimensions and develop experimental tasks suitable for different objectives, domains, and contexts, while carefully selecting appropriate measurement indicators. For example, in the domain of moral decision-making, moral dilemmas such as the trolley problem could be used to simultaneously collect decision time, skin conductance responses reflecting sympathetic nervous system activity, and event-related potential data—particularly activity in the anterior cingulate cortex associated with effort—to construct computational models of moral cognitive effort. In the domain of prosocial behavior, prosocial effort tasks could be employed in combination with transcranial magnetic stimulation (TMS) to modulate anterior cingulate cortex activity, while collecting eye movement trajectories, pupil dilation, and heart rate variability to quantify the degree of cognitive effort invested in altruistic decision-making. In the domain of sensory processing, multisensory integration paradigms such as sensory switching tasks could be used in conjunction with functional magnetic resonance imaging (fMRI) to observe brain activity related to effort (e.g., anterior cingulate cortex) and reward processing (e.g., caudate nucleus, nucleus accumbens, and striatum), revealing the neural activation patterns underlying cognitive effort in sensory regulation. Additionally, during data analysis, researchers could employ Bayesian modeling to develop cross-domain predictive models of cognitive effort and use multilevel structural equation modeling to examine the moderating effects of domain-specific cognitive effort.

Combining experimental paradigms with one' s own innovative experimental designs—for example, incorporating traditional "effort" ···

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