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THEORY ARTICLE

A systematic review of effort discounting research in humans: Current knowledge, recommendations, and future directions

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Abstract
Effort is a ubiquitous feature in the decision-making literature. Increasing numbers of studies examine the effect of effort requirements on behavior using a *discounting* framework, assessing the process by which the subjective value of an outcome decreases as the effort required to obtain it increases. Therefore, a review of methodological approaches, findings, and issues is timely. Accordingly, in this systematic review, we identified research studies examining effort discounting to explore how choice architecture factors used in delay discounting and other experimental manipulations affected effort discounting, and the mathematical descriptors used to summarize the relationship between subjective value and effort requirements. Our analysis suggests an area ripe for future research and identifies important knowledge gaps. These gaps are attributable to the use of divergent definitions of effort, as well as highly heterogeneous methodologies, which limit our ability to generate strong conclusions about the intersection between effort and delay discounting processes.

In daily life, people tend to choose a specific reward (reinforcer) more often if it costs less rather than more, all other things being equal. When people make such choices, they are trying to maximize the size, amount, or quality of the reward obtained or minimize the costs associated with the activity. However, people often encounter choices for which alternatives have seemingly discordant reward-cost dimensions, for example, going for a stroll in an award-winning botanical garden *versus* a strenuous hike in a nationally recognized scenic area. Considering multiple cost and reward dimensions can make it challenging to calculate metrics on which to base decisions aimed at maximizing outcomes. This difficulty elicits trade-off strategies and the use of rules of thumb. Examples of such methods include focusing solely on the reward characteristics or solely on the cost characteristics of the alternatives. In the short term, such trade-offs may not be problematic because making a single non-maximizing choice might not have critical consequences. However, the long-term consequences of repeated non-maximizing choices may include adverse social or clinical outcomes (Green and Myerson, 2013; Odum, 2011). For instance, repeated non-maximizing decisions driven by a trade-off strategy that avoids exerting effort may lead a person to repeatedly choose more sedentary activities (e.g., playing video games or watching TV) rather than engaging in activities that involve more physical movement (e.g., walking or playing a sport). The long-term consequences of such choices could be to gain weight and, possibly, to develop diabetes or heart disease.

The idea that individuals tend to select the reward requiring the least effort to obtain, all other things being equal, is formally known as the principle (or law) of least effort (Hull, 1943; Solomon, 1948) and is a subcategory of the larger-scope resource conservation principle (David et al., 2024; Kurzban, 2016). The principle of least effort is also consistent with behavioral economic principles in which effort is viewed as an economic cost that organisms try to minimize (e.g., Pinkston and Libman, 2017). These minimization principles have traditionally been applied to physical effort and can be measured using energy expenditure metrics or more proximal indices that reflect the properties of motor activity that are varied to manipulate physical effort requirements (strength/force/intensity, duration, and frequency). However, colloquially, *effort* is often used to describe cognitive or mental activities. Cognitive effort has been defined by Brehm and Self (1989) as a cognitive process with an intensity measured operationally in various ways (e.g., pupillary dilation and cardiovascular reactivity) with different properties (difficulty and duration). The degree to which both physical and cognitive effort can be equated conceptually is beyond the scope of this review to resolve. However, while physical and cognitive output are measured in different ways, manipulations to increase them appear similar, and perhaps minimization and resource conservation principles can be applied equally well to both types of effort.

A foundational assumption in these principles is that effort (physical or cognitive) is minimized because exerting it is subjectively aversive. Eisenberger (1992) pointed out that this view may be an oversimplification. In the natural environment, exerting more effort often leads to obtaining larger or more rewards. Learned associations between exerting effort and earning rewards may cause the sensation of exerting effort to become a conditioned reinforcer, increasing willingness to exert effort (Eisenberger, 1992; Pinkston and Libman, 2017). In addition, the generalized expectation that more effort yields more reward, beyond the actual delivery of more reward, could offset the negative valence induced by the prospect of completing the effort requirements. Both of these factors may cause a large effort alternative to have a higher subjective utility than might be predicted (e.g., Rachlin et al., 1981).

There are numerous procedures that can be used to examine the effects of physical or cognitive effort on commodity valuation, including willingness-to-pay and preference procedures. This review focuses on choice behavior to facilitate comparisons with a more mature resource conservation literature examining choice behavior between different waiting requirement alternatives (also known as temporal or delay discounting, intertemporal choice), where reward size, the delay to reward delivery, and the contextual associations with stimuli within the choice environment are demonstrable determinants of choice (e.g., Mazur, 1995).

Most procedures to examine delay discounting are built on classical psychophysical procedures, in which individuals choose between 2 alternatives on a choice trial: a smaller, sooner reward (SSR) and a larger, later reward (LLR), and either the delay or amount of one outcome is systematically varied between trials to determine the point at which organisms switch from choosing the LLR to the SSR, or vice versa (e.g., Mazur, 1987; Rachlin et al., 1991; Richards et al., 1997, 1999). This switch point is called the *indifference point* and represents the point of subjective equality between the SSR and the LLR. The indifference points have been the primary dependent variable in delay discounting procedures, used to assess the effects of reward size, reward delay, their interactions, and any moderating variables (see Madden and Johnson, 2010, for a discussion of procedural variants and alternative dependent variables).

Researchers have begun to apply methods developed in delay discounting research to examine choices between effort-requiring alternatives with differing reward outcomes (e.g., Mitchell, 1999; Phung et al., 2019). Many of these studies have adopted the term *effort discounting* and explored whether the mathematical functions used to describe changes in indifference points are a function of effort requirements. This latter endeavor is partly aimed at identifying a quantitative model that allows researchers to explain individual and group differences in decision-making biases concisely with a single summarizing number. In delay discounting, steeper slopes indicate a heightened preference for the SSR and have been associated with significant public health concerns, such as problem substance use and dependence, obesity, and gambling (e.g., Amlung et al., 2017; Bickel et al., 2012). Recognizing that response effort is essential in economic models of choice (Salamone et al., 2012), there is also an interest in whether it may be associated with disrupted mental health and mental disorders characterized by fatigue/anergia (National Institutes of Health, 2023) or with situations that require sustained effort such as maintaining abstinence from substance use (Garami and Moustafa, 2020).

The role of effort in determining choice behavior has a long history in behavioral research (e.g., Eisenberger, 1992; Hull, 1943). However, as discussed by Pinkston and Libman (2017) and Walter and Dickson (2023), many of its interactions with other variables remain lightly explored, making a review of the literature timely. Accordingly, the first aim of this systematic review was to assess which methods and manipulations have been applied to examinations of effort-related choices in humans and to compare their effects to those found for delay discounting. The second aim was to examine the mathematical models used to describe effort discounting patterns across those manipulations and effort domains.

1. Method

The *Cochrane Library*, the *International Prospective Register of Systematic Reviews* (*PROSPERO*), and the *Campbell Collaboration* are databases that contain different types of high-quality reviews about decision-making. All 3 were searched on June 1, 2022, to confirm that the current systematic review had not been published previously, with a subsequent search performed on April 21, 2024, for articles published after June 1, 2022. We used the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA; Page et al., 2021) criteria to perform the search steps.

1.1. Article identification

PsycInfo, PLOS ONE, and PubMed databases were searched with an open date to identify studies of effort discounting in humans. The advanced search was used for all databases and employed *Boolean* operators. We limited our search criteria to peer-reviewed articles written in the English language.

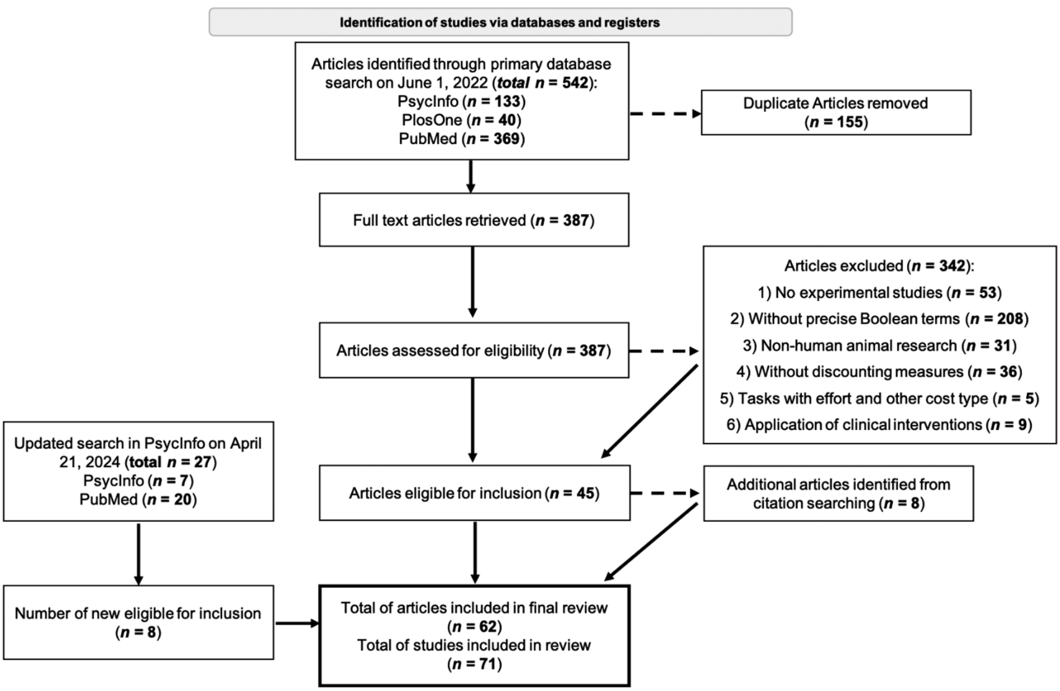

Figure 1. *PRISMA diagram displaying the process used to identify articles and studies.*

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Articles were included if the title, abstract, or keywords contained one of the following terms: **[effort discounting OR effort-discounting OR effort-based decision-making OR response effort]**. Note that quotation marks were not used in conjunction with the terms because we wanted to cast a wide net and not to exclude any potential studies. The searches in PsycInfo, PLOS ONE, and PubMed yielded 133, 40, and 369 records, respectively. Following the removal of duplicates, 387 articles remained (Figure 1). An additional 8 articles were identified for inclusion in PsycInfo and PubMed based on the subsequent search conducted on April 21, 2024. Some of these articles reported multiple experiments. Accordingly, *article* is used to refer to the entire published manuscript and *study* is used to refer to an experiment contained within the published manuscript.

1.2. Inclusion and exclusion criteria in systematic review

After removing duplicates, 387 articles were retrieved as full text and assessed for eligibility. The inclusion/exclusion criteria were applied in the following order:

1. Articles must be classified as peer-reviewed research articles and describe experimental studies, not reviews or book chapters.
2. Articles that did not include the precise Boolean terms listed earlier were excluded. Because we searched for terms without quotation marks and within the abstracts, our search identified the abstracts that included expressions such as ‘efforts were made to identify [. . .]’ and ‘some efforts are needed to [. . .]’, although effort discounting was not examined in the specific article.
3. Articles must present research using human participants. Our rationale for limiting the scope of the review in this way was that incorporating and critically comparing the human and nonhuman research would significantly augment the complexity of this review and, in our opinion, that literature deserves a more comprehensive treatment than we can accommodate here.
4. Articles must use at least one of the main 3 discounting measures mentioned by Odum (2011): indifference points, discounting slope parameters for any mathematical model fitted to the indifference points (e.g., k values), or the area under the curve (AUC) derived from indifference points (Myerson et al., 2001): $x_2 - x_1\ [(y_1 + y_2)/2]$, where the values x_1 and x_2 are the effort requirements, and y_1 and y_2 are the indifference points for those effort requirements. Because our review aimed to examine the literature in the context of discounting as a whole, our rationale for excluding studies without these discounting measures was to facilitate comparisons with other types of discounting (e.g., Odum et al., 2020; Rung and Madden, 2018).
5. Articles were excluded that examined effort discounting in conjunction with an additional contingency, such as a delay period or with a probability less than 1 (e.g., receiving a reward for exerting some effort after a waiting period). Our rationale for this exclusion was that it is unclear how these additional contingencies might interact with effort and thereby alter behavior, making the interpretation of the effects of the effort manipulation overly complex.

1.3. Data extraction

We decided which characteristics should be used to compare the included articles (i.e., sample size, study design, and discounting procedures). We extracted the data relevant to the selected characteristics and then checked the information for accuracy and completeness, with any discrepancies resolved by discussion of the characteristic in question. Finally, we identified emergent topics based on the consideration of the articles. The database generated during the current review is hosted on Open Science Framework (OSF): https://osf.io/smc9y/ and available from the corresponding author.

2. Results

A total of 71 studies were qualified for the systematic review from the 62 articles retrieved through the review process (Figure 1). As shown in Figure 2, the number of studies in effort discounting research has increased over the last 30 years, with a slight decline during the COVID-19 pandemic.

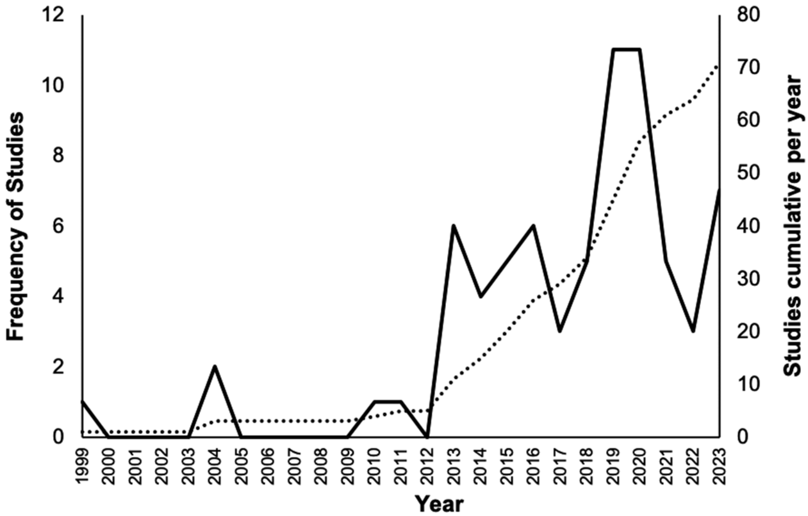

Figure 2. *Number of studies published annually and cumulatively during the period from the earliest study in 1999–2023.*
Note: The black continuous line represents the number of studies published, and the dotted line represents the studies cumulative per year.

2.1. *Choice architecture factors*

As shown in Table A1, most studies were conducted with young adults aged between 18 and 30 years (58%) and adults aged between 30 and 59 years (31%), 1 study used old participants aged 60–74 years (1%), 2 studies combined either young adults and older adults or adolescents and adults (4%), 2 studies recruited adolescents (3%), and 2 more studies with children (3%). Most of the studies were performed with healthy control participants (73%), 14 studies (20%) compared the effort discounting between controls and participants with a specific characteristic (e.g., depression, attention-deficit/hyperactivity disorder [ADHD], schizophrenia, smoking, and overweight), and 5 studies used participants with substance use (4%) or psychiatric diagnosis (3%) without control group.

Table A1 also shows the type of manipulation used to examine choice architecture and the commodity used. Overall, most of the studies varied the levels of effort required to obtain the larger reward for each participant without any other manipulation (63%), 6 studies varied the outcome size earned by completing the effortful response to examine the *amount effect* (8%), 6 studies compared discounting when the effortful response yielded a gain or a loss to examine the *sign effect* (8%), 5 studies (7%) combined 2 or more discounting manipulations (e.g., activity and amount, or activity and sign effect), 3 studies examined effort discounting using more than one commodity to assess the *domain effect* (4%), 3 studies compared discounting with different types of effortful activity (4%), whereas single studies examined real and hypothetical gains (1%), how discounting questions were presented (*Q* delivery; 1%), and discounting across multiple time points to assess stability (*Repeat*; 1%). The preponderance of the 71 studies used monetary rewards (89%), 3 studies compared monetary rewards and alcohol/cigarettes rewards (4%), and the remaining studies (7%) used another type of reward (e.g., time to view erotic stimuli, tokens, class credit, and placement in treatment program).

In the following subsections, we describe the effects of commodity/outcome manipulations and, where possible, compare these results to those obtained for similar manipulations in the delay discounting literature. The properties of effort are noted in italics for each condition using the categorization scheme provided in Figure 3 and discussed in the Domain Effects section.

2.1.1. Amount effect

In delay discounting, the rate of discounting varies inversely with the amount of the delayed reward. That is, delay discounting is more pronounced when the reward is $1,000 than when it is $10,000

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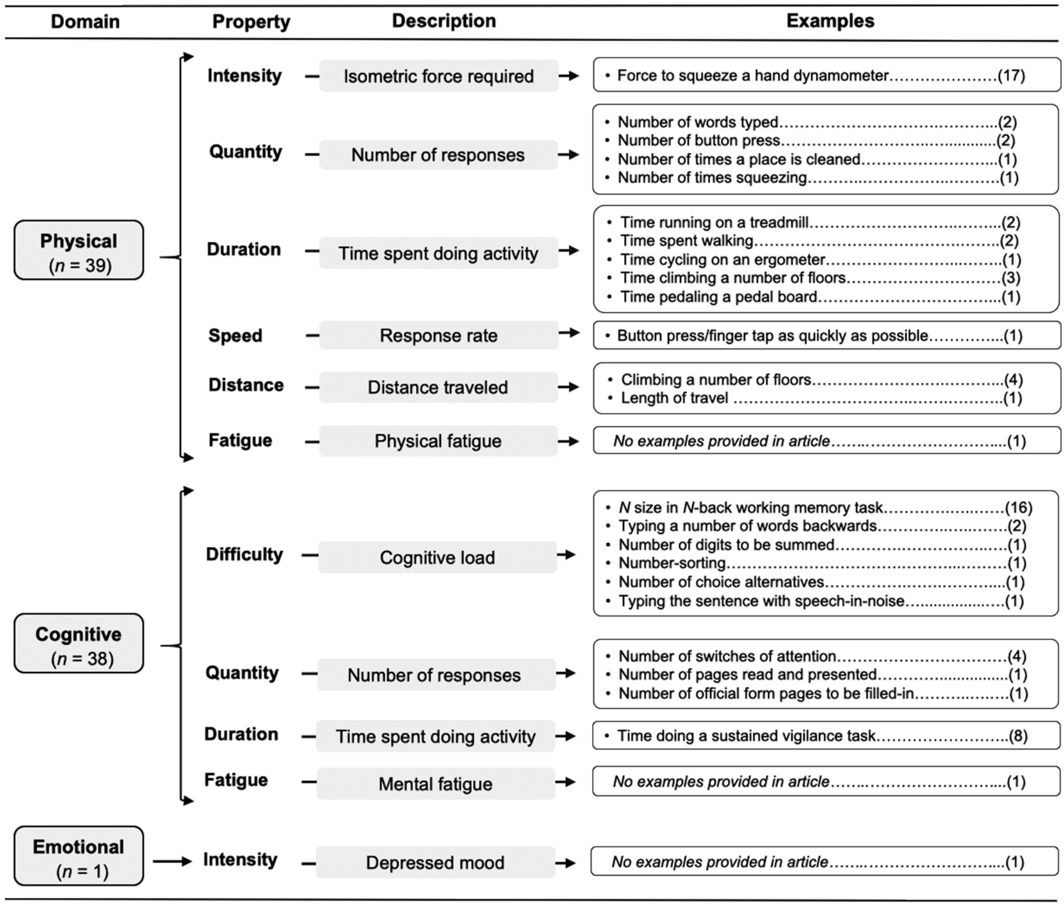

Figure 3. *Definitions of effort and their characteristics.*
Note: The numbers in parentheses indicate the number of studies using a specific definition of effort.

(Kirby, 1997). This inverse relationship has been documented in delay discounting studies involving hypothetical monetary rewards (e.g., Mellis et al., 2017; Raineri and Rachlin, 1993), nonmonetary outcomes such as vacation trips (Raineri and Rachlin, 1993), and medical treatments (Chapman, 1996).

The *amount effect* has been examined in effort discounting in 6 single studies, and 4 additional studies compared it with another manipulation. Białaszek et al. (2017) used 3 reward amounts (PLN 80, 400, and 3,000) with both physical (*intensity*) and cognitive effort (*difficulty*). An inverse relationship between amount and discounting was reported for both types of effort, like that observed for delay discounting. Ostaszewski et al. (2013) used 2 amounts (PLN 80 and 3,000) and replicated the amount effect for both physical (*distance*) and cognitive (*quantity*) effort discounting. Białaszek et al. (2019) also replicated the amount effect using a physical effort discounting task (*distance*) with 2 monetary rewards (PLN 100 and 20,000).

This latter finding (e.g., Ostaszewski et al., 2013) provides some support for the assertion that data about effort discounting can be cautiously generalized from physical to cognitive/nonphysical effort tasks, and vice versa. However, we also have to consider the instructions of the effort required in both tasks: for physical effort, the participants were told they hypothetically had to climb a set of stairs to the 3rd, 10th, 40th, or 100th floor to gain the specified reward, while for cognitive effort, the participants were told they hypothetically had to read and present 10, 100, 300, or 600 pages of text to gain the specified reward. The first condition seems to be clearly physical, and the second one appears to require

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2 activities: read and present. Reading clearly requires cognitive effort, but presenting may be viewed by participants as requiring both cognitive and physical effort. The stress and anxiety associated with presenting may also elicit an emotional effort component, but this is not easily distinguished from effects due to fear of failure and other performance-related emotional responses. Additional research is needed to determine whether the correlations were driven by perceptions that the cognitive effort task included a physical component.

Mies et al. (2019) also reported the same inverse effort-amount effect (€2 and €5) for a cognitive effort discounting task (*difficulty*) with real outcomes in both healthy controls and adolescents with ADHD. Note that the extent of discounting was similar for both groups, replicating the lack of difference first reported by Mies et al. (2018). Docx et al. (2015) also did not find statistically significant differences between the healthy controls and participants with schizophrenia in physical effort discounting (*intensity*) with monetary rewards (€1 and €5); further, the amount effect was not found within groups. Westbrook et al. (2013) reported a statistically significant difference between the amounts offered ($1 and $5) in older adults with a cognitive effort discounting task (*difficulty*). However, in young adults, the amount effect was not statistically significant. Finally, Mizak et al. (2021) reported moderate and strong evidence (i.e., with Bayes Factor) for the amount effect with 4 magnitudes (PLN 100, 300, 1,800, and 11,000) in both physical (*distance*) and cognitive (*quantity*) effort discounting for gains and losses (see Section 2.1.2. for additional supporting results Section 6.2).

In summary, most studies reported a similar amount effect in physical and cognitive effort discounting tasks to that reported in delay discounting: larger amounts were discounted less. Further, the amount effect is observed in participants with ADHD but not those with schizophrenia, so it is premature to conclude that any psychopathology moderates the amount effect in effort discounting.

2.1.2. Sign effect

In delay discounting, outcomes that involve a gain are more steeply discounted than outcomes that involve a loss. The *sign effect* is widely documented in delay discounting with hypothetical money (e.g., Green et al., 2014), and in health outcomes (Chapman, 1996). In this review, 6 single studies examined the sign effect in effort discounting, and 2 additional studies compared it with another manipulation (Table A1).

Byrne et al. (2022) found the sign effect in cognitive effort discounting (*duration*), with a significantly higher AUC for losses than for gains, indicating that people discounted less in the loss condition or that people are more self-controlled. Massar et al. (2020) replicated the sign effect across cognitive effort domains (*duration* and *difficulty*) in 3 studies within the same article, suggesting the robustness of this effect. Hsu and Vlaev (2014) observed a sign effect in higher income participants (income above the median U.S. income) but no effect in lower income participants in a physical effort task (*duration*). Crawford et al. (2022) also did not report a sign effect for older or younger participants in a cognitive effort discounting task (*difficulty*). Further, Nishiyama (2016) did not find statistically significant differences between the discounting rates or AUCs for gains and losses in physical, cognitive, and emotional effort discounting tasks. Only Mizak et al. (2021) reported the opposite sign effect in their study examining physical effort discounting (*distance*), that is, gains were discounted less steeply than losses.

Thus, many studies of effort discounting are consistent with the sign effect reported in delay discounting, while others report no effect. Although there are too few studies to draw firm conclusions, it is interesting that the sign effect was observed in studies in which the effort level was varied using the duration of activity (a temporal characteristic), while other properties of effort (*difficulty* and *distance*) did not exhibit the sign effect seen in studies of delay discounting.

2.1.3. Outcome effect/mode

Most studies examining delay discounting have used tasks featuring hypothetical delays and rewards, neither of which are experienced by participants (Madden and Johnson, 2010; Rachlin et al., 1991). The advantages of these experimental arrangements are both practical and ethical (Madden et al., 2004).

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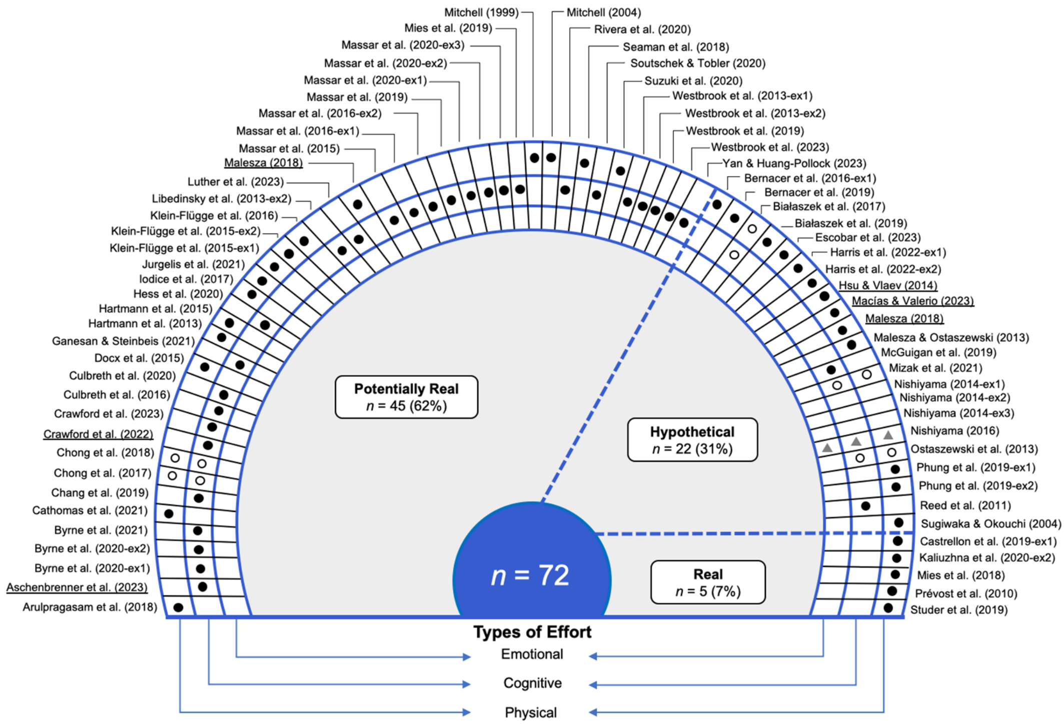

***Figure 4.** Spectrum display of all studies showing their outcome type and effort domain.*
Note: Malesza (2019) compared potentially real and hypothetical outcomes in the same physical effort discounting task, so the citation is listed twice, causing the number of studies in this figure to be listed as 72, one more than that in Figure 1 ($n = 71$). The underlined studies compared 2 effort discounting tasks in the same dimension (physical or cognitive). The filled circles indicate the publications that used one definition of effort (physical or cognitive). The open circles indicate publications, including both physical and cognitive effort. The gray triangles indicate publications, including physical, cognitive, and emotional effort. Because Nishiyama (2014) did not include operational definitions of effort, symbols are omitted for those 3 studies.

First, numerous choice trials can be assessed within a single session, allowing researchers to determine indifference points quickly. Second, using hypothetical delays and rewards allows the researcher to avoid concerns such as satiation, motivational changes, task fatigue, or other variables that may affect subsequent choices and to reduce study costs. Further, hypothetical rewards allow researchers to use larger ranges of reward magnitudes (e.g., $1,000 or $10,000) and reward types that may be problematic (e.g., alcohol for alcoholics or heroin for opiate/opioid users) to compare their effects on discounting.

However, the validity of those procedures for assessing human choices has been questioned over the years. The general conclusion drawn from comparing hypothetical and potentially real rewards (i.e., outcome type) is that there are no statistical differences between them (e.g., Johnson and Bickel, 2002; Madden et al., 2003). However, several exceptions have been reported (Kirby, 1997; Lawyer et al., 2011), leaving this as a potentially still open question.

Figure 4 displays both the outcome type (real/potentially real/hypothetical) and the effort domain (physical, cognitive, or emotional) across studies. Most studies used effort discounting tasks with potentially real outcomes (62%): one choice trial is selected at the end of the session, and the participant is required to complete the effort indicated as preferred on that trial to earn the outcome. Thirty-one percent of studies used hypothetical outcomes and effort requirements: participants did not experience either during trials or at the end of the session. Finally, a small proportion (7%) of studies employed real or tangible outcomes: participants experienced both the effort requirements and the rewards on each trial.

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Malesza's (2019) study is the only one that has compared hypothetical and potentially real rewards in physical effort discounting (*distance*). The tasks were presented in 2 sessions (order counterbalanced). In the potentially real condition, if the effortful reward was preferred, the participant and the researcher proceeded to the next building, which was 30 floors high (representing the maximum effort requirement), and climbed a specific number of floors. Malesza did not find a statistical difference between the AUCs or slope of the effort discounting function between conditions. However, there was a tendency for potentially real rewards to be discounted to a greater degree if the hypothetical reward condition occurred first than if the potentially real reward session was first. These findings are reassuring regarding the interval validity of fictional effort discounting assessments; however, replicating studies are needed.

2.2. Domain factors

2.2.1. Effort domain (types of effort)

As noted earlier, we identified 3 effort domains among the studies: physical, cognitive,[1] and emotional (Figure 3). Most studies examined a single effort domain (92%), though 6 studies examined 2 or 3 effort domains in the same article (8%). We first describe the findings for each domain and then the findings from studies comparing domains.

The total number of definitions (n = 78) does not match the number of published studies in Figure 1 (n = 71) because some articles included several effort domains. In the 3 experiments presented in Nishiyama (2014), operational definitions of effort are not provided. In total, 39 studies defined effort as a physical requirement, 38 used cognitive effort definitions, and 1 used an emotional definition of effort. Among the 71 studies included in the review, 5 compared physical and cognitive effort, 1 compared the 3 types of effort, 4 compared 2 physical effort discounting tasks, and 2 more compared 2 cognitive effort discounting tasks.

2.2.1.1. Physical effort

As shown in Figures 3 and 4, there are more examples of effort discounting using a physical, operational definition of effort than the cognitive or emotional definitions. Furthermore, several operational methods are employed to adjust the physical effort requirements. Those different methods can be thought of as creating properties of physical effort. The most frequent method was to vary the *intensity* of the effort required to obtain outcomes (17 studies) by varying the isometric force used to squeeze a hand dynamometer. Force requirements were derived from an individual's maximum voluntary contraction (MVC), obtained before participants begain choice trials by asking them to squeeze the hand dynamometer as hard as they could and to hold that for a fixed duration, say 10 seconds; this value was defined as the 100% MVC. Due to the nature of the consent process in these studies, participants were aware that their MVC would determine the subsequent effort requirements and could potentially exert less than the maximum to make the choice trials less onerous. Studies did control for this limitation.

In other studies, physical effort requirements have also been varied by altering the number of times an activity must be completed to earn an outcome (*quantity*) and/or the duration for which an activity must be sustained. The property of *quantity* (number) of responses required to earn a reward includes a range of response topographies, including washing a particular place a specific number of times (e.g., Sugiwaka and Okouchi, 2004) or typing a certain number of words (e.g., Phung et al., 2019).

The *speed* of performing an activity has also been used to vary effort requirements, for example, pressing a button as quickly as possible within a fixed period (Massar et al., 2016). Unlike studies using MVC, the effort required in these studies is typically not individualized (e.g., based on an individual's *maximum* speed); instead, these speed-based requirements have been implemented by providing participants with a fixed period and asking them to perform a specific number of responses

[1]Note that we use the term *cognitive effort discounting* to conform to the wider literature, which uses *cognitive* to refer to a putative process required to complete a specific behavioral task.

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during that period. Typically, the number of responses required has been varied, making this analogous to a fixed ratio schedule with a limited hold in instrumental conditioning. Across different conditions, the contingency can be fulfilled by varying the rate of responding within the limited hold period. It can also be completed by responding as quickly as possible under all conditions, but at different times within the period, for example, at the beginning (precrastination; Rosenbaum et al., 2014) or toward the end (procrastination). So far, information has not been reported about individual differences in strategy, nor have researchers formally speculated about the possible effects of these temporal strategies on choices in an effort discounting task.

Several limitations should be considered when selecting which properties of physical effort should be used in effort discounting tasks for those interested in pursuing research in this area. First, a lack of studies comparing discounting with the different properties of physical effort makes it difficult to compare these various methods, which vary in physical effort requirements. A recent study by Macías and Valerio (2023) indicated that the type of physical effort (climbing stairs or pedaling a bike) was associated with different levels of discounting, and the effect of increases in effort on discounting also varied as a function of the property of physical effort. Unfortunately, common effort metrics were not used to assist in making comparisons of the effort requirements of the different activities. Second, data are needed to assess whether these properties tap into a basic, common energy-focused currency of physical effort or whether the different temporal contributions result in some hybrid common currency. Third, to the best of our knowledge, only a single study has examined the reliability of physical effort discounting (Escobar et al., 2023), which indicated good reliability between physical effort discounting assessed at 3 timepoints over approximately 1 month. Additional studies examining reliability and repeatability are called for, in addition to studies to assist in the researched conceptualization of physical effort.

2.1.1.2. Cognitive effort

The cognitive effort required to earn rewards has most often been manipulated by varying the *difficulty* or cognitive load of a cognitive activity. As shown in Figure 3, the *N*-back *working memory* task is the most frequently used method to do this (16 studies). The cognitive effort discounting (COG-ED) paradigm, described by Westbrook et al. (2013), provides an excellent example of this type of task and involves 3 steps. Step 1: Participants practice an *N*-back task, in which they indicate whether the target letter presented on a computer screen is the same as or different from a previously presented letter, where *N* represents the number of letters preceding the target letter to be compared. In other words, 1-back indicates the previously presented letter should be compared to the target letter, 2-back indicates the one before that previously presented letter, and so on. Because target letters are presented as a continuous stream, the identity of the letters to be remembered changes and must be updated with each successive letter/stimulus presentation. As the *N* increases, the number of items to be remembered and continuously updated increases. Step 2: Participants respond to the effort discounting task through a series of choices between performing a harder *N*-back level ($N > 1$, high effort) for a larger monetary reward or an easier 1-back level (low effort) for a smaller monetary reward. Each time a choice is made, the amount of money offered is adjusted until an indifference point is found for that specific *N*-back/effort level. Step 3: One of the participant's choices is randomly selected (a *potentially real outcome*), which determines the level of *N*-back to be completed and the amount of money to be paid upon successful completion.

Other tasks manipulate cognitive effort through changes in attention, rather than working memory, in the *N*-Back task. For example, Chong et al. (2017, 2018) required participants to perform a rapid serial visual presentation task, where they were asked to attend to 1 of 2 simultaneously presented streams of stimuli and then indicate when a target was presented. Signals indicating which stream should be attended to occurred at pseudorandom intervals. The number of switches between streams was used to vary attentional and cognitive effort because it was assumed that more switches during the task required higher levels of effort (in *quantity*). After experiencing all possible levels of effort, participants were exposed to the choice trials to assess cognitive effort discounting. The tasks aimed

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to vary cognitive effort by changing the number of switches in selective attention over a fixed number of trials, but it might also be viewed as a *speed* property because attentional switches must occur at a higher rate during a fixed-duration task. However, the time in which the task must be completed is not constrained in most studies that manipulate cognitive effort by altering the frequency of an operation. This lack of constraint means that these tasks can be conceptualized as also changing the duration of effort required and creating a temporally codependent task (e.g., the number of pages of a textbook to be read in Ostaszewski et al., 2013). Future research is desperately needed to examine the potential complications of the temporal contributions to effort discounting.

2.1.1.3. Emotional effort

Only Nishiyama (2016) has attempted to examine emotional effort. The author provided a context with a negative emotion, and the different levels of effort were generated by asking participants to imagine '100 emotionally effortful tasks *(leading to a depressed mood)*' (p. 73; our italics). Technically, this is reminiscent of procedures developed by Rachlin et al. to examine social discounting (Jones and Rachlin, 2006). Unfortunately, Nishiyama (2016) did not provide examples of the imagined tasks in the article. Further, participants' success in imagining these tasks and altering their mood was not reported using standardized scales or physiological measures. Consequently, it is difficult to determine the degree to which emotional effort levels varied, and we do not know whether participants differed in their interpretation of the instructions. Some participants may have viewed depressed mood in terms of the colloquial expression of sadness, whereas others viewed it as a more profound mood disorder (e.g., Hockey, 2013). These factors make comparisons of individual differences in effort discounting difficult to interpret. Additional research in this critical area of emotional regulation is needed.

2.2.2. Comparison between effort domains

Six studies examined more than a single effort domain, that is, physical and cognitive, or physical, cognitive, and emotional (see Figure 4). Only the study by Nishiyama (2016) examined all 3 effort domains and reported that the effort discounting rates (slopes of discount functions) and the AUCs did not differ significantly in the effort domains. However, operational definitions of effort were not provided, and the lack of statistically significant differences between indices of discounting makes it challenging to interpret, given the putative differences in the subjective units of effort. Correlations between AUCs and individuals were not reported.

Five studies examined physical and cognitive effort with hypothetical outcomes. Ostaszewski et al. (2013) reported moderate correlations between AUC measures (r = .44–.58). In a methodologically similar study, Białaszek et al. (2017) reported that the same mathematical function provided the best fit to the physical and cognitive effort data and that there was a weak-moderate positive correlation between the parameters of this best-fitting effort discounting function (*rho* = .37–.53). In contrast, Chong et al. (2017, 2018) fixed the duration of each trial to ensure that participants' choices were not influenced by the delay and employed potentially real outcomes for both physical and cognitive effort tasks. The results indicated that the equation for the best-fitting function differed between them, so parameter correlations were not warranted. Mizak et al. (2021) reported moderate and strong evidence (i.e., with Bayes Factor) for the amount effect with 4 magnitudes in both physical (*distance*) and cognitive (*quantity*) effort discounting for gains and losses, but inter-individual correlations were not reported.

In summary, there appear to be weak-to-moderate correlations between discounting in different effort domains, but substantially more research is needed with careful calibration of subjective effort to be confident of this conclusion.

2.2.3. Comparison of effort activities

Six studies have examined 2 properties of a specific effort domain: 4 studies included tasks to examine different activities of physical effort (Harris et al., 2022, in 2 studies; Hsu and Vlaev, 2014; Macías

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and Valerio, 2023), and 2 studies examined activities of cognitive effort (Aschenbrenner et al., 2023; Crawford et al., 2022).

Only Harris et al. (2022; in 2 studies) attempted to differentiate effort levels of activities in a quantitative way based on the respiratory requirements of engaging in each activity (light, moderate, or vigorous breathing). Although limited by a between-groups design, both studies observed an interaction between activity intensity and effort level: imagining a vigorous activity resulted in steeper effort discounting as the duration of the required activity increased, compared to when a light activity was imagined. Hsu and Vlaev (2014) compared gains and losses for 3 physical activities (walking, standing, and sitting) with the same property in terms of effort requirements (duration of task performance). A steeper discount was found in the gain framing. The authors found correlations across activities: steeper discounting for an activity was associated with steeper discounting for other physical activities. They also reported a significant main effect of activity on effort discounting, with the AUC for walking being steeper than those for standing and sitting. Macías and Valerio (2023) conducted an experiment to assess the effects of 2 procedures (fixed sequence and titrating sequence of effort requirements) and 2 physical effort activities (climbing floors and pedaling) on data-systematicity and the rate of effort discounting. This is the first study showing no differences in the rate of effort discounting or the production of systematic data between procedures. However, an effect of the type of effort activity was found; discounting was steeper when the required effort was climbing floors compared to pedaling.

These studies suggest that steeper effort discounting was associated with more physically demanding activities. But again, additional studies examining these types of effort and effort level interactions are needed to determine whether these effects arise from a basic physical effort currency (some energy-based metric), with individual factor moderators.

For cognitive effort, Aschenbrenner et al. (2023) examined the effect of 2 activities: working memory and speech comprehension in healthy aging and preclinical Alzheimer's Disease participants. The results showed positive correlations between effort discounting using the 2 tasks, as well as age-related increases in cognitive effort discounting, as might be predicted by the effects of aging on intellectual capacity. Crawford et al. (2022) also compared 2 cognitive effort discounting tasks in healthy adults: working memory (e.g., *N*-back task) and speech comprehension (e.g., understanding spoken sentences in background noise). While performance was affected by increasing effort requirements on the tasks, multiple regression suggested a weak correspondence between them (r = .31). Thus, like physical effort discounting, there appears to be a weak-moderate correlation between assays of cognitive effort discounting that use different tasks. But again, substantially more work is needed to support this conclusion based on 2 articles.

2.2.4. Commodity domain

In delay discounting, the rate of discounting varies according to the outcome being discounted: money, drugs, or food (see Odum et al., 2020, for a review). We identified 3 studies that compared monetary and substance rewards (cigarettes and drinks) in effort discounting (Table A1). Mitchell (2004) examined cigarette smokers and assessed physical effort discounting (*intensity*) in 2 separate sessions with 2 experimental arrangements. One task involved choices between amounts of money in a typical discounting task. The other task involved combining a variable number of cigarettes and money, where cigarettes were always the effortless alternative and money was the effortful alternative. The rationale for the asymmetrical rewards was that smokers are constantly choosing between cigarette smoking and the hardness to obtain non-cigarette rewards, such as a healthier lifestyle. Participants performed these assessments after smoking ad libitum or after abstaining from smoking for 24 hours and obtained potentially real rewards based on the discounting tasks. Deprivation increased preference for immediate cigarettes over delayed money; however, individual variability was sufficiently high that the discounting parameter did not differ between conditions. In contrast, smoking abstinence did not affect the money–money task, underscoring the importance of the commodity in determining discounting rate. Similar results were found for the effort and probability discounting conditions.

Phung et al. (2019) compared physical effort discounting (*quantity*) in individuals who endorsed different numbers of items on the Alcohol Use Disorder Identification Test (Saunders et al., 1993). In both studies, participants completed 4 tasks: delay and effort discounting tasks with hypothetical monetary rewards, as well as delay and effort discounting tasks with hypothetical alcohol drink outcomes. Phung et al. assessed the domain effect in a more traditional way than did Mitchell's (2004) study with her use of asymmetrical rewards. Phung et al. (2019) reported that the participants were more willing to exert effort to obtain money than comparably valued alcohol (i.e., less discounting for money than alcohol). A similar result was obtained in the delay discounting task, replicating the established domain effect. Interestingly, unlike delay discounting, heightened effort discounting was associated with lower AUD severity when alcohol was the outcome but was unrelated when money was the outcome. This might suggest a qualitative difference between the 2 discounting processes.

2.2.5. Effort and other costs

The literature on discounting has served as a useful source of evidence to assess single-process theories on decision-making (Green and Myerson, 2004; Johnson et al., 2020). However, the amount effect on delay discounting and probability discounting (e.g., Green et al., 1999), the inflation effect (e.g., Ostaszewski et al., 1998), and culture (e.g., Du et al., 2002) have shown evidence against single-process theories.

We identified 12 studies that compared both effort and delay discounting, 2 studies that compared both effort and probability discounting, 5 studies that compared effort, delay, and probability discounting, and 1 study that compared effort, delay, probability, and social discounting.

Some studies support the differences between effort discounting and other cost types, based on modeling comparisons, deprivation states, clinical samples, and within-subject variability. For example, physical effort discounting was best predicted by a sigmoidal model (concave shape), whereas delay discounting was best predicted by the hyperbolic function (e.g., Klein-Flügge et al., 2015); sleep deprivation increased the rate of cognitive effort discounting, but did not alter delay discounting (e.g., Libedinsky et al., 2013); the adolescents with ADHD exhibited steeper delay discounting than healthy controls, but not for physical effort discounting. Escobar et al. (2023) reported moderate reliability of effort, delay, and probability discounting. However, the level of within-subject variability across time was significantly higher for effort discounting than for the other 2 discounting types. Further, models describing effort discounting differed from those describing delay and probability discounting. In contrast, other studies have reported associations between effort and different types of discounting costs. For instance, modest significant correlations between delay and physical effort discounting using the proportion choice and the discounting rates (using the hyperbolic model), but not with probability discounting (e.g., Castrellon et al., 2019); modest significant correlations between delay and physical effort (e.g., Malesza and Ostaszewski, 2013; Phung et al., 2019), as well as for cognitive effort using AUCs (e.g., Massar et al., 2015) with monetary rewards and with drinks as outcomes (e.g., Phung et al., 2019). Białaszek et al. (2019) reported low positive correlations between the AUC of delay and effort discounting and low negative correlations between the AUC of effort and probability discounting. Their factor analyses indicated that indifference points from each discounting task loaded onto different identifiable factors. However, when forced into a 2-factor solution, the effort and delay discounting indifference points were associated with a single factor, while other discounting processes (probability and social) loaded onto a different factor. The factor analytic approach is an exciting one for identifying underlying processes, but more research using this approach is required.

In conclusion, evidence suggests that there are performance dimensions that result in discounting differences between different cost domains, suggesting at the very least that any fundamental process is modulated by individual difference variables, but research is needed to explore these differences.

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2.2.6. Experimental manipulations

Surprisingly, few studies were identified by the systematic review criteria that have employed direct experimental manipulation to alter effort discounting. While a number of these studies can be viewed as manipulating subjective fatigue, they do not focus on one manipulation or one effort domain but rather reflect the interests of the principal investigator.

Iodice et al. (2017) manipulated the levels of fatigue (rest and fatigue sessions) in participants by asking them to spend time cycling on a bicycle ergometer at a submaximal performance level of ~70% of their VO2max. The results showed that fatigued participants increased their preference for less-costly offers and exhibited steeper physical effort discounting. Focusing on cognitive effort, Soutschek and Tobler (2020) assessed the effect of disrupting the functioning of the dorsolateral prefrontal cortex (DLPFC) with non-invasive brain stimulation before participants repeatedly decided whether to perform a cognitive effort discounting (working memory) task. A novel computational model revealed that disrupting the DLPFC reduced fatigue after accumulated effort and was associated with reduced discounting. Another series of studies has shown the effects of sleep deprivation on cognitive effort discounting tasks. Libedinsky et al. (2013-ex2) compared delay and effort discounting (*difficulty*) in healthy adults exposed to 2 sessions: one session was conducted after a normal night of sleep, and the other with sleep deprivation. The results showed that sleep deprivation did not affect the discounting of delayed rewards, whereas effort discounting was steeper during sleep deprivation compared to normal sleep. Massar et al. (2019) compared a cognitive effort discounting task (vigilance task; *duration*) and pupillometry at rest and after sleep deprivation sessions under different incentive conditions. Vigilance was impaired during sleep deprivation in a manner modulated by the reward value. Preference metrics indicated that the value of available rewards was discounted by task duration, an effect that was compounded by sleep deprivation. Thus, it appears that manipulations that influence a participant's fatigue can influence physical and cognitive effort discounting, presumably by affecting the subjective value of the effort required.

In contrast, as described earlier, Mitchell (2004) evaluated the effect of nicotine deprivation on regular smokers' physical effort (*intensity*). Deprivation increased preference for the no-effort cigarette alternative compared to effortful money. But importantly, it did not alter the decision-making processes for no-effort money versus effortful money, suggesting no effect of nicotine deprivation on the discounting process itself, only on the value of the outcome and thereby the level of effort discounting. These results underscore the importance of examining whether experimental manipulations affect outcome or effort-associated domains.

2.3. Mathematical models of effort discounting

A total of 37 studies (52%) fitted mathematical functions, 24 of them compared 2 or 3 models; many have been popularized in the delay literature. Often, these studies have labeled the fitted parameters in the same way as equations used for delay discounting data (e.g., k representing the discounting rate). However, sometimes, the parameter representing the effort discounting rate is labeled as l (e.g., Ostaszewski et al., 2013). The l-values are used here to distinguish effort functions from those referring to delay discounting explicitly. The interpretation of l-values is like that of k-values in delay discounting models: the larger the l-value, the more subjective value decreases as the effort required increases. Table A2 displays the 10 functions employed across the studies examined in this systematic review and the number of studies that have used them. Brief descriptions of the 10 models follow, grouped based on the number of free parameters in the model.

2.3.1. One-parameter model

The hyperbolic function (Mazur, 1987) has been the most frequently used 1-parameter model to describe how the subjective value of an outcome decreases as the effort requirement increases. This model is highly prevalent in the delay discounting literature, partly because its convex form easily predicts experimentally observed preference reversals: an individual chooses the LLR over the SSR when both are relatively far in the future, but chooses the SSR when the time to its delivery is relatively short. Although studies have demonstrated that the reversal phenomenon occurs in effort discounting, it seems likely based on anecdotal evidence. Another reason for the hyperbolic equation's popularity in the delay discounting literature is that indices of function fit (Akaike information criterion [AIC], Bayesian information criterion [BIC], RMSE, etc.) suggest that it describes the data better than the exponential decline model favored by economists. Both the hyperbolic and the exponential functions provide a convex shape of effort discounting.

The parabolic or quadratic function, the second most popular model fit to effort discounting data, has significant implications. It assumes that the subjective value of rewards increases or remains constant at lower effort requirements and then declines at higher effort levels. This suggests that the perceived value of a reward can be influenced by the effort required to obtain it. For example, luxury goods are viewed as more desirable because they are costlier to obtain (a Veblen good in economics). However, in most of the reviewed studies, effort is generally observed to reduce value across the range of effort values examined (but see Hartmann et al., 2013, 2014, and Introduction). Finally, linear models have also been examined, but infrequently (e.g., Chong et al., 2017, 2018; Hartmann et al., 2013). These indicate a constant diminution of subjective value as a function of effort and do not assume a convex or concave form of discounting curve over the examined effort range.

2.3.2. Two-parameter models

The models with 2 parameters consider both the discounting rate (l-values) and an additional free parameter, often s-values, to reflect individual psychophysical scaling of the effort increments. However, in the sigmoidal function, the second parameter, the turning point (p), plays a crucial role as it represents the inflection at which effort discounting becomes progressively less steep. This model requires subjective value to increase or reach an asymptotic level when effort levels are low and then decrease to asymptote as effort requirements become increasingly high. That is, the sigmoidal curve starts with a flat or concave shape and, following flexion, moves to a convex form.

The power function (Białaszek et al., 2017) implies that in effort discounting, the discounting curve can be concave rather than convex. This model is an extension of Hartmann et al. (2013) parabolic function, with an included s parameter as the exponent of individualized sensitivity to effort intensity. The power function's unique feature is that it does not asymptote when effort becomes increasingly high. The sigmoidal and power functions, with their added flexibility, allow for the generation of regions of concave and convex changes as a function of effort requirement, empowering researchers to model effort in a more nuanced way.

The 2-parameter (double) exponential (Myerson and Green, 1995) is a complex model that includes Euler's number (e) and a sensitivity parameter (s). This model, as described, shows that the subjective value will not decay to 0 as the effort increases but will instead approach an asymptote. Furthermore, in this model, zero effort will not result in the subjective value being the same as the objective amount; instead, it will be the objective amount plus the sensitivity parameter value. This value discrepancy may be conceptualized as suggesting a bonus when an outcome is effort-free. The hyperboloid models by Myerson and Green (1995) and Rachlin (2006) assume that the subjective value decreases more steeply with low effort requirements but less steeply with high effort levels. The position of the s parameter within each equation differs, and delay discounting literature suggests that this may result in significant theoretical and data approximation differences.

2.3.3. Comparing mathematical models

As shown in Table A3, 22 studies identified by this systematic review compared 2 or more mathematical functions. All of these comparisons included the hyperbolic function. Further, when only 2 models were compared, these were most likely to be hyperbolic with the exponential, indicating a clear bias in the

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field. When more than 2 models were compared, the parabolic/quadratic model was a popular choice for inclusion, accompanied by either the exponential or one of the linear models.

The strategy used in most of these studies was to fit the function of interest to indifference points for individuals, then examine which is associated with higher indices of fit: R^2 (if necessary, adjusted for the number of parameters in the compared model) or the AIC, BIC, or, in 2 studies, an unspecified Bayesian estimation procedure. Note that some studies fit curves through indifference points representing the point of subjective equality between effort alternatives (e.g., Iodice et al., 2017), whereas others fit curves through individual choices using logistic-based statistics (e.g., Klein-Flügge et al., 2015). It is an unexamined, empirical question as to whether this difference in approach affects the identification of best-fitting functions.

As can be seen in Table A2, 4 studies compared several mathematical functions among effort domains: 2 studies reported the same function showed the best fit for physical and cognitive effort discounting in a within-subject design; however, 1 study reported the power function (Białaszek et al., 2017) and another study reported the exponential (Nishiyama, 2016). The 2 other studies indicated that the hyperbolic model has the best fit to the cognitive effort, whereas the parabolic/quadratic model has the best fit to the physical effort (Chong et al., 2017, 2018). Table A2 illustrates the amount of research required to obtaining a consensus about an appropriate mathematical descriptor of effort discounting. Having a function that is almost universally accepted in the delay discounting literature has suggested numerous relationships with psychopathologies (e.g., Amlung et al., 2017) and arguably a function that can facilitate between study comparisons could serve a similar function for effort discounting.

3. Discussion

This systematic review of effort discounting in humans had 2 aims. The first was to survey the factors examined and manipulations used and to compare their effects to those found for delay discounting. The second was to examine the mathematical models used to describe effort discounting patterns. However, it quickly became apparent that effort has numerous operational definitions across studies, even within broad domains of effort (physical, cognitive, and emotional). Prior to discussing the review conclusions, definitions of effort will be examined.

3.1. What is effort?

The reviewed studies have used different effort domains (physical and nonphysical, such as cognitive/emotional) and different properties of operationalizing the effort requirements within an effort domain (intensity, frequency, etc.). When effort is defined as physical, we refer to the functional relationship between the magnitude of the topography of a behavior required to obtain an outcome (e.g., exerting force, walking, and climbing stairs) and the behavior that will be measured by using one of the properties shown in Figure 3. When effort is defined as cognitive, we refer to the functional relationship between the magnitude of various requirements of experimental tasks for obtaining outcomes (number of words to memorize and number of digits to add) and the brain structures or networks (memory work, attention, and vigilance), which will be measured through one of the properties shown in Figure 3.

Unfortunately, there has been no attempt to equate these different effort domains on any physical dimension, such as the rate of energy expenditure, or any subjective/psychological dimension, such as aversiveness. An early study attempted to express the requirements in terms of confidence that the effort requirement could be accomplished (Mitchell, 2004), but others have not used this metric, and it may not be a feasible metric for all types of effort (e.g., reading different amounts of text). From a theoretical perspective, effort discounting may be qualitatively different when individuals are confident that they can complete the effort but don't want to, versus cases in which there is uncertainty about whether the effort can be successfully completed. Further, clinicians and applied behavior analysts would conceivably design very different interventions to reduce effort discounting that was based on amotivation than based on the lack of confidence in one's abilities. Thus, examining confidence in

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successful effort completion may be an important factor contributing to the subjective value of the effort requiring alternatives, but its objective measurement may be challenging.

Focusing on different effort domains, it seems unlikely that a common currency can be identified. While fatigue and aversiveness may be common factors, identifying quantitative and qualitative factors contributing to each would remain an experimental problem. The lack of an easily identified common currency limits the applied and theoretical value of explicit comparisons between different types of effort within research studies at this time. It may appear useful to identify populations with divergent effects of increasing physical or cognitive effort, for example, high school athletes and mathletes. However, these effects may be attributable to the differences in effort levels examined, rather than the qualitative difference suggested by different mathematical functions yielding the best fit (Chong et al., 2017, 2018). The common currency question becomes more complex still when considering the conceptual fit of emotional effort with physical and cognitive effort. Expressing or repressing specific emotions, such as exhibiting interest and empathy in food service workers or suppressing fear and anxiety in healthcare workers, causes fatigue and is aversive. In principle, the value of avoiding these emotions could be quantified using an adjusting-amount effort discounting task, but substantial work is needed beyond that reported by Nishiyama (2016) before emotional effort discounting can be evaluated or compared to other types of discounting.

While it is unclear that physical and nonphysical types of effort should be lumped together conceptually, questions can be asked about whether different modes of manipulating effort (e.g., intensity and quantity) can be equated. The literature examining physical effort discounting has more examples than the nonphysical effort discounting literature. Further, it is easier to posit a common currency based on energy expenditure because of prior literature drawing parallels between instrumental conditioning procedures and foraging behavior (Rachlin et al., 1981). Based on prior work in basic and applied behavior analysis, physical effort has been defined and manipulated as a dimension of responding in 2 ways: force required and number of responses to earn a reinforcement. Both modes of manipulating effort can be reduced to the rate of energy expenditure, and it might be predicted that they should have equivalent effects on choice patterns (e.g., Collier and Jennings, 1969). However, actual measures of energy expenditure are not used to equate the effort requirements, nor are yoked studies performed to roughly equate the energy and temporal requirement (but see Floresco et al., 2008).

In summary, the subjective value of rewards decreases as the physical or cognitive effort requirements increase. However, generalizing between effort domains or properties of effort is not possible because research has not identified a common currency or behavioral process. Indeed, the feasibility of doing so is unclear, but additional research with yoked requirements is needed to determine whether there is a single underlying economic cost associated with effort discounting.

3.2. Effort and delay discounting

Among the 71 studies identified, 20 compared the degree of effort discounting with one or more different types of costs, most commonly, delay. Comparing the effects of manipulations expected to change choice architecture or discounting functions, as well as analysis procedures, there are unquestionably areas of similarity but also areas of divergence. In short, effort discounting is not delay discounting, despite the frequent study confounding that more effort requires more time to complete.

The first group of studies demonstrated that effort discounting differs from delay discounting, based on experimental manipulations, sample types, and data analysis methods. The use of sleep and nicotine deprivation (Libedinsky et al., 2013; Massar et al., 2019; Mitchell, 2004) significantly increased the degree of effort discounting compared to delay discounting. This suggests that individuals who engage in physiological states are less likely to favor decisions that require high effort, even if the rewards are greater. That is, working for a larger reward, as opposed to simply waiting for it, is less preferred in certain states of deprivation.

Another point of divergence is the use of exclusively concave models to examine the mathematical form of effort discounting, as opposed to the use of convex models for delay and probability

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discounting. The evidence in Table A3 revealed that a minority of studies reported the hyperbolic or hyperboloid models as better fits for effort discounting data, which could be dependent on the type of effort performed (cognitive *versus* physical) and the reported fit index. These findings underscore the potential impact of future work to investigate whether specific experimental conditions facilitate changes in the mathematical form of effort discounting. It is also essential to consider that only one study (Macías and Valerio, 2023) has provided evidence to suggest that Johnson and Bickel's (2008) criteria may not be the most appropriate for assessing the systematicity of effort discounting data when effort is performed across the trials. Therefore, different edges suggest that effort discounting and delay discounting are different choice processes.

The second group of studies unveiled varying degrees of association between effort and delay discounting. Notably, the strength of the correlations in the studies assessing delay and effort discounting has been weak to moderate. While the correlation analysis does reveal some level of association between the AUCs of both cost types, the degree of strength and the impact of methodological manipulations strongly suggest that delay and effort discounting are distinct and non-redundant choice processes.

A driver of similarity between effort and delay discounting is the degree to which experimental manipulations have similar effects in delay and effort discounting studies. The data indicate that this is the case and are especially compelling for the amount effect. The study by Ostaszewski et al. (2013) reported that the smaller reward was more steeply discounted than the larger one for 2 types of effort. Unfortunately, a delay discounting assessment was not included, precluding comparisons of the effect in both effort and delay discounting for these participants. However, this omission was addressed by Białaszek et al. (2019), who reported a similar amount of effect for effort and delay discounting. However, the clever inclusion of a factor analysis suggested that, despite the similarities, 2 different factor structures underlie effort and delay discounting. These factor analytic data underscore the adage that *many phenomena can be described by fitting a straight line, but that does not indicate that all describe the same process*. Identifying the concordant and divergent processes that yield these similar functional relationships will be an important contribution to future research.

However, the relatively small number of studies that compared delay and effort discounting (20 studies) makes it difficult to delineate robust conclusions about which conditions effort and delay discounting converge or diverge. Perhaps the scarcity of research up to 2012 (Figure 2) is partly due to the null findings for effort discounting reported in Mitchell (1999), compared to the smoker–nonsmoker delay discounting difference reported in her paper and in the companion paper by Bickel et al. (1999). However, there is reason for optimism. Over the last decade, there has been an uptick in published studies on effort discounting using experimental manipulations established in the delay discounting field (e.g., amount, sign, outcome, and domain effects) by using healthy participants and substance users. The experimental manipulations, sample types, and data analysis that allowed for observing differences between delay and effort discounting provide grounds for continuing to examine under which conditions the 2 choice processes differ.

3.3. Mathematical modelling

The concern about the definitions of effort takes on an added importance when trying to determine how to characterize effort discounting mathematically. Based on the studies that compared mathematical functions for describing the shape of effort discounting, we believe that such analysis could be critical for 2 aspects in the field: to examine whether the mathematical form of effort discounting (a) depends on the domain and properties in which effort is defined and (b) whether different mathematical models describe effort discounting data, unlike the models usually reported to describe delay and probability discounting (i.e., hyperbolic and hyperboloid models).

First, evidence is limited regarding differences between the domain of effort and the equation that best describes each. Although the hyperbolic model is the most commonly used in the studies identified here, only 4 studies directly compared the fit of different mathematical models to the indifference

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points of different effort domains. Chong et al.'s (2017, 2018) finding that the hyperbolic model better describes cognitive effort (switches of attention) than concave functions, and the parabolic model better describes physical effort (hand-dynamometer force) than the hyperbolic model, might suggest that these types of cognitive effort are more demanding than dynamometer force. This finding supports the hypothesis that the mathematical form of effort discounting differs not only as a function of domain but also by the type of property within each domain of effort. Future research is needed to clarify these differences and to consider possible confounding effects (e.g., IQ and physical activity level), stressing the importance of a thorough and meticulous research approach. However, it is essential to note that each domain of effort will have its specific measurement procedure, so comparisons across domains should be made with caution.

Second, of the 22 studies that compared 2 or more models, 9 reported that the hyperbolic model best fit effort discounting data (6 physical and 3 cognitive), of which 5 studies compared the hyperbolic model with concave models (see Table A3). Another set of studies showed that Rachlin's (2006) hyperboloid and hyperbolic models were better descriptors of delay (Klein-Flügge et al., 2015-ex1) and probability discounting (Escobar et al., 2023) than effort discounting, which was better described by concave functions. Overall, there is more substantial evidence that models with concave shapes (i.e., parabolic/quadratic, power function, and double exponential) better describe effort discounting data than models that describe delay or probability discounting. However, there are some exceptions where the hyperbolic model showed a better fit for time and effort discounting, but when compared to the exponential model (Prévost et al., 2010). Future research is needed to generate robust conclusions about the differences between effort discounting and other types of costs, based on theoretical models that suggest different choice processes.

3.4. Methodological refinements

Our review of the effort discounting literature suggests several steps that could be taken to facilitate our field's understanding of effort discounting. Our first recommendation stems from the observations that there is a high level of heterogeneity in effort discounting procedures across the studies. Accordingly, we recommend that method sections (or appendices and supplements) provide clear, detailed information, especially related to instructions given to participants about the nature of the effort required and any effort tasks performed to provide a *baseline experience* of the effort required. For instance, Westbrook et al. (2013, 2019, 2023) included a familiarization period in which participants practiced the effort task before proceeding to the discounting task. In studies assessing physical effort using the MVC with a dynamometer, the participants experienced the effort required using handgrip squeezing force before the choice trials (Białaszek et al., 2017; Mitchell, 1999, 2004). Escobar et al. (2023) also included a familiarization phase to calculate the mean number of steps for participants to use in the discounting tasks with hypothetical outcomes. We recommend baseline effort exposures, if possible, because these experiences play a crucial role in reducing response variability attributable to participants' memories of the specific type of exertion, which might be recent or distant, thereby enhancing the reliability of the research results.

Another recommendation relates to the alternatives used in effort discounting assessments. Most studies in the literature have presented participants with choices between a *no-effort* option and an *effortful* option. The above is analogous to the SSRs and LLRs offered in delay discounting. As argued by Richards et al. (1997), an immediate reward means that alternatives only differ on one dimension, and the interpretation of preferences is less complex. Accordingly, we recommend that effort discounting assessments include a no-effort alternative to facilitate understanding, although this does not preclude the inclusion of some choices in which both options require effort. Such manipulations might reveal interesting divergences between participants, as reported for delay discounting (Mitchell and Wilson, 2012).

Another point of divergence is the use of exclusively concave models to examine the mathematical form of effort discounting, as opposed to the use of convex models for temporal discounting.

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The evidence reported in Table A3 revealed that a minority of studies reported the hyperbolic or hyperboloid models as better fits for effort discounting data, which could be a function of the type of effort performed (cognitive *versus* physical) and the reported fit index. These findings underscore the potential for future work to investigate whether specific experimental conditions facilitate changes in the mathematical form of effort discounting. It is also essential to consider that only one study (Macías and Valerio, 2023) has provided evidence to suggest that Johnson and Bickel's (2008) criteria may not be the most appropriate for assessing the systematicity of effort discounting data when it is performed in trials. Therefore, different edges suggest that effort discounting and temporal discounting are different choice processes.

Following the previous suggestion, another methodological strategy could be to maintain a constant delay while varying the effort, or vice versa. This strategy is supported by the multidimensional discounting model proposed by Reynolds and Schiffbauer (2004), in which different types of costs converge simultaneously on each choice alternative to evaluate greener choices. The studies by Hayashi et al. (2018) and Andrews et al. (2025) are concrete examples of cross-consequence discounting procedures, in which delays and odds against, as well as odds against and social distances, were combined, respectively. These studies provide empirical evidence for the proposed research. Future studies could evaluate the effects of delay and risk on effort in cross-consequence discounting tasks. Or employ 2 × 2 factorial designs to assess interaction effects between effort and other types of costs (e.g., low/high effort × short/long delay).

For data analysis, we recommend that the results reported include plots of indifference points, including those for individuals, if feasible. Plots for individuals will also provide useful information about subgroups of participants and the appropriateness of function fits. We also recommend the corrected Akaike Information Criterion (AICc) or the BIC measures should be reported when the purpose of the article is to compare the mathematical forms of effort discounting (e.g., Białaszek et al., 2017), rather than R^2. The AICc is appropriate when examining the relative quality of 2 or more models by comparing goodness of fit with similar levels of complexity (number of fitted parameters), while the BIC adds an additional penalty parameter to give it the ability to compare models of different complexity (e.g., exponential *versus* hyperboloid).

3.5. Limitations

First, while our systematic review identified numerous papers with critical findings during our database and reference list searches, it is always possible that including additional terms such as 'effort motivation' or explicitly callling out names of specific procedures, such as 'COG-ED', could have identified additional research. Determination of critical terms is always a concern for systematic reviews, and gaps may provide an opportunity for future reviews with a more expanded focus. Second, we identified potential studies in the initial search to include; however, we decided to exclude them because they did not meet the criteria for classical discounting metrics. For instance, after identifying and classifying the 71 studies in our review, we noticed that some authors use *acceptance rates* in conjunction with ANOVAs or linear models to examine the degree of effort discounting or differences between effort discounting and various experimental conditions (e.g., Kurniawan et al., 2021). The rationale for including articles that used one or more of the discounting measures selected (i.e., indifference points, discounting slope parameters, or AUCs) was to facilitate comparisons with delay discounting, as the importance of that assay in biomedical research has been considerable (e.g., Odum et al., 2020; Rung and Madden, 2018). Looking forward, future reviews using expanded metrics of decision-making, like *acceptance rates*, would be important and enhance the usefulness of the research.

Third, the explicit emphasis on identifying studies with effort-based discounting procedures meant that the included studies assessed multiple levels of effort. This criterion excluded studies using single levels of effort, for example, studies using the effort expenditure for rewards task designed by Treadway et al. (2009). These procedures are often used to examine differences between groups of manipulation effects, making them highly important, while, at the same time, potentially confounded by between group differences in effort valuation. However, these assessments make a useful contribution and a jumping off point for future research and will be valuable to include in future reviews of effort-based decision-making.

4. Conclusions

Fewer studies have addressed effort discounting compared to the delay discounting literature. Several factors that make research examining effort-based decisions complex have been identified in this review, for example, what is effort? How can effort be operationally defined? How can effort be equated between individuals? These may be responsible for the slow increase in research studies. Throughout this review, we suggest numerous areas in which additional research would resolve questions about factors that influence the choice architecture and factors that could be used to change effort discounting, and we hope that this review encourages research in this field.

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Appendix

Table A1. *Characteristics of the included studies (n = 71).*

Authors	Year	Participant age category	Sample type	HC (*n*)	Non-HC (*n*)	Manipulation[a]	Commodity
Arulpragasam et al.	2018	Young adults	HC	28			Money
Aschenbrenner et al.	2023-ex1	Young; Older adults	HC; HC	300; 74		Activity	Money
Bernacer et al.	2016-ex1	Young adults	HC	57			Money
Bernacer et al.	2019	Young adults	HC	24			Money
Białaszek et al.	2017	Adults	HC	114		Activity; amount	Money
Białaszek et al.	2019	Adults	HC	160		Amount	Money
Byrne et al.	2020-ex1	Young adults	HC	24			Money
Byrne et al.	2020-ex2	Young adults	HC	17			Money
Byrne et al.	2022	Young adults	HC	24		Sign	Money
Castrellon et al.	2019-ex1	Adults	HC	84			Money
Cathomas et al.	2021	Adults	HC; major depressive disorder; schizophrenia	18	44; 42		Money
Chang et al.	2019	Adolescents–adults	HC; first episode psychosis	44	40		Money
Chong et al.	2017	Young adults	HC	34			Money
Chong et al.	2018	Young adults	HC; elite rowers	20	20		Money
Crawford et al.	2022	Young adults	HC	300		Activity; amount	Money
Crawford et al.	2023	Young; older adults	HC	310[b]		Sign	Money
Culbreth et al.	2016	Young adults	HC; schizoaffective disorder	25	25		Money
Culbreth et al.	2020	Adults	HC	31			Money

(Continued)

Table A1. (Continued).

Authors	Year	Participant age category	Sample type	HC (*n*)	Non-HC (*n*)	Manipulation[a]	Commodity
Docx et al.	2015	Young adults	HC; schizophrenia	30	40	Amount	Money
Escobar et al.	2023	Young adults	HC	23		Repeat	Money
Ganesan & Steinbeis	2021	Children	HC	79			Tokens
Harris et al.	2022-ex1	Young adults	HC	141		Activity	Money
Harris et al.	2022-ex2	Young adults	HC	232		Activity	Money
Hartmann et al.	2013	Young adults	Psychiatric		24		Money
Hartmann et al.	2014	Young adults	HC; schizophrenia	20	31		Money
Hess et al.	2021	Adults	HC	69; 80		Amount	Money
Hsu and Vlaev	2014	Adults	HC; overweight	76	84	Activity; sign	Money
Iodice et al.	2017	Young adults	HC	20			Money
Jurgelis et al.	2021	Adults	HC	103			Class credit
Kaliuzhna et al.	2020-ex2	Adults	Schizophrenia		31		Money
Klein-Flügge et al.	2015-ex1	Young adults	HC	23			Money
Klein-Flügge et al.	2015-ex2	Young adults	HC	14			Money
Klein-Flügge et al.	2016	Adults	HC	21			Money
Libedinsky et al.	2013-ex2	Young adults	HC	14			Money
Luther et al.	2023	Adults	HC; schizophrenia	26	27		Money
Macías and Valerio	2023	Adults	HC	49		Activity; Q delivery	Money
Malesza	2019	Young adults	HC	142		Real/hypo	Money
Malesza and Ostaszewski	2013	Young adults	HC	112			Money
Massar et al.	2015	Young adults	HC	23			Money
Massar et al.	2016-ex1	Young adults	HC	24			Money
Massar et al.	2016-ex2	Young adults	HC	24			Money

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Table A1. *(Continued).*

Authors	Year	Participant age category	Sample type	HC (*n*)	Non-HC (*n*)	Manipulation[a]	Commodity
Massar et al.	2019	Young adults	HC	26			Money
Massar et al.	2020-ex1	Young adults	HC	30		Sign	Money
Massar et al.	2020-ex2	Young adults	HC	30		Sign	Money
Massar et al.	2020-ex3	Young adults	HC	30		Sign	Money
McGuigan et al.	2019	Older adults	HC; Parkinson	20	20		Money
Mies et al.	2018	Adolescents	HC; ADHD	28	30		Money
Mies et al.	2019	Adolescents	HC; ADHD	17	16	Amount	Money
Mitchell	1999	Young adults	HC; smokers	20	20		Money
Mitchell	2004	Young adults	Smokers		11	Domain	Money and cigarettes
Mizak et al.	2021	Adults	HC	699		Activity; amount; sign	Money
Nishiyama	2014-ex1	Young adults	HC	32			Money
Nishiyama	2014-ex2	Young adults	HC	33			Money
Nishiyama	2014-ex3	Young adults	HC	28			Money
Nishiyama	2016	Young adults	HC	34		Sign	Money
Ostaszewski et al.	2013	Adults	HC	100		Activity; amount	Money
Phung et al.	2019-ex1	Adults	Drinkers		100	Domain	Money and alcoholic drinks
Phung et al.	2019-ex2	Adults	Drinkers		411	Domain	Money and alcoholic drinks
Prévost et al.	2010	Young adults	HC	16			Time to view erotic stimuli
Reed et al.	2011	Young adults	HC	146			Placement in a treatment program

(Continued)

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Table A1. *(Continued).*

Authors	Year	Participant age category	Sample type	HC (*n*)	Non-HC (*n*)	Manipulation[a]	Commodity
Rivera et al.	2020	Young adults	HC	55			Money
Seaman et al.	2018	Adults	HC	75			Money
Soutschek and Tobler	2020	Young adults	HC	60			Money
Studer et al.	2019	Adults	HC	59			Time to view erotic stimuli
Sugiwaka and Okouchi	2004	Young adults	HC	32			Money
Suzuki et al.	2021	Adults	HC	30			Money
Westbrook et al.	2013-ex1	Adults	HC	25; 25			Money
Westbrook et al.	2013-ex2	Adults	HC	17; 16		Amount	Money
Westbrook et al.	2019	Young adults	HC	21			Money
Westbrook et al.	2023	Adults	HC; depression; remitted depression	49	36; 67		Money
Yan and Huang-Pollock	2023	Children	HC; ADHD	32	46	Amount	Money

Note: ex = study within a published article; HC = healthy control participant group; Activity = different qualitative type of effortful activity required to receive outcomes, for example, climbing stairs or walking; Amount = size of the effortful outcome, for example, $2 or $5. Domain = outcome type, for example, money or cigarettes; Q delivery = method by which participants are exposed to choices, for example, adjusting or fixed alternatives; Real/hypo = whether outcome would be received or only hypothetically received; Repeat = task administered on multiple occasions; Sign = gain or loss of effortful outcome.
[a]In some articles, studies used different types of effort, but explicit comparisons were not made.
[b]Authors only reported the total sample size but did not indicate the sample size per group.

Table A2. *Mathematical models used to describe the effort discounting function across the studies.*

Parameters	Model	Formula	Formula source	N studies	Shape
One	Hyperbolic	$V = \frac{A}{(1+l\,E)}$	Mazur (1987)	32	Convex
	Parabolic/quadratic	$V = A - l\,E^2$	Hartmann et al. (2013)	15	Concave
	Exponential	$V = Ae^{-l\,E}$	Samuelson (1937)	11	Convex
	Linear-A	$V = A - l\,E$	Hartmann et al. (2013)	7	Straight
	Linear-B	$V = A * (1 - l\,E)$	Chong et al. (2018)	2	Straight
Two	Sigmoidal	$V = A\left(1 - \left(\frac{1}{1+e^{-l\,(E-p)}} - \frac{1}{1+e^{l*p}}\right)\left(1 + \frac{1}{e^{k*p}}\right)\right)$	Klein-Flügge et al. (2015)	6	Concave and convex
	Power function	$V = A - l\,E^s$	Białaszek et al. (2017)	5	Concave and convex
	Double exponential	$V = (A - s)\ e^{-l\,E} + s$	Myerson and Green (1995)	3	Concave
	Hyperboloid-A	$V = A/(1 + l\,E)^s$	Myerson and Green (1995)	3	Convex
	Hyperboloid-B	$V = A/(1 + l\,E^s)$	Rachlin (2006)	2	Convex

Note: V denotes the subjective value, and A represents the reward magnitude. The parameter l expresses the effort discounting rate. The parameter E represents the effort requirements. The total number of studies (n = 86) does not match the number of published studies shown in Figure 1 (n = 71) because 22 of the studies compared several mathematical models.

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Table A3. *Mathematical model comparison across the studies.*

Authors	Year	Effort domain	# Models compared	Models compared to hyperbolic	Index of fit	Best-fitting model per condition/group	Level[a]
Arulpragasam et al.	2018	Physical	4	Parabolic/quadratic; linear-A; power function	AIC, BIC	Power function	Aggregate
Bernacer et al.	2016-ex1	Physical	4	Parabolic/quadratic; exponential; double exponential	Adjusted R^2	Hyperbolic	Aggregate
Bernacer et al.	2019	Physical	4	Parabolic/quadratic; exponential; double Exponential	Adjusted R^2	Parabolic/quadratic	Aggregate
Białaszek et al.	2017	Cognitive; physical	7	Parabolic/quadratic; exponential; power function; double exponential; hyperboloid-A; hyperboloid-B	AIC, BIC	Power function (both domains)	Individual and aggregate
Chong et al.	2017	Cognitive; physical	4	Parabolic/quadratic; exponential; linear-B	AIC, BIC	Cognitive: hyperbolic; physical; parabolic/quadratic	Aggregate

(Continued).

Table A3. *(Continued).*

Authors	Year	Effort domain	# Models compared	Models compared to hyperbolic	Index of fit	Best-fitting model per condition/group	Level[a]
Chong et al.	2018	Cognitive; physical	3	Parabolic/quadratic; linear-B	AIC, BIC	Cognitive: hyperbolic (non-athletes), parabolic/quadratic (athletes); physical: parabolic/quadratic (athletes and nonathletes)	Aggregate
Escobar et al.	2023	Physical	3	Power function; hyperboloid-B	AICc	First time point (Power Function). Second and third time points (hyperboloid-B)	Aggregate
Hartmann et al.	2013	Physical	3	Parabolic/quadratic; linear-A	R^2	Parabolic/quadratic	Individual and aggregate
Jurgelis et al.	2021	Physical	3	Parabolic/quadratic; linear-A	AIC, BIC	Parabolic/quadratic	Aggregate
Klein-Flügge et al.	2015-ex1	Physical	5	Parabolic/quadratic; linear-A; sigmoidal; power function	Bayesian estimation	Sigmoidal	Aggregate
Klein-Flügge et al.	2016	Physical	2	Sigmoidal	Bayesian estimation	Sigmoidal	
Macías and Valerio	2023	Physical	2	Parabolic/quadratic	AICc	Hyperbolic	Individual and aggregate

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Table A3. *(Continued).*

Authors	Year	Effort domain	# Models compared	Models compared to hyperbolic	Index of fit	Best-fitting model per condition/group	Level[a]
Massar et al.	2019	Cognitive	4	Parabolic/quadratic; exponential; sigmoidal	AIC, BIC	Sigmoidal	Aggregate
Massar et al.	2020-ex3	Cognitive	5	Parabolic/quadratic; exponential; linear-A; sigmoidal	BIC	Parabolic/quadratic	Aggregate
McGuigan et al.	2019	Cognitive	3	Parabolic/quadratic; linear-B	AIC, BIC	Linear[b]	Aggregate
Nishiyama	2014-ex1	Physical	2	Exponential	AIC, R^2	Hyperbolic	Individual and aggregate
Nishiyama	2014-ex2	Physical	2	Exponential	AIC, R^2	Hyperbolic	Individual and aggregate
Nishiyama	2014-ex3	Physical	2	Exponential	AIC, R^2	Hyperbolic	Individual and aggregate
Nishiyama	2016	Cognitive; emotional; physical	2	Exponential	AIC, R^2	No meaningful difference	Individual and aggregate
Prévost et al.	2010	Physical	2	Exponential	R^2	Hyperbolic	Aggregate
Rivera et al.	2020	Cognitive	2	Sigmoidal	Unclear: AIC or BIC	Hyperbolic	Aggregate
Soutschek and Tobler	2020	Cognitive	3	Parabolic/quadratic; linear-A	R^2	Parabolic/quadratic	Aggregate

[a]Fits were conducted on either aggregate data (mean or median indifference points from the sample) or indifference points from individuals or both.
[b]Linear model by Chong et al. (2018).

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