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People Exert More Effort to Avoid Losses Than to Obtain Gains

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Loss aversion is a fundamental tenet of behavioral economics and has led to many real-world applications. These applications, and some laboratory studies, show that people perform better under loss-avoidance than under gain incentives. This increased performance under loss-avoidance incentives has ubiquitously been explained by the notion that loss aversion causes people to exert more effort to avoid losses than to obtain gains. Only limited work, however, has directly examined whether people indeed choose to exert more effort to avoid losses than to obtain gains. Our primary aim was therefore to test this proposition. In an experiment with adults ($N = 32$) and in a subsequent experiment with children and adolescents ($N = 29$), we found that participants indeed exerted more effort to avoid losses than to obtain numerically equivalent gains. The effect sizes were large, with the effect being evident for most individual participants. As a secondary aim, in the study with adults, we also investigated whether the greater effort to avoid losses related to loss aversion measured using a task involving choices between prospects. Unexpectedly, the greater effort to avoid losses persisted robustly even after controlling for the effects of loss aversion measured using the task involving choices between prospects. We discuss two possible interpretations for this finding: our effort task may have been a more sensitive assessment of loss aversion than the task involving choices between prospects; alternatively, the processes underlying how much effort people choose to exert may partially differ from those engaged by choices between prospects.

Keywords: cost, decision making, effort, loss aversion, motivation

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The notion that "losses loom larger than equivalent gains" (Kahneman & Tversky, 1979), often called "loss aversion" (Kahneman & Tversky, 1984; Tversky & Kahneman, 1991, 1992), is one of the most influential ideas in behavioral economics. The greater impact of losses relative to gains has been consistently shown in decisions under (Abdellaoui et al., 2007, 2008; Canessa et al., 2013; Gaechter et al., 2007; Kahneman & Tversky, 1979; Tom et al., 2007; Tversky & Kahneman, 1992; Yechiam et al., 2015) and even without (Gaechter et al., 2007; Highhouse & Johnson, 1996; Tversky & Kahneman, 1991) risk. For example, in gambling situations, people are reluctant to accept a gamble with equal probabilities of winning and losing the same amount (Abdellaoui et al., 2007; Tversky & Kahneman, 1992). Loss aversion is a central tenet of prospect theory, in which losses are assigned a greater absolute subjective value than equal-sized gains are (with losses and gains measured relative to a reference state; Tversky & Kahneman, 1981). Loss aversion is also well illustrated by the "framing effect," in which choices framed as losses have a greater impact on decisions than choices framed as gains do (Kahneman & Tversky, 1984; Tversky & Kahneman, 1981). Such an effect has even been demonstrated in nonhuman primates (M. K. Chen et al., 2006; Lakshminarayanan et al., 2011; but see Krupenye et al., 2015). Moreover, there is also evidence for "neural loss aversion," indicated by steeper slopes in neural responsivity to losses compared with gains (Canessa et al., 2013; Tom et al., 2007). Loss aversion has been found in children as young as 5 years old (Steelandt et al., 2013). Lastly, the greater impact of losses, compared with gains, even if not attributed to loss aversion, can be seen not only in choices but also in other measures, such as physiological arousal (Hochman & Yechiam, 2011; Wu et al., 2016; Yechiam et al., 2015) and attention (Lejarraga et al., 2019; Yechiam & Hochman, 2013).

Taking advantage of the greater impact of losses, simple framing manipulations have proven effective in enhancing work productivity (Hossain & List, 2012) and academic performance (Fryer et al., 2012; McEvoy, 2016). For example, in a factory, framing a bonus as a loss results in higher productivity than framing it as a gain does (Hossain & List, 2012). In undergraduate classes, a grading scheme that starts with all the points upfront and deducts points throughout the semester leads to better grades in objective assessments than one that starts with zero points and awards points after each exam or assignment (McEvoy, 2016; although Apostolova-Mihaylova et al., 2015, found this effect only for males). Framing teachers' incentives through loss aversion also

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increases student performance: students perform better in an exam if teachers are paid a bonus at the beginning of the year with the possibility of having to return part of it at the end of the year, depending on student achievement, than if teachers are paid an equivalent bonus at the end of the year (Fryer et al., 2012). Most, even if not all (Porat et al., 2014), laboratory studies have replicated the finding from these field studies that participants perform better under a loss frame than under a gain frame (X. Chen et al., 2020; Hochman et al., 2014; Imas et al., 2017). The same finding was also obtained in a street experiment (Hochman et al., 2014).

Both the real-life applications (Cullen et al., 1975; Fryer et al., 2012; Hossain & List, 2012; McEvoy, 2016) and the laboratory studies replicating their findings under more controlled conditions (X. Chen et al., 2020; Hochman et al., 2014; Imas et al., 2017) were based, implicitly or explicitly, on the premise that loss aversion would lead people to exert more effort to avoid losses than to obtain gains. Little work, however, has directly examined that premise. Indeed, both field studies (Apostolova-Mihaylova et al., 2015; Fryer et al., 2012; Hossain & List, 2012; Levitt et al., 2016; McEvoy, 2016) and most corresponding laboratory studies (Hochman et al., 2014; Imas et al., 2017) have measured *performance*, not effort. Although greater effort should lead to better performance, one cannot infer from better performance that the underlying process is greater effort. Doing so is a form of abductive reasoning: inferring the cause (greater effort) from an observed consequence (better performance). Abductive reasoning is useful, but only to the extent that alternative causes can be ruled out. Gain and loss frames, however, may differentially affect performance through many processes other than effort: for example, they could have differential consequences on affective state, which could modulate performance (see, e.g., Weiss & Cropanzano, 1996), or they could differentially affect attention (Yechiam & Hochman, 2013). The existence of these alternative explanations limits the strength of the abductive inference from better performance to better effort. This abductive inference, however, is ubiquitous in the literature. In fact, a closer look at the so-called "real-effort" paradigms that are typically used to study effort in the laboratory (Carpenter & Huet-Vaughn, 2019) reveals that they all measure performance on some task, rather than explicitly measuring the choice to exert effort. From an applied perspective, the focus on performance is often justified: one wants to know under which conditions people will perform best (in their various roles as students, employees, etc.). The problem resides in treating performance as a direct measurement of effort; it is not.

Some field studies included self-report of measures that could be seen as proxies for effort—for example, student hours of work or class attendance (Apostolova-Mihaylova et al., 2015; McEvoy, 2016) or hours that teachers spent performing various duties (Fryer et al., 2012)—but did not focus on how these measures varied as a function of the loss versus gain framing. In fact, these studies used these measures mostly as nuisance independent variables (Apostolova-Mihaylova et al., 2015; McEvoy, 2016), rather than as dependent variables, or, at best, analyzed them cursorily in tables with summary statistics, with null findings (Apostolova-Mihaylova et al., 2015; Fryer et al., 2012). Two field studies, however, provide more direct evidence for increased effort under loss than gain frames (Cullen et al., 1975; Merriman & Deckop, 2007). Specifically, students are more likely to complete an assignment if failing to complete it leads to a deduction of points than if completing it leads to a point bonus (Cullen et al., 1975), and employees who perceive their future bonus payments as amounts that can be lost report more effort at work (in addition to having better work performance) than employees who perceive those future bonus payments as potential gains (Merriman & Deckop, 2007). Still, the evidence from both studies, while certainly suggestive of increased effort under a loss frame, must be considered tentative. In the first study (Cullen et al., 1975), as the authors themselves note, gains and losses were inherently asymmetric because, for many students, a point loss could be the difference between a passing and a failing grade, which has much more meaningful ramifications than a grade improvement by an equivalent point gain. The second study (Merriman & Deckop, 2007) was observational and correlational, so it could not establish a causal relation between the perception of the future payment as a potential loss and the increased effort at work; moreover, effort was measured through self-report.

Further tentative evidence for greater effort under loss frames comes from the finding, in the laboratory, that participants work longer on tasks under a loss than under a gain frame (Hochman et al., 2014). This increased time on task is suggestive of greater effort, but, again, that interpretation is tentative. In fact, increased time could conceivably even reflect *less*, not more, effort, which would prolong the time needed for task completion (see, e.g., Trautwein, 2007). Moreover, participants reported that the task was more difficult under the loss frame (although objectively it was the same), which might explain why they spent longer working on it. In addition, task performance was irrelevant for participants' outcomes, so it is unclear that the longer times reflected effort to perform better on the task. On the other hand, participants also reported that they "were more motivated to work and invest more effort" under the loss frame, which does suggest, albeit through self-report, that indeed they might have exerted more effort under the loss frame.

The most direct evidence that people explicitly *choose* to exert more effort to avoid losses than to obtain gains comes from a recent laboratory study, published after the present work was finished, that separated the choice to exert effort from the subsequent execution of the effortful task (X. Chen et al., 2020). (As discussed below, we used the same approach.) That study found that young healthy adults, older healthy adults, and medicated patients with Parkinson's disease all chose to exert more effort to avoid losses than to obtain gains. Although that study provides perhaps the most compelling evidence that people choose to exert more effort to avoid losses, it has some limitations. The most important of those limitations is that, in both gain and loss-avoidance trials, successful trial execution was signaled by a cash-register sound, preceding trial feedback. A cash-register sound seems intuitively associated with gains, so it could have confounded the loss-avoidance trials. Moreover, the study included two separate blocks, one with only gain trials and the other with only loss-avoidance trials (with order counterbalanced across participants). For participants who had the gain block first, the cash-register sound could have become a positive conditioned reinforcer because of its pairing with the ensuing gains (with such conditioning possibly being potentiated by the intuitive association between a cash-register sound and gains). In that case, successful trial execution in the subsequent loss-avoidance block could be doubly reinforced: by both the avoidance of the loss and by the positive conditioned reinforcer. In turn, this double reinforcement in loss-avoidance trials could explain why effort was greater in those trials, for participants who had the gain block first. (The study did not analyze separately the data from participants with each block order.)

For completeness, we should note that two additional laboratory studies explicitly claimed to have shown increased effort under a loss than under a gain frame (Brooks et al., 2012; Hannan et al., 2005). In these studies, however, participants did not actually have to exert effort. Instead, consistent with a common tradition in economics, the studies used "stated effort" paradigms, in which "effort" is operationalized as a monetary cost (Charness et al., 2018). Despite some evidence showing similarities between this (artificial) operationalization of effort and true effort (Brüggen & Strobel, 2007; Dutcher & Salmon, 2015), the extent to which stated effort paradigms measure something akin to effort is questionable, so the field has tended to move away from these paradigms (Carpenter & Huet-Vaughn, 2019; Charness et al., 2018).

A further limitation with nearly all studies that have investigated performance under gain versus loss frames, both in the field and in the laboratory, is that these studies have used paradigms comparing pre- versus postpayment conditions (Apostolova-Mihaylova et al., 2015; Cullen et al., 1975; Fryer et al., 2012; Hochman et al., 2014; Hossain & List, 2012; Imas et al., 2017; McEvoy, 2016). In these paradigms, in the prepayment condition, participants are paid at the beginning of the experiment and may have to return part of that payment at the end of the experiment if they fail to meet a certain performance objective; in the postpayment condition, participants are paid at the end of the experiment, depending on their performance. The pre- and postpayment conditions constitute the loss and gain frames, respectively. The exact "payment" varies from study to study and can be in the form of money (Fryer et al., 2012; Hochman et al., 2014; Hossain & List, 2012), goods (Imas et al., 2017), or, for undergraduate students, grade points (Apostolova-Mihaylova et al., 2015; McEvoy, 2016), but the logic of the studies is the same. From an applied perspective, this focus on pre- versus postpayment manipulations makes perfect sense because these are precisely the types of contingences that can be manipulated easily in applied settings (e.g., through contracts or grading schemes). In terms of understanding the detailed psychological processes involved, however, this simple manipulation is subject to three important confounds, as discussed next.

The first key confound in pre- versus postpayment paradigms is that the two conditions likely elicit different demand characteristics. Specifically, the prepayment condition likely communicates more strongly to participants that the default behavior is to comply with the performance requirements, and participants may comply with this perceived expectation (Brooks et al., 2012; but see Hochman et al., 2014). This effect may be useful in real-life applications, but it constitutes a confound if the goal is to isolate the effects of losses versus gains on behavior.

A second confound in pre- versus postpayment paradigms is delay discounting. People discount future rewards relative to immediate rewards (Odum, 2011). In pre- versus postpayment paradigms, the payments are setup such that the pre- and postpayments are the same—that is, a given level of performance is paid the same amount under both conditions. By making the payments *objectively* the same under both conditions, however, these paradigms pay a *subjectively* lower amount in the postpayment condition because of the delay involved until payment in that condition. In turn, this could explain why people would perform worse in that condition. Such a confound could affect even experiments in which the delay until postpayment is only minutes, as people show delay discounting down to the level of minutes and even seconds (Lane et al., 2003; Lukinova et al., 2019). In fact, even activation in the ventral striatum for reward-predicting stimuli shows modulation by delays of just a few seconds (Gregorios-Pippas et al., 2009).

The final confound in pre- versus postpayment paradigms that we will mention, which applies specifically if one is seeking to isolate the effects of effort, is that these two conditions may conceivably induce different affective or mood states (not to mention potentially different living standards in field experiments). Affect and mood can influence performance in many ways other than effort (Weiss & Cropanzano, 1996), and the pre- versus postpayment design encumbers the disentanglement of these contributions.

To summarize the preceding discussion, there is substantial evidence, from both field and laboratory studies, that people *perform better under pre- than under postpayment incentives*. A likely explanation for this finding is that people *exert more effort under loss than under gain incentives*, but the evidence for this proposition is subject to various confounds, so it cannot be considered definitive. Our primary aim in this study was therefore to determine conclusively whether people indeed explicitly choose to exert more effort to avoid losses than to attain numerically equivalent gains. In a first experiment, we investigated this question in adults; in a second experiment, we replicated our findings in children and adolescents.

As a secondary, more exploratory aim, we also investigated the relation between the tendency to exert more effort to avoid losses and loss aversion assessed by a task involving choices between prospects (in the experiment with adults). Although the real-world applications (Fryer et al., 2012; Hossain & List, 2012; McEvoy, 2016) and the closely related laboratory findings (Hochman et al., 2014; Imas et al., 2017) were motivated by the vast laboratory evidence for loss aversion (Abdellaoui et al., 2007, 2008; Canessa et al., 2013; Gaechter et al., 2007; Highhouse & Johnson, 1996; Kahneman & Tversky, 1979, 1984; Tom et al., 2007; Tversky & Kahneman, 1981, 1991, 1992; Yechiam et al., 2015), there is an unappreciated conceptual and empirical gap between these two domains. Loss aversion has been established using laboratory tasks that involve choices between prospects involving gains and losses (Abdellaoui et al., 2007, 2008; Canessa et al., 2013; Gaechter et al., 2007; Highhouse & Johnson, 1996; Kahneman & Tversky, 1979, 1984; Tom et al., 2007; Tversky & Kahneman, 1981, 1991, 1992; Yechiam et al., 2015). The real-life applications (Cullen et al., 1975; Fryer et al., 2012; Hossain & List, 2012; McEvoy, 2016) and the closely related laboratory findings (Hochman et al., 2014; Imas et al., 2017), however, do not involve such choices; instead, they use different incentive structures, often across different participants, and find that incentives cast as avoidable losses produce better results than incentives cast as gains do.

We are aware of only one published study that has sought to bridge between these domains (Imas et al., 2017). That study related performance on a task under gain and loss frames to loss aversion measured using choices between prospects. Unfortunately, the results were inconclusive. The study found a marginally significant relation between loss aversion and performance under the loss but not under the gain frame, as predicted, when performance under the two frames was analyzed in separate analyses. However, when performance was analyzed in a single analysis, there was no interaction between loss aversion and the type of frame (loss vs. gain). Moreover, this study measured performance, which, as noted above, is only an indirect proxy for effort.

Although a link between loss aversion and greater effort to avoid losses is intuitive, it is not tautological or self-evident, for at least four reasons. First, stimuli with positive valence, such as gains, and stimuli with negative valence, such as losses, have been associated with behavioral activation and behavioral inhibition, respectively (Guitart-Masip et al., 2014). Given that effortful behavior requires behavioral activation, these associations might suggest that effort could be greater to obtain gains than to avoid losses. Second (but relatedly), increased dopamine is associated with greater effort (Beierholm et al., 2013; Hamid et al., 2015; Salamone et al., 2018), and dopamine plays a particularly prominent role in reward processing (Schultz, 2013), which might also imply that effort would be greater in gain contexts (but see more nuanced discussion of the role of dopamine in both gain and loss-avoidance contexts in the Discussion section). Third, approach and avoidance motivation have been suggested to form two fundamental characteristics of temperament (Elliot & Thrash, 2002, 2010), so there could be substantial variation in the extent to which individuals exert effort to obtain gains versus to avoid losses. Fourth, other theories of personality suggest that the same "behavioral approach system" might be engaged by situations of reward and nonpunishment (Gray, 1990)—corresponding, in our case, to gains and loss avoidance, respectively—which might suggest that effort could be the same in both cases.

To assess whether people exert more effort to avoid losses than to attain numerically equivalent gains, we used a task that had been used previously to study participants' willingness to exert effort for gains only (Gold et al., 2013), modifying it to include both gain and loss-avoidance trials. We also modified the task to minimize possible confounds with delay discounting and risk discounting. We chose this task because, rather than measuring performance, it involves explicit decisions between engaging in a high-effort (HE) or a low-effort (LE) option, so it directly assesses participants' willingness to exert effort. Moreover, with our modification, the task allowed us to assess participants' willingness to exert effort as a function of various magnitudes of gain and loss, in a within-subjects design. Finally, as discussed in more detail below, the task minimizes the problems with pre- versus postpayment paradigms identified above.

To allow us to investigate the relation of relative effort in loss-avoidance versus gain trials to loss aversion assessed with a more classical (i.e., non-effort-related) paradigm, participants in the experiment with adults also performed a gambling task that we developed to estimate loss aversion using choices between prospects. Participants in the experiment with children and adolescents did not perform this task because their data was collected as part of a different project involving children and adolescents with psychiatric disorders (that did not include that task). The data for children and adolescents that we present in this article pertains to the participants recruited as controls for that project.

Method

Participants

Participants in the experiment with adults were 32 young adults (21 women, age range = 20–28 years) recruited at a biomedical research institute in Lisbon (Instituto de Medicina Molecular, Faculdade de Medicina, Universidade de Lisboa, Portugal). Participants in the experiment with children and adolescents were 29 children and adolescents (15 female, age range = 7–17 years, M_{age} = 11.4 years, SD = 2.9) recruited as controls for the aforementioned project with children and adolescents with psychiatric disorders. Both experiments complied with all relevant ethical regulations and were approved by the joint Ethics Commission of the Lisbon Academic Medical Center and Centro Hospitalar Lisboa Norte. All participants in both experiments provided written informed consent. In the experiment with children and adolescents, parents or other legal guardians of all children and adolescents also provided written informed consent. Participants were not compensated financially in either experiment.

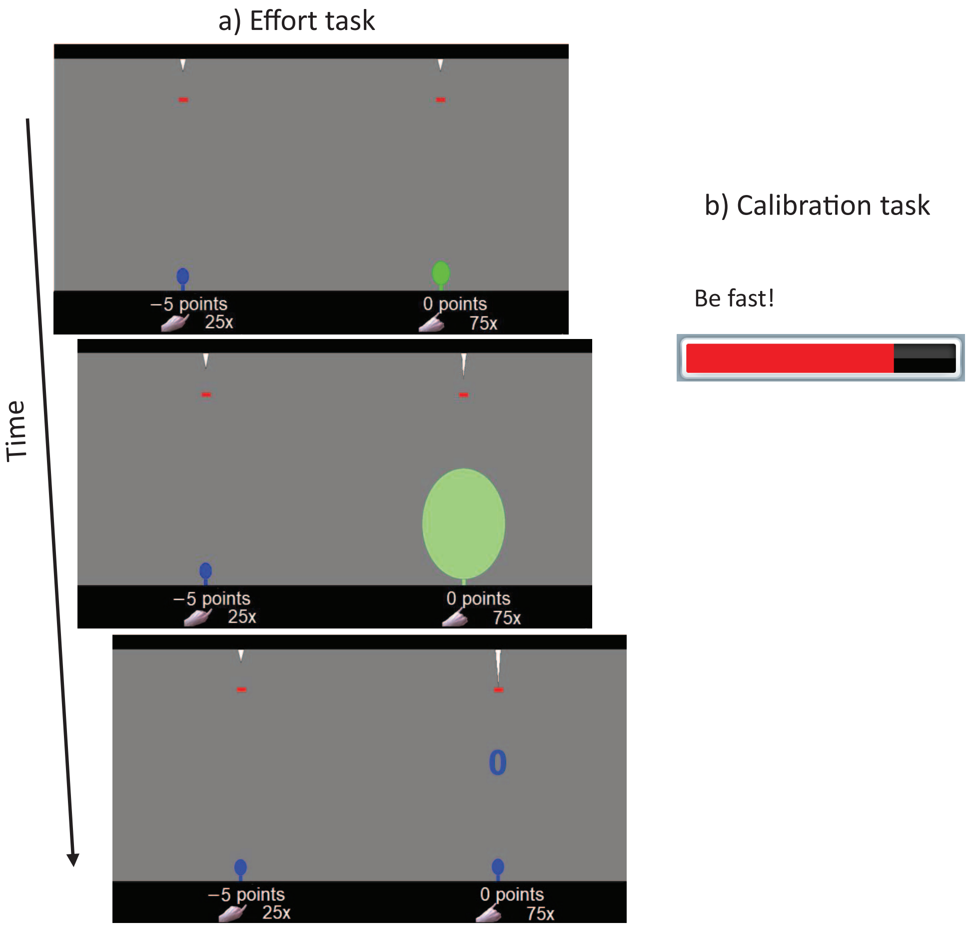
Materials and Procedure

Effort Task

On each trial of the effort task, participants had to inflate one of two balloons; one balloon corresponded to a low-effort (LE) option (pressing the spacebar 25 times with the index finger of the nondominant hand) and the other to a high-effort (HE) option (pressing the spacebar 75 times with the pinky finger of the nondominant hand; Figure 1a). Trials belonged to one of two conditions: gain or loss-avoidance. In gain trials, the HE option resulted in a gain of points, and the LE option did not win or lose points; in loss-avoidance trials, the LE option resulted in a loss of points, and the HE option prevented that loss, not winning or losing points. In both trial types, therefore, the HE was more advantageous (winning points in gain trials and avoiding point loss in loss-avoidance trials). Trials varied in the magnitude of gain or loss involved, with absolute values consisting of all integers between 1 and 6. In other words, the points that could be won by choosing the HE option in gain trials were 1, 2, 3, 4, 5, and 6; similarly, the points that could be lost by choosing the LE option in loss-avoidance trials were −1, −2, −3, −4, −5, and −6. There were therefore 12 trial types: six magnitudes for each of the two conditions (gain and loss-avoidance).

At the start of each trial, the points and effort associated with each balloon were indicated below the corresponding balloon (Figure 1a, top). Participants had to choose to inflate the balloon on the left or right by pressing a left or right button, respectively. If the participant took longer than 8 s to choose, an aversive sound occurred together with a screen message urging the participant to choose. When participants made their choice, the chosen balloon turned green, and the peak in the ceiling above that balloon started to fall toward the corresponding red line (Figure 1a, middle). Participants inflated the balloon by pressing the spacebar; they had to inflate the balloon until the red line before the peak reached that line. The time that the peak took to reach the red line corresponded to a previously determined individual calibration time for the participant obtained using a calibration task (described below). If

Figure 1
Example Trials of the (a) Effort and (b) Calibration Tasks



Note. On each trial of the effort task (a), participants had to inflate one of two balloons. The trial shown in the figure is a loss-avoidance trial with outcomes −5 and 0 for the low-effort (LE) and high-effort (HE) options, respectively. On each trial of the calibration task (b), participants filled a bar by pressing the spacebar 75 times with the pinky finger of their nondominant hand as fast as they could. The experiment was conducted in Portuguese; we show all screenshots in English to facilitate comprehension. All items shown in the screenshots were clearly visible to participants, but in the scaled screenshots in panel a, the red line and the text became difficult to see; we selectively enlarged those items here to better illustrate what participants saw.

the balloon reached the red line before the peak did, the trial was successful, but feedback was only shown after the peak reached the red line. This procedure ensured that, for each participant, the reinforcement delay was constant across all trials (thereby eliminating confounds because of delay discounting, as discussed below). If the participant was unable to inflate the balloon until the red line before the peak reached the line, the trial was repeated. This procedure was aimed at minimizing the influence on choice of participants' potential different expectations about the likelihood of successfully completing HE versus LE options (thereby minimizing confounds because of risk discounting, as discussed below). If the participant finished inflating the balloon before the peak reached the line, when the peak did hit the line, the balloon disappeared, and the participant was shown feedback with the number of points that corresponded to the chosen balloon (Figure 1a, bottom); the total accumulated points were not shown.

The task was divided into continuous (nonsignaled) blocks, with each block consisting of one trial for each of the 12 trial types, in random order. In each block, the HE choice appeared 50% of the time on the left side and 50% of the time on the right side. In the experiment with adults, the task consisted of four blocks; in the experiment with children and adolescents, it consisted of three blocks (so that it was shorter and therefore more amenable to children). There were no other differences in the task between the two experiments.

Participants were told that they started with 0 points and that their goal was to have as many points as possible at the end of the game. They were instructed about all possible trial types and underwent a brief four-trial training phase to become acquainted with the task. The training phase was equal to the effort task but consisted of only four predetermined trials: two gain trials (0 vs. 1 and 0 vs. 6) and two loss-avoidance trials (−1 vs. 0 and −6 vs. 0).

These trials were presented in a fixed but intermingled order. Participants were advised to choose the HE balloon on some trials and the LE balloon on others to get a better sense for the effort required in each. They were informed that points in this phase did not matter.

An important but often neglected consideration in effort-discounting tasks is the possible confound with delay discounting and/or risk discounting. Delay and risk discounting can be confounds because performing the HE option often takes longer and is associated with a greater probability of failing (Chong et al., 2016). Results that are attributed to effort discounting may therefore, in some cases, be attributable, in whole or in part, to delay and/or risk discounting. To eliminate confounds because of differential delays, our version of the task used a common fixed reinforcement delay for all LE and HE options (obtained individually for each participant from a prior calibration task; see below). To minimize confounds because of differential probabilities of success, participants could repeat a trial if they failed to terminate it in time. To further preclude interpretational difficulties because of probability discounting, successful completion of a trial led deterministically to the outcome shown. In short, our task allowed the direct comparison of effort for outcomes with the same magnitude in gain versus loss-avoidance conditions while controlling for delay and risk discounting (but see section "Limitations in the Control for Risk Discounting in the Effort Task" in the online supplemental material).

Our task minimizes, to the extent possible, the important confounds that affect pre- versus postpayment paradigms (discussed above). The first confound is that the pre- and postpayment conditions likely induce different demand characteristics. In our task, gain and loss-avoidance trials are continuously intermixed, and the stated goal is simply to end up with as many points as possible, so this differential effect on demand characteristics should be minimized. The second confound is that delay discounting differentially affects the subjective value of the payment in the pre- versus postpayment conditions. Our task is carefully designed so that the delay to the outcome is exactly the same in all trials and therefore in loss-avoidance and gain conditions. The final confound is that the pre- versus postpayment conditions might differentially impact affect and mood, which could influence performance in ways other than effort. In our task, we explicitly measure the willingness to exert effort; in addition, the rapid succession of intermixed loss-avoidance and gain trials should minimize differences in affective or mood states between the loss-avoidance and gain conditions.

Calibration Task

Before execution of the effort task, participants performed a calibration task designed to obtain a participant-specific calibration time that was used subsequently to normalize the difficulty of the effort task. In the calibration task, on each trial, participants pressed the spacebar as fast as they could 75 times with the pinky finger of their nondominant hand to fill a bar presented in the middle of the screen (Figure 1b). The task had five trials. (Pilot tests indicated that more trials tended to induce excessive boredom and fatigue.) We defined each participant's individual calibration time as the average of the times for the last four trials. Handedness was assessed using the Edinburgh Handedness Inventory (Oldfield, 1971). Participants were not told that performance on this task would be used to calibrate the effort task. The calibration task was equal in the experiment with adults and the experiment with children and adolescents.

Gambling Task

In the study with adults, following completion of the effort task, participants completed a gambling task that we developed to estimate loss aversion using choices between prospects. In this task, motivated by others (Abdellaoui et al., 2007, 2008; Zhong et al., 2009), participants were presented with gambles with the same (50%) probability of gaining or losing potentially different numbers of points (Figure S1 in the online supplemental materials). (All figures whose number is preceded by an "S" are found in the online supplemental materials.) On each trial, participants could choose the gamble or a safe choice with 100% probability of not winning or losing points. The points presented in the gamble were adjusted dynamically using the bisection method (Figures S2 and S3 in the online supplemental materials) so as to calculate *indifference points*: gambles whose acceptance and refusal are equally likely (Abdellaoui et al., 2007, 2008). We calculated 12 indifference points for each participant: the negative equivalents for the positive integers between 1 and 6, and the positive equivalents for the negative integers between -1 and -6 (i.e., we calculated equivalents for all values used in the effort task).

Data Analysis

We analyzed the data using MATLAB R2015a and R Version 3.5.2. To detect and remove outliers using Cook's distance (see below), we used R packages influence.ME (Nieuwenhuis et al., 2012) and lme4 (Bates et al., 2015).

Effort Task

For the main analyses of the effort task, we used mixed-effects logistic regression, with the proportion of HE trials as the dependent variable and with magnitude (1, 2, . . . , 6) and valence (gain vs. loss) as the independent variables. The most general formulation of the model was:

$$\log\frac{p(\mathrm{HE})}{1-p(\mathrm{HE})} = \beta_{\mathrm{i}} + \beta_{\mathrm{i,diff}} \times \mathit{LossTrial} + \beta_{\mathrm{s}} \times \mathit{Magnitude} + \beta_{\mathrm{s,diff}} \times \mathit{LossTrial} \times \mathit{Magnitude},$$

where the "i" and "s" subscripts represent intercepts and slopes, respectively, the "diff" subscript represents a difference between loss-avoidance trials and gain trials, *LossTrial* is 1 in loss-avoidance trials and 0 in gain trials, and *Magnitude* represents the absolute value of the trial loss or gain. Hence, $\beta_{\mathrm{i,diff}}$ and $\beta_{\mathrm{s,diff}}$ represent the difference in intercept and slope, respectively, between loss-avoidance and gain trials. We used model selection, using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), to test whether the data was best captured by this more general model or by its nested models: a model with different intercepts but a common slope (i.e., with $\beta_{\mathrm{s,diff}} = 0$), a model with different slopes but a common intercept (i.e., with $\beta_{\mathrm{i,diff}} = 0$), or a model with common intercept and slope (i.e., with $\beta_{\mathrm{s,diff}} = 0$ and $\beta_{\mathrm{i,diff}} = 0$). In all models, all coefficients had both fixed and random effects, following the recommendation to include the maximal random-effects structure justified by the design (Barr et al., 2013). Both the AIC and the BIC indicated that the best model had different intercepts but a common slope (see Results); therefore, the difference in HE choices between loss-avoidance and gain trials was captured by the intercept, $\beta_{i,diff}$. To assess the significance of this intercept, we used a likelihood ratio test (see, e.g., Barr et al., 2013; Singmann & Kellen, 2020). We conducted exactly the same analyses of the effort task in the experiment with adults and the experiment with children and adolescents.

Gambling Task

As mentioned above, in the study with adults, we used the gambling task to obtain a set of 12 indifference points for each participant (Figure S1 in the online supplemental materials), where each indifference point consists of a pair with equivalent negative and positive values. We analyzed the data using a simple linear mixed model in which the dependent variable was the positive component of the indifference point, and the independent variable was the absolute value of the negative component of the indifference point. We fixed the intercept at 0 and estimated the slope. Each participant's individual slope, λ, was given by the sum of the slope's fixed effect and the slope's random effect for that participant. The resulting slope, λ, represents the participant's loss-aversion coefficient (i.e., how the participant values losses relative to numerically equivalent gains). Depending on whether λ is larger or smaller than 1, the participant is *loss averse* or *gain seeking*, respectively (i.e., the participant tends to emphasize losses more than gains or vice versa, respectively; Abdellaoui et al., 2007, 2008). When testing whether the fixed effect for λ was significantly greater than 1, we used the Satterthwaite approximation to the denominator degrees of freedom (see, e.g., Kuznetsova et al., 2017).

Visual inspection of the data at the individual-participant level showed that some points were clear outliers and violated a participant's own preferences (see Results). We therefore removed from analysis points with a Cook's distance greater than three times the mean Cook's distance.

Relation Between the Effort and Gambling Tasks

In the study with adults, we assessed whether increased effort in the loss-avoidance condition was explained away by the measure of loss aversion obtained in the gambling task, using three approaches. First, we assessed the correlation between a coefficient that captured increased effort in loss-avoidance trials and λ (see Results). Second, we transformed the magnitude of the losses by multiplying their absolute value by λ, thereby bringing losses and gains into a common magnitude scale that already accounted for the loss aversion measured in the gambling task. We tested whether participants still exhibited more effort for loss-avoidance than for gain trials in this transformed scale; if so, then their hypothesized increased effort in loss-avoidance than in gain trials would not be explained away by the measure of loss aversion obtained in the gambling task. Third, we transformed the magnitude of losses or of gains (in two separate analyses) using the specific equivalent values obtained empirically in the gambling task, as another way of bringing losses and gains into a common magnitude scale; then, again, we tested whether participants still exhibited more effort for loss-avoidance than for gain trials after these transformations.

Results

Effort Task

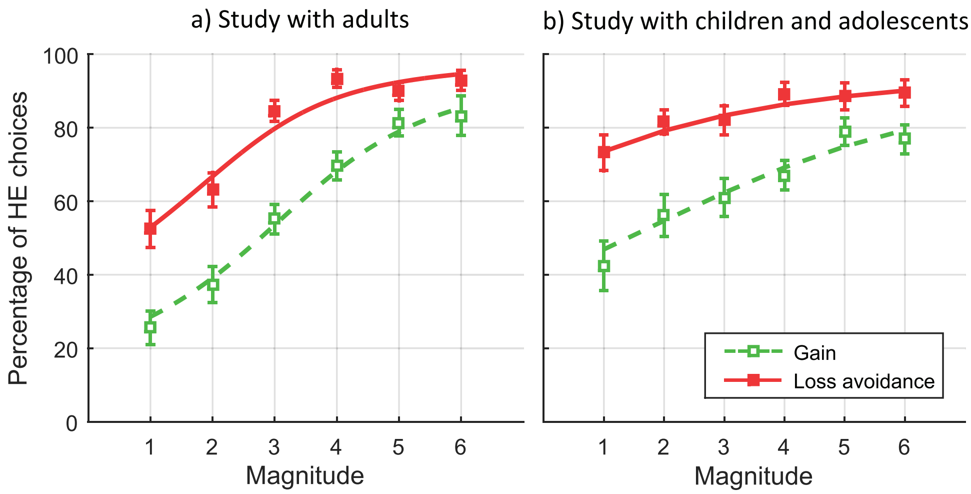
Data collection in the experiment with children and adolescents started after data had been collected and analyzed in the experiment with adults. In fact, we first wanted to ensure that we obtained robust findings in adults before starting to use the task in children and adolescents. Thus, the findings in the experiment in children and adolescents truly constitute an independent replication, in a sample with a very different age range, of the findings in adults. Still, given that the data analyses and findings are completely parallel in both experiments, for simplicity we present the findings from both experiments together.

Participants exerted more effort in loss-avoidance than in gain trials in both experiments (see Figure 2). This effect was so robust that it was shown individually by most participants in both experiments (see Figure 3). The overall mean percentage of HE choices was significantly larger for loss-avoidance than for gain trials (79% vs. 59%, respectively, for the experiment in adults, and 84% vs. 64%, respectively, for the experiment in children and adolescents), with a large effect size, in both the experiment with adults, $t(31) = 6.72$, $p < .001$, Cohen's $d = 1.19$, 95% confidence interval (CI) for the difference [14%, 27%], and the experiment with children and adolescents, $t(28) = 4.67$ $p < .001$, Cohen's $d = 0.87$, 95% CI for the difference [11%, 29%] (Figure S4 in the online supplemental materials). This effect was also shown individually by most participants in both experiments (Figure S4 in the online supplemental materials).

To better characterize the effects of valence (loss avoidance vs. gain) on effort across the various magnitudes (1 through 6), we used the aforementioned mixed-effects logistic regression with choice as the dependent variable, and with valence and magnitude as independent variables. We used model selection to test whether the data was better characterized by an effect of valence on the intercept, the slope (the coefficient that multiplies the magnitude), both, or neither. Both the AIC and the BIC indicated that the best model had a different intercept for loss-avoidance versus gain trials but the same slope (i.e., magnitude had the same effect across the two valences) in both experiments (see Table 1). The BIC provided extremely strong evidence that this was the best model: in both experiments, the Schwarz weights showed that the probability of this model being the best model was approximately 1 (Wagenmakers & Farrell, 2004); moreover, all other models had BIC values that were larger by well more than 10 (Raftery, 1995). The evidence provided by the AIC was less definitive in the comparison between the model with two intercepts and one slope versus the model with two intercepts and two slopes, especially in the experiment in adults, but it also favored the former model considerably (Burnham & Anderson, 2002); specifically, the ratio of the Akaike weights (Wagenmakers & Farrell, 2004) showed that the model with two intercepts and one slope was 4.56 and 49 times more likely than the model with two intercepts and two slopes in the experiment with adults and the experiment with children and adolescents, respectively, when using the AIC—which is notable because the AIC tends to underpenalize model complexity, thereby

Figure 2

Group Results in the Effort Task in (a) the Study With Adults (N = 32) and (b) the Study With Children and Adolescents (N = 29)



Note. The figure shows the mean (±*SEM*) percentage of high-effort (HE) choices in gain (open green squares) and loss-avoidance (filled red squares) conditions for each magnitude (integers between 1 and 6). Error bars represent within-subjects *SEM*s by applying Morey's correction (Morey, 2008). Lines—dashed green and solid red for the gain and loss-avoidance conditions, respectively—represent the fit from a mixed-effects logistic regression for each study (see Method). See the online article for the color version of this figure.

favoring more complex models (Dziak et al., 2019). The finding that the best model had two intercepts but one slope is consistent with the approximately parallel nature of the curves for the two valences in both experiments (see Figure 2). In the chosen model, the coefficient that captured the difference in intercept for the loss-avoidance trials relative to the gain trials, $\beta_{i,diff}$, was positive, indicating more effort in loss-avoidance trials, and strongly significant, in both the experiment with adults, $\chi^2(1) = 14.28$, $p <$ .001, and the experiment with children and adolescents, $\chi^2(1) = 9.00$, $p < .001$. This coefficient was also large: 1.45, 95% CI [1.04, 1.86], in the experiment with adults, and 1.40, 95% CI [0.86, 1.93], in the experiment with children and adolescents, which means that the odds ratio (*OR*) was 4.26, 95% CI [2.83, 6.42], in the experiment with adults, and 4.06, 95% CI [2.36, 6.89], in the experiment with children and adolescents. In other words, the odds of choosing the HE option over the LE option were 4.26 and 4.06 times greater in a loss-avoidance trial than in a gain trial with the same magnitude in the experiment with adults and the experiment with children and adolescents, respectively. (The close correspondence between the numerical value of the *OR* in the two experiments, with such different age ranges, is striking.) Moreover, this coefficient was positive for every individual participant in both experiments (Figure S5 in the online supplemental materials). After failing to successfully complete a HE option, participants in the experiment with adults were more likely to retry it in loss-avoidance than in gain trials (section "Analysis of Failed Trials" in the online supplemental materials), which provides further evidence for increased effort in loss-avoidance relative to gain trials.

There was no correlation between calibration time and total effort, represented by the total proportion of HE choices, in either the experiment with adults, $r(30) = .04$, $p = .843$, 95% CI [−.32, .38], or the experiment with children and adolescents, $r(26) = -.16$, $p = .418$, 95% CI [−.50, .23]. (Calibration data for one of the children was missing.) Visual inspection also did not suggest any systematic nonlinear relation between calibration time and total effort in either experiment (Figure S6 in the online supplemental materials). Furthermore, entering the calibration time as a subject-level covariate in the mixed-effects logistic regression for each experiment did not change any of the findings (not shown).

Gambling Task

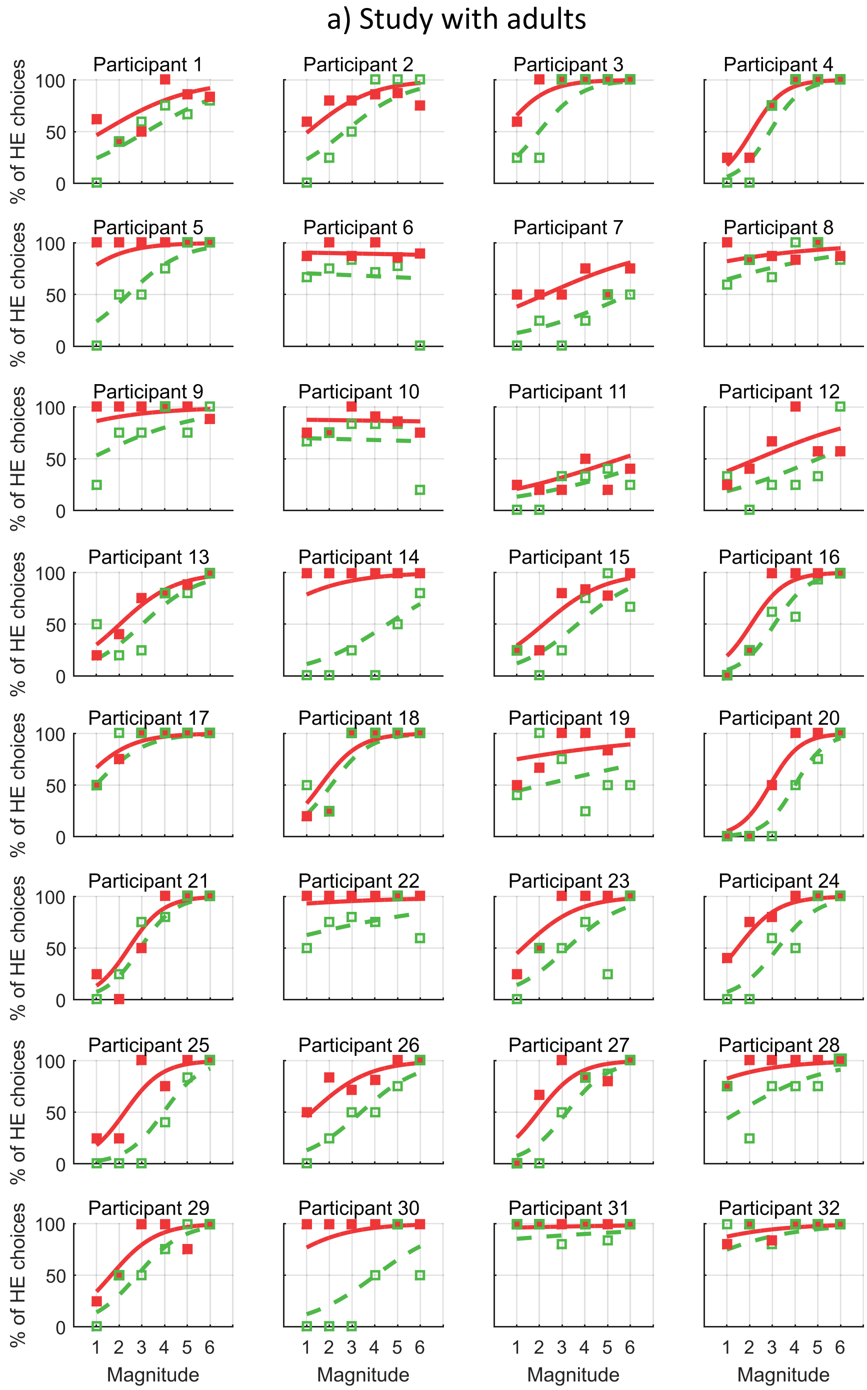
Visual inspection of the data for the gambling task in the study with adults showed some outlying data points that violated consistency within individual participants (Figure S7 in the online supplemental materials). We therefore removed outliers using Cook's distance. This procedure excluded 22 out of the 384 indifference points (6%) and resulted in better fits at the individual-participant level (Figure S7 in the online supplemental materials), smaller residuals closely clustered around 0 (Figure S8 in the online supplemental materials), and a substantially better fit overall (R^2 for the simple linear mixed model of .70 vs. .59 in the analyses without and with outliers, respectively). The fixed-effect for the loss-avoidance coefficient, λ, was significantly greater than 1, $F(1, 29.65) = 6.03$, $p = .020$, $\lambda = 1.18$, 95% CI [1.04, 1.32], showing that, on aggregate, participants were loss averse (see Figure 4).

Relation Between the Tasks

We tested whether the participants who exerted more effort in loss-avoidance relative to gain trials in the effort task also exhib-

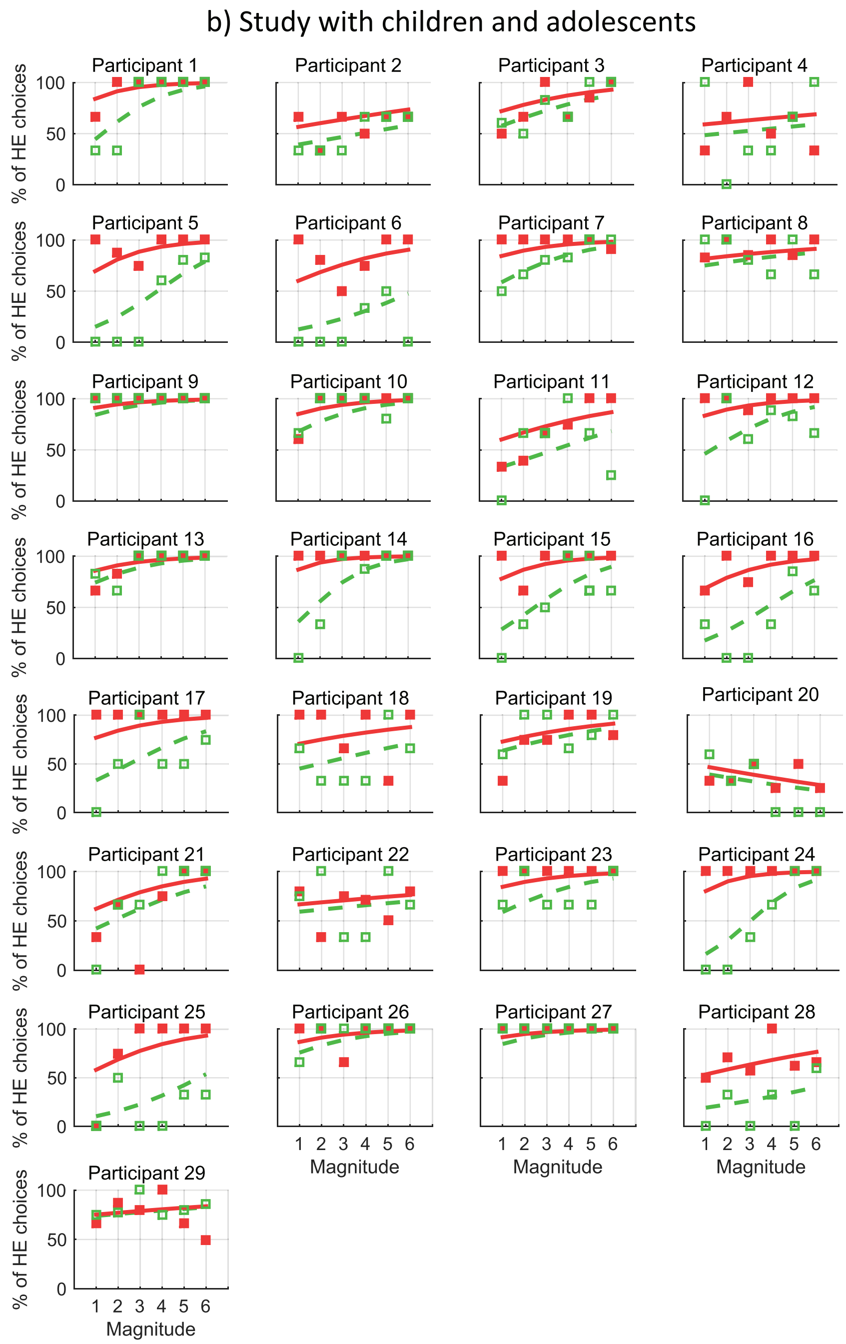
Figure 3

Individual Results in the Effort Task in (a) the Study With Adults and (b) the Study With Children and Adolescents



Note. The figure shows the percentage (%) of high-effort (HE) choices for each participant, in gain and loss-avoidance conditions, for each magnitude (integers between 1 and 6). Squares represent the data, with open green squares and solid red squares representing the gain and loss-avoidance conditions, respectively. Lines represent the individual fit obtained by summing the individual's random effects to the fixed effects from a mixed-effects logistic regression for each experiment (see Method); dashed green and solid red lines represent the gain and loss-avoidance conditions, respectively. See the online article for the color version of this figure. (*Figure continues on next page.*)

Figure 3. (*continued*)



ited more loss avoidance in the gambling task, in the study with adults, by assessing the Pearson correlation between the values of $\beta_{i,diff}$ and λ (considered for individual participants by adding each participant's random effect to the fixed effect). That correlation was small and not significant, $r(30) = .14$, $p = .443$, 95% CI [−.21, .47] (Figure S9 in the online supplemental materials), suggesting that the increased effort in loss-avoidance trials might not derive mainly from loss aversion as measured with the gambling task. Of course, such an argument is based on arguing for the null hypothesis (of no correlation), which is always fraught with difficulties. A more direct demonstration that the increased effort in loss-avoidance trials goes beyond the effect of loss aversion measured with the gambling task comes from the finding that when the losses from the effort task were multiplied by the individual loss aversion λ coefficients, the $\beta_{i,diff}$ coefficient remained positive and highly significant, $\chi^2(1) = 11.65$, $p < .001$, $\beta_{i,diff} = 1.31$, 95% CI [0.87, 1.77], $OR = 3.71$, 95% CI [2.39, 5.87] (see Figure 5). In fact, the effect was almost as large as when

Table 1
Model Comparison

Measure	1 Intercept, 1 slope	2 Intercepts, 1 slope	1 Intercept, 2 slopes	2 Intercepts, 2 slopes
		Adults		
AIC	1,019	890	926	893
ΔAIC	129	0	36	3
wAIC	~0	0.82	~0	0.18
BIC	1,039	925	962	949
ΔBIC	114	0	37	24
wBIC	~0	~1	~0	~0
		Children and adolescents		
AIC	792	708	734	716
ΔAIC	84	0	26	8
wAIC	~0	0.98	~0	0.02
BIC	812	743	769	770
ΔBIC	69	0	26	27
wBIC	~0	~1	~0	~0

Note. The table shows, for both the experiment with adults (top) and the experiment with children and adolescents (bottom), (1) the values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for each of the four models tested; (2) the differences in AIC values, ΔAIC, between the AIC for each model and the AIC for the best model (Burnham & Anderson, 2002), as well as the differences in BIC values, ΔBIC, between the BIC for each model and the BIC for the best model (Raftery, 1995); (3) the Akaike weights (wAIC) and Schwarz weights (wBIC) for each model, which can be interpreted as the probability that the model is the best model, given the data and the set of candidate models, using the AIC and BIC, respectively (Wagenmakers & Farrell, 2004). In both experiments, both the AIC and the BIC indicate that the best model is the model with 2 intercepts and 1 slope. Values of AIC and BIC were rounded to integers; values of wAIC and wBIC were rounded to two decimal places; values of wAIC and wBIC shown as ~0 or ~1 were 0 or 1, respectively, even when rounded to four decimal places.

the losses were not transformed ($\beta_{i,diff} = 1.31$ vs. $\beta_{i,diff} = 1.45$, respectively). Moreover, most individual participants still showed greater effort in the loss-avoidance condition even after this transformation (Figure S10 in the online supplemental materials).

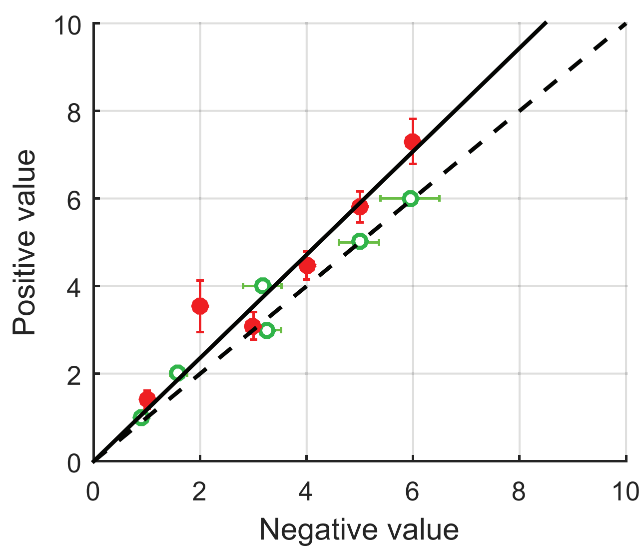
A limitation with even this more stringent test is that it uses λ, which in turn assumes a linear effect of loss aversion. To circumvent this additional limitation, we conducted two additional analyses that did not use a model to transform gains into equivalent losses or vice versa. In one analysis, for each participant, we transformed the gains into equivalent losses by directly using the loss equivalents obtained in the gambling task for each specific magnitude; in the other analysis, we similarly transformed the losses into equivalent gains by directly using the gain equivalents obtained in the gambling task for each specific magnitude. Again, $\beta_{i,diff}$ remained almost as large as when there was no transformation and also remained highly significant, both when using the loss equivalent of gains, $\chi^2(1) = 10.44$, $p < .001$, $\beta_{i,diff} = 1.28$, 95% CI [0.82, 1.74], $OR = 3.60$, 95% CI [2.27, 5.70], and when using the gain equivalent of losses, $\chi^2(1) = 13.07$, $p < .001$, $OR = 4.10$, 95% CI [2.66, 6.30]. These various analyses show compellingly that the tendency to exert greater effort in loss-avoidance than in gain conditions persists even after fully controlling for the effects of loss aversion measured using the gambling task, in the study with adults.

Discussion

Summary

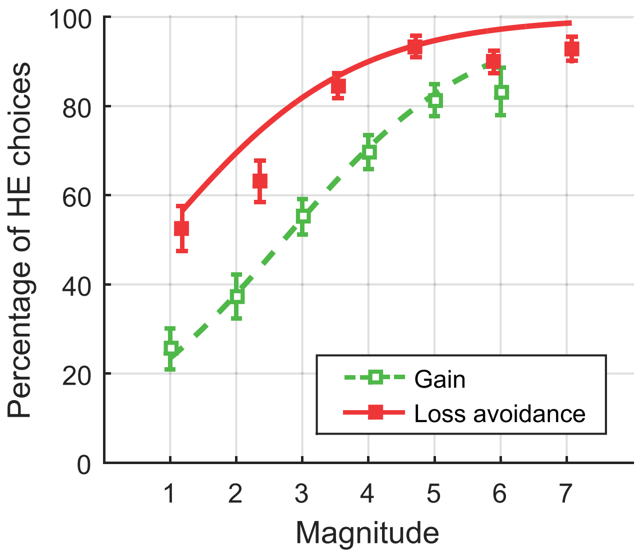
We found that, when choosing between courses of action requiring high versus low effort, people are substantially more likely to choose to exert high effort if doing so avoids a loss than if it earns a numerically equivalent gain. We obtained this finding first in an experiment with adults and replicated it in a second experiment with children and adolescents. The finding was so robust that it was clearly visible for most individual participants in both experiments—which seems especially noteworthy for the children and adolescents, considering their relatively young age (M_{age} = 11.4 years, $SD = 2.9$). This finding had a large effect size in both experiments, with uncannily similar *OR*s in the two experiments: 4.26 in the experiment with adults and 4.06 in the experiment with children and adolescents. This remarkable similarity in *OR*s, together with the robustness of the effect across individual participants in both experiments, suggests that this effect might constitute a fundamental regularity in human behavior—although such a proposition would, of course, need to be tested across laboratories, contexts, and cultures.

Figure 4
Group Results in the Gambling Task in the Study With Adults (N = 32)



Note. The figure shows the mean (±*SEM*) positive equivalents for each magnitude of the negative values (red filled circles, vertical error bars) and the mean (±*SEM*) negative equivalents for each magnitude of the positive values (open green circles, horizontal error bars). Error bars are within-subjects error bars, obtained using Morey's correction (Morey, 2008). Outliers were removed using Cook's distance (see Method). The solid line represents a linear fit corresponding to the fixed effect of a linear mixed model (see Method); the dashed line has a slope of 1. The fact that the solid line has a slope greater than that for the dashed line indicates that, on aggregate, participants were loss averse. Results for individual participants are shown in Figures S11 and S12 in the online supplemental materials. See the online article for the color version of this figure.

Figure 5
Effect of Converting the Losses to Equivalent Gains in the Effort Task in the Study With Adults (N = 32)



Note. We converted the losses to equivalent gains on a participant-by-participant basis by multiplying the absolute value of each loss (with magnitudes −6 through −1) by the participant's individual λ coefficient. Open green squares and solid red squares represent the percentage of high-effort (HE) choices in the gain and loss-avoidance conditions, respectively. For visualization purposes, the percentage of HE choices for the loss-avoidance condition was aligned to the fixed effects: in other words, converting losses to equivalent gains on a participant-by-participant basis resulted in the points for the loss-avoidance condition spanning a multitude of values on the *x*-axis; to be able to average them to better visualize them, we aligned each point with its corresponding equivalent-gain fixed effect. Error bars represent within-subjects *SEM*s by applying Morey's correction (Morey, 2008). Lines—dashed green and solid red for the gain and loss-avoidance conditions, respectively—represent the fit from a mixed-effects logistic regression. See the online article for the color version of this figure.

Relation to Prior Studies

Our findings of greater effort to avoid losses than to obtain gains are consistent with much evidence from the field (Cullen et al., 1975; Fryer et al., 2012; Hossain & List, 2012; McEvoy, 2016) and the laboratory (X. Chen et al., 2020; Hochman et al., 2014; Imas et al., 2017) but add to that evidence in two ways. First, as discussed earlier, our design addresses various limitations of prior studies. Our findings demonstrate, arguably more definitively than other work (X. Chen et al., 2020), that people *explicitly choose* to exert more effort to avoid losses than to obtain gains. This demonstration supports the longstanding presupposition that the better performance in loss frames is due, at least in part, to greater effort. Of course, our findings do not exclude other possible contributions to better performance under loss frames (see, e.g., Yechiam & Hochman, 2013).

Second, our findings show that this effect extends robustly to children and adolescents. A study that predated much of the work on loss aversion showed, as mentioned earlier, that high-school students were more likely to complete an assignment if failing to do so led to a point loss than if doing so led to a point gain (Cullen et al., 1975). A more recent field study provided suggestive, albeit not statistically significant, evidence that students at a broader range of grades performed better in a test under a loss than under a gain frame (Levitt et al., 2016). How best to motivate children and adolescents, at school or at home, has obvious practical interest. Yet, most studies have focused on adults (X. Chen et al., 2020; Fryer et al., 2012; Hochman et al., 2014; Hossain & List, 2012; Imas et al., 2017; McEvoy, 2016).

Different Systems for Appetitive and Aversive Outcomes?

Model selection indicated confidently that the best model had different intercepts, rather than different slopes, for losses versus gains, in both the experiment with adults and the experiment with children and adolescents. We interpret the difference in intercepts for losses versus gains as consistent with longstanding ideas that there may be two distinct, even if partially overlapping (Pessiglione & Delgado, 2015) and fluid (Berridge, 2019), psychological and neural systems, one for aversive outcomes and one for appetitive outcomes (e.g., Bradley & Lang, 2007; Carver & White, 1994; Corr, 2004; Posner et al., 2005; Tye, 2018). These two systems, in fact, may underlie two fundamental axes of temperament (Elliot & Thrash, 2002, 2010). The involvement of a loss or a gain, possibly regardless of magnitude, may engage the aversive or appetitive system, respectively, with differential effects on effort. We discuss our finding that the slope did not seem to differ for losses versus gains below.

Differences From Field Studies

Our effort task deliberately diverged from aspects of the field studies that have investigated performance under loss versus gain frames (Apostolova-Mihaylova et al., 2015; Cullen et al., 1975; Fryer et al., 2012; Hossain & List, 2012; McEvoy, 2016). For example, as discussed earlier, we avoided using a pre- versus postpayment design because of the confounds with such designs. These breaches in isomorphism between our study and field studies were important to permit robust conclusions regarding whether people choose to exert more effort to avoid losses than to obtain gains. Of course, such breaches in isomorphism imply that the relevance of our findings to the field studies cannot simply be presumed and should be tested. An interesting question is whether individual results in our effort task predict differences in performance in gain versus loss frames in the field.

Another aspect in which our effort task diverged from field studies was that the type of work required in our task—the finger presses—was unlike the work typically required in the real world. Although, as noted earlier, the so-called "real-effort" paradigms that are often used to study effort in the laboratory measure performance, not effort, they have the advantage that the work they require more closely mimics real-world work (Carpenter & Huet-Vaughn, 2019). One could combine our design, involving choices between effort levels under various magnitudes of gain and loss, with more ecologically realistic tasks, such as those in real-effort tasks. Specifically, instead of choosing between the two types of finger presses, participants might choose between two versions of a real-effort task, one more effortful than the other.

Despite the contrived nature of the finger presses, they have three important advantages. First, the difference in effort required for the two types of finger presses is robust, universal, and less dependent on extraneous variables. Real-effort tasks have used things such as arithmetic or computer operations (Carpenter & Huet-Vaughn, 2019), where the effort required depends on skill and experience, making it difficult to have an experiment that is suitable across ages, education levels, and so forth. In contrast, our finding of extraordinarily similar *OR*s in the experiment with adults and the experiment with children and adolescents demonstrates the broad applicability of our manipulation. Second, finger presses take a short time to complete, making it practical to collect many trials per subject (unlike real-effort tasks, which typically produce only one datapoint per subject). Third, similar manipulations using finger presses have been used to investigate effort disturbances in psychiatric disorders (e.g., Barch et al., 2014; Berwian et al., 2020; Fervaha et al., 2013; Gold et al., 2013; Treadway, Bossaller, et al., 2012), the neural substrates of effort (e.g., Arulpragasam et al., 2018; Treadway, Buckholtz, et al., 2012), and the pharmacological modulation of effort (e.g., Wardle et al., 2011), tying our manipulation to a rich body of literature.

Implications and Applications

Our findings have implications and applications in various areas beyond behavioral economics.

Neuroscience

As noted earlier, increased dopamine is associated with greater effort (Beierholm et al., 2013; Hamid et al., 2015; Salamone et al., 2018), and dopamine plays a particularly prominent role in reward processing (Schultz, 2013). Our finding of greater effort to avoid losses might therefore seem to pose a conundrum. This conundrum may be partly resolved, however, by the evidence that dopamine also plays a role in situations in which aversive outcomes can be avoided (Gentry et al., 2019; Lloyd & Dayan, 2019; Oleson & Roberts, 2019). Indeed, work with patients with Parkinson's disease suggests that dopamine plays a role in modulating effort not only to obtain gains (Chong et al., 2015; Le Bouc et al., 2016; Porat et al., 2014) but also to avoid losses (X. Chen et al., 2020; Porat et al., 2014). Whether the greater effort to avoid losses that we found is due to greater dopamine release in loss-avoidance than in gain-seeking situations is an important question for future research.

Psychiatric Disorders

Although several studies have investigated effort in psychiatric disorders (e.g., Barch et al., 2014; Berwian et al., 2020; Fervaha et al., 2013; Gold et al., 2013; Treadway, Bossaller, et al., 2012), they have generally focused on effort to get good outcomes (usually operationalized as gains). Effort to avoid bad outcomes (operationalized as losses in our task), however, may be more relevant for some disorders (e.g., anxiety disorders).

School Behavior Management and Parent Management Training

School behavior management systems and parent management training often use reinforcement (Alberto & Troutman, 2012; Dunlap et al., 2009; Kazdin, 2005), sometimes systematized using token economies (Doll et al., 2013; Kazdin, 2005). Our findings suggest that children and adolescents might exert more effort if, in a token economy, points are awarded upfront, with the possibility of loss, than if they are progressively gained.

This idea would have to be balanced with the importance of reinforcement contingent on a behavior for the transformation of that behavior into a habit (Graybiel, 2008; Maia, 2009). Loss avoidance through an effortful behavior is a form of active avoidance (Maia, 2012), which generates the same signals—positive prediction errors—that support habit learning through positive reinforcement (Maia, 2010; Moutoussis et al., 2008). Thus, loss avoidance could be effective at supporting habit formation; indeed, avoidance learning can lead to habit learning (LeDoux et al., 2017). Some evidence, however, suggests that to learn to perform a behavior, gains may be more effective than the avoidance of losses, whereas to stop a behavior, losses contingent on the behavior may be more effective than gains contingent on nonperformance of the behavior (Guitart-Masip et al., 2012). In any case, we should emphasize that our study investigated the decision to exert effort but not habit learning or unlearning, which are fundamental for long-term behavior change (Duhigg, 2012; Wood & Rünger, 2016). In addition, in the real world, point losses might be perceived as punishments, which can have nefarious effects (Kazdin, 2005, 2013). Still, our findings in children and adolescents, together with the available evidence from field studies in adults (Fryer et al., 2012; Hossain & List, 2012), undergraduate students (McEvoy, 2016), and high-school students (Cullen et al., 1975), as well as the tentative evidence from students at a broader range of grades (Levitt et al., 2016), all suggest that future research should investigate whether school behavior management systems and parent management training could take advantage of the greater effort to avoid losses.

Personality and Temperament

An interesting line of research concerns the relation of our findings to personality constructs (e.g., whether increased effort to avoid losses relates to harm avoidance). In fact, it would be important to develop a questionnaire with subscales measuring effort to avoid bad outcomes and to obtain good outcomes. The BIS/BAS questionnaire, for example, has a subscale—BAS Drive—that taps into effort to obtain good outcomes (Carver & White, 1994; but see Chumbley & Fehr, 2014), but it does not have a subscale for effort to avoid bad outcomes. Similarly, the Approach-Avoidance Temperament Questionnaire (ATQ; Elliot & Thrash, 2010) has several items that relate to the energizing effect of positive stimuli but none that address the energizing effect of avoiding negative stimuli. (The ATQ has one item related to escape, but escape and active avoidance are different; Maia, 2012.) Other questionnaires better address effort to obtain good outcomes and avoid bad outcomes, but in narrow domains (e.g., Elliot & Church, 1997).

We found that nearly all individual participants in our two samples chose to exert more effort to avoid losses than to obtain gains. Another study found the same effect in nearly all participants in its three samples (X. Chen et al., 2020). The seemingly near universality of this effect, while not denying variation in the extent to which people are motivated by positive or negative stimuli (Elliot & Thrash, 2002, 2010), suggests that the postulate that "bad is stronger than good" (Baumeister et al., 2001) may apply to nearly everyone.

Relation Between Greater Effort to Avoid Losses and Loss Aversion

We found that the greater effort to avoid losses persisted after controlling for loss aversion measured with a gambling task using choices between prospects. Moreover, the tendency to exert more effort to avoid losses in the effort task did not correlate with the loss-aversion coefficient from the gambling task. There are two possible interpretations for these findings. One possibility is that our gambling task was not a sufficiently sensitive assessment of loss aversion. Weighing for this possibility, the loss-aversion coefficient that we obtained in our gambling task was on the low end of existing studies: we obtained a median λ of 1.07 versus 1.31 in a meta-analysis (Walasek et al., 2018)—although there are many studies that do not even find loss aversion (Gal & Rucker, 2018; Yechiam & Hochman, 2013). Indeed, there is great variability across studies in estimates of λ (Walasek et al., 2018), which, moreover, are modulated by various factors (Ert & Erev, 2013; Mrkva et al., 2020; Neumann & Böckenholt, 2014; Walasek & Stewart, 2015, 2019). Thus, our estimate of λ may not have been sufficiently reliable.

Another possibility is that the processes underlying how much effort people choose to exert may partially differ from those engaged by choices between prospects. Perhaps weighing for this possibility, our findings with the effort task show an intriguing difference from classical conceptualizations of loss aversion. In both the experiment with adults and the experiment with children and adolescents, magnitude seemed to have the same effect for losses and gains: model selection indicated that the slope did not differ between them. In standard conceptualizations of loss aversion, in contrast, losses have greater steepness than gains (Kahneman & Tversky, 1979).

A partial dissociation between the processes underlying how much effort people choose to exert and those engaged by choices between prospects may seem unintuitive. Related dissociations, however, make such a partial dissociation at least plausible. For example, the brain has different systems for motivation, including effort, versus hedonic pleasure (Berridge, 2018), and, at least in animals, effort choices do not always align with choices that do not require effort (Salamone et al., 2017). As another example, the BIS/BAS scale has separate factors for BAS Drive and Reward Responsiveness (Carver & White, 1994), which may relate more to effort and non-effort-related preferences, respectively—albeit, in both cases, for appetitive outcomes (but see Chumbley & Fehr, 2014, for surprising evidence that Reward Responsiveness, not BAS Drive, relates to how hard people work).

As mentioned in the Introduction, a prior study that investigated the relation of performance under loss versus gain frames to loss aversion found suggestive, but inconclusive, evidence for a relation between the two (Imas et al., 2017). As noted throughout this article, performance measures cannot be considered equivalent to effort measures; still, that study provides tentative evidence for a relation between greater effort to avoid losses and loss aversion. Our study, in contrast, provides tentative evidence for a possible dissociation between the two. In both cases, the evidence is subject to important caveats, so a definitive conclusion about this relation will require more research.

Conclusions

Our results demonstrate conclusively that both adults and children and adolescents choose to exert more effort to avoid losses than to obtain numerically equivalent gains. As we discussed, this finding has broad implications and applications.

Context

What motivates people is a fundamental question in psychology. We found that both adults and children and adolescents choose to exert more effort to avoid losses than to obtain numerically equivalent gains, using a simple task that produced very large effect sizes and results so robust that they were evident at the individual-subject level. These results, and this specific task, will likely be of interest to many areas of psychology and beyond. We discussed their relevance for areas as diverse as behavioral economics, school behavior management, parent management training, psychopathology, personality, and the neuroscience of effort. The implications and applications of these results, and even of the specific task that we developed, are too numerous for any single laboratory to pursue them all. We highlighted some of these implications, applications, and avenues for future research. Our hope is that others will tackle these and related issues in their various disciplines, with multiple perspectives and methods.

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