Do Losses Promote More Reflection Than Gains?

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Do Losses Promote More Reflection Than Gains?

In prospect theory, “losses loom larger than gains” (Kahneman & Tversky, 1979). Loss aversion, originally described in decisions under risk, has been used to explain and illustrate a variety of economic phenomena, such as the endowment effect (Thaler, 1980), labor supply decisions (C. Camerer et al., 1997), or the status-quo bias (Samuelson & Zeckhauser, 1988), and a variety of financial phenomena, such as the equity premium puzzle (Benartzi & Thaler, 1995), financial asset prices (Barberis, 2013) or the disposition effect (Shefrin & Statman, 1985), among other behavioral effects (see Camerer, 2004, 2005 for a review). Although loss aversion happens in choice, several studies have shown asymmetries in the responses to losses and gains beyond choices.

For example, Sokol-Hessner et al. (2009) measured skin conductance of participants making choices between mixed gambles and safe amounts of money in which the outcome was presented immediately after choosing. Skin conductance reflects emotion regulation by the autonomic nervous system. Participants showed a greater skin conductance response to loss outcomes than to gain outcomes, suggesting that losses triggered increased emotion regulation. Hochman and Yechiam (2011) conducted a similar experiment using a slightly different task while participants’ pupil dilation and heart rate were being measured. Participants had to select between two buttons each associated to a gamble. By clicking a button participants could see a realization of the gamble. Hochman and Yechiam observed that following a loss, participants had a greater pupil diameter and increased heart rate than following a gain.

Furthermore, Tom et al. (2007) conducted an fMRI study exploring the neural basis of loss aversion. Participants were presented with a set of mixed gambles of equiprobably gains and losses that they could accept or reject. Though the gambles were not realized and therefore no outcomes were presented, dorsal and ventral striatum and ventromedial prefrontal areas showed differential neural activation between potential losses and potential gains. Similarly, other studies have reported asymmetries between (potential and experienced) losses and gains in prefrontal areas, striatum, and amygdala (Canessa et al., 2013, 2017; Chib et al., 2012; Sokol-Hessner et al., 2013) (see Rick, 2011 and Sokol-Hessner & Rutledge, 2019 for a review).

Relatedly, Lejarraga et al. (Lejarraga et al., 2012a; Lejarraga & Hertwig, 2017) explored how the domain of choice (losses vs. gains) influences search effort in decisions from experience. In one study using the sampling paradigm, participants saw two buttons on a screen, each representing an unknown distribution payoff. Participants could learn about the two options by clicking on the buttons. Participants first went through a sampling stage, in which they could explore both buttons as many times as they desired at no cost before making a final consequential choice. Lejarraga and Hertwig (2017) observed that participants making choices in the domain of losses searched the options more extensively (i.e., they drew larger samples) than when making choices in the domain of gains. In another study using the partial-feedback paradigm, participants made choices between two buttons, again each button was associated to an unknown payoff distribution. The difference with the sampling paradigm is that there was no sampling stage. To learn about the options, participants had to make consequential choices and learn from feedback. This partial-feedback paradigm entails an exploration-exploitation tradeoff (Sutton & Barto, 1998), where participants can obtain an expected outcome from a known distribution (exploitation) or choose another option to learn about it (exploration). Here again, participants in the loss domain searched longer than participants in the gain domain, in that they showed a higher alternation rate between options in the loss than in the gain domain. Taken together, the studies of Lejarraga et al indicate that individuals tend to explore more when facing the threat of losses than the promise of gains both when the search is costly and when it is free. This asymmetry was present in both studies even though there was no loss aversion in participant's choices. These results are consistent with the observation that people explore options longer when they bargain to avoid losses than when they bargain for gains (Camerer et al., 1993), and also take longer to make a decision to avoid a loss in choices between gambles (Gonzalez et al., 2005; Payne, et al., 1993).

The observation that losses promote more exploratory search and longer response times, both in choice and bargaining suggest that people persist more to avoid a loss than to obtain a gain. Precisely, Goldsmith and Dahr (2013) studied to what extent potential losses make people persist longer in their attempt to solve four anagrams. The authors observed that, in an undergraduate sample, participants who worked on the anagrams to avoid a loss persistet almost 60% longer than participants who were trying to obtain gains (15.3 vs. 9.6 minutes, respectively), although performance did not differ. Similarly, in a larger online sample in the US, respondents in the loss condition persisted 29% longer before they gave up on an unsolvable anagram.

Other studies have shown that losses improve performance and learning, for example in probability learning (Bereby-Meyer & Erev, 1998), perceptual classification (Maddox et al., 2006), binary choice (Haruvy & Erev, 2002), among other tasks (Dawson et al., 2016; Pope & Schweitzer, 2011). To illustrate, Yechiam and Hochman (2013a) conducted 5 studies using experience-based and description-based choices between two options and examined the effects of losses on performance. Specifically, these studies showed that the presence of losses increased the rate of choices for the option with a higher expected value, even when the choice ran counter to the expected effect of loss aversion. The authors proposed that losses influenced attentional and contrast-based processes in choice, instead of influencing the subjective valuation as loss aversion assumes. Yechiam's and Hochman's loss-attention account (2013b) explains patterns of behavior that loss aversion cannot explain, such as the increased arousal following losses in the absence of loss-aversive choices.

To the extent that attention is essential to reflection, we expect that the presence of potential losses (1) lead people to deploy attentional resources for longer periods, promoting more persistent reflection; and (2) this longer reflection improves the chances that the task is solved successfully, thus promoting better performance. We pre-registered these hypotheses in the Open Science Foundation (https://osf.io/7cvub).

To test these hypotheses, we conducted two experimental studies in which participants encountered a series of problems that required reflection, and that solving them could lead to gains or losses. Do people reflect more to avoid a monetary loss than to gain an equivalent monetary amount? Addressing this question has potentially far-reaching implications in domains where motivation drives performance, such as education or the management of human resources. If people reflect better or more to avoid losses, a manager could introduce potential losses in the incentive structure of employees to promote more reflective thinking about problems improving the chances that problems are solved. If losses indeed have an effect on reflection, then adding losses to people's incentives could lead employees to make more logical or rational decisions or lead managers to think more deeply about strategic issues. Indeed, laboratory experiments have shown that adding potential losses to the incentive structure, such as in contracts or bonuses, increased productivity (Fryer et al., 2012; Hossain & List, 2012).

Study 1

Method

Procedure

The experiment was a between-subjects design with 1 factor (treatment) and 2 levels (gains and losses) and 6 dependent variables that measure different aspects of reflection: reflection on semantic space, with the *Memory task* (Hills et al., 2015); reflection on problem-solving, with the task *Tower of Hanoi* (Simon, 1975); non-strategic reflection, with the original 3-question version of *Cognitive Reflection Test* (CRT, Frederick, 2005) and *syllogisms* (Baron et al., 2015); and strategic reflection, with the *Guessing game* and the *Beauty contest* (Nagel, 1995) (see table 1 for detailed descriptions of each task). Response times and performance were collected for each task.

The experiment consisted of two sessions. In the first session, participants were randomly assigned to each condition and completed an unrelated task. Participants in the loss condition completed a long version and received 16 EUR, whereas participants in the gain condition completed a short version and received 4 EUR. Three days after completing the first session, the experimenter sent an email to the participants with two goals. First, the email reinforced the reward participants had obtained in the first session; second, the email was a reminder to return to the laboratory to complete the experiment. This procedure aimed to strengthen the manipulation by increasing the feeling of ownership (Beggan, 1992; Eidelman & Crandall, 2012; Strahilevitz & Loewenstein, 1998). One week before the first session, in the second session, participants had to complete the 6 tasks described above (see Table 1 for a complete description). Participants in the gain condition faced the tasks with the incentive to win additional money—up to a maximum of 16 EUR—and participants in the loss condition faced the tasks with the incentive not to lose money they had earned in the previous session—a most they could lose 12 EUR, leaving them with a minimum potential payoff of 4 EUR. The final payoff was determined by their performance on two randomly chosen tasks. This study's procedures, sample, and main analyses were pre-registered at the Open Science Foundation (https://osf.io/7cvub).[1] Screenshots of the study are available in the Appendix.

Participants

Participants were recruited from the Decision Science Laboratory participant pool, which is primarily comprised of members of the academic community at the University of the Balearic Islands where the experiment was conducted. Although 348 participants completed the first session—meeting the pre-registered sample size—the final sample for analysis is comprised of the 298 participants who completed both sessions (184 females, 61.74%) with ages between 17 and 70 (M = 24.1 and SD = 8.42). This sample gives us a 91.3% power to detect an effect size of 0.0625 as measured by f-squared in a global effects MANOVA at the standard .05 alpha error probability.

[1] A previous study, almost identical to Study 1, was also registered and conducted. Results indicate that the manipulation of losses and gains was not adequate. Results did not differ in any meaningful dimension across domains and verbal reports of participants indicate that the condition was not sufficiently salient. The lessons learned in this study led us to revise the incentive scheme and the manipulation of losses and gain for Study 1.

Table 1

Aspect of reflection	**Task**	**Description**	**Reference**	**Persistence Measure**	**Performance Measure**	**Incentive Rule[2]**
Reflection on semantic space	Memory task	*Name as many animals as you can remember during 10 minutes.*	Hills et al., 2015	Average response time to recall each animal.	Number of valid words provided. The more words, the better performance.	6€ if the participant animals' pool included the random animal picked from a dictionary by the experimenter.
Reflection on problem-solving	Tower of Hanoi	*Move the entire stack to another bar, obeying the following rules: (1) Only one disk can be moved at a time; (2) Each move consists of taking the top disk from one of the piles; and (3) You cannot place a larger disc on top of a smaller disc.*	Simon, 1975	Average response time for each movement.	Whether the participant solved the problem or not.	6€ if the participant solved the problem or not.
Non-strategic reflection	Cognitive Reflection Test	*Answer the three original questions from CRT. Example: A bat and a ball cost $1.10 total. The bat costs $1.00 more than the ball. How much does the ball cost?*	Frederick, 2005	Total response time for answering the three questions.	Number of correct responses. From 0 to 3 correct responses.	2€ for each correct answer.
	Syllogisms	*Confirm a conclusion of a deductive argument that is inferred from two premises. Example: All squid like vitamin A.Wuzzies like vitamin A. If these two statements are true, can we conclude from them that wuzzies are squids?*	Baron et al., 2015	Average response time for each syllogism.	Number of correct responses. From 0 to 12 correct responses.	40 cents for each correct syllogism.
Strategic reflection	Beauty contest	*Choose a number between 0 and 100 (both included). The winner will be the person*	Nagel, 1995	Total response time for giving a number.	Number provided. The lower, the better performance.	6€ for the winner participant in that experimental session.

[2] Two out of the six task were selected randomly for each experimental session. Participants were rewarded based on the Incentive Rule of these two selected tasks. For instance, in an experimental session which the tasks selected were the Cognitive Reflection Test and the Syllogisms, the participants won/not lost 2€ for each correct answer in the CRT and 40 cents for each correct syllogism.

		whose number is closest to two-thirds (2/3) of the average of all numbers chosen.				
	Guessing game	*Now you are paired with another participant. Choose a number between 100 and 500 (both included). The winner will be the person whose number is closest to 1.2 times the number chosen by the other participant.*	Nagel, 1995	Total response time for giving a number.	Number provided. The higher, the better performance.	6€ for the winner participant of each pair.

Results

Persistence of Reflection

Participants reflected longer in completing the tasks to avoid a loss than to reap a gain. MANOVA across the six tasks shows that there was a significant difference in log-transformed[3] response times between participants in the gain and loss condition (Pillai's Trace = .1021, $F(6, 291) = 5.5119$, $p < .0001$). Indeed, all tasks' response times were longer in the loss domain except for responses to the guessing game. Follow-up tests show that only the differences in response times in syllogisms were significant (according to Welch T-tests with Bonferroni correction to minimize the risk involved in multiple testing). As expected, participants in the loss condition reflected longer (28.19 seconds on average to complete each of the 15 syllogisms) than participants in the gain condition (24.31 seconds), $t(279.91) = -4.2713$, Bonferroni $p = .0002$ (Figure 1). In the memory task, participants in the loss condition took 8.79 seconds to recall an animal name while those in the gain condition took 8.28 seconds ($t(276.15) = -2.1279$, Bonferroni $p = .2054$). Similarly, in the tower of Hanoi task, participants in the loss condition took 3.29 seconds on average per movement and participants in the gain condition took 3.13 seconds per movement ($t(286.04) = -1.3497$, Bonferroni $p > .95$); in the Beauty Contest, participants in the loss condition took an average of 6.75 and those in the gain condition took 6.73 seconds ($t(289.74) = -.1030$, Bonferroni $p > .95$). Finally, in the Cognitive Reflection Task, those in the loss condition took 200.17 seconds on average to answer the 3 questions and those in the loss condition took 185.32 seconds ($t(287.18) = -1.0974$, Bonferroni $p > .95$). In the Guessing Game, however, participants in the gain condition took on average 11.89 seconds while participants in the loss domain took 9.67 seconds, $t(289.71) = 2.033$, Bonferroni $p = .2576$). In sum, across six problems, participants

[3] We log-transformed response times to better meet the assumptions of the MANOVA, improving multivariate normality and achieving homogeneity of covariances and variances. The pattern of results remains unchanged for the analysis without transformation.

facing the possibility of losing money reflected longer than participants facing the possibility of winning money.

Performance

Although participants reflected longer to solve the battery of tasks, their persistence did not manifest in better performance. Results of MANOVA indicate that there were no significant differences in performance across the six tasks between the gain and loss domains (Pillai's Trace = .0416, $F(6,291) = 2.104$, $p = .0528$) (see Figure 2 and Table 1). Post hoc analyses show that participants in the gain domain performed better than participants in the loss domain in the memory task, producing on average 66 vs. 59 words, respectively ($t(276.37) = 2.8631$, Bonferroni $p = .0271$). There was no other significant difference across conditions in performance in the other tasks. In the tower of Hanoi, the proportion of participants who solved the problem was similar between conditions: 96.3% of the participants solved in the gain domain and 93.3% of the participants in the loss domain ($t(294.43) = 1.1637$, Bonferroni $p > .95$). Similarly, responses in the Beauty Contest were no different across conditions—46 and 49, gain and loss domain, respectively, $t(278.57) = -1.1987$, Bonferroni $p > .95$ —and neither they were in the guessing game—265 and 266, in the gain and loss domain, respectively, $t(283.06) = -.1430$, Bonferroni $p > .95$. There were also no differences in performance in syllogisms (7.4 vs. 7.3 correct responses in losses and gains, respectively, $t(284.98) = -.4843$, Bonferroni $p > .95$); and neither in the number of correct responses in the CRT (1.13 in gains and 1.07 in losses), $t(280.4) = .4570$, Bonferroni $p > .95$. The general pattern speaks unambiguously. Potential losses did not seem to have promoted better performance as expressed by the similar performance across domains in six different reflection tasks.

Aggregate-level analysis

As a complementary analysis, we transformed and scaled all performance variables into the same metric, and aggregated the variables to have a single unit of performance. We then compared performance across conditions with a Welch T-test. We performed the same transformation and scalation for response times variables. Both tests support our observation that losses led to longer response times than gains, t(290.5) = -3.1889, p = .0

016, and to no different performance (2.58 vs. 2.60, respectively), t(275.21) = -.2737, p = .7845 (Figure 3).

Discussion

Study 1 explored whether potential losses promote longer reflection than potential gains and whether longer reflection increases the chances of successfully solving problems. Results show that people who faced the potential to lose up to 12 EUR reflected significantly longer than people who faced the possibility to win 12 EUR. These results are consistent with previous findings that losses tend to increase persistence in problem-solving (Goldsmith & Dhar, 2013), choice (Porcelli & Delgado, 2009; Xue et al., 2009), and bargaining (Camerer et al., 1993), and with studies that show longer exploration rates for losses than for gains (Lejarraga et al., 2012a; Lejarraga & Hertwig, 2017).

However, our results in Study 1 do not align with our predictions derived from the loss-attention account, as we did not observe that losses increased the likelihood of solving problems relative to gains. Results seem to suggest that losses indeed have an effect on attention and thus on the persistence of reflection, but the tasks that we employed in Study 1 were not sufficiently sensitive to translate the increased reflection times into better performance. Some evidence indicates that losses tend to increase effort in easier, mechanical, tasks. For example, participants who encountered the dull task of pressing the space bar to avoid losses were pressed more times than participants who had to press the space bar to reap gains (Farinha & Maia, 2021). Similar results were observed using the *real-effort* task of moving a slider sequentially to a randomly assigned point along the bar. Participants who had a contract framed in terms of losses performed better than those who faced a contract framed in terms of gains (Imas et al., 2016). Blute, List, and van Soest (2020) find similar results for folding envelopes. Although these tasks did not entail reflection or any intellective effort, they suggest that the effect of losses could be observed in easy, rather, than difficult tasks. When a participant faces a sufficiently difficult task, such as the tasks used in our Study 1, more effort may not increase performance.

To explore the effects of losses on reflective effort, and whether it can translate into better performance, in Study 2 we replaced the tasks from Study 1 with anagrams as Goldsmith and Dahr (2013), but in addition to them, we vary difficulty systematically. Anagrams have been used in the past to evaluate and manipulate and control cognitive effort (Dewhurst & Hitch, 1999; Foley et al., 1989; Foley & Foley, 2007; Mayzner & Tresselt, 1958; Tyler et al., 1979a). We hypothesized that: (1) losses promote more heightened reflection than gains as measured in longer response times independently of anagram difficulty; (2) in easy anagrams, longer reflection is translated into better performance as measured by a higher probability of solving anagrams and a higher number of anagrams solved in the domain of losses relative to gains; and (3) in difficult tasks, longer reflection does not translate into better performance. These hypotheses were pre-registered (https://osf.io/eqf8b).

Study 2

Method

For this study, we designed a between-subjects design with 1 factor (treatment), 2 levels ("gains" and "losses"), and 2 dependent variables (performance and response time), where participants have to solve as many anagrams as they preferred during 3 blocks (easy, medium, and difficult blocks). Block order was fixed for all participants to avoid fatigue effects and learned helplessness from the most difficult anagrams. Anagram order within blocks was also fixed.

Procedure

Participants were randomly assigned to the losses (gains) condition and completed a baseline task which consisted of writing words that appeared on the screen. For that task, participants received 15 EUR (5 EUR). Then, they were told that they must solve as many anagrams as they preferred within each of the three blocks, and we would create a ranking of all the participants based on the number of anagrams solved. People in the gain condition were told that the first 1/3 of the participants who solved more anagrams in the study would gain 10EUR; the second 1/3 of those who solved more anagrams would gain 5 EUR; and the last 1/3 would gain nothing (apart from their initial 5 EUR). People in the loss condition were told that the first 1/3 of the participants who solved more anagrams in the study would lose nothing from their 15 EUR; the second 1/3 of those who solved more anagrams would lose 5 EUR; and the last 1/3 would lose 10 EUR and remain 5 EUR.

Thus, all participants started with the first easy block and solved as many anagrams as they wanted until they pressed the button "finish block" and they continued to the second medium difficulty block to repeat the process. Participants could also skip anagrams.

Material

Originally, an anagram is “a word, phrase, or name formed by rearranging the letters of another word, phrase, or name” (Oxford Languages). For this study, we define an anagram as a set of letters arranged in a pseudorandom order without meaning that can be rearranged using all the letters into a meaningful word. For example, the unique solution to the anagram “ceiescn” is “science”. To create the set of anagrams, we used Paivio et al. (1968) word poll of 925 English nouns as a starting point. Each word was rated by a group of subjects in terms of concreteness, imagery, and meaningfulness, and has been used before with similar purposes (Tyler et al., 1979b). We translated the nouns to Spanish and excluded compound nouns, repeated nouns, and ambiguous translations. As we wanted to offer the participant the possibility to answer with any meaningful word, we used a dictionary from the Real Academia Española (RAE)[4] to identify, for each noun, all the meaningful words that could be constructed with the same letters. For each solution, we computed the frequency in the natural language[5] and Levenshtein distance between each solution and the anagram. Finally, we constructed anagrams using three rules for re-arranging the letters[6] and checking that the anagram proposed had no meaning. The resulting pool of anagrams amounted to 878. For each anagram, we had several measures of difficulty: (1) which re-arrangement rules created the anagram, (2) the number of letters, (3) the number of solutions, (4) an index comprised by the Levenshtein distance and the frequency of the solution. For anagrams with more than one solution, the index used the highest frequency and shortest distance among solutions. The last step in preparing the anagrams for Study 2 involved modeling difficulty and validating the model experimentally.

Anagram Validation and Difficulty Rating

To validate the pool of anagrams created, we conducted a study in which 50 participants encountered a subset of 60 anagrams from the pool. Participants could provide a solution or skip the anagram; in which case the anagram was coded as not solved. With the

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[4] JorgeDuenasLerin. (2024, May 22). *diccionario-espanol-txt*. GitHub. https://github.com/JorgeDuenasLerin/diccionario-espanol-txt

[5] Frequency from a large Spanish corpus from different sources: Cañete, J. (2019) *Compilation of Large Spanish Unannotated Corpora* [Data set]. Zenodo. https://doi.org/10.5281/zenodo.3247731

[6] Following a similar procedure to Mayzner & Tresselt (1958), we created 3 functions that re-arrange words. The first rule moves N letters randomly, N is the length of the word floor divided by 3 (i.e., a word 12345 could result in 12534). The second rule splits the word into 2 parts and re-arranges them (e.g., 45123). The third function splits the word into 2 parts and intercalates the characters in them (e.g., 31425). The third rule creates the most difficult anagrams.

data collected, we modeled the probability of solving an anagram with a generalized linear model (with a logistic link function) with the 4 predictor variables mentioned above. Then, after estimating the coefficients of each variable, we used the model to estimate the difficulty of each anagram in the full pool of 878 anagrams. After a pilot study, 601 new anagrams were created following the same procedure, this time using nouns from “1000 palabras básicas en español”[7] (Wiktionary, 2024). The final pool amounted to 1480 anagrams. Finally, we created the difficulty blocks by allocating the easiest 50% of anagrams (i.e., 740) in the easy block, the subsequent 25% in the medium difficulty block, and the last 25% in the difficult block.

Participants

The planned sample of participants was 350 (as pre-registered, https://osf.io/eqf8b), and excluded people who had participated in Study 1. Because collecting this number of participants in the laboratory was beyond our capacity, we supplemented the recruitment with online participants, first examining that their behavior was comparable. We first recruited 107 participants in the laboratory from the Decision Science Laboratory and 48 participants from Prolific who spoke Spanish as a first language. We then compared the behavior of the two samples and confirmed that they could be reasonably pooled together. The comparison is shown in the Appendix.

After checking that the samples were similar, we finished the recruitment through Prolific obtaining a sample of 250 additional participants. Two participants from Prolific were lost due to technical problems, resulting in a total sample (i.e., from presential at the University of the Balearic Islands and from Prolific) of 355 participants (175 females, 174 males, 1 transgender, 5 non-specified) with ages between 18 and 65 (M = 29.75 and SD = 10.04). Fifteen participants who presented unexpectedly high accuracy in the difficult block

[7]Apéndice:1000 palabras básicas en español. (2024, February 27). In *Wiktionary*. https://es.wiktionary.org/wiki/Ap%C3%A9ndice:1000_palabras_b%C3%A1sicas_en_espa%C3%B1ol#Sustantivos

(i.e., more than 95%) were excluded from the analysis for the suspicion that they could have used external aid to solve the anagrams[8].

Results

Persistence of Reflection

We separated the analysis of response times using two linear mixed models, one for solved and one for unsolved anagrams[9]. The model included the log-transformed[10] response times as a dependent variable and, as fixed effects, the condition (gains or losses), whether the participant completed the experiment online or in the laboratory, the estimated difficulty of the anagram (easy, medium, or difficult), and the interaction between condition and difficulty. We also included random intercepts for each participant.

For solved anagrams, difficulty had a marked effect on response times, with easy anagrams involving the shortest reflection (5.65 s on average), followed by difficult anagrams (9.18 s on average, β =.5828, SE =.0152, t = 38.32, p < .0001), and anagrams of medium difficulty involving the longest reflection (14.21 s on average), (β = .8682, SE =.01493, t = 58.16, p < .0001). The fact that participants deployed more time on medium anagrams than on difficult anagrams might reflect a change in expectations. Participants in the difficult block were more prone to skip, lowering the time limit expected to solve or skip an anagram. Indeed, participants solved 95.5% of easy anagrams, 53.7% of medium, and 43.5% of difficult ones (Figure 4). In contrast to Study 1, facing potential losses did not promote longer reflection than gains, (β = .0033, SE = .0345, t = .096, p = .9232). However, reflection was longer in the loss condition when the task became more difficult, reflected in a significant

[8] Results remain practically unchanged when potential cheaters are left in the analyses.
[9] The separation of the analysis was not pre-registered. We realized that the response times of skipped anagrams were not indicative of reflection.
[10] We log-transformed response times to better meet the assumptions of linear mixed models, improving the homogeneity of variances and the normal distribution of model residuals. The transformation pattern of results remains unchanged for the analysis without transformation, and it is reported in the Appendix.

interaction between the loss condition and the medium level of difficulty (β = .0718, SE = .0201, t = 3.59, p = .0003), and between the loss condition and the difficulty level (β = .094, SE = .0203, t = 4.63, p < .0001) (Figure 4).

In unsolved anagrams, we find similar patterns. Participants gave up faster as the task became more difficult. Concretely, participants tried for 29.83 seconds on average in the easy block, 25.72 seconds on average in the medium block (β = -.5463, SE = .0358, t = -15.26, p < .0001), and 12.65 seconds on average in the difficult block (β = -1.365, SE = .0362, t = -37.77, p < .0001). There was no significant difference between response times in the loss and gain condition (β = -.1465, SE = .0966, t = -1.52, p = .1301), but participants in the loss condition took longer to give up as the task became more difficult, reflected in both medium anagrams (β = .1136, SE = .0484, t = 2.35, p = .0190) and difficult anagrams (β = .1382, SE = .0484, t = 2.87, p = 0.0041) (Figure 5).

Performance

To measure the probability of solving anagrams and the effect of the condition, we used a binomial generalized linear mixed model fitted by maximum likelihood using Laplace approximation. Again, the model included, as fixed effects, the condition (gains or losses), whether the participant completed the experiment online or in the laboratory, the estimated difficulty of the anagram (easy, medium, or difficult), and the interaction between condition and difficulty. We also included random intercepts for each participant.

As expected, more difficult anagrams were less likely to be solved. Concretely, while easy anagrams had a probability of 97.04% to be solved, medium anagrams had a 55.21% probability, significantly lower (β = -3.43, SE = .0502, z = - -68.24, p < .0001), and difficult anagrams were indeed the less likely to be solved, with a probability of 46.39% of being solved (β = -3.86, SE = .0508, z = -76.03, p < .0001). Whether participants faced potential losses or gains made no difference in the chances of solving the anagram (β = -.09, SE =

.1014, $z = -.84$, $p = .4008$). Against our hypothesis, losses led to a higher probability of solving the anagram as the task became more difficult, as indicated by a significant coefficient for the interaction between difficulty and condition in both medium and difficult levels. Concretely, while easy anagrams had a 97.28% probability of being solved in the gain condition and 96.81% in the loss condition, the medium level had 54.29% for gains and 56.14% for losses ($\beta = .24$, $SE = .0676$, $z = 3.55$, $p = .0004$), and difficult anagrams had 44.20% for gains and 48.58% for losses ($\beta = .36$, $SE = .0673$, $z = 5.35$, $p < .0001$) (Figure 6). In other words, while the probability of solving an anagram in the easy block was slightly higher for gains, as the task became more difficult the probability of solving an anagram became higher for losses. Finally, participants in the laboratory were more likely to solve an anagram relative to people participating online, (70.84% of solving the anagram for participants in the laboratory relative to 61.59% for participants online, $\beta = -.36$, $SE = .0976$, $z = -3.67$, $p = .0002$).

To explore the number of anagrams solved, we also performed a linear mixed model fitted by restricted maximum likelihood (REML) with the total number of anagrams solved per difficulty per participant. The model followed the previous fixed and random effects structure: the condition, the participation at the lab/Prolific, the difficulty, and the interaction between condition and difficulty as fixed-effects predictors, and a random intercept for each participant as random effects. As expected, the medium and the difficult levels showed a significant effect on the number of solved anagrams in the medium block ($\beta = -131.99$, $SE = 6.689$, $t = -19.73$, $p < .0001$) and in the difficult block ($\beta = -132.11$, $SE = 6.689$, $t = -19.75$, $p < .0001$). Participate in the lab had a significant positive effect compared to participating through Prolific ($\beta = 20.20$, $SE = 4.289$, $t = 4.71$, $p < .0001$). Neither the condition ($\beta = 1.10$, $SE = 6.634$, $t = 0.17$, $p = .868$) nor the interaction of the condition with difficulty had significant relevance for the number of anagrams solved; either on medium ($\beta = 3.29$, $SE =$

9.193, t = 0.36, p = .720) or difficult block (β = 3.22, SE = 9.199, t = 0.35, p = .727) (Figure 7).

Discussion

Based on Study 1 and previous findings of how losses influence effort, we expected that losses would improve performance in easy problems, but not in difficult ones. Our results, however, show a different pattern. Participants who faced potential losses solved more anagrams of medium and high difficulty than participants facing gains, but not in easy ones. Using anagrams of varying difficulty, Study 2 allowed us to observe that losses can improve performance in more difficult problems. As in Study 1, losses led to longer reflection than gains, but the effect was not observed in easy anagrams, suggesting that, as performance, a certain level of difficulty is necessary to observe the differential effects of losses on reflection.

Conclusion

The human mind does not treat gains and losses equivalently. While losses have been claimed to loom larger than gains in choice, they also influence a variety of related processes. Importantly, losses lead to more exploratory search (Camerer et al., 1993; Hertwig et al., 2018; Lejarraga et al., 2012b) and longer persistence (Goldsmith & Dahr, 2013; Gonzalez et al., 2005; Payne, et al., 1993) two patterns of behavior that suggest that people ponder their behavior longer when losses are at stake. If people, indeed, devote more cognitive resources to avoid losses than to reap gains, then it is possible that they are also more like to solve problems when facing losses. In two studies, we observed that, indeed, losses led to longer persistence losses, but they did not generally improve performance. In study 2, however, where we used anagrams of varying difficulty, we observed that this longer persistence had no effect on easy anagrams, but as the task became more difficult, a difference in performance emerged. Losses led to better performance in more difficult anagrams.

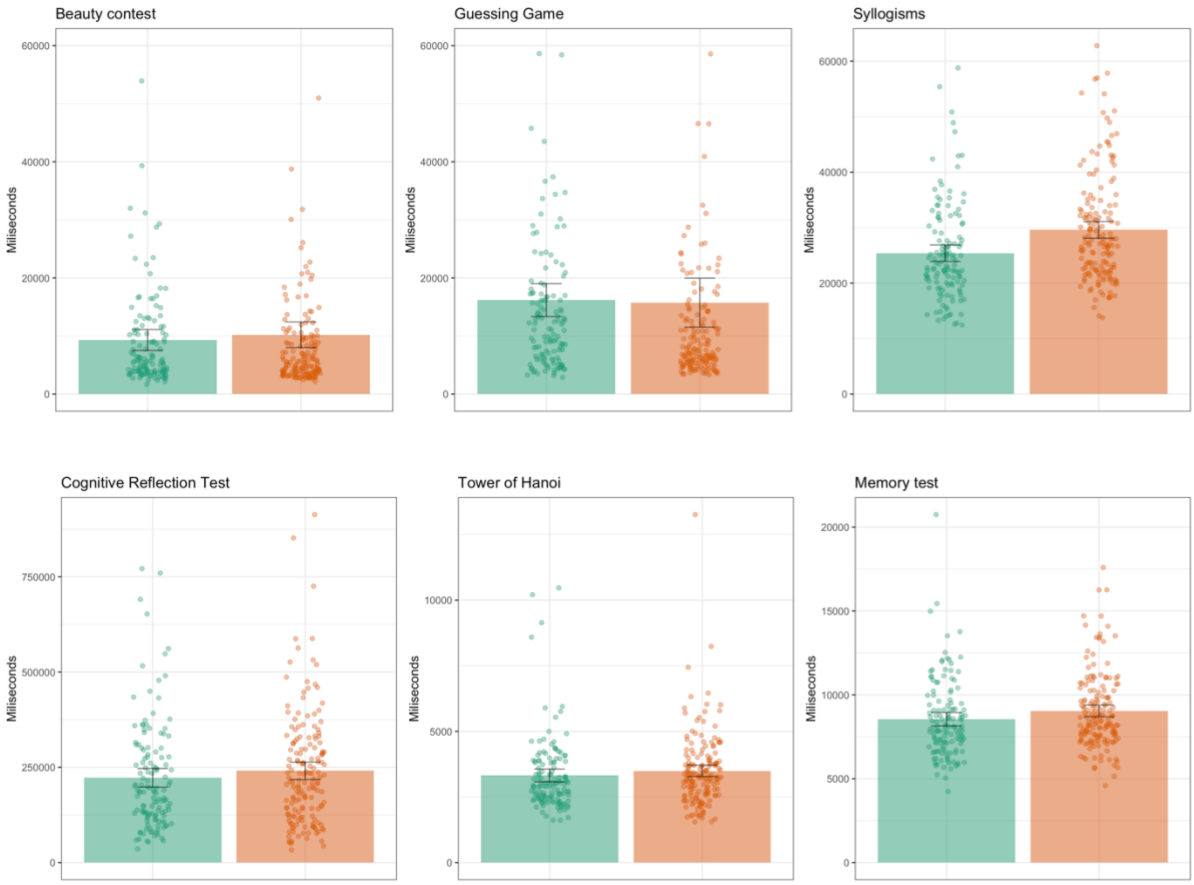
General Discussion

Can losses improve performance? Our results suggest that the effect of losses on reflection is nuanced. Losses seem to increase the persistence of reflection, but its effect on performance was small and difficult to detect. There are different possible explanations for this pattern of results. First, our results show that the effect of losses on performance depends on the task's difficulty. Research on “real-effort” tasks that require little or no intellective effort, suggests that losses do indeed promote more effort in easy, mechanical tasks. Based on this observation, we believed that losses would have a similar impact on easy intellective tasks, but not on difficult ones. We observed the opposite. It is possible that in too-easy intellective tasks, the effect of incentives is trivial. However, in more difficult tasks that demand motivation to complete, incentives are therefore more functional, and it is in these problems in which losses may have a differential impact. This possible explanation explains the results of Study 2 but would only explain the results in Study 1 if tasks were found easy. To address this possibility, we examined performance in Study 1 and, for the problems that have an unambiguous correct response (Tower of Hanoi, Syllogysms, and the Cognitive Reflection Test), most participants solved the problems correctly.

An alternative explanation involves the possibility that longer response times have been incorrectly interpreted as persistence. Let us take Study 1 in Goldsmith and Dahr (2013) as an illustration. Participants who attempted to solve anagrams to avoid a loss took 60% longer time than participants who pursued gains, but their performance did not differ. In other words, participants in the loss conditions took longer to achieve the same output. Therefore, this pattern of results may reflect not only longer persistence but also more inefficient reflection in the domain of losses (or more efficient processing in the domain of gains). This interpretation is in line with the observation that participants in Study 4 (Goldsmith & Dhar, 2013) predicted that they would persist longer, enjoy more, and be more motivated in the gain instead of the loss condition. It is reasonable to expect that this pattern of predictions should translate into more persistence in the domain of gains, not losses, which is what the authors observed. Whether longer response times reflect more persistence in reflection, inefficient reflection, or both, remains an open question to be addressed in future research. Modeling performance and response times simultaneously, as with drift-diffusion models (Ratcliff, 1978; Ratcliff et al., 2016), should shed light on a more accurate interpretation.

Figure 1

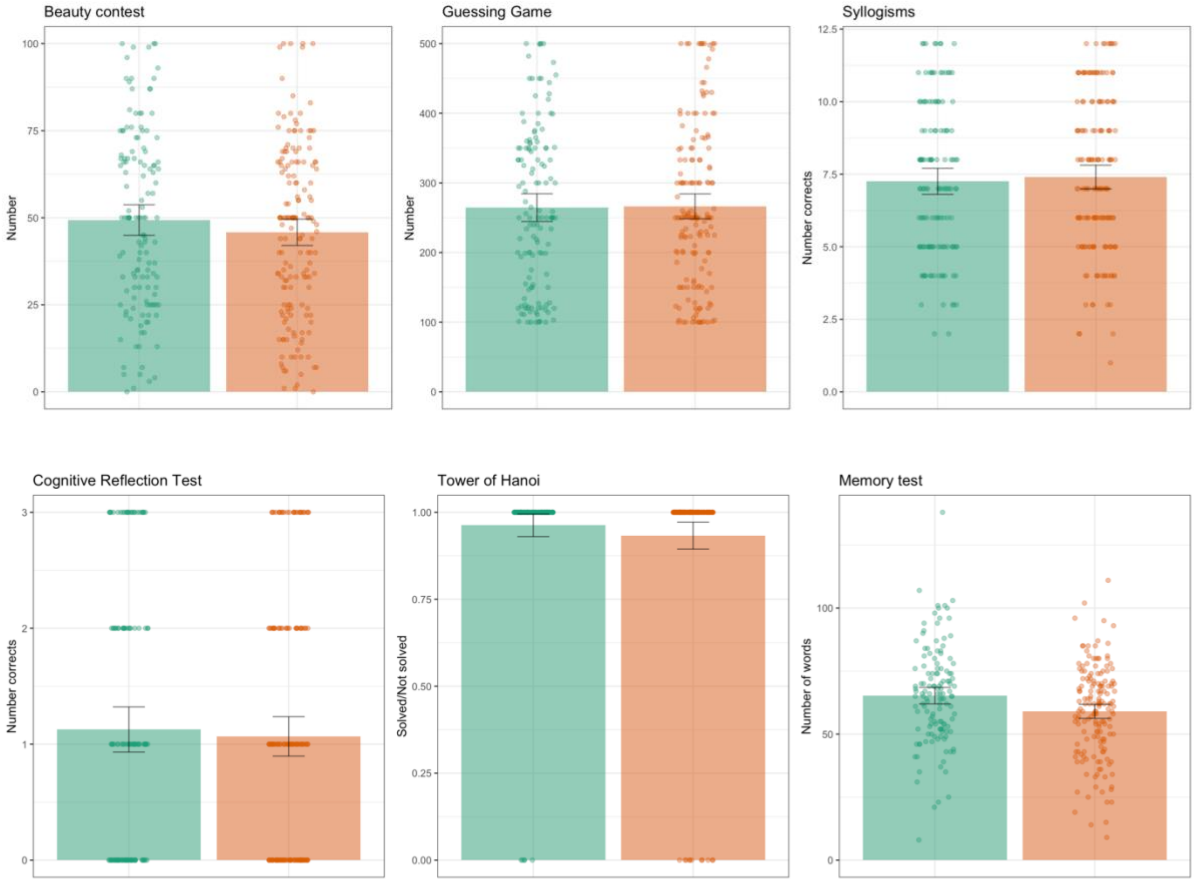
Response times in Study 1 in each of the six reflection tasks



Note: Each graph shows response times in the six tasks in the gain condition (green) and in the loss condition (orange). The dots depict the distribution of response times. The bar in each plot reflects the mean of the distribution and the error bars represent a 95% confidence interval.

Figure 2

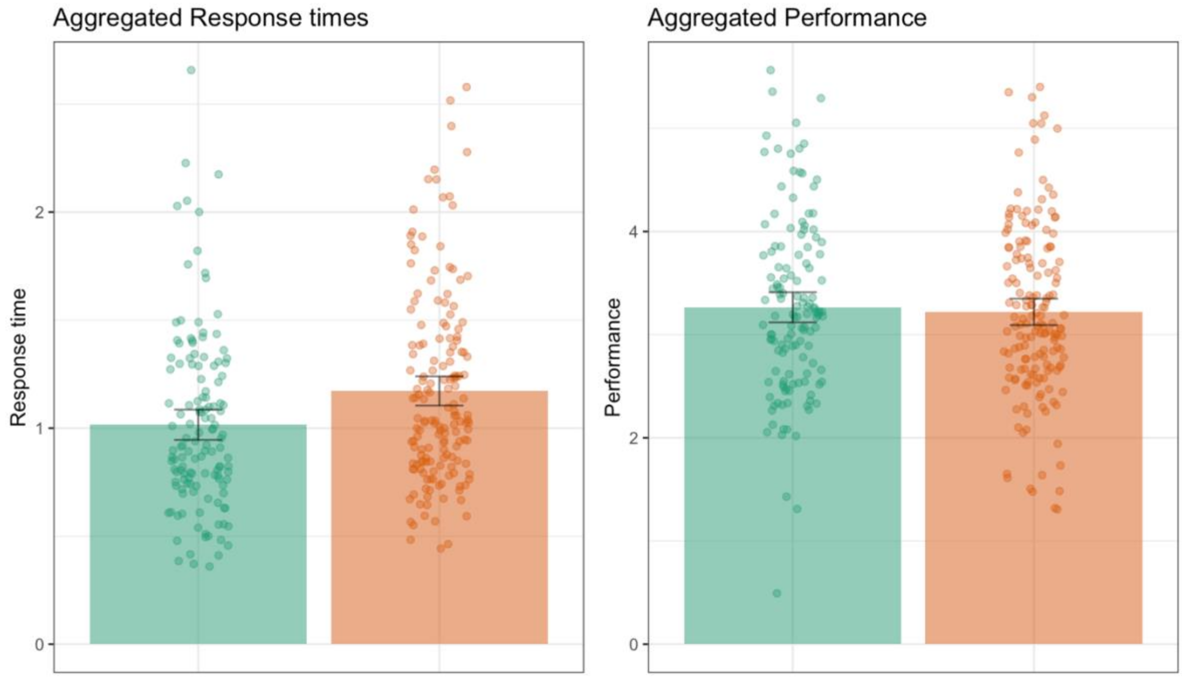
Performance in Study 1 in each of the six reflection tasks



Note: Each graph shows performance in one of the six tasks that participants encountered tasks in the gain condition (green) and in the loss condition (orange). The dots depict the distribution of responses. The bar in each plot reflects the mean of the distribution and the error bars represent a 95% confidence interval.

Figure 3

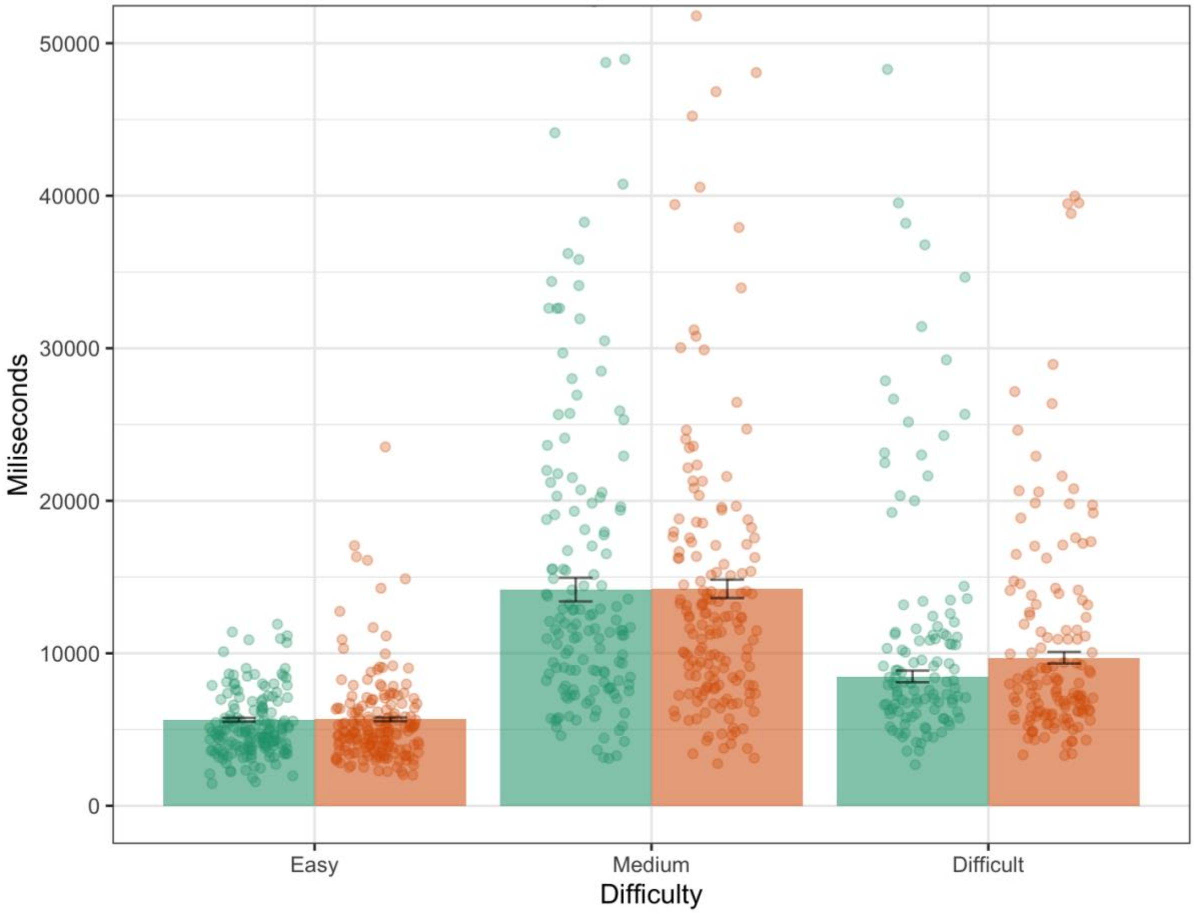
Response times for solved anagrams in Study 2



Note: Normalized and aggregated response time variables (left) and performance variables (right) for the gain (green) and the loss (orange) conditions. Error bars indicate 95% confidence intervals.

Figure 4

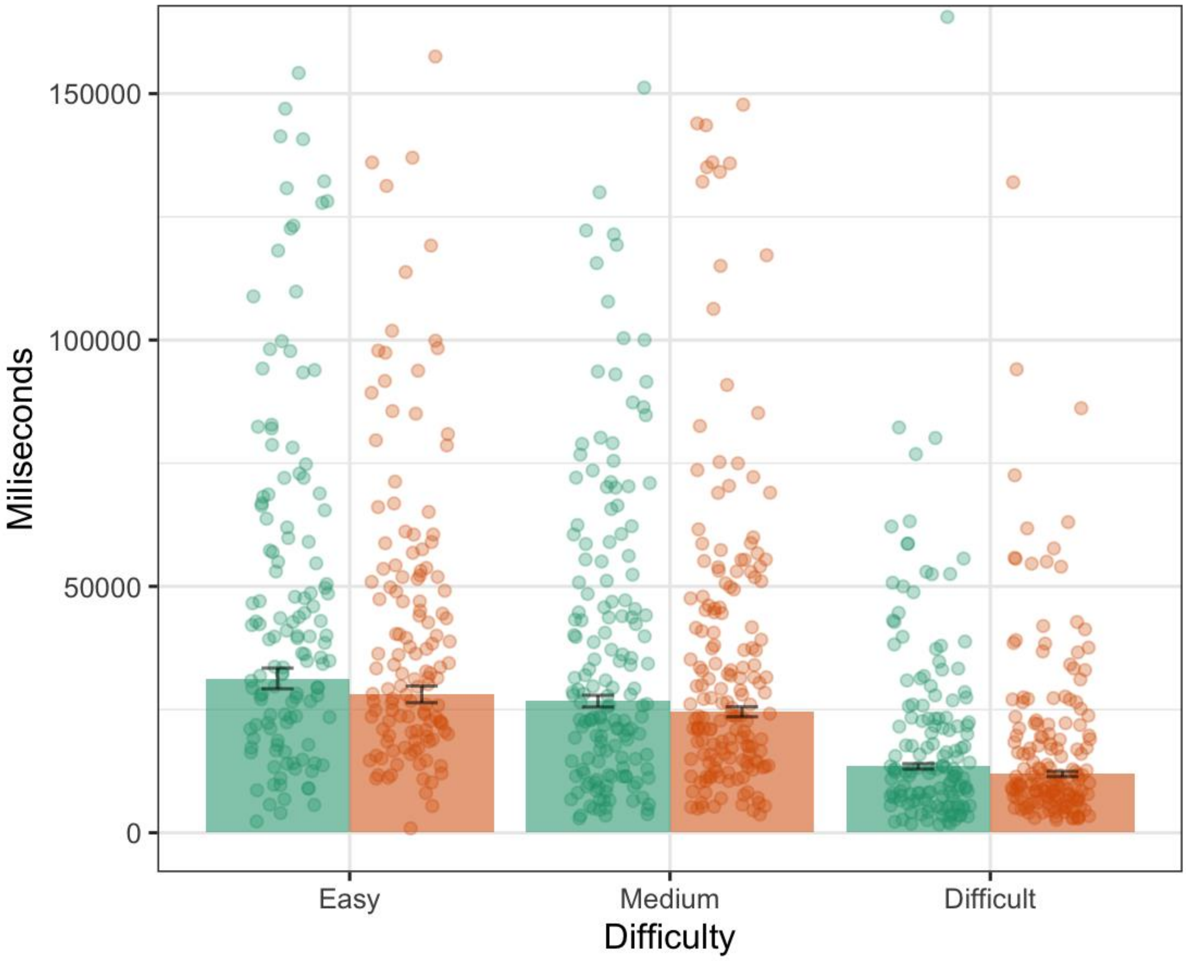
Response times for solved anagrams in Study 2



Note: Error bars indicate 95% confidence intervals.

Figure 5

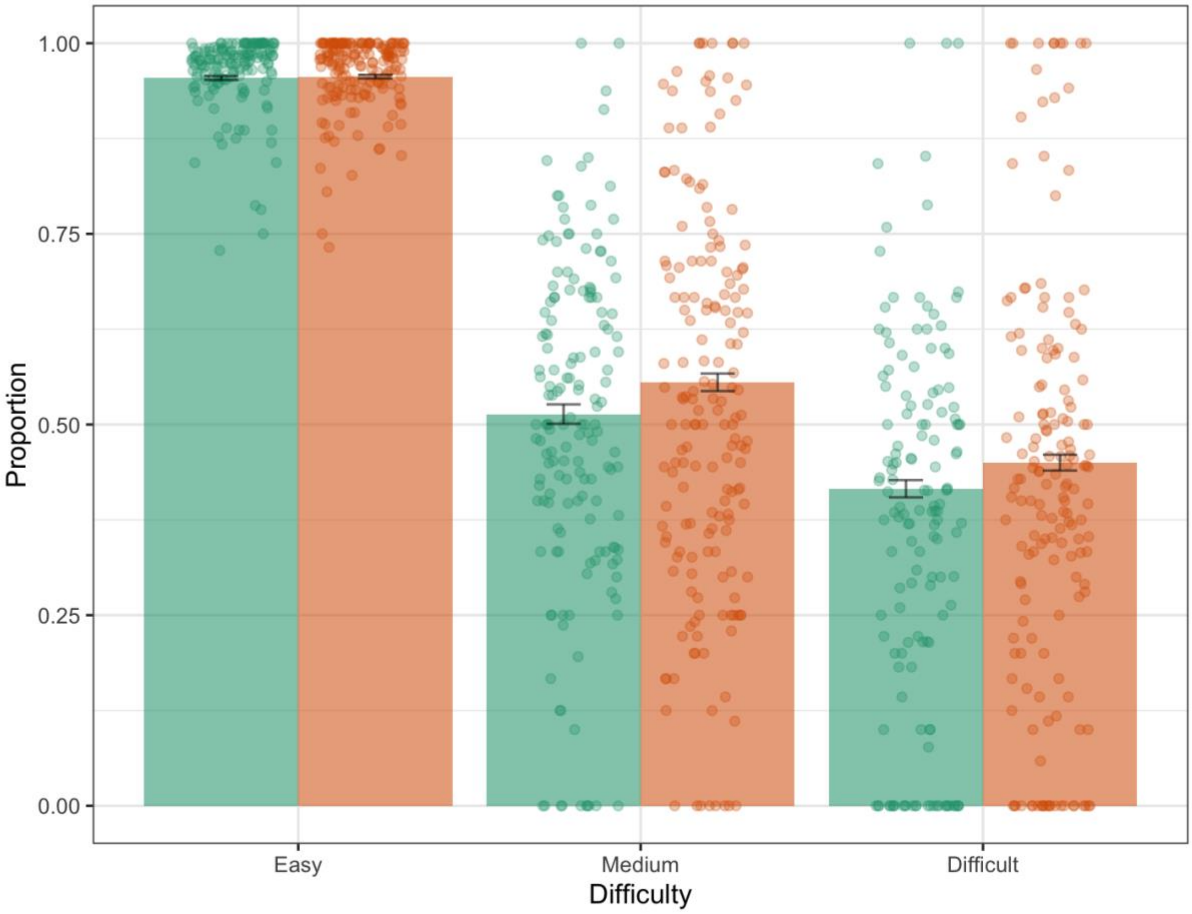
Response times for unsolved anagrams in Study 2



Note: Error bars indicate 95% confidence intervals.

Figure 6

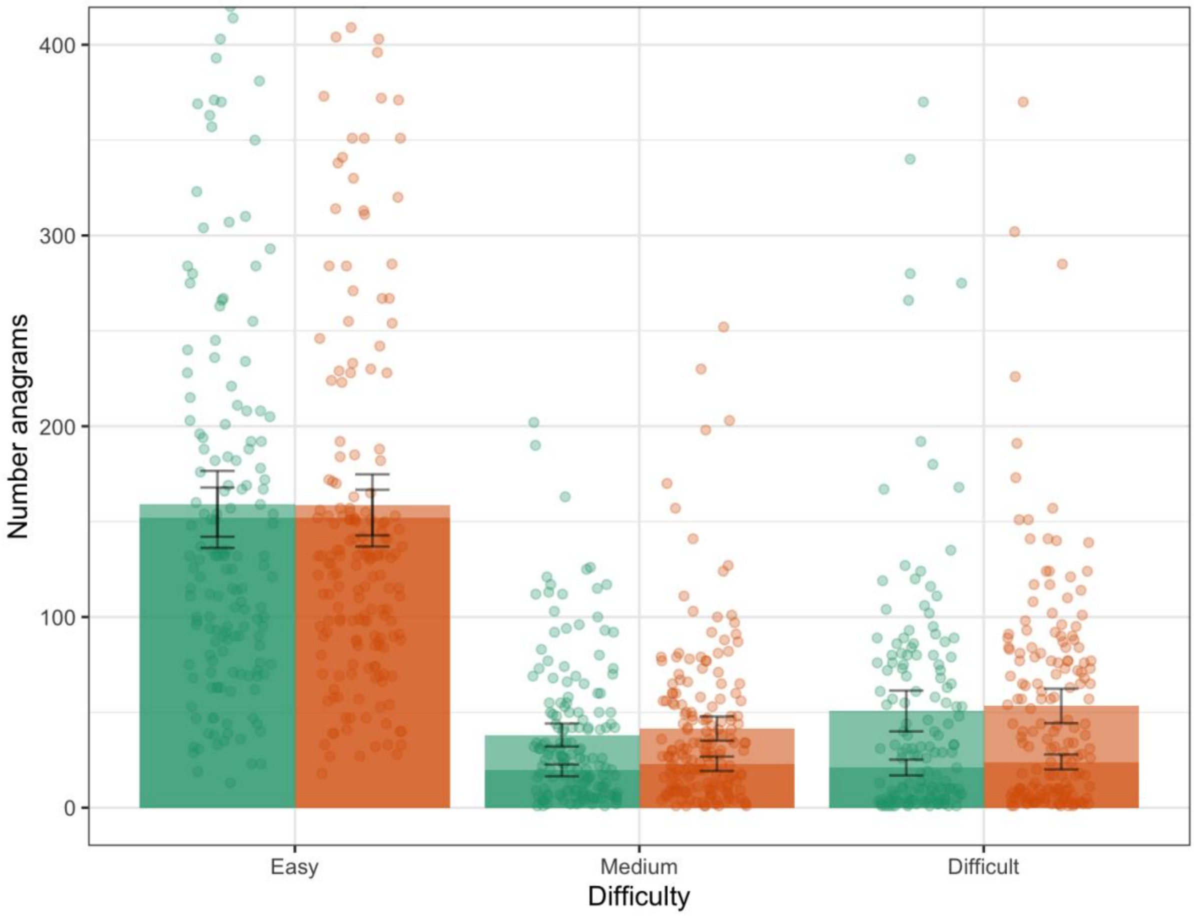
Performance in Study 2 as measured by the proportion of anagrams solved



Note: Proportion of anagrams solved (anagrams seen/anagrams solved) per difficulty and condition. Error bars indicate 95% confidence intervals.

Figure 7

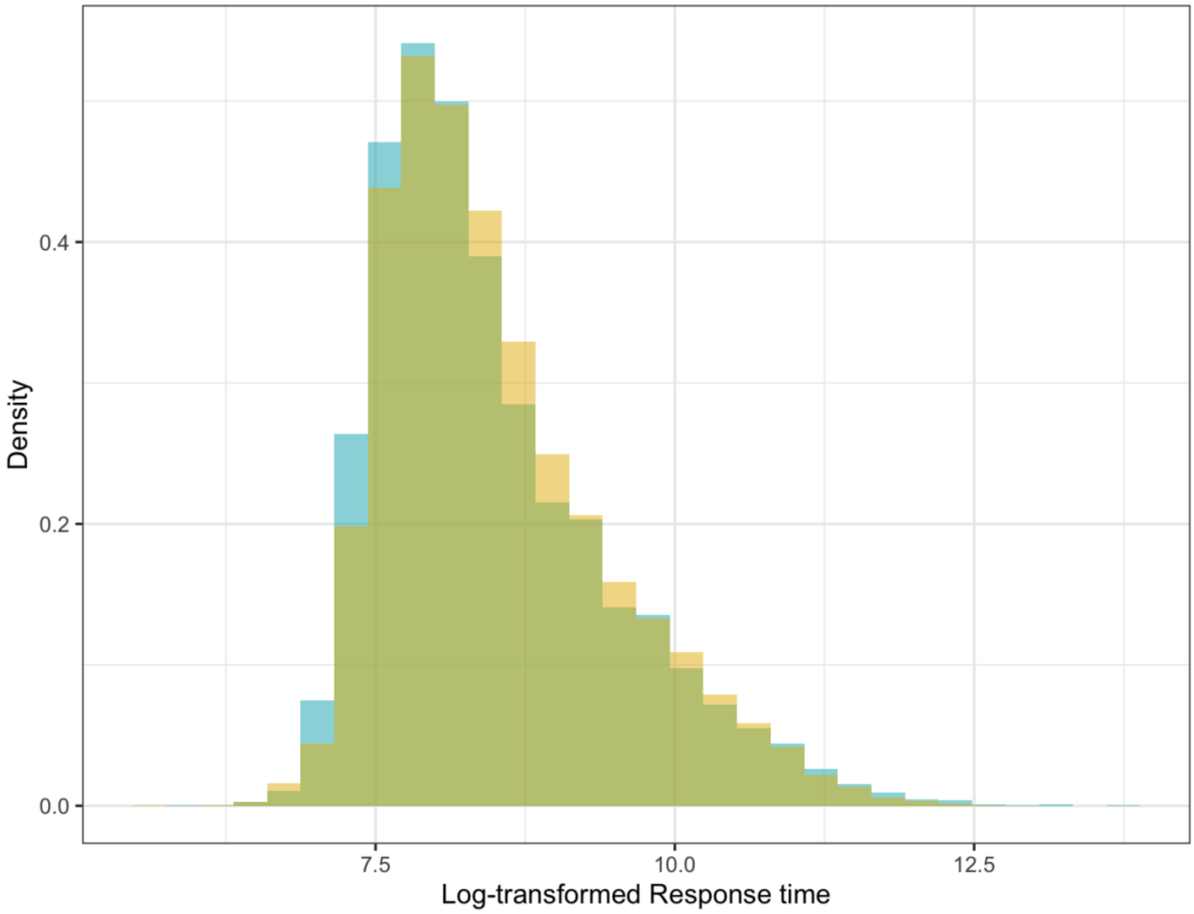
Number of anagrams seen and solved



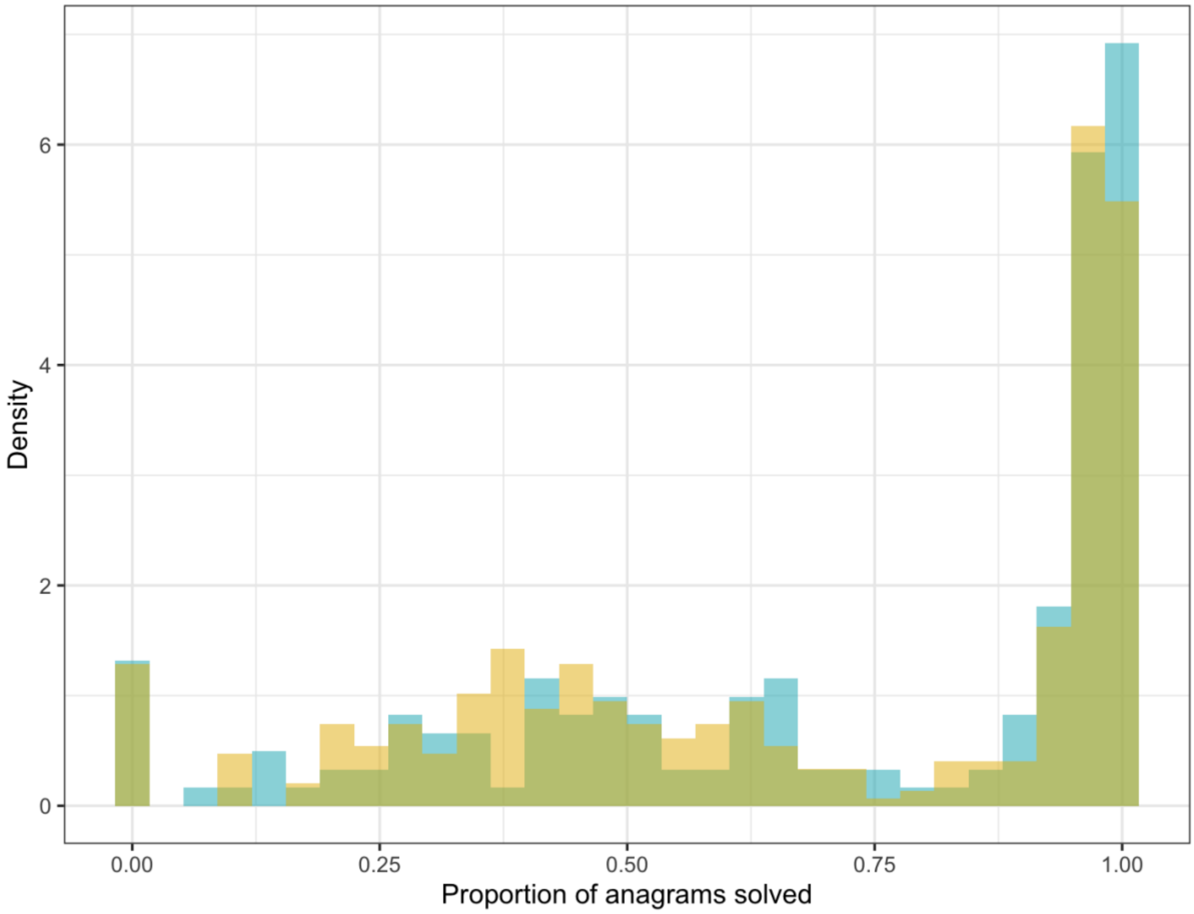
Note: The transparent bars indicate the number of anagrams seen and the solid bars indicate the subset of anagrams solved. Error bars represent 95% confidence intervals. The dots represent the distribution of anagrams seen per participant.

Appendix

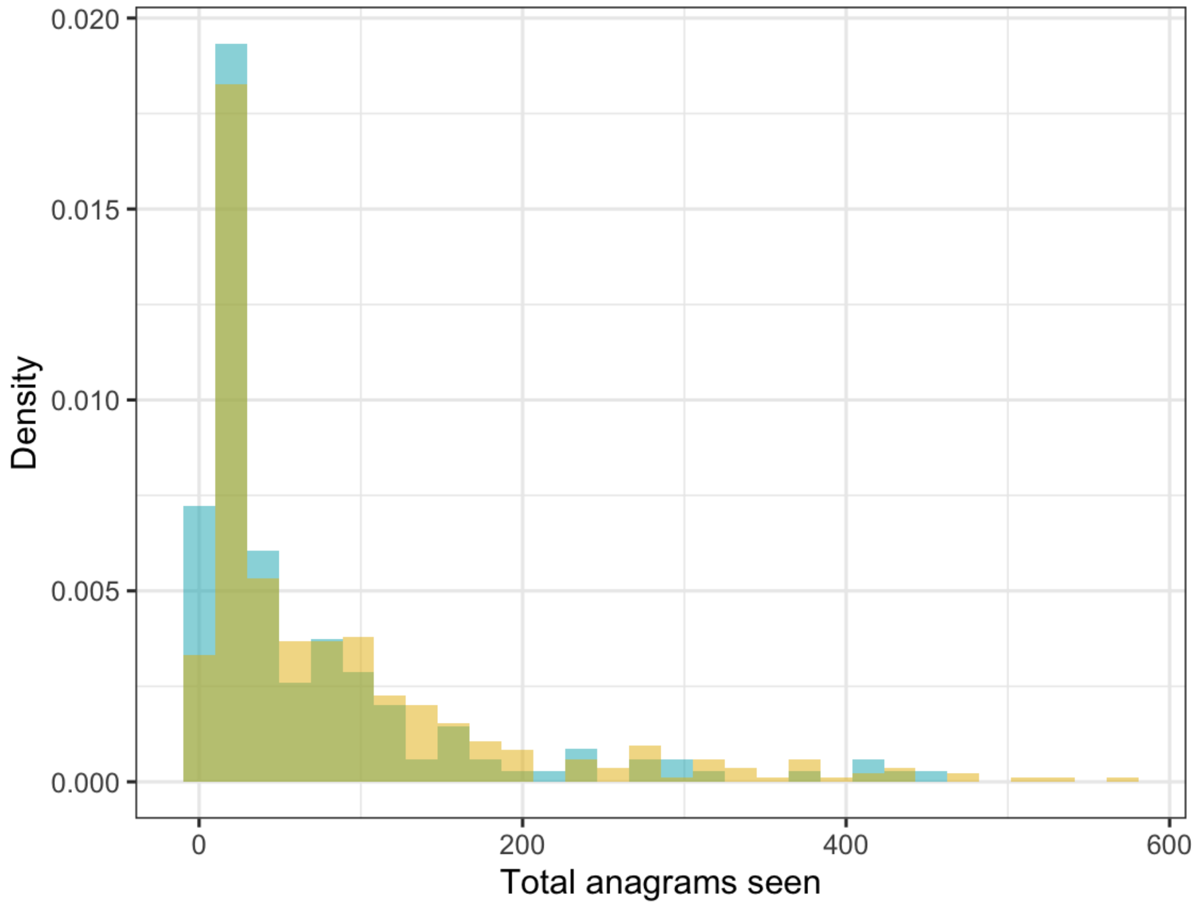
Comparison Laboratory vs Prolific



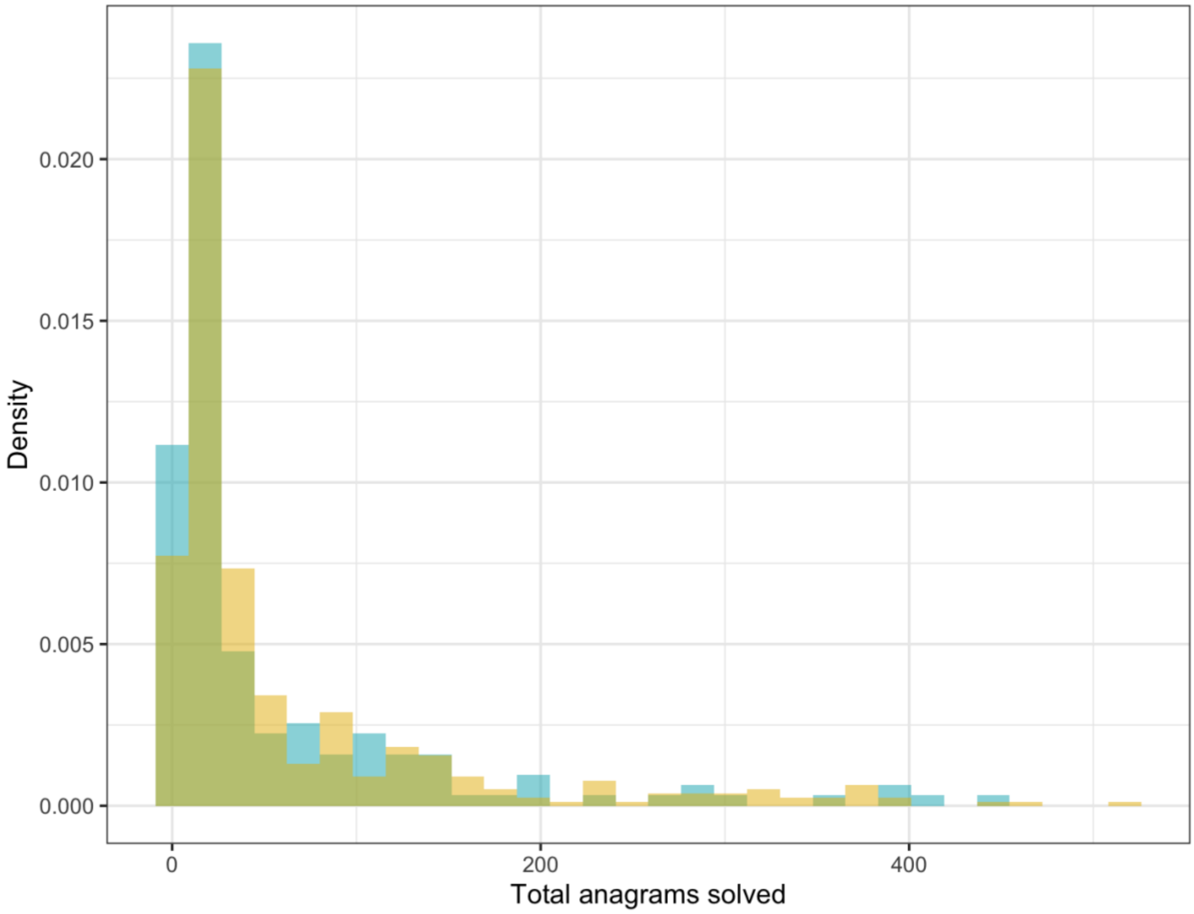
Note: The plot represents the distribution of log-transformed response times for laboratory (yellow) and Prolific (blue) participants solving anagrams. The overlapping area (green) represents the similarity between samples.



Note: The plot represents the distribution of the proportion of anagrams solved per participant and difficulty, for laboratory (yellow) and Prolific (blue) participants. The overlapping area (green) represents the similarity between samples.



Note: The plot represents the distribution of the total anagrams seen per participant and difficulty, for laboratory (yellow) and Prolific (blue) participants. The overlapping area (green) represents the similarity between samples.



Note: The plot represents the distribution of the total anagrams solved per participant and difficulty, for laboratory (yellow) and Prolific (blue) participants. The overlapping area (green) represents the similarity between samples.

Persistence of Reflection untransformed response time in Study 2

Unsolved anagrams

	Estimate	Std. Error	t	p value
(Intercept)	52241.4	2453	21.297	p < 0.001
Losses Condition	-6083.6	3071.2	-1.981	0.0485
Medium Difficulty	-12032.8	887.2	-13.562	p < 0.001
Difficult Difficulty	-28029.9	896.3	-31.274	p < 0.001
Laboratory	-7828.3	3144.5	-2.490	0.0134

Losses Condition x Medium Difficulty	4699.0	1199.2	3.919	0.0001
Losses Condition x Difficult Difficulty	7312.3	1193.1	6.129	p < 0.001

Solved anagrams

	Estimate	Std. Error	t	p value
(Intercept)	6019.6	279.65	21.526	p < 0.001
Losses Condition	-50.7	341.80	-0.148	0.8822
Medium Difficulty	8794.0	238.03	36.946	p < 0.001
Difficult Difficulty	3323.7	242.35	13.714	p < 0.001
Laboratory	-1054.3	360.59	-2.924	0.0037
Losses Condition x Medium Difficulty	489.5	319.15	1.534	0.1251
Losses Condition x Difficult Difficulty	1602.1	323.34	4.955	p < 0.001

Anagrams seen

To explore the number of anagrams seen, we also performed a linear mixed model fitted by restricted maximum likelihood (REML) with the total number of anagrams seen per difficulty per participant and the total number of anagrams solved per difficulty per participant. Structure: the condition, the participation at the lab/Prolific, the difficulty, and the interaction between condition and difficulty as fixed-effects predictors, and a random intercept for each participant as random effects. As expected, the medium and the difficult levels showed a significant effect for the number of seen anagrams (medium: β =- 121.14, SE

= 8.043, $t = -15.06$, $p < .0001$; difficult: $\beta = -112.68$, SE = 8.043, $t = -14.01$, $p < .0001$). Participating in the lab had a significant positive effect compared to participating through Prolific in the anagrams seen ($\beta = 34.58$, SE = 5.353, $t = 6.46$, $p < .0001$). Neither the condition ($\beta = 1.67$, SE = 8.088, $t = 0.21$, $p = .837$) nor the interaction of the condition with difficulty had significant relevance for the number of anagrams seen (medium: $\beta = 3.35$, SE = 11.054, $t = 0.30$, $p = .762$; difficult: $\beta = 3.86$, SE = 11.062, $t = 0.35$, $p = .727$) (Figure 6).

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