

# Quantifying the Subjective Value of Distinct Working Memory Processes

Danai Papadopetraki<sup>1</sup>

Supervisors: Monja I. Froböse<sup>1</sup>, Bram Zandbelt<sup>1</sup>

<sup>1</sup>*Radboud University Nijmegen, Donders Institute for Brain, Cognition and Behaviour, The Netherlands*

**Background:** Distracter resistance is the ability to focus in the face of intervening stimuli and flexible updating is the ability to insert new stimuli into our working memory. Both working memory processes are important for adaptive living, yet we often observe performance failure. This failure has been traditionally attributed to a fixed cognitive capacity. Nonetheless, it has been consistently shown that motivation can strongly impact performance decrements. How does motivation affect performance? Value-based decision-making theories propose that task engagement is regulated by our brains via a cost-benefit analysis rendering task valuation key to understanding performance. Cognitive effort discounting studies quantified the subjective value of working memory tasks and showed that the attributed value decreased with increasing task demand. However, the subjective values of distracter resistance and flexible updating have not yet been quantified separately. **Aims:** First, we aimed to quantify the subjective values of distracter resistance and flexible updating, two key working memory processes. We hypothesised that the value of task engagement will decrease as a function of task difficulty. Our second aim was to assess if one of the two processes is valued more than the other. We hypothesised that distracter resistance is perceived as costlier. **Methods:** We designed a delayed-match-to-sample task to expose participants to increasing levels of distracter resistance and flexible updating. To quantify the subjective values, we employed a modified cognitive effort discounting task. **Results:** We provided strong evidence that subjective value decreases as a function of demand and weak evidence that distracter resistance is assessed as costlier compared to flexible updating. **Discussion:** Our results extend our knowledge about cognitive effort valuation and value-based decision-making. We corroborate other reports that people tend to conserve mental effort and suggest that distinct working memory processes can have differential subjective values.

*Keywords: working memory, distracter resistance, flexible updating, value-based decision-making, effort-discounting*

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Corresponding author: Danai Papadopetraki; E-mail: [danaepapadopetraki@gmail.com](mailto:danaepapadopetraki@gmail.com)

Imagine the situation in which a student has to write an essay while her roommate is playing loud music. It is important for the student to remain focused on her essay despite the distraction of the appealing music coming from next door. Distracter resistance is the ability to focus in the face of intervening stimuli and robustly maintain current representations in working memory (Hazy, Frank, & O'Reilly, 2007). Now imagine that the student's roommate, instead of playing music, was calling for help because the house was on fire. In that case, it would be optimal for the student to switch her attention from writing the essay to the information coming from the roommate. Updating is the ability to flexibly insert new stimuli into working memory. Distracter resistance and flexible updating are two distinct working memory functions that are both required for adaptive living (Ernst, Daniele, & Frantz, 2011). Distracter resistance is crucial for maintaining our focus and completing our long-term goals. Flexible updating is important in order to adapt to environmental changes and to explore new opportunities (Hazy et al., 2007). Yet we often observe performance failure. For distracter resistance, performance failure usually occurs in the form of excessive distractibility. As for updating, people sometimes fail to update by exhibiting "stickiness", where information that is no longer relevant tends to persist in working memory.

Why do we often fail when working memory processes are involved? Traditionally, variance in working memory performance has been attributed to variance in cognitive capacity. The higher our working memory capacity, the better our performance in a specific task. However, these fixed models fail to explain situations in which performance can be improved by manipulating motivation or reward (Padmala & Pessoa, 2011). For example, monetary rewards reduce performance decrements that occur as a function of time on task. To account for such observations, newer, more dynamic models have been proposed that can incorporate factors like motivation and reward.

These models advocate that allocation of working memory resources is determined via a cost-benefit analysis where the costs of task engagement are weighted against the rewards (Botvinick & Braver, 2015; Kurzban, Duckworth, Kable, & Myers, 2013). Going back to our original example, the costs of time and/or effort of working on the essay could be weighed against the rewards of getting a good grade and learning more about the specific topic. As the importance (i.e., value) of the benefits increases, so does engagement in writing the essay. These

value-based decision-making theories can account for reward effects on performance, but can also incorporate other likely contributing components like emotions, beliefs and past history.

If the above accounts hold, the valuation of working memory functions becomes crucial while trying to interpret and analyse human behaviour. Previously, it has been observed that when faced with a choice, participants preferred less cognitively demanding tasks (Kool, McGuire, Rosen, & Botvinick, 2010). In line with the cost-benefit theory, demand avoidance was reduced when monetary incentives were offered. Thus, all else being equal, people seem to perceive their cognitive effort as costly. This subjective cost of effort can be quantified using discounting paradigms, where the costs of a task are being measured as a function of rewards that participants are willing to forego (discount) in order to avoid performing the given task. Discounting paradigms have been applied extensively in the field of neuroeconomics and have lately been used to quantify physical and mental effort (Westbrook, Kester, & Braver, 2013; Massar, Lim, Sasmita, & Chee, 2016).

Such a cognitive effort discounting task was introduced in a recent study (Westbrook et al., 2013). Cognitive load was manipulated using the well-established N-back working memory task. Participants made choices between a higher level of the N-back task for a higher reward (i.e., more money) or a lower level for a lower reward (i.e., less money). The offer of the easy task at which participants were indifferent between the two options -their indifference point (IP)- was used as an estimate of subjective cognitive effort. The subjective value of the task decreased as a function of demand, suggesting that participants evaluate cognitive effort as costly enough to forego significant rewards in order to avoid it.

This was a landmark study for cognitive effort valuation, but a lot of questions remain unanswered. For instance, are all working memory functions/tasks perceived as costly? And, are some working memory functions perceived more costly than others? For example, previous studies have shown that participants perform better at flexible updating compared to distracter resistance (Fallon & Cools, 2014; Fallon, Van Der Schaff, Ten Huurne, & Cools, 2015). Does that difference partly reflect a difference in valuation? Using existing paradigms does not allow to address these questions. The N-back task requires both distracter resistance and flexible updating intermixed, while studies that have disentangled the two processes (Fallon & Cools,

2014; Fallon et al., 2015) were not designed to be discountable because they lack different levels of difficulty. Here, we aimed to address these remaining issues by designing a novel paradigm that allows to quantify the subjective values of distracter resistance and flexible updating individually.

Based on the above we proposed two research questions. 1) Are distracter resistance and flexible updating perceived as costly? We formulated the null and alternative hypotheses as follows.  $H_0$ : The subjective value of distracter resistance and flexible updating is not discounted by participants and the discounting does not increase as a function of demand.  $H_A$ : The subjective values of distracter resistance and flexible updating are discounted by participants and the discounting increases as a function of demand. 2) Is flexible updating perceived as less costly than distracter resistance? We generated the null and alternative hypothesis as follows.  $H_0$ : The subjective value of distracter resistance is the same as the subjective value of flexible updating.  $H_A$ : The subjective value of distracter resistance is smaller than that of flexible updating.

To address our two research questions, we designed a novel working memory paradigm that can evoke varying levels of distracter resistance and updating separately in different trials. During the working memory task participants experienced different demands of both relevant processes. Then using a cognitive discounting task, we quantified and compared the costs of the two working memory functions.

## Methods

### Participants

28 participants (19 women), aged between 18-29 years old were tested in total. Participants had normal or corrected-to-normal vision. Colour blind participants were excluded. The study was approved by the local ethics committee (CMO region Arnhem/Nijmegen, The Netherlands) and all participants provided written informed consent, according to the declaration of Helsinki. They were financially compensated by €8 per hour for their participation. Four data sets were discarded due to technical problems, so we ended up with 24 data sets (17 women, 18-29 years old, mean = 23.5, insert s.d.

### Experimental design

The experiment lasted about 130 minutes and consisted of four tasks performed at a computer and questionnaires that participants filled in the

end. The first task (~7 min) was a colour sensitivity test aiming to check if participants were sensitive to the colourful stimuli used later. Then participants proceeded with the colour wheel memory task to acquire experience with varying demand of the two working memory processes of interest (~10 min practice and 30 min task). The third task (~5 min practice and 55 min task) was a cognitive effort discounting paradigm that was used to estimate the subjective values and address our research questions. The last computer-based task was a redo of the color wheel task (~10 min). Finally, participants filled in some experiment-related questionnaires (~5 min).

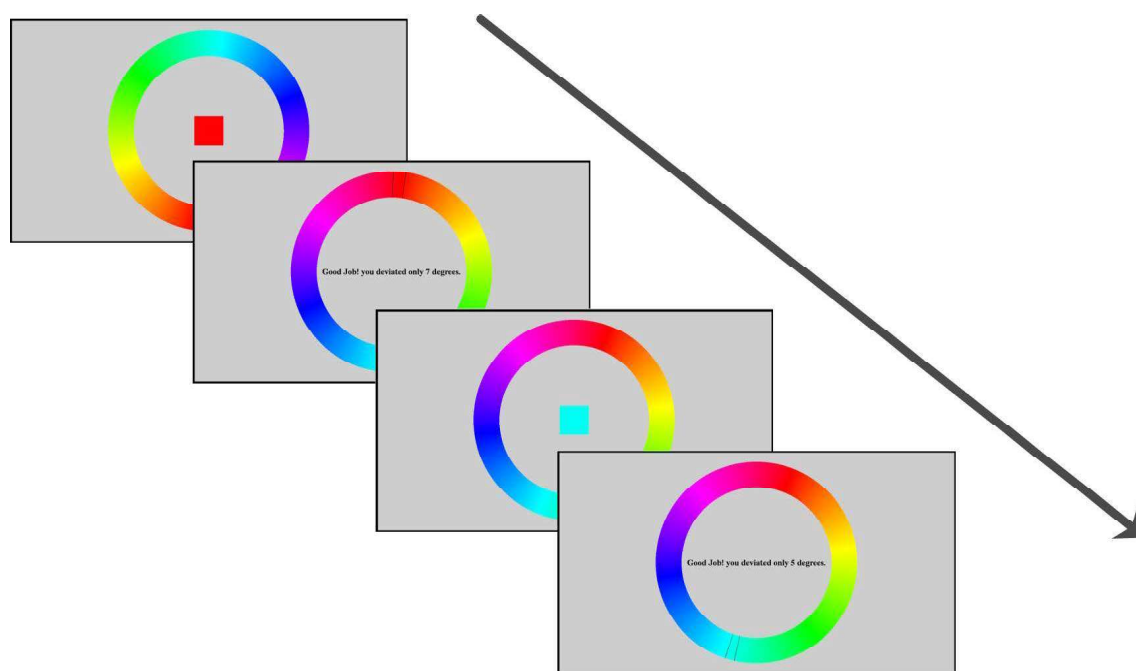
### Paradigms

All three paradigms were entirely programmed in MATLAB (release 2013a) using the Psychophysics Toolbox extensions (version 3.0.12) on a Windows 7 operating system. The screen resolution was 1920 × 1080 pixels. The background colour for all paradigms was grey (R: 200, G: 200, B: 200).

**Colour sensitivity task.** For our working memory task (described in 3.3.2) we used colourful stimuli and a colour wheel, so it was crucial that our participants' colour vision was not impaired. To test their sensitivity to our stimuli we developed a version of the colour wheel task without a working memory component.

The stimuli used for the colour sensitivity task were a colour wheel, black lines and coloured squares. The colour wheel was created by 512 successive coloured arcs of equal angle ( $512/360^\circ = 1.42^\circ$ ), each arc carrying a different colour. The radius of the wheel was 486 pixels. To form the wheel into a ring a smaller circle was superimposed, whose radius was ~362 pixels. The centre of both the wheel and the circle coincided with the centre of the screen. The 512 colours of the colour wheel arcs were generated using the hsv MATLAB colourmap. The black lines were  $0.4^\circ$  black arcs.

In every trial of this task, participants viewed the colour wheel and a coloured square in the middle of the screen (Fig. 1). They were instructed to look at the colour of the square and use the mouse to click on the corresponding shade on the colour wheel. To indicate that their response was recorded a black line appeared on the colour wheel and successively another black line appeared designating the location of the correct colour. Feedback consisted of the actual deviance plus a positive message ("Good job! You deviated only \_\_\_ degrees.") and was provided only when responses deviated less than  $10^\circ$ .



**Fig. 1.** Two example trials of the colour sensitivity task. Participants viewed a coloured square in the middle of the screen and they had to click on the corresponding colour on the colour wheel. A black line indicated the selected colour and a successive line the correct colour. If the selected colour deviated  $10^\circ$  or less from the correct colour they received feedback that they performed well. The task was self-paced and participants performed 24 trials. They successfully completed the task if their average deviance was less than  $15^\circ$ .

To test a representative sample of the colour wheel we split the wheel in 12 main arcs, each of which consisted of 512/12 colour categories. Participants were tested in two different shades from each colour category. So, they performed in total 24 trials of this task. The presentation of the trials as well as the orientation of the colour wheel was randomised. The responses were self-paced and total task duration was approximately 7 min.

The main dependent variable in this task was deviance in degrees from the correct colour. If their average deviance was less than  $15^\circ$  by the end of the task, the experiment continued. Otherwise, they had one more chance to perform the colour sensitivity task, but if failed again they would be excluded.

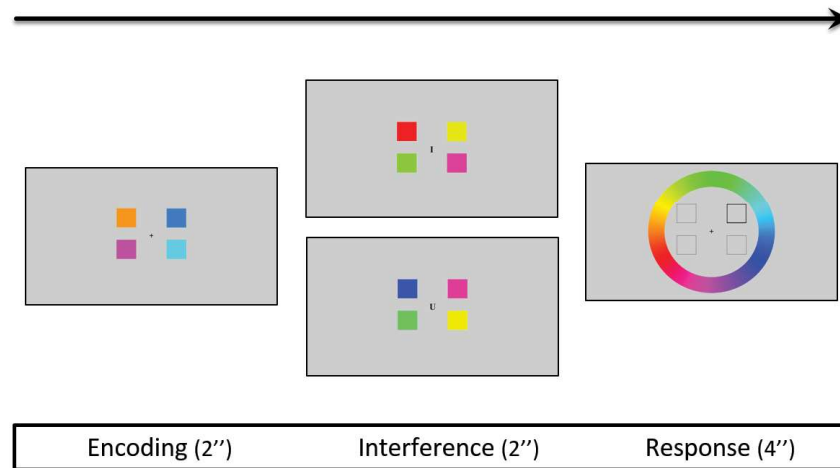
### **Colour wheel working memory task.**

After successfully completing the colour sensitivity task, participants proceeded with the colour wheel working memory task. In this part, participants experienced varying demands of distracter resistance and flexible updating. This task was based on a short-recall task (Zhang & Luck, 2008) and delayed-match-to-sample tasks (Fallon & Cools, 2014) that have previously been used to disentangle between the two working memory processes of interest.

The stimuli displayed during this paradigm were

a colour wheel, coloured squares, black frames of squares, a fixation cross, black lines and central letter cues. The colour wheel was generated as described above. The number of squares varied from one to four and they could be located in four different positions. The centres of the squares formed a rectangle with dimensions  $248 \times 384$  pixels. Each of the four squares was  $100 \times 100$  pixels in size. To choose the colours of the squares we split the colour wheel in 12 main arcs of 42 colours each and only used the 15 central colours of each arc. The arcs from which the colours would be sampled per trial were defined manually, but the exact shade (Red-Green-Blue values [RGB]) was randomly selected. The letter cues were “I” and “U”, coloured black and presented at the centre of the screen.

Every trial of the task consisted of three phases separated by two delay periods (Fig. 2). During the encoding phase, participants viewed the fixation cross and one to four coloured squares for two seconds. The number of squares displayed (set size 1-4) represented the demand of the trial. A delay of two seconds succeeded, during which only the fixation cross was displayed. Then the interference phase followed. In this phase, participants viewed the same number of squares as during encoding, at the same locations, but with different colours. Instead of a fixation cross, one of the two letter



**Fig. 2.** An illustration of the colour wheel working memory task. Every trial of the task consists of three phases. In encoding phase (2 sec), participants need to memorise coloured squares. After a delay of 2 sec, during interference phase (2 sec), a letter indicates if it is a distracter resistance (I for ignore) or an updating (U for update) trial. In Ignore trials participants need to maintain in their memory the colours from encoding phase and not be distracted by the new intervening stimuli. In Update trials, participants have to let go of their previous representations and update into their memory the stimuli from interference phase. Another delay separates interference with response phase. This delay is 2 sec for ignore and 6 sec for update trials due to time differences in target stimuli. During response phase, participants see a colour wheel and black frames of the same squares; they have 4 sec to click on the target colour for the highlighted square. Demand is manipulated by varying the number of squares from one to four. The example displayed here is of the highest demand.

cues was presented during interference in the middle of the screen. The cue would be determined by the condition of the trial: “I” for distracter resistance trials and “U” for flexible updating. The second delay duration was also dependent on trial condition, being two seconds for distracter resistance and six for updating trials. Finally, during the *response* phase participants saw black frames of the same squares, one of which was highlighted, the colour wheel and the fixation cross. If the participant responded within four seconds, a black line appeared on the colour wheel, otherwise, they were instructed to respond faster. The total duration of response phase was five seconds.

For the encoding phase, participants were instructed to always memorise the colours and locations of all presented squares. The instructions for the interference phase differed based on the condition as suggested by the letter cue. In distracter resistance trials (referred to as ignore trials from now on), they needed to maintain in their memory the colours from encoding phase and not be distracted by the new intervening and distracting stimuli. In flexible updating trials (referred to as update trials from now on), participants had to let go of their previous representations and update into their memory the stimuli from the interference phase. Thus, the colours that needed to be remembered

for distracter resistance were the ones from the encoding phase, while for updating trials the ones from interference phase should be remembered. As the encoding phase was four seconds before interference, the second delay was longer for updating trials. Participants were to indicate the colour for only one, highlighted square. They had to identify the target colour on the colour wheel and click using a mouse, within four seconds. Only the first response counted. A black line indicated their response. Only during practice trials, a second line appeared at the correct colour and positive feedback was displayed if they were performing well. During the task, no feedback was provided. Participants were instructed to fixate in the middle of the screen throughout the task. This instruction was given in order to dissuade them from adopting the strategy to close their eyes during ignore trials in order to avoid being distracted.

Participants first underwent a practice session of 16 trials and then performed two identical blocks of the task. A block consisted of 64 trials, resulting from repeating each combination of difficulty (four levels = set size 1-4) and condition (two levels = ignore and update) eight times. Depending on the difficulty level of the trial, a group of two to eight colours was used to create the trial stimuli, each colour coming from one of the 12 arcs.

Colours of the same arc never appeared more than once in the same trial. To make sure that ignore and update trials were as similar and counterbalanced as possible, the colours of the squares used and the target colours were the same for both conditions. However, as the relevant colours appeared during encoding for Ignore and during interference for update, we made sure that the same group of stimuli also appeared in reversed order between these two phases. So, the same groups of coloured squares were presented four times per set size and in total 32 groups of colours were used. To decrease learning effects due to repetition, we split the same stimuli groups between the two blocks. To control for differences between the two hemispheres in representation of colour (Gilbert, Regier, Kay, & Ivry, 2006), the left and right squares were equally highlighted for both conditions. Moreover, the same colours were highlighted for all four set sizes. The total duration of the colour wheel working memory task was approximately 40 minutes.

**Discounting choice task.** After participants gained adequate experience of all four levels of update and ignore via the colour wheel working memory task, they proceeded with the third part of the experiment: the discounting choice task. The aim of this paradigm was to quantify the subjective value participants assigned to the cognitive engagement they experienced during the colour wheel task. The design of the task was inspired by the temporal and cognitive effort discounting literature (Westbrook et al., 2013; Kable & Glimcher, 2007). There were two versions of choice trials to address our two research questions. In both versions two options accompanied with an amount of money were offered and the options defined what participants would do in the last part of the experiment. Both the rewards and the redo were real and not hypothetical to promote task validity.

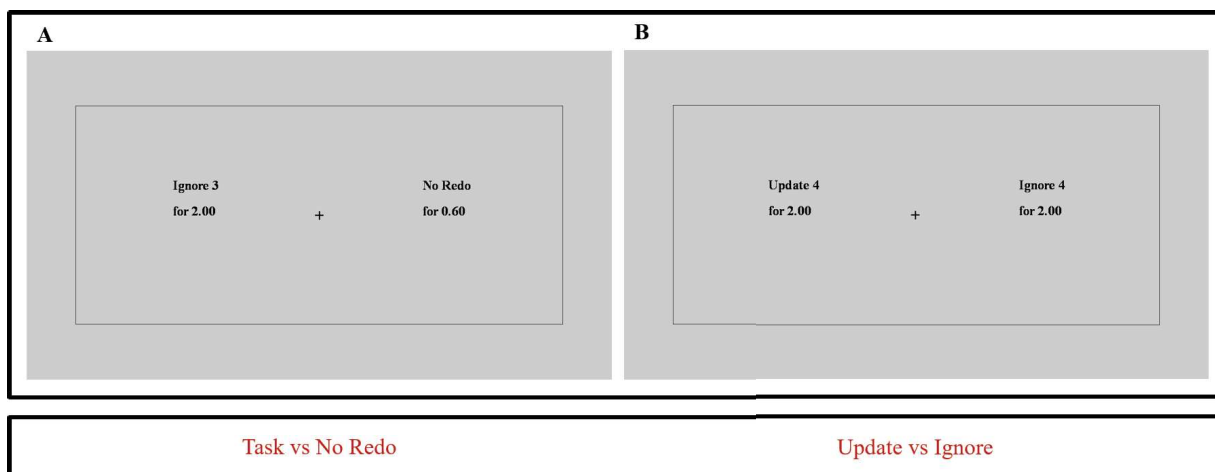
The stimuli used for this paradigm were word cues, a fixation cross, a black rectangle and a black square. The rectangle was located in the centre of the screen with dimensions  $1600 \times 720$  pixels. The square dimensions were  $250 \times 250$  pixels. The word cues displayed were “Ignore”, “Update”, “No Redo” and “for”; the two first were accompanied by a number from one to four (referring to the set size) and the last one by a sum of money varying from €0.1 to €4.

In every trial of the task participants saw a rectangle containing two options and a fixation cross. The options could be “No Redo” or any set size of ignore or update, for example “Ignore 2”.

Below each option (60 pixels) a monetary reward was displayed, for example “for 2€”. Participants could choose the left or right option by pressing 1 or 2 on the keyboard and they had six seconds to respond. When participants made a choice, a black square surrounding the selected offer appeared to indicate their response was recorded.

At this stage, participants were instructed that there were two more parts in the experiment. In the last part, they would have the opportunity to earn a bonus monetary reward by redoing one to three blocks of the colour wheel task. However, the amount of the bonus and the type of trials they would repeat would be based on the choices they made on the choice task. The framework in this task was extremely important because we wanted to minimise influences of research question irrelevant factors. To highlight the importance of every choice, we instructed them that of all the choices they made (of both versions) the computer would select only one randomly and the bonus and redo would be based on that single choice. To minimise effects of error avoidance in valuation, we informed participants that accuracy during the redo part would not influence whether they receive the monetary reward, as long as their performance was comparable to the first time they did the colour wheel task (part 2 of experiment).

***Task vs No Redo: Choices between working memory task and no task.*** These trials addressed the first research question: whether distracter resistance and flexible updating subjective values decrease as a function of task demand. Here, participants had to choose between repeating a level of ignore or update (effort offer) and not redoing the colour wheel task at all (no-effort offer), see Figure 3A. “If they chose the “No Redo” option they were instructed that they would be able to use their time as they pleased (e.g., by using their phones) but they would still have to stay in the testing lab so that time spent on the experiment was the same for both options. Otherwise, if the option to repeat the task was selected, the redo trials would consist of mostly the selected choice condition and level. “Mostly” is important because if they always did the same condition during the redo, they would be able to predict whether they had to update or ignore. We emphasised that they should take their time, not rush their response and consider both the money and their experience while doing the colour wheel task.



**Fig. 3.** Two versions of discounting choice task trials. **A.** Task vs No Redo. In this version participants have to choose between repeating a level of ignore or update and not repeating the colour wheel task at all (“No Redo”). The task option offer remains fixed at €2 and the “No Redo” option varies from €0.1 to €2.2. **B.** Update vs Ignore. For these trials participants have to choose between repeating either ignore or update of the same demand. Ignore offers are always fixed at €2 and update varies from €0.1 to €4. Trial duration is 6 sec.

***Ignore vs Update: Choices between distracter resistance and flexible updating.***

This version aimed to investigate whether distracter resistance is perceived as costlier than flexible updating by directly contrasting them. In these trials participants had to choose between doing the same level of either ignore or update (Fig. 3B).

The amount they were offered for the “No Redo” option (no-effort offer) varied from €0.10 to €2.20 in €0.20 steps, while the task option (effort offer) was always fixed at €2.00. The €2.20 option for “No Redo” was included to verify whether there were participants who strongly preferred performing the task, even if that meant foregoing rewards. As we hypothesised that ignore would be costlier, in this case ignore (hard offer) was kept steady at €2 and update (easy offer) was varying from €0.10 to €4 in €0.20 steps. All possible pairs of options were 96 for “task vs no redo” choices (12 amounts  $\times$  2 conditions  $\times$  4 set sizes) and 84 for “ignore vs update” choices (21 amounts  $\times$  4 set sizes). As there is evidence that choice is probabilistic rather than deterministic (Rieskamp, 2008), every pair of options was sampled three times. We decided on three repetitions of the pairs based on a simulation analysis using pilot data (Online supplementary Fig. S1) in order to optimise the trade-off between indifference point estimation and task duration. Each participant performed three blocks that contained in total 288 trials of “task vs no redo” trials and 255 trials of “ignore vs update”. There was a short practice session of 12 trials, where

the amounts offered were the same for all options (€2) to avoid anchor effects. The trials of the two versions were interleaved (mixed) and randomised within each block. To avoid location effects, we counterbalanced the left-right presentation of the two options. So, for example, “No Redo” was presented left on half of the trials and right on the other half. Total task duration was about 55 minutes.

We decided to use fixed sets of offers and not a titrated staircase procedure to estimate subjective values because staircase procedures do not sample the entire logistic regression curve, rather the curve is estimated. Our version of effort discounting task sampled the logistic regression curves adequately because all participants were faced with the entire range of offer options.

**Redo.** After participants finished three blocks of the discounting choice task one of their choices was pseudo-randomly selected. Specifically, the computer only sampled from “ignore vs update” choices of level 3 or 4. Participants always did one block of 24 trials of the colour wheel task. Two-thirds of these trials were their preferred condition (ignore/update) and the set size was based on the parity of their subject number. We decided to never choose the “No Redo” option or the lower levels to maintain experimenter credibility for other participants. The redo data were not analysed and participants always received the bonus regardless of their performance.

**Debriefing questionnaires.** After the end of the experiment we requested participants to complete questionnaires. We explicitly asked them to report their preference by asking “Which trials did you prefer?”.

## Variables

**Colour sensitivity task.** The main dependent variable was accuracy as deviance in degrees from the correct colour.

### Colour wheel working memory task.

The independent variables for this paradigm were set size (four levels: 1-4) and condition (two levels: Ignore, Update) and we measured accuracy as deviance in degrees from the target and response times in seconds from probe onset as dependent variables.

**Discounting choice task.** For the discounting task, we measured participant choices and the independent variables were set size, condition and easy/no-effort offer.

## Data analysis

We analysed our data using both frequentist and Bayesian statistics. All statistical analyses were performed using open source software JASP (version 0.7.5.6; Wagenmakers et al., 2016) on a Windows 7 operating system.

**Table 1.**

Bayes Factor Interpretation (Lee & Wagenmakers, 2013). At a value of 1, the data are inconclusive and we have no evidence to support either hypothesis. As the BF deviates from 1 evidence for either the alternative or the null hypothesis is enhanced.

$B_{10}$	Interpretation
> 100	Extreme evidence for $H_1$
30 – 100	Very strong evidence for $H_1$
10 – 30	Strong evidence for $H_1$
3 – 10	Moderate evidence for $H_1$
1 – 3	Anecdotal evidence for $H_1$
1	No evidence
1/3 – 1	Anecdotal evidence for $H_0$
1/10 – 1/3	Moderate evidence for $H_0$
1/30 – 1/10	Strong evidence for $H_0$
1/100 – 1/10	Very strong evidence for $H_0$
< 1/100	Extreme evidence for $H_0$

As scepticism against classical statistical tools increases (Ioannidis, 2005), more and more scientists turn to alternative analysis methods such as Bayesian statistics (Wagenmakers et al., 2016). The main strength of Bayesian statistics is that they allow us to quantify evidence for our hypotheses instead of forcing an all-or-none decision and an arbitrary cut-off of significance. Bayesian statistics can also provide evidence for the null hypothesis, thus distinguishing between undiagnostic data (“absence of evidence”) and data supporting  $H_0$  (“evidence of absence”). Another important benefit is that we are able to monitor evidence as data accumulate and we can continue sampling without biasing the result. Due to all the above advantages, we decided that our main conclusions will be drawn based on the Bayesian analyses.

However, frequentist statistics are well-established and widely-acknowledged tools, so more scientists are familiar with their rationale and interpretation. To ensure that our results are interpretable by as many researchers as possible and to also compare their outcomes we additionally included classical statistics.

Bayesian statistics allow model comparison, but also provide evidence for individual effects. When possible, we reported Bayesian model comparison ( $BF_{10}$ : Bayes factor of model against the null) as well as Bayesian and frequentist effects analyses ( $BF_{\text{INCLUSION}}$ : Bayes factor of Bayesian model averaging). Refer to Table 1 for a Bayes Factor interpretation. We used the default JASP Cauchy priors for all Bayesian statistics (Wagenmakers et al., 2016). Regarding frequentist statistics, we considered a  $p$ -value of .05 or smaller as significant. In the cases where sphericity was violated, we reported the Greenhouse-Geisser corrected  $p$ -values.

**Colour sensitivity task analysis.** The data from this task was only used to establish that participants are sensitive enough to our colour wheel. We calculated the overall average deviance in degrees.

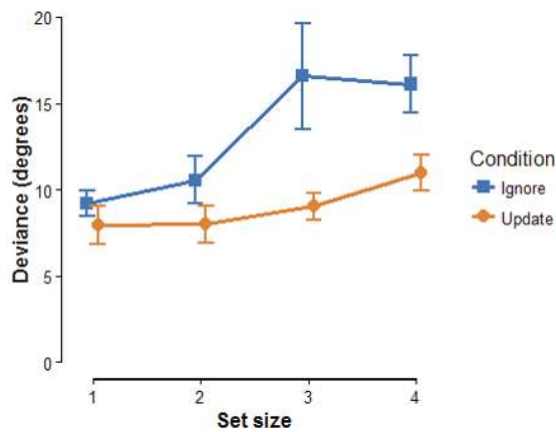
**Colour wheel task data analysis.** We computed the median deviance and median reaction time for all levels of ignore and update. The rationale behind choosing the median was that it is less sensitive to extreme values. For example, 90° and 180° accuracy scores are both wrong responses, but the latter affects the mean much more strongly. Then we used the above scores for the statistical analysis using classical and Bayesian  $2 \times 4$  repeated measures analysis of variance (ANOVA) with condition (Ignore/Update) and set size (levels 1-4) as within-subject factors.



**Table 2.**

Descriptive statistics for colour wheel task deviance.

Condition	Set size	Mean	SD
Ignore	1	9.20	3.29
	2	10.55	4.96
	3	16.57	18.70
	4	16.11	12.34
Update	1	7.92	3.18
	2	7.99	3.05
	3	9.04	3.85
	4	10.96	6.48



**Fig. 4.** Accuracy across 24 participants in colour wheel working memory task. Accuracy represented as deviance in degrees from the correct colour is displayed here as a function of set size for distracter resistance (ignore) and flexible updating (update) trials. The data are best explained by the model including condition and set size ( $BF_{10} = 1179$ ). Error bars indicate the standard error of the mean (SEM).

**Outlier criteria.** As outliers, we defined participants performing below chance level ( $90^\circ$  deviance) or whose accuracy in either condition was deviating more than 3 standard deviations from the mean.

**Discounting choice task data analysis.** As an estimate of subjective value, we computed participants’ Indifference Points. The indifference points can be interpreted as the financial amount offered for the presumably less effortful option (no redo or update) at which participants are equally likely to choose one or the other, thus the probability of accepting either option would be .5. With the main

dependent variable being choice, a dichotomous variable, we calculated the probabilities of accepting the presumably easier offer using binomial logistic regression analysis in MATLAB and extracted the indifference points for the different conditions.

**Choices between working memory task and no task.** Having determined the indifference points for all levels of both working memory tasks per participant, we continued with the statistical analysis using classical and Bayesian  $2 \times 4$  repeated measures ANOVA to assess our first hypothesis that subjective value decreases with demand for distracter resistance and updating. Confirmation of this hypothesis would require that the model including set size is more likely than the null model or the presence of a set size effect with  $p$ -value smaller than .05. We also performed Bayesian and classical one sample  $t$ -tests on the indifference points across levels for both conditions to assess if the subjective value of the working memory functions was overall lower than the no task subjective value. The task offer was always €2 so a subjective value lower than 2 would imply that participants were discounting the task option.

**Choices between distracter-resistance and updating.** We then computed each participants’ indifference points collapsing across levels of “ignore vs update” choice trials to evaluate our hypothesis that ignore has a lower subjective value than update using Bayesian and classical one sample  $t$ -tests. As ignore was set at €2, subjective values lower than 2 confirm that participants were willing to forego rewards to repeat update instead of ignore trials. Additionally, we calculated indifference points for all levels separately and used a  $1 \times 4$  ANOVA with set size as a factor to assess if the preference for update varies with demand.

**Exclusion criteria.** Participants who consistently chose only one option (presumably easier or hard) would be excluded from the analysis, as we would not be able to estimate an indifference point for them. Similarly, participants who deviated more than 3 standard deviations from the mean were also excluded as outliers.

## Results

### Colour sensitivity task

All participants passed the colour sensitivity task and continued to the main paradigm. Their average

**Table 3.**

Model comparison for accuracy in colour wheel working memory task.

Models	$p(M)$	$p(M   \text{data})$	$BF_M$	$BF_{10}$	% error
Null model (including subjects)	.2	5.685e-4	0.002	1	
Condition	.2	.041	0.173	73	0.82
Set size	.2	.006	0.023	10	0.88
Condition + Set size	.2	.690	8.914	1214	1.57
Condition + Set size + Condition × Set size	.2	.262	1.420	461	11.34

*Note.* All models include subjects.

deviance was 6.79 ( $SD = 1.20$ ; median = 4.8,  $SD = 0.87$ ) degrees. We report the median here as well for easy comparison with the colour wheel working memory task results.

### Colour wheel working memory task

Having determined performance outside a working memory context, we analysed performance under conditions requiring distractor resistance and flexible updating. All participants performed overall above chance level (mean deviance less than  $90^\circ$ ). Based on our criteria, no outliers were detected.

**Deviance.** Figure 4 shows colour wheel working memory task accuracy across set sizes for both conditions. See Table 2 for descriptive statistics. The Bayesian model comparison (Table 3) showed strongest support for the model including set size and condition ( $BF_{10} = 1179$ ); the runner-up model was  $\sim 2.5$  times less likely and it was the one including both main effects and their interaction ( $BF_{10} = 460$ ). The effects analysis for deviance confirmed that accuracy decreased with increasing set size ( $F(3, 23) = 4.676, p = .022, BF_{INC} = 15.234$ ) and that participants performed better at update compared to ignore trials ( $F(1, 23) = 9.986, p = .004, BF_{INC} = 104.358$ ), see Table 4 for Bayesian effects. The interaction effect here was not significant ( $F(3, 1.597) = 2.329, p = .122, BF_{INC} = 1.420$ ). Overall, the

findings demonstrate that accuracy decreased with demand and was better for update trials.

**Reaction times.** Figure 5 depicts reaction times for ignore and update trials as a function of set size and Table 5 presents descriptive statistics for RTs. According to the Bayesian model comparison (Table 6), the best model was the one including condition, set size and the interaction between the two ( $BF_{10} = 1.667e+26$ ). Effects analyses (Table 7) confirmed that participants were faster in ignore compared to update trials ( $F(1, 23) = 20.111, p < .001, BF_{INC} = 310$ ), a very strong set size effect ( $F(1.6, 23) = 51.617, p < .001, BF_{INC} = \infty$ ) and a strong interaction effect ( $F(2.22, 23) = 7.21, p = .001, BF_{INC} = 111$ ). The analyses suggest that RTs varied with demand and that participants were faster for distractor resistance trials, but this difference depended on task demand.

### Discounting choice task

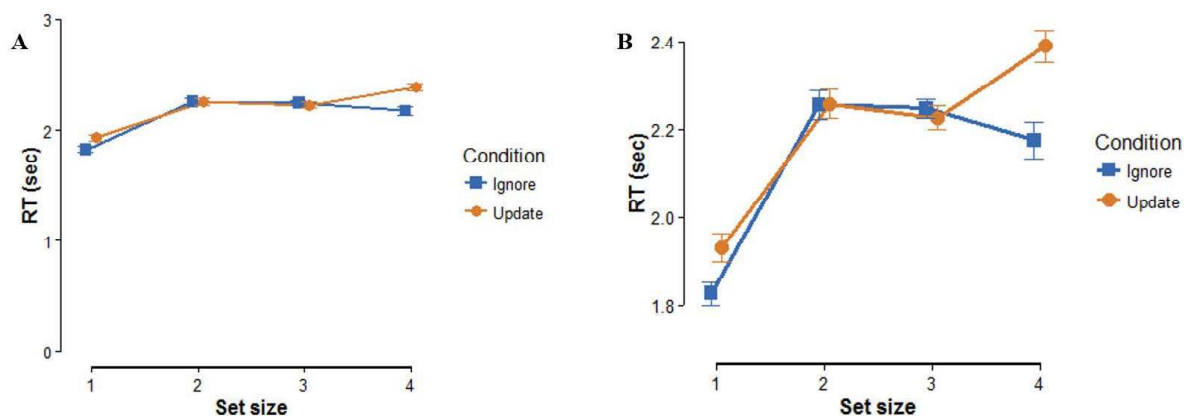
**Choices between task and no task.** After analysing performance on increasing levels of updating and distractor resistance, we proceeded to quantify the subjective value participants assigned to them.

Figure 6A-B depicts the logistic regression curves of an example participant whose indifference points could be adequately sampled for both update (A) and ignore (B) conditions. As the task offer was

**Table 4.**

Bayesian analysis of effects in accuracy.

Effects	$p(\text{inclusion})$	$p(\text{inclusion}   \text{data})$	$BF_{\text{Inclusion}}$
Condition	.6	.994	104
Set size	.6	.958	15
Condition × Set size	.2	.262	1.4



**Fig. 5A.** Reaction times for 24 participants in colour wheel working memory task. RTs are shown as a function of set size for distracter resistance (ignore) and flexible updating (update). **B.** Same results scaled. These results are best explained by the model including condition, set size and their interaction ( $BF_{10} = 1.667e+26$ ). Error bars represent the standard error of the mean.

always €2, the smaller the indifference point from €2, the more the task value was discounted. For four participants, we could not estimate indifference points for at least one of the two conditions, so they were excluded. Two of them always chose the “No Redo” option, one of them always chose the task option and one of them always chose “No Redo” for update trials and task for ignore trials.

The indifference points across set size for 20 participants for distracter resistance and updating are displayed in Fig. 7A-B and descriptive statistics in Table 8A-B. The analysis (Table 9) showed that the model including set size and condition ( $BF_{10} = 85$ ) is the model that is best supported by our data and that this model is ~1.4 times more likely than the one including only condition ( $BF_{10} = 60$ ). The best model according to Bayesian model comparison is condition

and set size ( $BF_{10} = 85$ ), 1.4 times more likely than the runner-up model which is set size alone ( $BF_{10} = 59.86$ ). Individual effects analyses (Table 10) provide very strong evidence for a set size effect ( $F(1, 19) = 4.145, p = .043, \eta^2 = 0.179, BF_{INC} = 48$ ). The one sample t-test showed extreme support for both processes being discounted (for ignore, t-test [IP < 2]:  $t = -5.552, p < .001$ , Cohen’s  $d = -1.235, BF_{.0} = 1917$ ; for update, t-test [IP < 2]:  $t = -4.66, p < .001$ , Cohen’s  $d = -1.042, BF_{.0} = 346$ ). Regarding the effect of condition on the data frequentist statistics show significance, but the Bayesian analysis signifies that the data are inconclusive ( $F(1, 19) = 6.901, p = .017, \eta^2 = 0.266, BF_{10} = 1.081$ ). Finally there is limited evidence against an interaction effect ( $F(3, 19) = 1.342, p = .270, \eta^2 = 0.066, BF_{INC} = 0.34$ ). Overall, the results show that participants significantly

**Table 5.**

Descriptive statistics for RTs in colour wheel working memory task.

Condition	Set size	Mean	SD
Ignore	1	1.83	0.32
	2	2.26	0.28
	3	2.25	0.26
	4	2.17	0.36
Update	1	1.93	0.29
	2	2.26	0.29
	3	2.23	0.28
	4	2.39	0.27

**Table 6.**

Model comparison for RTs in colour wheel working memory task.

Models	$p(M)$	$p(M   \text{data})$	$BF_M$	$BF_{10}$	% error
Null model (including subject)	.2	5.791e-27	2.316e-26	1.0	
Condition	.2	7.691e-27	3.076e-26	1.3	1.05
Set size	.2	.002	0.009	3.710e+23	0.75
Condition + Set size	.2	.033	0.135	5.620e+24	2.68
Condition + Set size + Condition $\times$ Set size	.2	.965	111	1.667e+26	5.74

*Note.* All models include subjects.

**Table 7.**

Bayesian analysis of effects for RTs.

Effects	$p(\text{inclusion})$	$p(\text{inclusion}   \text{data})$	$BF_{\text{Inclusion}}$
Condition	.6	.998	310
Set size	.6	1.0	$\infty$
Condition $\times$ Set size	.2	.965	111

**Table 8A.**

Descriptive statistics for “task vs no redo” indifference points.

	Mean	SD
Ignore	1.44	0.46
Update	1.50	0.48

**Table 8B.**

Descriptive statistics for “task vs no redo” indifference points across set size.

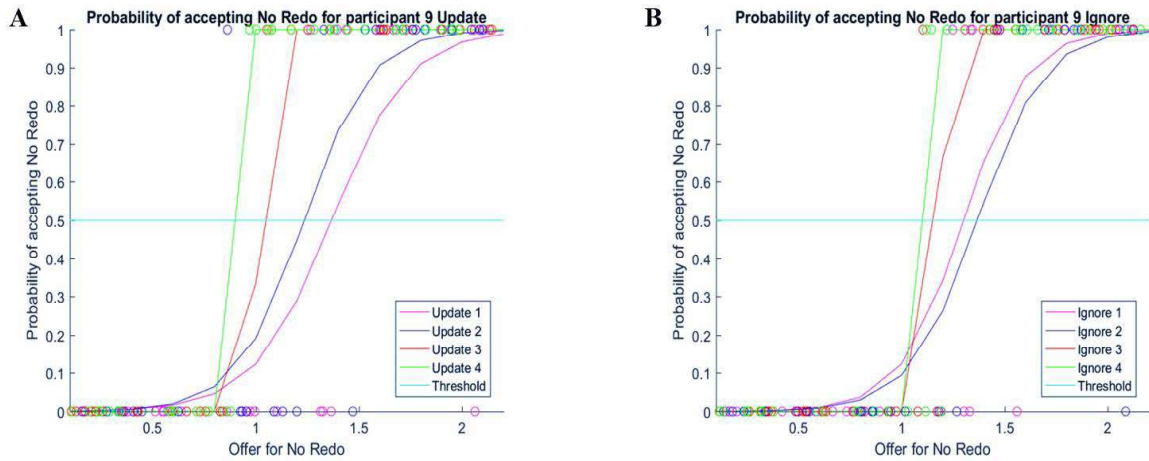
	Mean	SD
1	1.50	0.50
2	1.52	0.41
3	1.42	0.47
4	1.31	0.55
1	1.53	0.46
2	1.54	0.45
3	1.54	0.52
4	1.41	0.58

discounted the working memory task option and that discounting increased with task difficulty, in line with our first hypothesis. We also show preliminary evidence that distracter resistance is discounted more than updating.

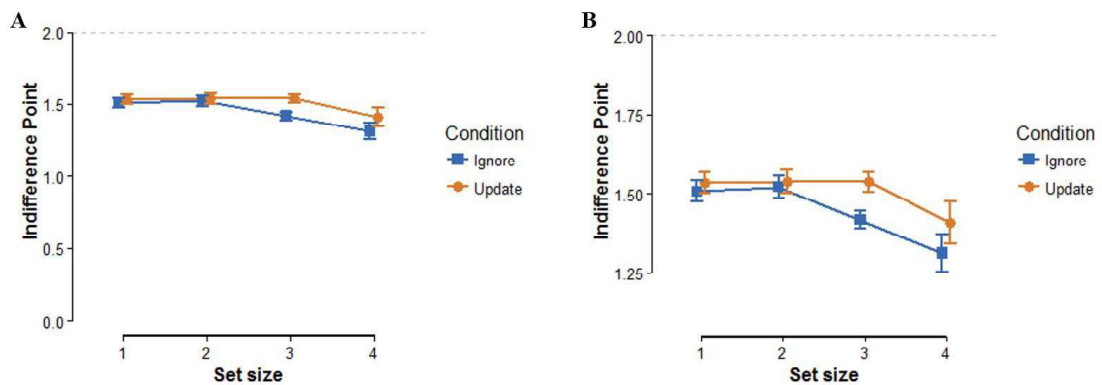
### Choices between Distracter resistance and Updating.

Having established that both our working memory processes were discounted by participants, we aimed to see if they were willing to discount rewards in order to perform updating over distracter resistance. As ignore offer was fixed at €2, a subjective value (indifference point) smaller than 2 indicates a preference for update, while a subjective value larger than 2 a preference for ignore. Figure 8 depicts regression curves of two example participants, one discounting ignore and the other discounting update. We excluded two participants from this analysis. One because we could not estimate any indifference points (always chose ignore) and another because they deviated more than 3 standard deviations from the mean.

For descriptive statistics see Table 11. In Figure 9 we report the average indifference points per set size for 22 participants. In accordance with our second hypothesis, the overall average subjective value of “ignore vs update” choices is less than 2



**Fig. 6.** Logistic regression curves for “task vs no redo” choices of one participant. We present the probability of accepting the “no redo” (no task) offer (y-axis) as a function of the amount of money offered for “No Redo” (x-axis). Task offer is always €2 for both conditions and all set sizes. The estimated indifference point is the offer for “no redo” where the possibility of choosing to do the task or the “no redo” option is equal (i.e., .5). **A. & B.** Example participant for update (A) and ignore (B) condition. Indifference points decrease for the higher demand levels.



**Fig. 7A.** “Task vs no redo” Indifference Points as a function of set size across 20 participants. **B.** Same results scaled. As the task offer was fixed at €2, the more the indifference points deviate from 2 the more participants were willing to discount the task option. The results displayed are better explained by a model including set size and condition ( $BF_{10} = 85$ ). Error bars represent the SEM.

**Table 9.**

Model comparison for “task vs no redo” indifference points.

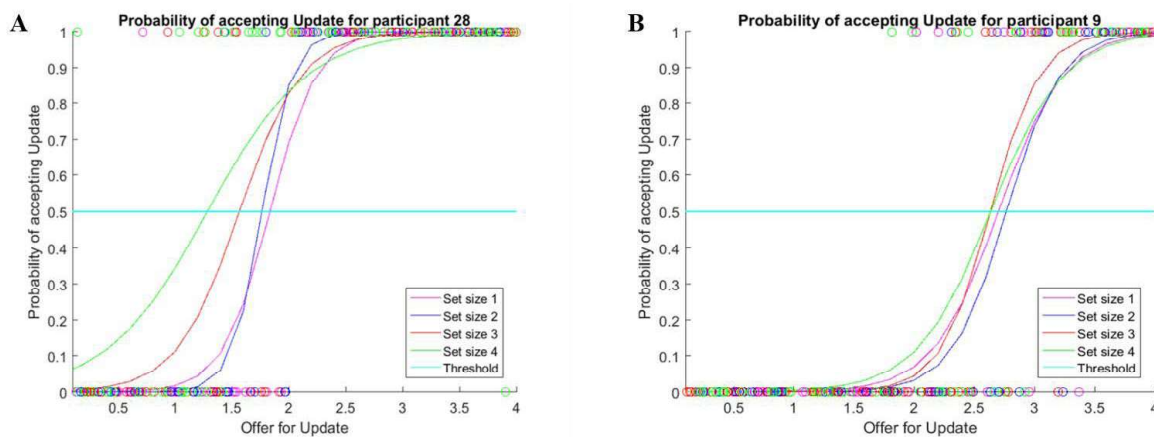
Models	$p(M)$	$p(M   data)$	$BF_M$	$BF_{10}$	% error
Null model (including subject)	.2	.006	0.025	1.0	
Condition	.2	.007	0.030	1.2	3.92
Set size	.2	.375	2.403	60	0.49
Condition + Set size	.2	.532	4.554	85	1.19
Condition + Set size + Condition × Set size	.2	.079	0.342	13	2.20

*Note.* All models include subjects.

**Table 10.**

Analysis of effects for “task vs no redo” indifference points.

Effects	$p(\text{inclusion})$	$p(\text{inclusion} \mid \text{data})$	$BF_{\text{Inclusion}}$
Condition	.6	.618	1.08
Set size	.6	.986	48
Condition $\times$ Set size	.2	.079	0.34



**Fig. 8.** Example logistic regression curves for “ignore vs update” indifference points. We see the probability of choosing the update offer as a function of the amount of money offered for update. Ignore offer is always €2 for both conditions and all set sizes. The indifference points are the offers for update that the probability of accepting it is .5, meaning that participants are equally likely to choose on offer or the other. **A.** Example participant willing to discount rewards in order to avoid ignore trials (preference for update). **B.** Example participant willing to discount rewards in order to avoid the harder levels of update trials (preference for ignore).

**Table 11.**

Descriptive statistics for “Ignore vs Update” indifference points (IP 1-4: indifference points for set size 1-4).

	IP	IP1	IP2	IP3	IP4
Mean	1.9	1.92	1.89	1.90	1.89
SD	0.26	0.24	0.28	0.25	0.32

(1.899), indicating a preference for flexible updating trials. This hypothesis is ~1.8 times more likely than the null and the classical t-test indicates a statistical significant effect (t-test [IP < 2]:  $t = -1.848, p = .039$ , Cohen’s  $d = -0.394, BF_{10} = 1.8$ ). The output of the one-way repeated-measures ANOVA shows weak support for the data under the null hypothesis that subjective value is not influenced by set size ( $F(2.197, 63) = 0.407, p = .687, \eta^2 = 0.019, BF_{10} = 0.096$ ). Our results provide anecdotal confirmation for our second hypothesis that participants are willing to discount rewards in order to repeat flexible updating

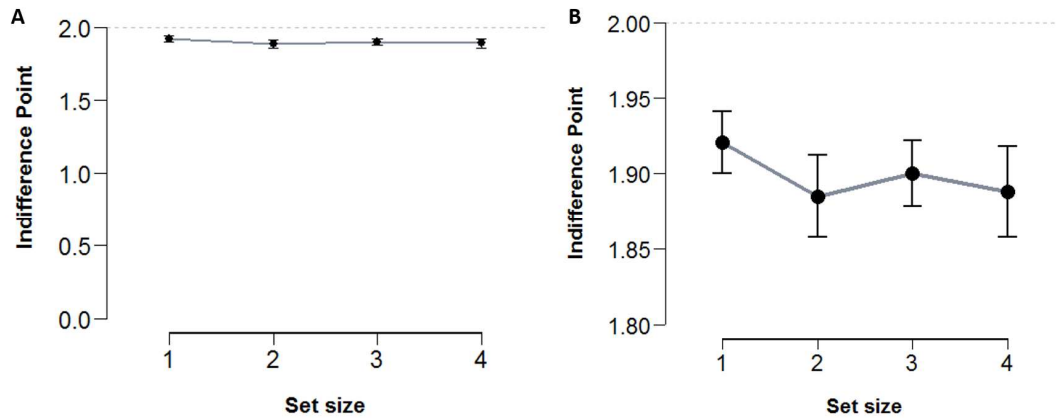
trials over distracter resistance.

As the evidence for our second hypothesis was small we performed a sequential analysis to see how evidence accumulated as a function of sample size (Fig. 10). The analysis suggested that evidence for the alternative hypothesis was increasing with increasing sample size, so a larger sample could provide greater confidence in favour of our second hypothesis.

## Questionnaires

During debriefing, out of 22 participants included in the analysis, 17 indicated that they preferred update trials and 5 reported a preference for ignore trials.

**Two groups of preference.** We considered the idea that there are two groups of participants with opposing preferences and by grouping them together we masked underlying effects. Indeed, we saw in this study, as well as in previous pilot studies (Online supplementary Fig. S2), that the majority

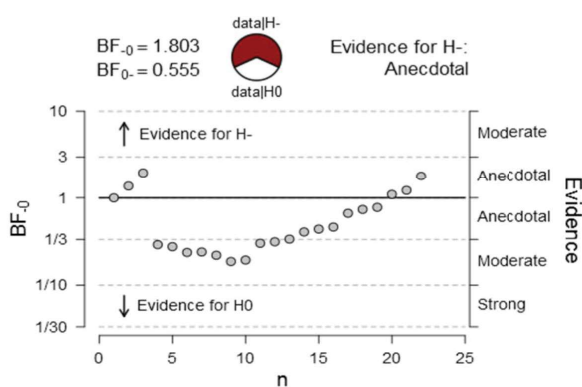


**Fig. 9.** Indifference points for “ignore vs update” choices across 22 participants. **A.** “ignore vs update” Indifference Points as a function of set size. **B.** Same results scaled As ignore was fixed at €2, indifference points smaller than 2 indicate a willingness to discount rewards to avoid repeating ignore compared to update trials. The statistical analysis showed anecdotal evidence for a preference for update as the hypothesis that overall indifference points are smaller than 2 is 1.8 times more likely than the null hypothesis ( $BF_{-0} = 1.803$ ).

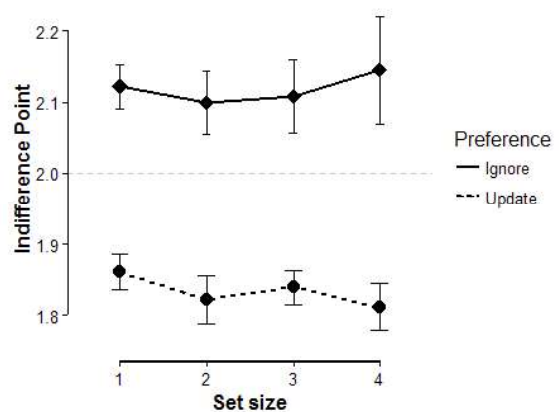
of participants preferred update, but a smaller percentage reported preference for ignore (4.4). We followed this idea further and divided participants in two groups based on their written preference for either condition and then analysed their choices again.

In Figure 11 we graphed the indifference points per set size for the two groups separately. The indifference points of the 17 participants who reported a preference for update are indeed clearly smaller than 2 (mean = 1.835,  $SD = 0.1578$ ) and the evidence of the hypothesis that the mean is smaller than 2 is extreme (t-test [IP < 2]:  $t = -4.306$ ,  $p < .001$ , Cohen’s  $d = -1.044$ ,  $BF_{10} = 128$ ). On the other

hand, IPs of the 5 subjects who indicated to prefer ignore tend to be higher than 2 (mean = 2.117,  $SD = 0.4$ ), but the sample size is of course very small to produce reliable statistics (t-test [IP > 2]:  $t = 0.645$ ,  $p = .277$ , Cohen’s  $d = 0.288$ ,  $BF_{10} = 0.663$ ). With the exception of two participants, written preference and preference expressed by indifference points were aligned (one reported preference for ignore, while discounting ignore and the other a preference for update while discounting update).



**Fig. 10.** Sequential analysis for the hypothesis that indifference points are smaller than 2 (preference for update) and the null. Evidence for the alternative hypothesis is growing with increasing sample size.



**Fig. 11.** “Ignore vs Update” indifference points of two groups of participants split based on written preference for either distracter resistance (ignore) or flexible updating (update) trials. The update group consists of 17 participants and ignore group consists of 5. Indifference points of 2 signify no discounting, thus, no preference between the two functions. Error bars represent SEM.

## Discussion

In the current project, we set out to quantify the subjective valuation of distinct working memory processes to address our research questions. We asked whether working memory processes are perceived as costlier when demand increases and also whether two distinct key processes of working memory carry a differential cost.

The results show that engaging in updating and distracter resistance is costly and that costs increase as working memory demand grows. The results also provide some support for distracter resistance being perceived as more costly than updating.

### Are working memory tasks costly?

Regarding our first research question, we asked whether distracter resistance and flexible updating are costly. Indeed, we have strong evidence to conclude that value discounting increased with demand, being highest for the higher set sizes. Participants discounted the value of distracter resistance overall by 28% and the value of flexible updating by 25%.

These findings extend current knowledge on the value of cognitive engagement. First of all, we show that people are aversive to cognitive demand, even willing to decline rewards in order to avoid demanding tasks. This is in line with earlier work showing that participants prefer to avoid higher levels of the N-back task (Kool et al., 2010). Our results further generalise these conclusions in a new working memory task while at the same time disentangling the subjective value of distracter resistance and flexible updating. Here we show that both functions are perceived as costly. In addition, our design strengthened the validity of reported findings by using a discounting procedure that accounts for the possibility of choices being probabilistic. Earlier studies on cognitive effort used staircase procedures that sample every choice option only once (Westbrook et al., 2013; Massar et al., 2016).

Unlike previous discounting studies we also gave participants the opportunity to choose the effortful option for less money. As expected, most participants declined this offer, but the subjective value of three participants was higher than 2 for at least one of the two working memory processes, indicating a preference for repeating the working memory task. This outcome may seem incongruent with our hypothesis, but it is not necessarily the case. One account for this may be that for those

participants, cognitive engagement may be perceived as more valuable than both the monetary rewards we offered and the cost of engagement, in line with the concept of “learned industriousness”. For example, socially reinforced rewards or an internal sense of accomplishment might lead to these choices. Another reasoning could be that these participants preferred to repeat the task than to be bored. Indeed, there have been studies suggesting that people would rather receive electrical shocks than do nothing at all (Wilson et al., 2014), suggesting that boredom carries a cost in itself. We aimed to minimise that prospect by offering them the option to surf the internet or use their phones while waiting. Either way, the majority of participants were inclined to discount rewards to avoid the working memory task and not the other way around.

We interpret this significant discounting of our task as evidence that people are averse to high working memory demand. An alternative explanation for the observed effects could be error-avoidance. To diminish such influences, we highlighted that accuracy during the redo would not define whether participants receive the monetary rewards or not. So, mistakes did not bear any external costs in our design, but we cannot exclude intrinsic costs. Moreover, simple error-avoidance seems like an unlikely explanation for the still significant discounting of the easiest set size, at which participants performed very well (less than 10° deviance from target colour) and comparable with performance without a working memory component (~3° more).

But what makes working memory tasks costly? The answer to this question remains an enigma and is the source of a lot of debate in the scientific community. One promising theory inspired by cost-benefit decision-making theories views the cost of cognitive engagement as an opportunity cost (Kurzban et al., 2013). As per this account, our working memory resources cannot be allocated to an infinite number of tasks simultaneously, which means that we perform any task at the expense of all other alternative tasks. So, while the value of these alternative options increases, the cost of focusing on the current task increases as well up to the point where performance fails or we even disengage completely. This model could potentially explain our results. In the “task vs no redo” version of the discounting choice paradigm, the “No Redo” option clearly carries a smaller opportunity cost compared to the “Task” option because participants can use their time as they please. In addition, our data show that willingness to do the task can be manipulated with incentives. Despite the above, with the



current design, we cannot make a case between the opportunity cost and other theories such as resource depletion. To assess that in the future, we could vary the opportunity of pleasurable alternative activities during tasks or free time. However, the lines of research are not necessarily mutually exclusive. For example, as proposed by Harvey (2013), dopamine is a “resource” depleted in Parkinson’s patients drastically affecting performance, but it is also a key neurotransmitter in valuation.

### **Are some working memory functions perceived as costlier?**

In accordance with our second hypothesis, we showed anecdotal evidence that distracter resistance has lower subjective value than flexible updating. Overall discounting, in this case, was around 5% and it showed no consistent variance with set size. The results of the frequentist analysis showed significant discounting of ignore, but Bayesian statistics support for this hypothesis is not strong. Further evidence that there may be a difference is that in “task vs no redo” choices the best model involved condition in addition to set size; the effects analysis was significant for frequentist statistics but inconclusive for Bayesian. This discrepancy between classical and Bayesian analyses is not surprising or uncommon. An empirical comparison of the two methods in 855 t-tests showed that that  $p$ -values between .01 and .05 often correspond to anecdotal evidence in favour of the alternative hypothesis in Bayesian terms (Wetzels et al., 2011).

We are replicating previous accounts that participants perform better at updating (Fallon & Cools, 2014; Fallon et al., 2015). We adapted previous versions, such that the two processes are contrasted without the confounding factor of a shorter time delay between relevant stimulus and response for update trials. However, this made update trials overall longer by 4 seconds, so it is even more interesting that participants preferred update despite a higher cost of time.

How can we interpret this preference? Again, the opportunity cost framework might be able to elucidate this observation, if we consider attending to the incoming stimuli in the ignore condition as a missed opportunity. Furthermore, it has been often stated that processing salient stimuli is an automatic, easy and fast bottom-up procedure while resisting this processing is goal-directed top-down and controlled (Corbetta & Shulman, 2002; Ernst, Daniele, & Frantz, 2011). Consequently, distracter

resistance is more computationally costly, although participants only need to encode new stimuli once. When comparing ignore and update, error-avoidance might also contribute to the observed results. Most participants were more accurate in updating trials, but the average difference between the two conditions was only 5 degrees for the highest demand level and even lower for the lower levels. This is not a very striking difference, but participants could still be able to identify it and be affected by it. To account for error-avoidance effects, following studies could attempt to match performance between the two conditions or provide “fake” feedback to influence participants’ beliefs about their performance.

Nonetheless, the preference for update was small and the support for this preference limited. The latter may very well be because our sample size was inadequate. Indeed, the sequential analysis indicated that a larger sample size would most likely solidify this conclusion. To draw confident conclusions, Bayesian analysis gives the possibility to continue sampling until either hypothesis reaches a Bayes factor of at least 10. Another factor for a small effect might be the time difference between the trials of the two conditions. Despite minuscule, it may have been picked up by time-sensitive participants and caused a research question-unrelated aversion to updating trials. It seems reasonable that discounting was smaller for “ignore vs update” choices than “task vs no redo” choices. As we have shown that both processes are perceived as costly, the value of no working memory task is understandably higher than the value of one over the other. The opportunity cost of no task is also much lower compared to a better preferred, but still experimentally-defined task. We also examined the idea that there are individual differences in preference for ignore or update processes that were masked when we averaged. Although our study was not a priori designed to sample for groups and we cannot make any such statements, in an exploratory analysis we split participants in two groups based on reported preferences on a questionnaire. This analysis indicated that reported preferences generally aligned with choices on the discounting task and that most participants preferred update. However, a minority preferred the ignore trials. If these individual differences in valuation do in fact exist, it would be interesting to investigate in future studies what the underlying reasons for this differential valuation are. Past work has shown that dopaminergic medication improved overall distracter resistance at the expense of flexible updating (Fallon et al., 2015), however we also know that effects of psychostimulants

vary greatly with individual baseline measures of dopamine (Cools & D'Esposito, 2011). How does a preference for ignore versus update relate to baseline measures of dopamine and psychostimulant effects on cognition? A role for dopamine in effort-based decision-making would be consistent with studies in physical effort, where it has been shown that in Parkinson's patients dopamine medication increases selection of high effort/high reward trials (Chong et al., 2015), while dopamine depletion decreases willingness to exert effort in humans and rodents (Salamone, Correa, Farrar, & Mingote, 2007; Floresco, Tse, & Ghods-Sharifi, 2008). There is recent suggestive evidence from rodent studies that dopaminergic medication also modifies valuation and choices of cognitive effort (Cocker, Hosking, Benoit, & Winstanley, 2012). These findings together raise the questions whether dopamine, a neurotransmitter implicated in motivation (Salamone & Correa, 2012), is involved in valuation of cognitive effort and invites future research. Another potentially relevant neurotransmitter is noradrenaline that seems to be involved in switching modes between task engagement (exploitation) and disengagement (exploration) (Jepma, Te Beek, Wagenmakers, Van Gerven, & Nieuwenhuis, 2010).

## Value-based decision-making

Our findings are also consistent with a value-based decision-making process for cognitive resource allocation. We saw that participants overall showed aversion to both working memory processes, preferring "No Redo" option when the rewards were comparable. However, as the offer for "No Redo" was substantially decreasing, most participants were willing to shift their preference and actually chose to do the task. Likewise, most participants shifted their preference for ignore or update. This finding showcases the importance of motivation on task engagement, similarly to results by a recent study in sustained attention (Massar et al., 2016). Finally, the possibility for a role of error-avoidance in our results does not necessarily challenge value-based decision-making because fear of failure can be assessed as a cost in itself.

## Limitations

One likely caveat of the study is that there were participants for whom we were not able to sample an indifference point. To avoid that in the future, we could increase the offer range. Another limitation

is that we did not perform eye-tracking to exclude that participants closed their eyes in ignore trials. Nonetheless, in order to know that it was an ignore trial participants had to at least initially attend to the stimuli. Additionally, the performance results themselves suggest that participants were indeed at least to some extent distracted during ignore trials, evidenced by lower performance.

## Future directions

Although preliminary, our results suggest that different working memory processes may carry different subjective costs. If confirmed, it could highlight the importance of choosing a working memory paradigm when studying cognitive effort. Additionally, identifying differences in valuation can also help us understand performance failure and variance, but also pave the way to. In this direction, future studies could sample for two groups, one valuing updating more and one valuing distracter resistance, and then positron emission tomography (PET) and/or pharmacological studies for dopamine and noradrenaline could help us gain some insight to the underlying mechanisms of this variance in preference.

Our results could also have potential implications for attention deficiency hyperactivity disorder (ADHD) research. For one, reduced performance may reflect differences in valuation. Moreover, we know that ADHD patients show deficiencies in resisting distraction and operate in a more stimulus-driven fashion (Swanson et al., 1998). On the other hand, flexible updating has been linked with creativity and innovation and there are indeed reports that ADHD patients show increased levels of creativity (Abraham, Windmann, Siefen, Daum, & Güntürkün, 2006). Future studies could assess whether ADHD patients discount distracter-resistance more than updating and if this valuation can be manipulated with incentives. If that is the case, novel educational strategies could be developed that aim to increase motivation and take their flexibility into account.

## Conclusions

Concluding, this study provides new insights to the novel and growing fields of cognitive effort discounting and value-based decision-making. Specifically, we showed that with increasing demand on working memory processes the subjective valuation decreased, both for the process of distracter resistance and flexible updating. We

also provided evidence that distracter resistance is perceived as relatively costlier. These results remain to be further established and their underlying mechanisms investigated by future research.

## References

- Abraham, A., Windmann, S., Siefen, R., Daum, I., & Güntürkün, O. (2006). Creative thinking in adolescents with attention deficit hyperactivity disorder (ADHD). *Child Neuropsychology*, *12*(2), 111-123.
- Botvinick, M., & Braver, T. (2015). Motivation and cognitive control: from behavior to neural mechanism. *Annual Review of Psychology*, *66*, 83-113.
- Brainard, D. H. (1997). The psychophysics toolbox. *Spatial vision*, *10*, 433-436.
- Chong, T. T. J., Bonnelle, V., Manohar, S., Veromann, K. R., Muhammed, K., Tofaris, G. K., ... & Husain, M. (2015). Dopamine enhances willingness to exert effort for reward in Parkinson's disease. *Cortex*, *69*, 40-46.
- Cocker, P. J., Hosking, J. G., Benoit, J., & Winstanley, C. A. (2012). Sensitivity to cognitive effort mediates psychostimulant effects on a novel rodent cost/benefit decision-making task. *Neuropsychopharmacology*, *37*(8), 1825-1837.
- Cools, R., & D'Esposito, M. (2011). Inverted-U-shaped dopamine actions on human working memory and cognitive control. *Biological psychiatry*, *69*(12), e113-e125.
- Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature reviews neuroscience*, *3*(3), 201-215.
- Ernst, M., Daniele, T., & Frantz, K. (2011). New perspectives on adolescent motivated behavior: attention and conditioning. *Developmental cognitive neuroscience*, *1*(4), 377-389.
- Fallon, S. J., & Cools, R. (2014). Reward acts on the pFC to enhance distracter resistance of working memory representations. *Journal of cognitive neuroscience*, *26*, 2812-2826.
- Fallon, S. J., Van Der Schaff, M. E., Ten Huurne, N., & Cools, R. (2015). Methylphenidate improves cognitive stability at the expense of cognitive flexibility. Manuscript submitted for publication.
- Floresco, S. B., Tse, M. T. L., & Ghods-Sharifi, S. (2008). Dopaminergic and glutamatergic regulation of effort- and delay-based decision making. *Neuropsychopharmacology*, *33*(8), 1966-1979.
- Gilbert, A. L., Regier, T., Kay, P., & Ivry, R. B. (2006). Whorf hypothesis is supported in the right visual field but not the left. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(2), 489-494.
- Harvey, N. (2013). Depletable resources: necessary, in need of fair treatment, and multi-functional. *Behavioral and Brain Sciences* *36*(06), 689-690.
- Hazy, T. E., Frank, M. J., & O'Reilly, R. C. (2007). Towards an executive without a homunculus: computational models of the prefrontal cortex/basal ganglia system. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *362*(1485), 1601-1613.
- Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS med*, *2*(8), 0696-0701.
- JASP Team. (2016). JASP (version 0.7.5.6) [Computer software].
- Jepma, M., Te Beek, E. T., Wagenmakers, E. J., Van Gerven, J. M. A., & Nieuwenhuis, S. (2010). The role of the noradrenergic system in the exploration-exploitation trade-off: a psychopharmacological study. *Frontiers in human neuroscience*, *4*, 170.
- Kable, J. W., & Glimcher, P. W. (2007). The neural correlates of subjective value during intertemporal choice. *Nature neuroscience*, *10*(12), 1625-1633.
- Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision making and the avoidance of cognitive demand. *Journal of Experimental Psychology: General*, *139*(4), 665-682.
- Kurzban, R., Duckworth, A., Kable, J. W., & Myers, J. (2013). An opportunity cost model of subjective effort and task performance. *Behavioral and Brain Sciences*, *36*(06), 661-679.
- Lee, M. D., & Wagenmakers, E. J., (2013). Bayesian cognitive modeling: A practical course. Cambridge University Press.
- Massar, S. A. A., Lim, J., Sasmita, K., & Chee, M. W. L. (2016). Rewards boost sustained attention through higher effort: A value-based decision making approach. *Biological Psychology*, *120*, 21-27.
- Padmala, S., & Pessoa, L. (2011). Reward reduces conflict by enhancing attentional control and biasing visual cortical processing. *Journal of cognitive neuroscience*, *23*(11), 3419-3432.
- Rieskamp, J. (2008). The probabilistic nature of preferential choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *34*(6), 1446-1465.
- Salamone, J. D., & Correa, M. (2012). The mysterious motivational functions of mesolimbic dopamine. *Neuron*, *76*(3), 470-485.
- Salamone, J. D., Correa, M., Farrar, A., & Mingote, S. M. (2007). Effort-related functions of nucleus accumbens dopamine and associated forebrain circuits. *Psychopharmacology*, *191*(3), 461-482.
- Swanson, J. M., Sergeant, J. A., Taylor, E., Sonuga-Barke, E. J. S., Jensen, P. S., & Cantwell, D. P. (1998). Attention-deficit hyperactivity disorder and hyperkinetic disorder. *The Lancet*, *351*(9100), 429-433.
- Wagenmakers, E. J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, A. J., & Morey, R. D. (2016). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin and Review*.
- Wagenmakers, E. J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., & Morey, R. (2016). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin and Review*.
- Westbrook, A., Kester, D., & Braver, T. S. (2013). What is the subjective cost of cognitive effort? Load, trait, and aging effects revealed by economic preference. *PLoS*

*One*, 8(7), e68210.

- Wetzels, R., Matzke, D., Lee, M. D., Rouder, J. N., Iverson, G. J., & Wagenmakers, E. J. (2011). Statistical evidence in experimental psychology: An empirical comparison using 855 t tests. *Perspectives on Psychological Science*, 6(3), 291-298.
- Wilson, T. D., Reinhard, D. A., Westgate, E. C., Gilbert, D. T., Ellerbeck, N., Hahn, C., ... & Shaked, A. (2014). Just think: The challenges of the disengaged mind. *Science*, 345(6192), 75-77.
- Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, 453(7192), 233-235.