

¹ When easy is not preferred: A discounting paradigm to assess load-independent task
² preference

³ Josephine Zerna^{†,1}, Christoph Scheffel^{†,1}, Corinna Kührt¹, & Alexander Strobel¹

⁴ ¹ Faculty of Psychology, Technische Universität Dresden, 01069 Dresden, Germany

⁵ Author Note

⁶ The authors made the following contributions. Josephine Zerna: Conceptualization,
⁷ Data curation, Methodology, Funding acquisition, Formal analysis, Investigation, Project
⁸ administration, Software, Visualization, Writing - original draft, Writing - review &
⁹ editing; Christoph Scheffel: Conceptualization, Methodology, Funding acquisition,
¹⁰ Investigation, Project administration, Software, Writing - review & editing; Corinna Kührt:
¹¹ Formal analysis, Writing - review & editing; Alexander Strobel: Conceptualization,
¹² Resources, Supervision, Funding acquistion, Writing - review & editing. [†] Josephine Zerna
¹³ and Christoph Scheffel contributed equally to this work.

¹⁴ Correspondence concerning this article should be addressed to Josephine Zerna,
¹⁵ Zellescher Weg 17, 01069 Dresden, Germany. E-mail: josephine.zerna@tu-dresden.de

16

Abstract

17 When individuals set goals, they consider the subjective value (SV) of the anticipated
18 reward and the required effort, a trade-off that is of great interest to psychological research.
19 One approach to quantify the SVs of levels of a cognitive task is the Cognitive Effort
20 Discounting Paradigm by Westbrook and colleagues (2013). However, it fails to
21 acknowledge the highly subjective nature of effort, as it assumes a unidirectional, inverse
22 relationship between task load and SVs. Therefore, it cannot map differences in effort
23 perception that arise from traits like Need for Cognition, since individuals who enjoy
24 effortful cognitive activities likely do not prefer the easiest level. We replicated the analysis
25 of Westbrook and colleagues with our adaptation, the Cognitive and Affective Discounting
26 (CAD) Paradigm, which quantifies SVs without assuming that the easiest level is preferred,
27 thereby enabling the quantification of SVs for tasks without objective order of task load.
28 Results show that many participants preferred a more or the most difficult level. Variance
29 in SVs was best explained by a declining logistic contrast of the n -back levels and by the
30 accuracy of responses, while reaction time as a predictor was highly volatile depending on
31 the preprocessing pipeline. Participants with higher Need for Cognition scores perceived
32 higher n -back levels as less effortful and found them less aversive. Effects of Need for
33 Cognition on SVs in lower levels did not reach significance, as group differences only
34 emerged in higher levels. The CAD Paradigm appears to be well suited for assessing and
35 analysing task preferences independent of the supposed objective task difficulty.

36 *Keywords:* effort discounting, registered report, specification curve analysis, need for
37 cognition, n -back

38 Word count: 7000

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41 **Introduction**

42 In everyday life, effort and reward are closely intertwined¹. With each decision a
43 person makes, they have to evaluate whether the effort required to reach a goal is worth
44 being exerted, given the reward they receive when reaching the goal. A reward is
45 subjectively more valuable if it is obtained with less effort, so the required effort is used as
46 a reference point for estimating the reward value¹. However, the cost of the effort itself is
47 also subjective, and research has not yet established which function best describes the
48 relationship between effort and cost². Investigating effort and cost is challenging because
49 “effort is not a property of the target task alone, but also a function of the individual’s
50 cognitive capacities, as well as the degree of effort voluntarily mobilized for the task, which
51 in turn is a function of the individual’s reward sensitivity” (p. 209)².

52 One task that is often used to investigate effort is the *n*-back task, a working memory
53 task in which a continuous stream of stimuli, e.g. letters, is presented on screen.
54 Participants indicate via button press whether the current stimulus is the same as *n* stimuli
55 before, with *n* being the level of difficulty between one and six³. The *n*-back task is well
56 suited to investigate effort because it is an almost continuous manipulation of task load as
57 has been shown by monotonic increases in error rates, reaction times⁴, and brain activity in
58 areas associated with working memory^{5,6}. However, its reliability measures are mixed, and
59 associations of *n*-back performance and measures such as executive functioning and fluid
60 intelligence are often inconsistent⁴.

61 A way to quantify the subjective cost of each *n*-back level has been developed by
62 Westbrook, Kester, and Braver⁷, called the Cognitive Effort Discounting Paradigm
63 (COG-ED). First, the participants complete the *n*-back levels to familiarize themselves
64 with the task. Then, 1-back is compared with each more difficult level by asking the

65 participants to decide between receiving a fixed 2\$ for the more difficult level or the flexible
66 starting value of 1\$ for 1-back. If they choose the more difficult level, the reward for 1-back
67 increases by 0.50\$, if they choose 1-back, it decreases by 0.50\$. This is repeated five more
68 times, with each adjustment of the 1-back reward being half of the previous step, while the
69 reward for the more difficult level remains fixed at 2\$. The idea is to estimate the point of
70 subjective equivalence, i.e., the monetary ratio at which both offers are equally preferred⁷.
71 The subjective value (SV) of each more difficult level is then calculated by dividing the
72 final reward value of 1-back by the fixed 2\$ reward. Westbrook et al.⁷ used these SVs to
73 investigate inter-individual differences in effort discounting. Younger participants showed
74 lower effort discounting, i.e., they needed a lower monetary incentive for choosing the more
75 difficult levels over 1-back.

76 The individual degree of effort discounting in the study by Westbrook et al.⁷ was also
77 associated with the participants' scores in Need for Cognition (NFC), a personality trait
78 describing an individual's tendency to actively seek out and enjoy effortful cognitive
79 activities⁸. Westbrook et al.⁷ conceptualized NFC as a trait measure of effortful task
80 engagement, providing a subjective self-report of effort discounting for each participant
81 which could then be related to the SVs as an objective measure of effort discounting. On
82 the surface, this association stands to reason, as individuals with higher NFC are more
83 motivated to mobilize cognitive effort because they perceive it as intrinsically rewarding.
84 Additionally, it has been shown that individuals avoid cognitive effort only to a certain
85 degree, possibly to retain a sense of self-control⁹, a trait more prominent in individuals
86 with high NFC^{10–12}. However, the relation of NFC and SVs might be confounded, since
87 other studies utilizing the COG-ED paradigm found the association of NFC and SVs to
88 disappear after correcting for performance¹³ or found no association of NFC and SVs at
89 all¹⁴. On the other hand, task load has been shown to be a better predictor of SVs than
90 task performance^{7,15,16}, so more research is needed to shed light on this issue.

91 With the present study, we alter one fundamental assumption of the original

92 COG-ED paradigm: That the easiest n -back level has the highest SV. We therefore
93 adapted the COG-ED paradigm in a way that allows the computation of SVs for different
94 n -back levels without presuming that all individuals inherently prefer the easiest level.
95 Since we also aim to establish this paradigm for the assessment of tasks with no objective
96 task load, e.g., emotion regulation tasks¹⁷, we call it the Cognitive and Affective
97 Discounting Paradigm (CAD). In the present study, we validated the CAD paradigm by
98 conceptually replicating the findings of Westbrook et al.⁷. Additionally, we compared the
99 effort discounting behavior of participants regarding the n -back task and an emotion
100 regulation task. The full results of the latter are published in a second Registered Report¹⁷.
101 The COG-ED paradigm has been applied to tasks in different domains before, showing
102 that SVs across task domains correlate¹⁴, but these tasks had an objective order of task
103 load, which is not the case for the choice of emotion regulation strategies or other
104 paradigms where there is no objective order of task load.

105 Our hypotheses were derived from the results of Westbrook et al.⁷. As a manipulation
106 check, we hypothesized that with increasing n -back level the (1a) the signal detection
107 parameter d' declines, while (1b) reaction time and (1c) perceived task load increase.
108 Regarding the associations of task load and effort discounting we hypothesized that (2a)
109 SVs decline with increasing n -back level, and (2b) they do so even after controlling for
110 declining task performance. And finally, we hypothesized that the CAD paradigm can show
111 inter-individual differences in effort discounting, such that participants with higher NFC
112 have (3a) lower SVs for 1-back but higher SVs for 2- and 3-back, (3b) lower perceived task
113 load across all levels, and (3c) higher aversion against 1-back but lower aversion against 2-
114 and 3-back. Each hypothesis is detailed in the Design Table in the Supplementary Material.

115 Methods

116 We report how we determined our sample size, all data exclusions (if any), all
117 manipulations, and all measures in the study^{cf. 18}. The paradigm was written and

¹¹⁸ presented using *Psychopy*¹⁹. We used *R* with *R Studio*^{20,21} with the main packages *afex*²²
¹¹⁹ and *BayesFactor*²³ for all our analyses.

¹²⁰ **Ethics information**

¹²¹ The study protocol complies with all relevant ethical regulations and was approved
¹²² by the ethics committee of the Technische Universität Dresden (reference number
¹²³ SR-EK-50012022). Prior to testing, written informed consent was obtained. Participants
¹²⁴ received 24€ in total or course credit for participation.

¹²⁵ **Design**

¹²⁶ **CAD Paradigm.** Figure 1 illustrates how different modifications of the COG-ED
¹²⁷ paradigm⁷ return SVs that do or do not reflect the true preference of a hypothetical
¹²⁸ participant, who likes 2-back most, 3-back less, and 1-back least (for reasons of clarity there
¹²⁹ are only three levels in the example). The COG-ED paradigm, which compares every more
¹³⁰ difficult level with 1-back sets the SV of 1-back to 1, regardless of the response pattern.

¹³¹ Adding a comparison of the more difficult levels with each other allows the SVs of those two
¹³² levels to be more differentiated, but leaves the SV of 1-back unchanged. Adding those same
¹³³ pairs again, but with the opposite assignment of fixed and flexible level, does approach the
¹³⁴ true preference, but has two disadvantages. First, the SVs are still quite alike across levels
¹³⁵ due to the fact that every more difficult level has only been compared with the easiest
¹³⁶ level, and second, having more task levels than just three would lead to an exponential
¹³⁷ increase in comparisons. Therefore, the solution lies in reducing the number of necessary
¹³⁸ comparisons by presenting only one effort discounting round for each possible pair of levels
¹³⁹ after determining for each pair which level should be fixed and which should be flexible.

¹⁴⁰ This is determined by presenting each possible pair of levels on screen with the question
¹⁴¹ “Would you prefer 1 € for level A or 1 € for level B?”. Participants respond by clicking the
¹⁴² respective on-screen button. Each pair is presented three times, resulting in 18 presented

¹⁴³ pairs, which are fully randomized in order and in the assignment of which level is on the left
¹⁴⁴ or right of the screen. For each pair, the level that was chosen by the participant at least
¹⁴⁵ two out of three times will be used as the level with a flexible value, which starts at 1 €
¹⁴⁶ and is changed in every iteration. The other level in the pair will be set to a fixed value of
¹⁴⁷ 2 €. Then, the effort discounting sensu Westbrook et al.⁷ begins, but with all possible pairs
¹⁴⁸ and with the individually determined assignment of fixed and flexible level. The order in
¹⁴⁹ which the pairs are presented is fully randomized, and each pair goes through all iteration
¹⁵⁰ steps of adding/subtracting 0.50 €, 0.25 €, 0.13 €, 0.06 €, 0.03 €, 0.02 € to/from the
¹⁵¹ flexible level's reward (each adjustment half of the previous one, rounded to two decimals)
¹⁵² before moving on to the next one. This procedure allows to compute SVs based on actual
¹⁵³ individual preference instead of objective task load. For each pair, the SV of the flexible
¹⁵⁴ level is 1, as it was preferred when faced with equal rewards, and the SV of the fixed level
¹⁵⁵ is the final reward of the flexible level divided by 2 €. Each level's "global" SV is calculated
¹⁵⁶ as the mean of this level's SVs from all pairs in which it appeared. If the participant has a
¹⁵⁷ clear preference for one level, this level's SV will be 1. If not, then no level's SV will be 1,
¹⁵⁸ but each level's SV can still be interpreted as an absolute and relative value, so each
¹⁵⁹ participant's effort discounting behaviour can still be quantified. The interpretation of SVs
¹⁶⁰ in Westbrook et al.⁷ was "The minimum relative reward required for me to choose 1-back
¹⁶¹ over this level". So if the SV of 3-back was 0.6, the participant would need to be rewarded
¹⁶² with at least 60 % of what they are being offered for doing 3-back to do 1-back instead,
¹⁶³ forgoing the higher reward for 3-back. In this study, the SV can be interpreted as "The
¹⁶⁴ minimum relative reward required for me to choose any other level over this level".
¹⁶⁵ Therefore, an SV of 1 indicates that this level is preferred over all others, while SVs lower
¹⁶⁶ than 1 indicate that in at least one pair, a different level was preferred over this one.

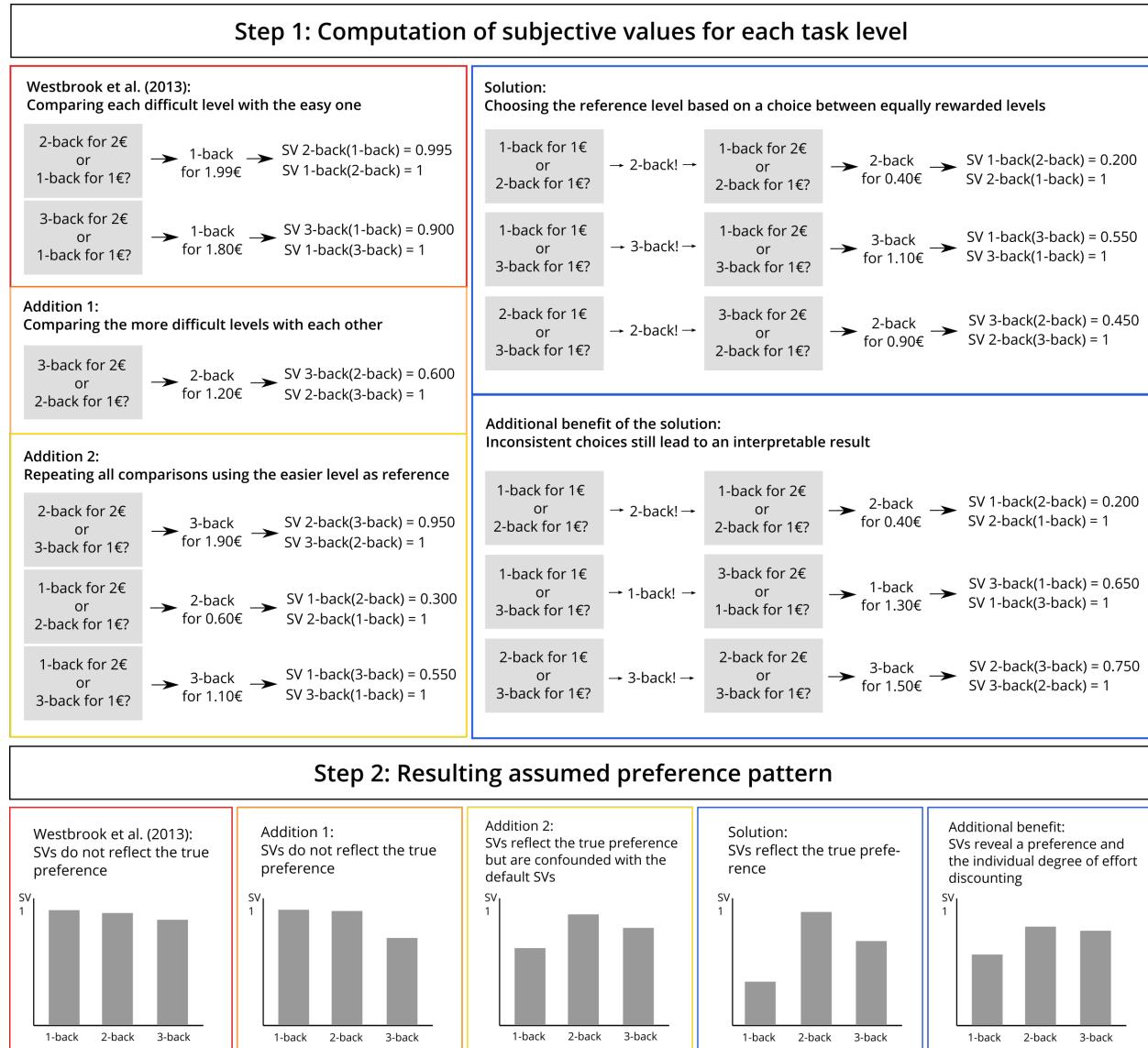


Figure 1. An example for subjective values for an n -back task with three levels, returned by different modifications of the COG-ED paradigm for a hypothetical participant with the true preference $2\text{-back} > 3\text{-back} > 1\text{-back}$. The grey boxes are the choice options shown to the participant. The participant's final reward value of the flexible level is displayed after the first arrow. The resulting subjective value of each level is displayed after the second arrow, in the notation "SV 3-back(1-back)" for the subjective value of 3-back when 1-back is the other choice. The Solution and Additional Benefit panel follow the same logic, but are preceded by a choice between equal rewards, and the participant's first choice indicated by an exclamation mark.

168 **Study procedure.** Healthy participants aged 18 to 30 years were recruited using
 169 the software *ORSEE*²⁴. Participants completed the personality questionnaires online and

then visited the lab for two sessions one week apart. NFC was assessed using the 16-item short form of the Need for Cognition Scale^{25,26}. Responses to each item (e.g., “Thinking is not my idea of fun”, recoded) were recorded on a 7-point Likert scale. The NFC scale shows comparably high internal consistency (Cronbach’s $\alpha > .80$)^{26,27}. Several other personality questionnaires were used in this study but are the topic of the Registered Report for the second lab session¹⁷. A full list of measures can be found in our Github repository. In the first session, participants provided informed consent and demographic data before completing the computer-based paradigm. The paradigm started with the *n*-back levels one to four, presented sequentially with two runs per level, consisting of 64 consonants (16 targets, 48 non-targets) per run. The levels were referred to by color (1-back black, 2-back red, 3-back blue, 4-back green) to avoid anchor effects in the effort discounting procedure. To assess perceived task load, we used the 6-item NASA Task Load Index (NASA-TLX)²⁸, where participants evaluate their subjective perception of mental load, physical load, effort, frustration, performance, and time pressure during the task on a 20-point scale. At the end of each level, participants filled out the NASA-TLX on a tablet, plus an item with the same response scale, asking them how aversive they found this *n*-back level. After the *n*-back task, participants completed the CAD paradigm on screen and were instructed to do so as realistically as possible, even though the displayed rewards were not paid out on top of their compensation. They were told that one of their choices would be randomly picked for the final run of *n*-back, the data of which was not analyzed as it only served to incentivise truthful behavior and stay close to the design of Westbrook et al.⁷. After the CAD paradigm, participants filled out a short questionnaire on the tablet, indicating whether they adhered to the instructions (yes/no) and what the primary motivation for their decisions during the effort discounting procedure was (avoid boredom/relax/avoid effort/seek challenge/other).

The second session consisted of an emotion regulation task with negative pictures and the instruction to suppress facial reactions, detach cognitively from the picture content,

197 and distract oneself, respectively. The paradigm followed the same structure of task and
198 effort discounting procedure, but participants could decide which strategy they wanted to
199 reapply in the last block. Study data was collected and managed using REDCap electronic
200 data capture tools hosted at Technische Universität Dresden^{29,30}.

201 **Sampling plan**

202 Sample size determination was mainly based on the results of the analyses of
203 Westbrook et al.⁷ (see Design Table). The hypothesis that yielded the largest necessary
204 sample size was a repeated measures ANOVA with within-between interaction of NFC and
205 n -back level influencing SVs. Sample size analysis with *G*Power*^{31,32} indicated that we
206 should collect data from at least 72 participants, assuming $\alpha = .05$ and $\beta = .95$. However,
207 the sample size analysis for the hypotheses of the second lab session revealed a larger
208 necessary sample size of 85 participants to find an effect of $d = -0.32$ of emotion regulation
209 on facial muscle activity with $\alpha = .05$ and $\beta = .95$. To account for technical errors, noisy
210 physiological data, or participants who indicate that they did not follow the instructions,
211 we aimed to collect about 50% more data sets than necessary, $N = 120$ in total.

212 **Analysis plan**

213 Data collection and analysis were not performed blind to the conditions of the
214 experiments. We excluded the data of a participant from all analyses, if the participant
215 stated that they did not follow the instructions, if the investigator noted that the
216 participant misunderstood the instructions, or if the participant withdrew their consent.
217 No data was replaced. The performance measure d' was computed as the difference of the
218 z -transformed hit rate and the z -transformed false alarm rate³³. Reaction time (RT) data
219 was trimmed by excluding all trials with responses faster than 100 ms, as the relevant
220 cognitive processes cannot have been completed before^{34,35}. Aggregated RT values were
221 described using the median and the median of absolute deviation (*MAD*) as robust

estimates of center and variability, respectively³⁶. Error- and post-error trials were excluded, because RT in the latter is longer due to more cautious behavior^{37,38}. To test our hypotheses, we performed a series of rmANOVAs and an MLM with orthogonal sum-to-zero contrasts in order to meaningfully interpret results³⁹.

Manipulation check. Declining performance was investigated by calculating an rmANOVA with six paired contrasts comparing d' between two levels of 1- to 4-back at a time. Another rmANOVA with six paired contrasts was computed to compare the median RT between two levels of 1- to 4-back at a time. To investigate changes in NASA-TLX ratings, six rmANOVAs were computed, one for each NASA-TLX subscale, and each with six paired contrasts comparing the ratings between two levels of 1- to 4-back at a time.

Subjective values. For each effort discounting round, the SV of the fixed level was calculated by adding or subtracting the last adjustment of 0.02 € from the last monetary value of the flexible level, depending on the participant's last choice, and dividing this value by 2 €. This yielded an SV between 0 and 1 for the fixed compared with the flexible level, while the SV of the flexible level was 1. The closer the SV of the fixed level is to 0, the stronger the preference for the flexible level. All SVs of each level were averaged to compute one "global" SV for each level. An rmANOVA with four different contrasts were computed to investigate the association of SVs and the n -back levels: Declining linear (3,1,-1,-3), ascending quadratic (-1,1,1,-1), declining logistic (3,2,-2,-3), and positively skewed normal (1,2,-1,-2). Depending on whether the linear or one of the other three contrasts fit the curve best, we applied a linear or nonlinear multi-level model in the next step, respectively.

To determine the influence of task performance on the association of SVs and n -back level, we performed MLM. We applied restricted maximum likelihood (REML) to fit the model. As an effect size measure for random effects we first calculated the intraclass correlation (ICC), which displays the proportion of variance that is explained by differences between persons. Second, we estimated a random slopes model of n -back level (level 1,

fixed, and random factor: 0-back, 1-back, 2-back, 3-back) predicting SV nested within subjects. As Mussel et al.⁴⁰ could show, participants with high versus low NFC not only have a more shallow decline in performance with higher *n*-back levels, but show a demand-specific increase in EEG theta oscillations, which has been associated with mental effort. We controlled for performance, i.e., d' (level 1, fixed factor, continuous), median RT (level 1, fixed factor, continuous) in order to eliminate a possible influence of declining performance on SV ratings.

$$SV \sim level + d' + medianRT + (level|subject)$$

Level-1-predictors were centered within cluster as recommended by Enders & Tofighi⁴¹. By this, the model yields interpretable parameter estimates. If necessary, we will adjusted the optimization algorithm to improve model fit. We visually inspected the residuals of the model for evidence to perform model criticism. This was done by excluding all data points with absolute standardized residuals above 3 SD. As effect size measures, we calculated pseudo R^2 for our model and f^2 to estimate the effect of *n*-back level according to Lorah⁴².

The association of SVs and NFC was examined with an rmANOVA. We subtracted the SV of 1- from 2-back and 2- from 3-back, yielding two SV difference scores per participant. The sample was divided into participants with low and high NFC using a median split. We then computed an rmANOVA with the within-factor *n*-back level and the between-factor NFC group to determine whether there is a main effect of level and/or group, and/or an interaction between level and group on the SV difference scores. Post-hoc tests were computed depending on which effect reached significance at $p < .01$. To ensure the validity of this association, we conducted a specification curve analysis⁴³, which included 63 possible preprocessing pipelines of the RT data. These pipelines specify which transformation was applied (none, log, inverse, or square-root), which outliers were excluded (none, 2, 2.5, or 3 MAD from the median, RTs below 100 or 200 ms), and across

272 which dimensions the transformations and exclusions were applied (across/within subjects
273 and across/within n -back levels). The rmANOVA was run with each of the 63 pipelines,
274 which also included our main pipeline (untransformed data, exclusion of RTs below
275 100 ms). The ratio of pipelines that lead to significant versus non-significant effects
276 provides an indication of how robust the effect actually is.

277 The association of subjective task load with NFC was examined similarly. We
278 calculated NASA-TLX sum scores per participant per level, computed an rmANOVA with
279 the within-factor n -back level and the between-factor NFC group, and applied post-hoc
280 tests based on which effect reached significance at $p < .01$. And the association of
281 subjective aversiveness of the task with NFC was examined with difference scores as well,
282 since we expected this curve to mirror the SV curve, i.e. as the SV rises, the aversiveness
283 declines, and vice versa. We subtracted the aversiveness ratings of 1- from 2-back and 2-
284 from 3-back, yielding two aversiveness difference scores per participant. Then, we
285 computed an rmANOVA with the within-factor n -back level and the between-factor NFC
286 group, and applied post-hoc tests based on which effect reached significance at $p < .01$.

287 The results of each analysis was assessed on the basis of both p -value and the Bayes
288 factor BF_{10} , calculated with the *BayesFactor* package²³ using the default prior widths of
289 the functions *anovaBF*, *lmBF* and *ttestBF*. We considered a BF_{10} close to or above 3/10 as
290 moderate/strong evidence for the alternative hypothesis, and a BF_{10} close to or below
291 .33/.10 as moderate/strong evidence for the null hypothesis⁴⁴.

292 Pilot data

293 The sample of the pilot study consisted of $N = 15$ participants (53.3% female,
294 $M = 24.43$ ($SD = 3.59$) years old). One participant's data was removed because they
295 misunderstood the instruction. Due to a technical error the subjective task load data of
296 one participant was incomplete, so the hypotheses involving the NASA Task Load Index

were analyzed with $n = 14$ data sets. The results showed increases in subjective and objective task load measures with higher n -back level. Importantly, SVs were lower for higher n -back levels, but not different between 1- and 2-back, which shows that the easiest level is not universally preferred. The LMM revealed n -back level as a reliable predictor of SV, even after controlling for declining task performance (d' and median RT). NASA-TLX scores were higher with higher n , and lower for the group with lower NFC scores, but NFC and n -back level did not interact. All results are detailed in the Supplementary Material.

304 Data availability

305 The data of this study can be downloaded from osf.io/vnj8x/.

306 Code availability

307 The paradigm code, the R script for analysis, and the R Markdown file used to
308 compile this document are available at osf.io/vnj8x/.

309 Protocol registration

310 The Stage 1 Registered Report protocol has been approved and is available at
311 osf.io/qa2bg/.

312 Results

313 Adjustments for Stage 2

314 There were two necessary adjustments of the methods. First, we failed to update the
315 necessary sample size after the analyses changed with the first review round. Instead of the
316 72 subjects stated above, the largest minimum sample size was actually 53 subjects (see
317 hypothesis 1b in the Design Table in the Supplementary Material). And secondly, we

needed to re-assign the SCA to the MLM in hypothesis 2b, to which it belonged in the initial submission. Following the advice of the reviewers, we had separated the NFC analysis from the MLM, and wanted to apply the SCA to the new NFC analysis (hypothesis 3a), as this was one of our main points of interest. However, since hypothesis 3a does not contain any RT data and the SCA is therefore only useful for the MLM in hypothesis 2b, we applied it to the MLM.

324 Sample

325 Data was collected between the 16th of August 2022 and the 3rd of February 2023.
326 All of the $N = 124$ participants who filled out the online questionnaires came to the first
327 lab session. Based on the experimenters' notes, we excluded the data of seven participants
328 from analysis for misunderstanding the instruction of the n -back task, and the data of one
329 participant who reported that they confused the colours of the levels during effort
330 discounting. Our final data set therefore included $N = 116$ participants (83.60% female,
331 $M = 22.40$ ($SD = 3$) years old), which is 2.2 times more than what the highest sample size
332 calculation required.

333 Manipulation checks

334 The performance measure d' did not change across n -back levels
335 ($F(2.85, 327.28) = 0.01, p = .999, \hat{\eta}_G^2 = .000, 90\% \text{ CI } [.000, .000], BF_{10} = 3.31 \times 10^{-3}$), but
336 the median RT did ($F(2.46, 283.05) = 98.67, p < .001, \hat{\eta}_G^2 = .192, 90\% \text{ CI } [.130, .248]$,
337 $BF_{10} = 2.28 \times 10^{34}$). Specifically, the median RT was higher for the more difficult level in
338 every contrast, with two exceptions: It did not differ between 2- and 4-back, and it was
339 higher for 3- than for 4-back (Table 1).

Table 1

Paired contrasts for the rmANOVA comparing the median reaction time between n-back levels

Contrast	Estimate	SE	df	t	p	BF ₁₀	η_p^2	95%CI
1 - 2	-0.12	0.01	345.00	-11.80	0.000	1.75×10^{30}	0.29	[0.22, 1.00]
1 - 3	-0.16	0.01	345.00	-16.20	0.000	8.80×10^{45}	0.43	[0.37, 1.00]
1 - 4	-0.12	0.01	345.00	-12.50	0.000	4.79×10^{34}	0.31	[0.25, 1.00]
2 - 3	-0.04	0.01	345.00	-4.47	0.000	5,538.45	0.05	[0.02, 1.00]
2 - 4	-0.01	0.01	345.00	-0.71	0.894	0.10	1.45e-03	[0.00, 1.00]
3 - 4	0.04	0.01	345.00	3.76	0.001	6.35×10^6	0.04	[0.01, 1.00]

Note. The column Contrast contains the n of the n -back levels. SE = standard error, df = degrees of freedom, t = t-statistic, p = p-value, CI = confidence interval.

340 All NASA-TLX subscale scores increased across n -back levels. The effort subscale
 341 ($F(2.20, 253.06) = 203.82, p < .001, \hat{\eta}_G^2 = .316, 90\% \text{ CI } [.250, .375], \text{BF}_{10} = 2.47 \times 10^{34}$)
 342 increased across all levels, but the magnitude of change decreased from 1- to 2-back
 343 ($t(345) = -12.35, p_{\text{Tukey}(4)} < .001, \text{BF}_{10} = 4.24 \times 10^{19}$) to 3- to 4-back ($t(345) = -2.72,$
 344 $p_{\text{Tukey}(4)} = .035, \text{BF}_{10} = 174.38$). Three subscales had significant differences between all
 345 contrasts except for 3- versus 4-back: While ratings on the frustration and time subscales
 346 were higher for more difficult levels ($F(2.50, 287.66) = 68.06, p < .001, \hat{\eta}_G^2 = .172, 90\% \text{ CI }$
 347 $[.112, .227], \text{BF}_{10} = 5.26 \times 10^{15}$, and $F(2.21, 254.65) = 51.08, p < .001, \hat{\eta}_G^2 = .117, 90\% \text{ CI }$
 348 $[.065, .168], \text{BF}_{10} = 3.94 \times 10^9$, respectively), ratings on the performance subscale decreased
 349 with higher n ($F(2.49, 285.97) = 95.33, p < .001, \hat{\eta}_G^2 = .241, 90\% \text{ CI } [.176, .299],$
 350 $\text{BF}_{10} = 1.55 \times 10^{24}$). Ratings on the mental subscale consistently increased across all levels
 351 ($F(1.99, 228.35) = 274.47, p < .001, \hat{\eta}_G^2 = .375, 90\% \text{ CI } [.309, .432], \text{BF}_{10} = 1.64 \times 10^{43}$).
 352 Ratings on the physical subscale were higher for more difficult levels
 353 ($F(1.68, 192.93) = 15.91, p < .001, \hat{\eta}_G^2 = .041, 90\% \text{ CI } [.009, .075], \text{BF}_{10} = 60.54$), apart
 354 from the contrasts 2- versus 3-back ($t(345) = -2.34, p_{\text{Tukey}(4)} = .092, \text{BF}_{10} = 10.45$) and 3-
 355 versus 4-back ($t(345) = -1.07, p_{\text{Tukey}(4)} = .705, \text{BF}_{10} = 0.47$). The full results of these
 356 manipulation checks are listed in Table S.1 to S.8 in the Supplementary Material.

³⁵⁷ **Decline of subjective values**

³⁵⁸ When asking participants what motivated their decisions in the effort discounting,
³⁵⁹ 11.2% stated that they wanted to avoid boredom, 22.4% stated that they wanted a
³⁶⁰ challenge, 34.5% stated that they wanted to avoid effort, and 4.3% stated that they wanted
³⁶¹ to relax. The remaining 27.6% of participants used the free text field and provided reasons
³⁶² such as “I wanted a fair relation of effort and reward.”, “I wanted the fun that I had in the
³⁶³ more challenging levels.”, “I wanted to maximize reward first and minimize effort second.”,
³⁶⁴ or “I did not want to perform poorly when I was being paid for it.”. Figure S.1 in the
³⁶⁵ Supplementary Material shows the different motivations in the context of the SVs per
³⁶⁶ n -back level.

³⁶⁷ The rmANOVA showed a significant difference between the SVs across n -back levels
³⁶⁸ ($F(1.98, 227.98) = 65.65, p < .001, \hat{\eta}_G^2 = .288, 90\% \text{ CI } [.222, .347], \text{BF}_{10} = 1.58 \times 10^{64}$). All
³⁶⁹ four pre-defined contrasts reached significance (Table 2), so a purely linear contrast can be
³⁷⁰ rejected.

Table 2
Contrasts for the rmANOVA comparing the subjective values between n -back levels

Contrast	Estimate	SE	df	t	p	η_p^2	95%CI
Declining Linear	1.11	0.08	345.00	13.40	<.001	0.34	[0.28, 1.00]
Ascending Quadratic	0.15	0.04	345.00	4.14	<.001	0.05	[0.02, 1.00]
Declining Logistic	1.22	0.09	345.00	13.00	<.001	0.33	[0.26, 1.00]
Positively Skewed Normal	0.75	0.06	345.00	12.70	<.001	0.32	[0.26, 1.00]

Note. SE = standard error, df = degrees of freedom, t = t-statistic, p = p-value, CI = confidence interval.

³⁷¹ The declining logistic contrast had the highest effect estimate ($t(345) = 12.97,$
³⁷² $p < .001$), suggesting a shallow decline of SVs between 1- and 2-back, and 3- and 4-back,
³⁷³ respectively, and a steeper decline of SVs between 2- and 3-back.

³⁷⁴ Consequently, we had to adapt the multi level model to incorporate this non-linear

³⁷⁵ trend. To apply the contrast to the n -back levels, we had to turn the variables into a
³⁷⁶ factor, with two consequences: Centered variables cannot be turned into factors, so we
³⁷⁷ entered the variable level in its raw form, and factors cannot be used as random slopes, so
³⁷⁸ the model is now defined as:

$$SV \sim level + d' + medianRT + (1|subject)$$

³⁷⁹ This means that the intercept still varies between subjects, but there are no random slopes
³⁸⁰ anymore. To provide more than one observation per factor level, we used the two rounds
³⁸¹ per n -back level per subject, rather than n -back levels per subject. The ICC of the null
³⁸² model indicated that there is a correlation of $r = .10$ between the SVs of a subject, i.e. that
³⁸³ 9.59% of variance in SVs can be explained by differences between participants. We did not
³⁸⁴ use an optimization algorithm to improve the fit of the random intercept model. A total of
³⁸⁵ 9 data points from 6 participants were excluded, because the residuals exceeded 3 SD
³⁸⁶ above the mean. The results of the final model are displayed in Table 3.

Table 3

Results of the multi level model on the influence of n-back level (as a declining logistic contrast) and task performance on subjective values.

Parameter	Beta	SE	df	t-value	p-value	f^2	Random Effects (SD)
Intercept	0.95	0.02	507.45	59.45	<.001		0.09
n-back level	-0.04	0.02	800.15	-2.36	<.001	0.64	
d'	0.02	0.00	798.75	5.60	<.001	0.04	
median RT	0.02	0.07	798.58	0.30	0.768	0.00	

Note. SE = standard error, df = degrees of freedom, SD = standard deviation.

³⁸⁷ An exploratory ANOVA was used to compare the fit of the final model with a linear
³⁸⁸ random intercept model, confirming that the two models were different from each other
³⁸⁹ ($\chi^2(2) = 34.48, p < .001$), and with an Akaike Information Criterion of $AIC = -492.61$
³⁹⁰ and a Bayesian Information Criterion of $BIC = -454.02$ the declining logistic model was

superior to the linear model ($AIC = -462.12$, $BIC = -433.18$). The final model had an effect size of $f^2 = 0.64$ for the n -back levels and $f^2 = 0.04$ for d' , which are considered large and small, respectively⁴⁵. This means that the n -back level explained 64.20% and d' explained 3.95% of variance in SVs relative to the unexplained variance, respectively. The beta coefficient indicated that with every 1-unit increase in d' , the SV increased by 0.02.

The effect size of the median RT was $f^2 = 0.00$.

To investigate the dependency of the model results on the RT preprocessing, we conducted a specification curve analysis (Figure 2).

INSERT FIGURE 2 HERE

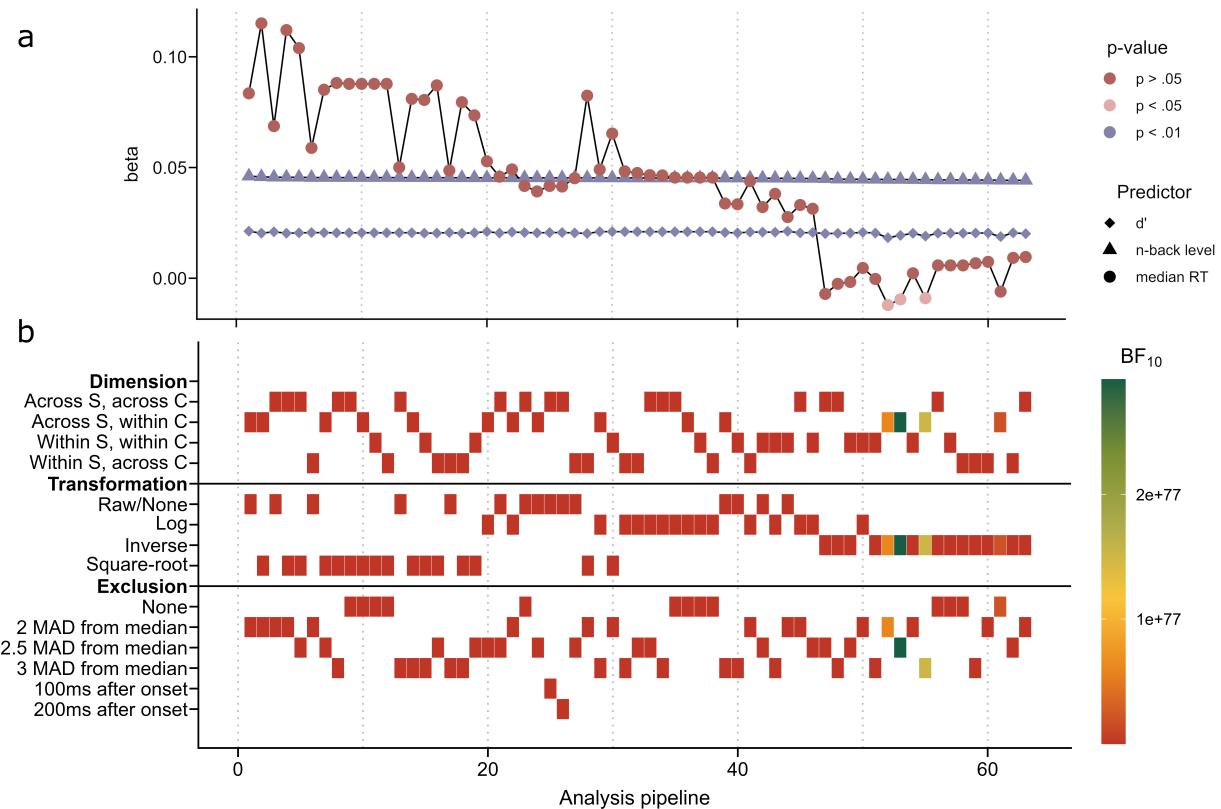


Figure 2. Results of the multi-level model for each of the 63 preprocessing pipelines. The lower panel indicates the type of preprocessing, the upper panel shows the beta coefficient of each predictor and its p-value. The colourbar indicates the BF_{10} . The pipelines are sorted in descending order of the magnitude of the n-back level beta.

Regardless of the preprocessing pipeline, n -back level and d' were significant

⁴⁰¹ predictors of SVs, and had stable effect estimates across all pipelines. The only pipelines in
⁴⁰² which the median RT was a significant predictor of SVs, were the three pipelines with the
⁴⁰³ highest Bayes Factors. These three pipelines contain data that has been inverse
⁴⁰⁴ transformed across subjects but within conditions, i.e. within the round of an n -back level.

⁴⁰⁵ **Differences between NFC groups**

⁴⁰⁶ Figure 3 shows a scatterplot of SVs per n -back level, colored depending on the
⁴⁰⁷ participant's NFC score. There is a concentration of participants who have assigned their
⁴⁰⁸ highest SV to 1-back, and this concentration fades across n -back levels. At the same time,
⁴⁰⁹ there is a subtle separation of SVs across n -back levels, depending on the participant's
⁴¹⁰ NFC score: While the SVs of those with higher NFC scores remain elevated, the SVs of
⁴¹¹ those with lower NFC scores decline more strongly. Specifically, $n = 71$ participants had an
⁴¹² absolute preference for 1-back, $n = 18$ for 2-back, $n = 9$ for 3-back, and $n = 13$ for 4-back.
⁴¹³ There were $n = 5$ participants who did not have an absolute preference for any n -back
⁴¹⁴ level, i.e. none of their SVs was 1.

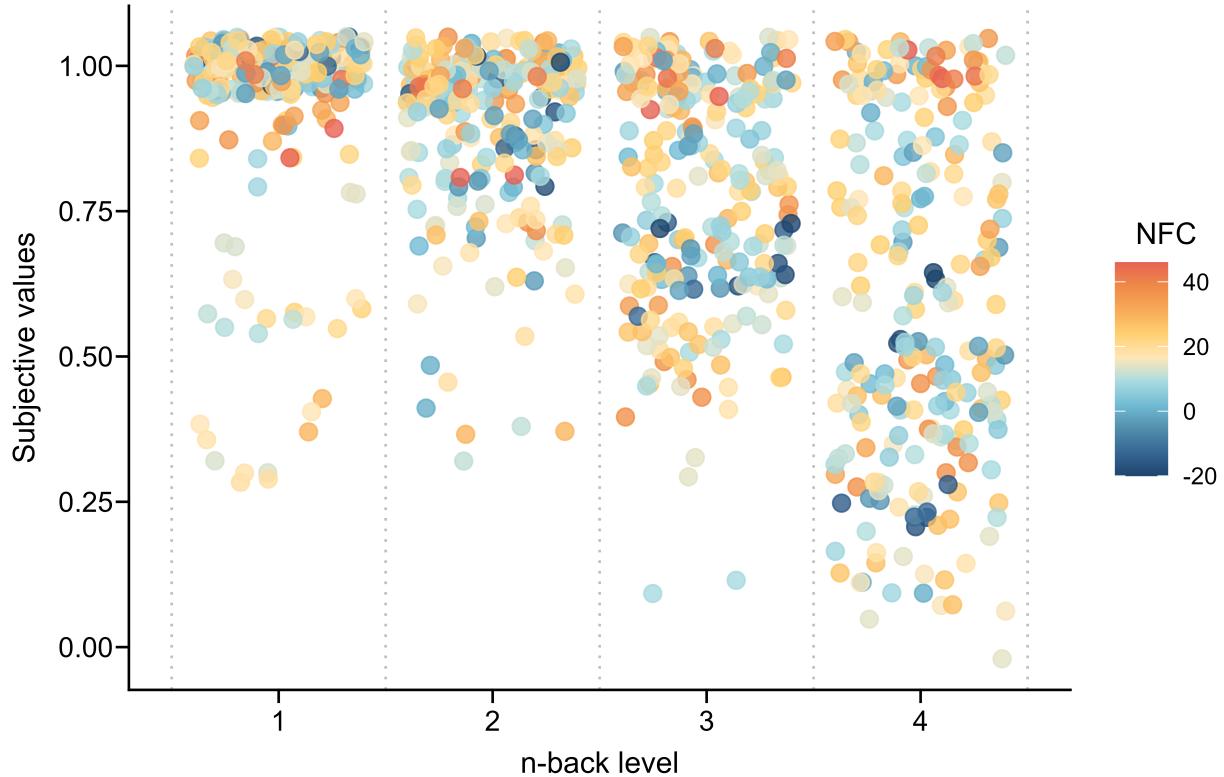


Figure 3. Subjective values per n-back level. Each dot indicates a participant, the colours indicate their Need for Cognition (NFC) score. $N = 116$. There is a horizontal jitter of 0.4 and a vertical jitter of 0.05 for visual clarity.

416 The median NFC was 16, with $n = 57$ subjects below and $n = 59$ above the median.

417 We used an rmANOVA to investigate whether the difference between the SVs of 1- and
 418 2-back, and 2- and 3-back, respectively, depended on whether a participant's NFC score
 419 was above or below the median. There was a main effect of the *n*-back level
 420 ($F(1, 114) = 9.13, p = .003, \hat{\eta}_G^2 = .040, 90\% \text{ CI } [.002, .115], \text{BF}_{10} = 12.68$), but neither a
 421 main effect of the NFC group ($F(1, 114) = 3.18, p = .077, \hat{\eta}_G^2 = .013, 90\% \text{ CI } [.000, .068]$,
 422 $\text{BF}_{10} = 0.56$) nor an interaction of NFC group and *n*-back level ($F(1, 114) = 0.46, p = .499$,
 423 $\hat{\eta}_G^2 = .002, 90\% \text{ CI } [.000, .037]$). Post-hoc tests showed that the difference between the SVs
 424 of 2- and 3-back is slightly more negative than the difference between 1- and 2-back
 425 ($t(114) = -3.02, p = .003$), but there were large inter-individual differences, especially for
 426 2- and 3-back (left panel of Figure 4). This means that across the whole sample, there was

⁴²⁷ a steeper decline in SVs from 2- to 3-back than from 1- to 2-back, but some participants
⁴²⁸ showed a completely opposite pattern.

⁴²⁹ INSERT FIGURE 4 HERE

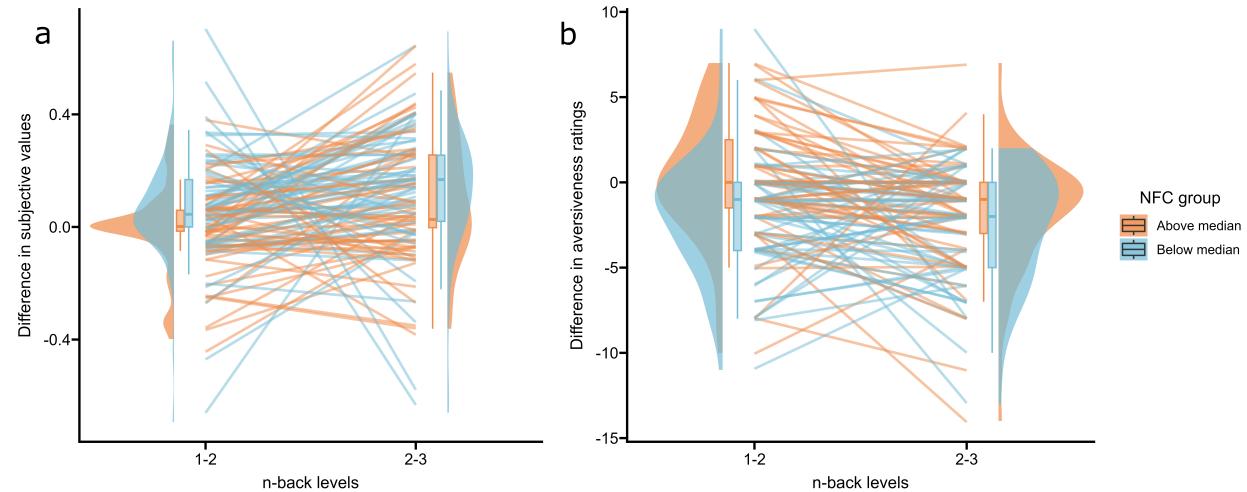


Figure 4. Difference scores for subjective values (left) and aversiveness ratings (right) when subtracting 2- from 1-back and 3- from 2-back. Each line indicates a participant, the colours indicate their Need for Cognition (NFC) score. $N = 116$.

⁴³⁰ The rmANOVA on the association between NFC scores and NASA-TLX scores
⁴³¹ revealed a main effect of n -back level ($F(2.10, 239.56) = 154.50, p < .001, \hat{\eta}_G^2 = .223, 90\%$
⁴³² CI [.159, .282], $BF_{10} = 2.22 \times 10^{45}$) and an interaction between n -back level and NFC
⁴³³ scores ($F(2.10, 239.56) = 4.93, p = .007, \hat{\eta}_G^2 = .009, 90\% \text{ CI } [.000, .025]$), but no main effect
⁴³⁴ of NFC scores ($F(1, 114) = 3.22, p = .075, \hat{\eta}_G^2 = .022, 90\% \text{ CI } [.000, .084]$,
⁴³⁵ $BF_{10} = 1.75 \times 10^2$). Post-hoc tests showed that the participants with NFC scores below the
⁴³⁶ median had higher NASA-TLX scores for 3-back ($t(114) = -2.15, p = .033, BF_{10} = 11.15$)
⁴³⁷ and for 4-back ($t(114) = -2.89, p = .005, BF_{10} = 336.88$) than those with NFC scores
⁴³⁸ above the median. Regardless of NFC scores, NASA-TLX scores were higher for the more
⁴³⁹ difficult level in each pair of n -back levels (Figure 5).

⁴⁴⁰ INSERT FIGURE 5 HERE

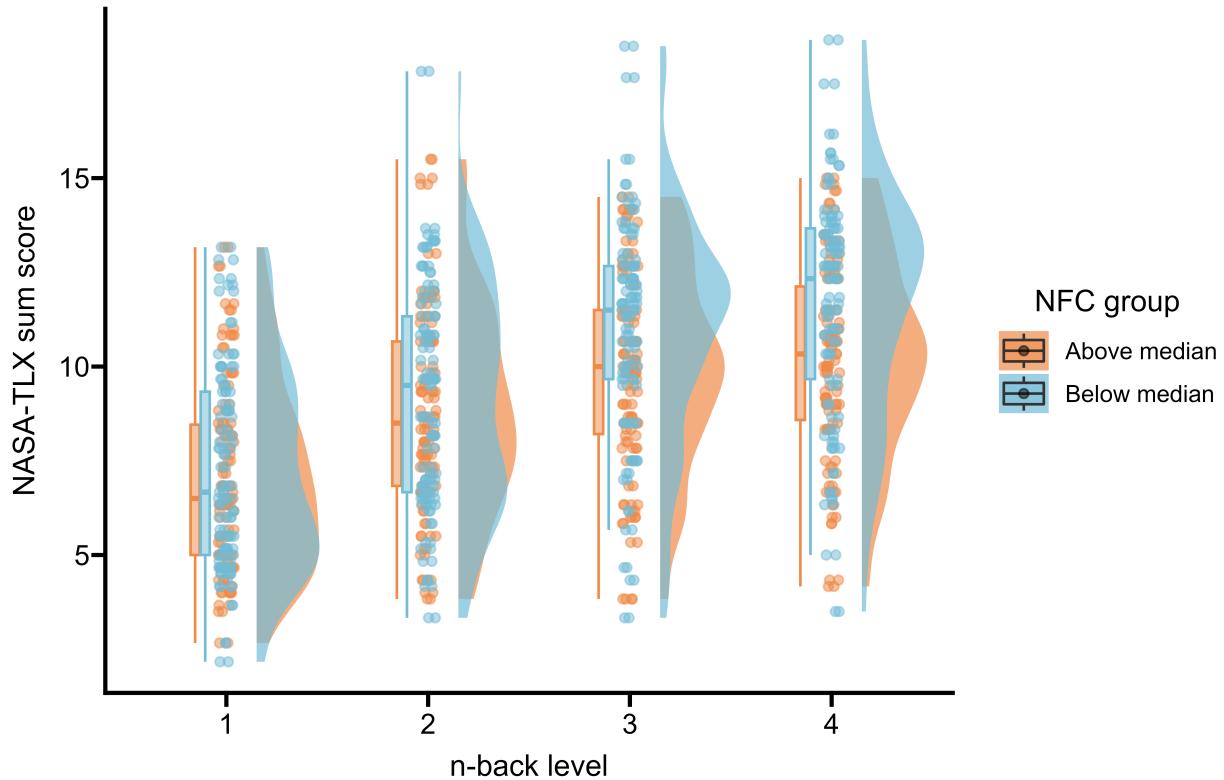


Figure 5. NASA-TLX sum scores for each n -back level. Colours indicate Need for Cognition (NFC) score above or below the median. $N = 116$.

With another rmANOVA we investigated whether the difference between the aversiveness scores of 1- and 2-back, and 2- and 3-back, respectively, depended on whether a participant's NFC score was above or below the median. There was a main effect of NFC group ($F(1, 114) = 8.43, p = .004, \hat{\eta}_G^2 = .043, 90\% \text{ CI } [.003, .119], \text{BF}_{10} = 14.26 \pm 0.00\%$) and a main effect of the n -back level ($F(1, 114) = 10.21, p = .002, \hat{\eta}_G^2 = .034, 90\% \text{ CI } [.000, .105]$), but no interaction ($F(1, 114) = 2.59, p = .110, \hat{\eta}_G^2 = .009, 90\% \text{ CI } [.000, .058]$). Post-hoc tests revealed that participants with NFC scores below the median reported higher aversiveness than participants with NFC scores above the median ($t(114) = 2.90, p = .004$) (right panel of Figure 4). Regardless of NFC, the difference of the aversiveness scores of 2- and 3-back was smaller and more negative than that of 1- and 2-back ($t(114) = 3.20, p = .002$), but again, there were large inter-individual differences.

The full results of these analyses of NFC group differences can be found in Table S.11 to

453 S.15 in the Supplementary Material.

454 **Exploratory analysis**

455 To investigate the apparent group difference between the SVs of participants with
456 NFC scores below and above the median in higher n -back levels, we computed an
457 rmANOVA with the within-factor level (1 to 4) and the between-factor NFC group
458 (below/above median). There was no main effect of NFC group ($F(1, 114) = 2.63$,
459 $p = .108$, $\hat{\eta}_G^2 = .007$, 90% CI [.000, .053], 2.95×10^{-1}), but a main effect of the n -back level
460 ($F(2.01, 229.39) = 67.39$, $p < .001$, $\hat{\eta}_G^2 = .295$, 90% CI [.228, .354], 2.70×10^{30}) and an
461 interaction ($F(2.01, 229.39) = 3.24$, $p = .041$, $\hat{\eta}_G^2 = .020$, 90% CI [.000, .044]). Post-hoc
462 tests for the main effect of level showed that SVs were lower for the more difficult n -back
463 level in each paired contrast except for 1- versus 2-back. Post-hoc tests for the interaction
464 effect showed that the NFC groups only had a significant difference in SVs for 4-back,
465 where participants below the NFC median had lower scores ($\Delta M = 0.11$, 95% CI
466 [0.01, 0.22], $t(114) = 2.13$, $p = .036$). Despite not reaching significance, 1-back was the only
467 level in which participants with NFC scores above the median seemed to have lower SVs
468 than those with scores below the median ($\Delta M = -0.05$, 95% CI [-0.11, 0.01],
469 $t(114) = -1.50$, $p = .136$). The full results of this exploratory analysis of NFC group
470 differences can be found in Table S.16 and S.17 in the Supplementary Material.

471 **Discussion**

472 This Registered Report aimed to adapt the Cognitive Effort Discounting Paradigm
473 (COG-ED) paradigm by Westbrook et al.⁷, which can estimate subjective values of
474 different n -back levels, into the Cognitive and Affective Discounting (CAD) paradigm,
475 which can estimate SVs of tasks without defaulting to the objective task load as a
476 benchmark. For this purpose, we changed the way in which the discounting options are
477 presented to the participants, based the anchor on their own choices, and computed SVs

478 across multiple combinations of task levels. The analyses were closely aligned with those in
479 Westbrook et al.⁷ to demonstrate the changes in SVs brought about by the new paradigm.
480 This study also applied the CAD paradigm to an emotion regulation task, the results of
481 which are detailed in a second Registered Report¹⁷.

482 **Manipulation checks**

483 The performance measure d' did not differ across n -back levels, but the RT increased
484 from 1- to 2- to 3-back and then remained on a high level for 4-back. This points to three
485 important characteristics of the n -back task in this context. Firstly, RT as a valid
486 group-level indicator of performance might only be useful for levels up to $n = 3$, and could
487 be used to investigate inter-individual differences for $n > 3$. Secondly, there is a
488 speed-accuracy tradeoff in the first three levels, that might even re-emerge in higher levels,
489 where d' would decline and RT would remain stable. And lastly, the fact that neither
490 accuracy nor speed is an informative performance measure by itself has been observed
491 before⁴⁶ and both show different associations with various measures of intelligence⁴,
492 suggesting that they should always be reported as separate indices. Additionally, d' might
493 not have differed across n -back levels because the manipulation of task load is not strictly
494 continuous. Several participants said that they perceived 3-back as more difficult than
495 4-back because they found it is easier to remember chunks of stimuli when n was an even
496 number than when n was an odd number.

497 All NASA-TLX subscales differed across n -back levels, but the effort and mental load
498 subscales were the only ones to consistently increase across all levels. This would support
499 the notion of the n -back task offering a continuous manipulation of task load, at least
500 subjectively. Ratings on the frustration and time subscales increased and ratings on the
501 performance subscale decreased until 3-back and then remained stable. This pattern is
502 akin to the RT, which also increased and then remained stable. Ratings on the physical
503 load subscale increased with n -back levels, but not between 2- and 3-back and 3- and

504 4-back, respectively.

505 **Decline of subjective values**

506 The rmANOVA with different pre-defined contrasts showed that all fit the SVs to a
507 different degree, and that the SVs do not simply decline linearly across n -back levels. The
508 best fit was a declining logistic curve, reflecting that the majority of participants preferred
509 1-back and that SVs for 2-back were also high, before having more inter-individual variance
510 for 3- and 4-back. Thomson and Oppenheimer⁴⁷ argue that the different effort curves that
511 have been observed for different tasks are likely due to the fact that we still understand
512 quite little about how and why different manipulations of effort work. For example, the
513 n -back task is likely not a continuous manipulation of task load, as discussed above.

514 However, the declining logistic curve is similar to the sigmoidal curve that had the best fit
515 in a different effort paradigm⁴⁸, which the authors explained with the low effect of low
516 energy costs, suggesting there are still common features of effort across different tasks and
517 domains. The MLM with the logistic contrast showed that the n -back level explained the
518 majority of variance in SVs, while the performance measure d' also explained some variance
519 in SVs, albeit less. With increasing n -back level and decreasing d' , the SV decreased. The
520 median RT was not a significant predictor in this model, which was somewhat surprising
521 because RT but not d' yielded significant differences across levels in the manipulation
522 checks. However, participants might have deliberately or subconsciously used the feedback
523 they received at the end of each round, i.e. twice per n -back level, as an anchor during the
524 effort discounting. This feedback was based on correct responses and not on RT, so if
525 participants based their effort discounting choices at least partly on this feedback, they
526 were either motivated to repeat a task in which they performed well and/or they were
527 reluctant to accept a larger reward for a task in which they did not perform well. Since
528 more participants reported effort avoidance as their motivation in the effort discounting
529 than those who reported seeking a challenge, we can assume that they were more

530 motivated to repeat a task in which they performed well because their good performance
531 coincided with low effort.

532 The declining logistic n -back levels and d' remained significant predictors of SVs
533 throughout all 63 preprocessing pipelines in the specification curve analysis, with betas
534 that varied by less than 0.01. In contrast to this stood the variability of the median RT
535 betas, which ranged from about 0.11 to -0.01, and reached significance in only three
536 pipelines. These three pipelines had the highest BF_{10} and applied inverse transformation
537 to the RT data, across subjects but within conditions, and excluded data based on the
538 MAD. Interestingly, the curve of median RT betas in the upper panel of Figure 2 mirrored
539 the rectangular pipeline indicators in the transformation rows of the lower panel, so the
540 transformation choice influenced the median RT much more than the dimension or the
541 exclusion choice did. As Fernandez et al.⁴⁹ found, applying more than one preprocessing
542 step to the reaction time data of a Stroop task increased the risk of false positives beyond
543 $\alpha = .05$, and transformation choices inflated this risk more than outlier exclusion or
544 aggregation choices did. Our data seems to corroborate this finding for n -back tasks as
545 well. Surprisingly, the d' betas appear almost unaffected by the preprocessing pipeline,
546 even though d' was computed after the outlier exclusion. This indicates that researchers
547 who are interested in the correctness rather than the speed of responses can choose a simple
548 preprocessing pipeline without risking false positives through elaborate transformations.

549 Differences between NFC groups

550 The majority of participants (61.20 %) had an absolute preference for 1-back over the
551 other levels, but that also means that there were 34.50 % who had an absolute preference
552 for 2-, 3-, or 4-back, and 4.30 % who preferred no specific level over all others. It shows that
553 when given the choice, there is a large number of participants who do not prefer the easiest
554 level, confirming the necessity of an effort discounting paradigm that works independent of
555 the objective task load. The CAD paradigm provides the means to depict these preferences.

556 Despite the visual separation of the SVs of participants with very low and high NFC

557 scores in higher n -back levels, the NFC group did not reach significance in predicting SVs.

558 This was likely due to the bandwidth of SVs of participants with NFC scores around the

559 median, and due to the fact that the difference appeared most pronounced for 4-back, and

560 we only analyzed the difference scores between 1- and 2-back and 2- and 3-back. As the

561 exploratory analysis showed, only 4-back yielded a significant group difference, and SVs of

562 participants with NFC scores above the median were higher for 2- to 4-back and lower for

563 1-back. The analysis of NASA-TLX scores showed that the sum score increased with every

564 n -back level, and that participants with NFC scores below the median had higher

565 NASA-TLX scores for 3- and 4-back than those below the median. This demonstrates that

566 higher n -back levels have a higher discriminatory power regarding inter-individual

567 differences in subjective effort perception. This was also supported by the fact that higher

568 n -back levels were perceived as more aversive, and participants with NFC scores below the

569 median reported higher aversion than those with NFC scores above the median.

570 Limitations

571 When developing a new paradigm, it is challenging to decide on the optimal analysis

572 strategy, as every hypothesis is based on expected data patterns rather than previous

573 findings. While the Stage 1 review process made the analyses as robust as possible, there

574 were still unknown factors that should be addressed by future studies. For instance, the

575 differences between participants with higher and lower NFC should be investigated with

576 extreme groups rather than a median split, especially in academic samples where NFC can

577 be expected to be higher on average and more narrow in range. Additionally, we expected

578 the SVs of participants with lower NFC scores to peak at 1-back and the SVs of those with

579 higher scores to peak at 2-back, but the way the SVs of both groups appeared to drift

580 apart in the higher n -back levels suggests that an analysis of those levels would be more

581 fruitful in determining group differences. Future studies could create a stronger separation

582 between the concepts investigated in this study, and model the SVs and their task-related
583 influencing factors first, before looking at (non-linear) associations with personality.
584 Another important point is the instruction, not just for the *n*-back task, but for the effort
585 discounting as well. We had to exclude several participants for misunderstanding the task
586 instruction, so we will add a visual instruction or a training next time. And even though
587 the participants were instructed to do the effort discounting with the aim to be satisfied
588 with their choices instead of trying to increase the rewards, we cannot be sure that they
589 did so. One might also argue that the 2 € reward range was not large enough to be an
590 incentive for effort expenditure. However, findings by Bialaszek et al.⁵⁰ suggest that
591 participants are actually more sensitive to effort when the reward is small Nevertheless, we
592 exceeded the largest required sample size by 2.20 times, which gives our analyses high
593 statistical power, and we adhered to the agreed upon analyses of Stage 1.

594 Conclusion

595 Effort and reward are two highly subjective concepts with relevance in daily life.
596 With each decision an individual makes, they must weigh the required effort against the
597 expected reward to decide if and how to behave in that situation. So far, effort discounting
598 paradigms have relied on the assumption that the task that is objectively easiest is the one
599 that is preferred by everyone, and each more difficult task is simply being devalued
600 compared to the easy one. However, effort-related traits such as Need for Cognition suggest
601 that this is not the case. Therefore, we developed a paradigm that allows effort discounting
602 independent of objective task load, which we tested using an *n*-back task. The results
603 showed that many participants indeed preferred a more or even the most difficult *n*-back
604 level. Spanning the entire sample, these preferences took the shape of a declining logistic
605 curve across *n*-back levels. While the subjective value declined with increasing levels, it
606 increased with better performance as measured in d' , and was unaffected by the reaction
607 time. Participants with Need for Cognition scores above the median reported lower

608 subjective task load in and less aversion to more difficult levels. However, they did not
609 have higher subjective values per se, which was likely due to our choice of median split and
610 our assumption that these group differences would emerge in lower levels. In fact, the
611 reaction time and self-report data suggest that individual differences emerge especially
612 from 3-back upwards, emphasizing the need for tasks with high discriminatory power and
613 effort discounting paradigms with flexible, participant-centered mechanisms. The CAD
614 paradigm offers this flexibility, and we encourage future studies to question traditional
615 assumptions in the field of effort discounting in the light of these findings, and to re-use
616 this data set for exploratory analyses.

617

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728 JZ visualized the results. JZ and CK prepared the original draft. All authors reviewed,
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Competing Interests

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The authors declare no competing interests.