Measuring individual differences in cognitive effort avoidance

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Abstract

When given the chance to choose between two tasks, one will more likely choose the easier, less demanding task. This effect has been shown in various domains and referred to as the law of minimum effort or demand avoidance. The measure of demand avoidance that is currently used is the proportion of low-demand choices. We show that the current measure is not appropriate for accurately assessing individual differences in demand avoidance, because the process of demand selection is contingent upon the process of demand detection. Subsequently, we suggest a new measure of demand avoidance that combines demand detection and demand selection. We show that the new measure of demand avoidance correlates in the expected direction (i.e., negatively) with established measures of willingness and ability to carry out cognitively demanding tasks. We propose a novel, performance-based measure of cognitive effort avoidance that can be used to enhance the validity of research in cognition, perception, and neurosciences.

Keywords: Law of minimum effort; cognitive demand detection; cognitive demand selection

Introduction and background

Physical and cognitive effort avoidance in humans and other animals have been reported many times in many contexts. Some authors suggest that effort avoidance is a trait-like characteristic that manifests itself in a variety of tasks and contexts (Kool & Botvinick, 2014; Westbrook, Kester, & Braver, 2013). Many studies in cognitive neurosciences rely on the participants' willingness to expend effort to comply with experimenter instructions and task demands. Westbrook et al. (2013) suggest that a trait-like bias toward low cognitive effort is a pervasive confound in cognitive and neuroscience research: many measures of attentional/cognitive control may reflect not only ability but also motivation. If there is a trait-like bias that underlies how much effort participants are willing to put into an experiment and it can be objectively measured, it should be controlled for. This bias may also underlie the effect known as "insufficient effort responding" which has been invoked to pose a significant threat to the validity of survey-based research (Liu, Bowling, Huang, & Kent, 2013). Questionnaire-based measures of demand avoidance such as the industriousness scale (Jackson, Wood, Bogg, Walton, Harms, & Roberts, 2010), the need for cognition scale (Cacioppo & Petty, 1982), and the mental effort tolerance questionnaire (Dornic, Ekehammar, & Laaksonen, 1991) may have the well-known limitations of self-reports, such as the social desirability bias and the consistency motif (Podsakoff & Organ, 1986). Thus, our ability to accurately measure effort avoidance in a variety of task settings is critical to the validity of performance-based and survey-based research.

Kool and colleagues (2010) designed the demand selection task (DST) and showed that, on average, people manifest demand avoidance in a variety of cognitive tasks. Here, we use two variants of DST. One of the two is the task-switching variant of DST adapted from Kool et al. (2010), hereafter referred to as DST-S. At each trial, the participants could choose between two options, a low-demand and a high-demand one. Within each option, the participants were presented with a task-switching paradigm. They had to execute one of two tasks (digit magnitude and digit parity) indicated by a cue (digit color). The probability of switching between the two tasks was set to 0.1 for the low-demand option and 0.9 for the high-demand option. Thus, the demand manipulation for DST-S is implemented at the trial-sequence level (i.e., only a sequence of trials can be characterized as low- or high-demand). The probability of switching between two tasks in a sequence of trials has been shown to be a relatively poor indicator of effort for many participants (Gold, Kool, Botvinick, Hubzin, August, & Waltz, 2014; Dunn & Risko, submitted).

We developed a new DST variant based on the global-local task (Navon, 1977), hereafter referred to as DST-GL. The reason for adding a new DST variant to our studies is twofold: (1) we wanted to test that demand avoidance is indeed a trait-like characteristic, that is, it is somewhat consistent within an individual across different tasks and (2) we wanted to test a new way of implementing different levels of demand in the two options. At each trial, the participant performs a global/local task, that is, must report either the small or the large letter of a stimulus that represents a large letter made of small letters. A color cue indicates whether the large or the small letter should be reported. When the large and the small letters are identical, the stimulus is said to be congruent; when they are different, the stimulus is said to be incongruent. The task is more demanding when the stimulus is incongruent as compared to a congruent stimulus. The probability of a stimulus to be incongruent was set to 0.1 for the low-demand option and 0.9 for the high-demand option. Unlike in the DST-S, the demand manipulation in DST-GL is implemented at the trial level (i.e., each trial can be characterized as low- or high-demand). We expected that a trial-level demand manipulation would be easier to detect than a trial-sequence-level demand manipulation. Both DST variants are based on paradigms that involve exertion of cognitive control. The assumption is that there is a tight link between perception of effort and tasks that engage the processes associated with cognitive control (Botvinick & Braver, 2015).

Kool et al. (2010; 2013) used the proportion of low-demand choices as a measure of demand avoidance. In this paper, we argue that Kool et al.'s measure of demand avoidance ignores the process of demand detection, which weakens its ability to reliably characterize demand avoidance in different individuals and populations. When one uses Kool et al's measure of demand avoidance, a large number of participants appear as demand indifferent. In Kool et al.'s (2010) studies 4 and 5 (for which individual rates of demand avoidance are presented), 56% and 63% of the participants, respectively, appear to be demand indifferent. However, Dunn and Risko (submitted) suggest that failure to detect differences in demand between the two options may account for choices around chance level (i.e., what Kool et al. characterize as demand indifference). They show that when detection of demand differences is made easier (e.g., by providing a salient cue) the rate of demand avoidance significantly increases. Thus, what Kool et al.' measure of demand avoidance captured was not demand indifference but rather inability to detect the demand manipulation. From an individual-differences perspective, it is problematic when more than half of the participants' demand avoidance cannot be validly measured.

In this paper, we report our recent research aiming to develop a performance-based, objective, and unbiased measure of cognitive effort avoidance.

Empirical studies

The main objective is to find ways in which the DST paradigm could be improved. A first question related to this objective is whether demand avoidance can be manifested implicitly without the participants being aware of the demand differences between the two options. Prior theoretical and empirical work (e.g., Kool et al., 2010) suggests that demand avoidance is ubiquitous: it applies to animals and humans in physical and cognitive domains. Could it manifest itself automatically or implicitly? Suggestive evidence for implicit demand avoidance has been provided. For example, Kool et al. (2010) analyzed post-task self-reports and found that 12 of 42 participants were not aware of the demand manipulation; of these 12 participants, 8 showed significant demand avoidance. We developed an ACT-R model that accounted for Kool et al.'s data based on implicit procedural and declarative learning mechanisms without the need for an explicit demand detection process (Larue & Juvina, 2016). These findings and modeling results suggest that explicit demand detection may not be necessary for demand selection. This would be consistent with results from other decision making tasks in which many subjects report to be unaware of their decision making biases (e.g., De Martino, Kumaran, Seymour, & Dolan, 2006). If this were to be the case for the DST as well, it would make it a valuable tool for characterizing cognitive effort avoidance, because it would avoid the known pitfalls of self-report measures. A performance-based, objective, and unbiased measure could replace self-report measures of demand preference. If demand avoidance implicitly manifested itself in behavior, the participants would choose the low-demand option even when not instructed to settle on one option. In Kool et al.'s (2010) studies, the participants were instructed to "feel free" to choose one option more often. We reasoned that there was a possibility that the participants might have taken this instruction as a suggestion to settle on one option. In our first study, we eliminated that part of the instruction and tested whether the participants "implicitly" settled on the low-demand option. To the extent that demand avoidance is an implicit bias, it should not depend on this instruction: the participants should "sense" the difference in demand for cognitive control between the two options and settle on the low-demand one. In our second and third studies, we reintroduced the suggestion to settle on one option and added instructions that facilitated demand detection to various extents. The assumption was that a certain level of demand detection was necessary for the participants' demand preference to manifest itself in their behavior. Consequently, the proportion of participants showing demand indifference was hypothesized to decrease in study 2 and further in study 3 as compared to study 1. In addition, we hypothesized that the proportion of demand indifferent participants will be lower in DST-GL than in DST-S, because demand differences are easier to detect in DST-GL than in DST-S.

A second question of interest is whether demand avoidance is a trait-like bias consistent within individuals across tasks or paradigms. Several authors have suggested that the answer to this question is "yes" (Westbrook, Kester, & Braver, 2013), but the evidence supporting this answer is at best sparse. Kool et al. (2010) found demand avoidance in a variety of paradigms, but they did not check for within-subject consistency across paradigms. We administered two different variants of DST (i.e., task switching and global/local) within subjects to test the hypothesis of consistency between variants. If demand avoidance is proven to be consistent within individuals, a subsequent question is whether it correlates with other personality traits that are (presumably) conceptually related. For example, given that the demand manipulation involves exertion of cognitive control, demand avoidance is expected to correlate to some extent with trait measures of cognitive control. In line with this prediction, Kool et al. (2013) reported that demand avoidance correlated negatively with self-control and inter-temporal choice. Moreover, one would expect a negative correlation between demand avoidance and need-for-cognition, given that the latter has been defined as a "tendency to engage in and enjoy effortful cognitive endeavors" (Cacioppo, Petty, Kao, & Rodriguez, 1986, p. 1033). Both individuals who are high on demand avoidance and those who are low on need for cognition have been characterized as cognitive misers (Cacioppo et al., 1986; Dunn & Risko, submitted). In addition, we used a number of other relevant personality measures (i.e., self control, attentional control, grit, and intelligence - Raven) to test if demand avoidance consistently correlates with them in the expected direction. Specifically, we expect to find a negative correlation between demand avoidance and all these trait measures of cognitive control.

Method for studies 1, 2, & 3

In study 1, forty-two undergraduate students from Wright State University participated. A 2 (DST variant: DST-S, DST-GL) by 2 (Demand option: low demand, high demand) within subjects design was employed. The DST-S was programmed in Java based on the specifications of the original DST (Kool et al., 2010). At each trial, participants were presented with two options, a low-demand and a high-demand option equally distant from the center of the screen. The two options were presented as distinctly colored and patterned circles. Once the participant placed the mouse over one of the circles, a colored digit was revealed in the center of the circle, either yellow or green, to which a response had to be made. When digits were colored green, the participants had to make a parity judgment. When digits were colored yellow, the participants had to make a magnitude judgment. The probability of switching between the magnitude and the parity tasks was 0.1 for the low-demand option and 0.9 for the high-demand option. The instructions were minimal. They did not contain the suggestion to settle on one option that was present in Kool et al.'s (2010) research.

After the DST-S was completed, the DST-GL variant was administered in the same way. The order of administering DST-S and DST-GL was not counterbalanced to maintain our ability to compare the DST-S results with results from other studies (Kool et al., 2010 and 2013). The last step in the study procedure was the completion of the abridged version of the self-control scale (Tangney, Baumeister, & Boone, 2004).

In study 2, we stated in the instruction that participants had to explore the two options until they understood how they differed from each other and then select one of them to execute as fast and accurately as possible. We also added more personality measures of executive control: the need for cognition scale (Cacioppo & Petty, 1982), the attentional control scale (Derryberry & Reed, 2002), the grit scale (Duckworth & Quinn, 2009), and a sample of items from the Raven intelligence test (Raven, Raven, & Court, 2003). Thirty-five undergraduate students from Wright State University participated in the study. The design, apparatus, stimulus and procedure were the same as in study 1.

In study 3, we further attempted to facilitate the process of demand detection. We hypothesized that the participants who still had difficulties detecting the demand manipulation could benefit from being told what the nature of this manipulation was. Thus, we added information in the instruction pointing to what the difference between the two options was about, that is, *switching* in DST-S and *congruency* in DST-GL. However, we did not mention which one of the two options had a higher probability of switching (or congruency) or that one of the options was less demanding. Thirty-seven undergraduate students from Wright State University participated in the study. The design, apparatus, stimulus and procedure were the same as in study 2.

Analysis of the pooled dataset[1]

Given that the three studies presented above only differ with regard to pre-task instructions, it is useful to pool all data in a single dataset. This allows us to analyze the effect of instruction changes across studies and gives us more power to estimate the correlations between demand avoidance and trait measures of executive control (disclaimer: the three studies were not conducted concurrently).

Recall that study 1 did not include any hint that a difference between the two options might exist or a suggestion for the participants to settle on one option. In study 2 and more so in study 3, we added instructions intended to facilitate detection of demand differences. These manipulations resulted in increasing levels of demand avoidance (see Fig. 1) and decreasing levels of demand indifference from study 1 to study 3.

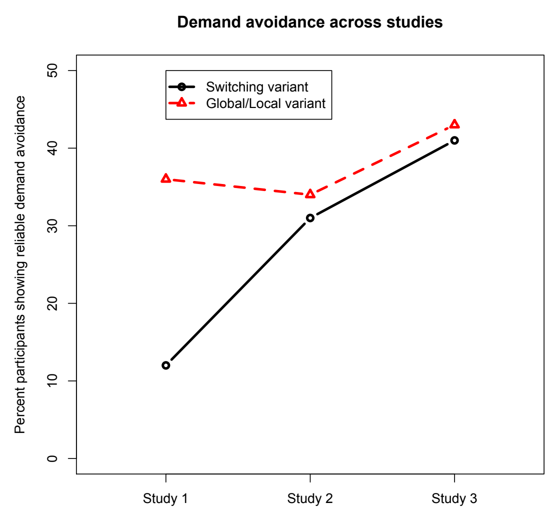

Figure 1. Demand avoidance increases with study

Since the proportion of demand indifferent participants decreases when demand detection is facilitated, one could question whether the so-called demand indifference (Kool et al., 2010; 2013) is truly indifference or is just failure to detect demand differences. We analyzed the participants' answers to the debriefing questions and classified the participants in two categories: those who detected and those who did not detect the demand manipulation. The participants who detected the demand manipulation were more likely to manifest significant demand avoidance (20) than indifference (6) and the participants who did not detect

[1] The data on which the conclusions of this paper rely are publically available at http://psych-scholar.wright.edu/astecca

the demand manipulation were more likely to appear as demand indifferent (29) than demand avoidant (17). This is evidence for a significant relationship between demand detection and demand selection (*chi-square* = 9.08, p = 0.003). Interestingly, a relatively large number of participants (17) show significant demand avoidance and report unawareness of demand differences between the two options. This suggests that, at least in some participants, demand avoidance can manifest itself implicitly, in line with Kool et al.'s (2010) findings.

To compute the correlations between demand avoidance and executive control, we combined demand avoidance in DST-S and DST-GL by taking the average of the two scores. The correlation between demand avoidance and self control is negative (as in Kool et al., 2013) but non-significant, $r(112) = -0.18$, $p = 0.17$. The correlation between demand avoidance and grit is also negative and non-significant, $r(43) = -0.09$, $p = 0.57$. These two correlations are in the expected direction, albeit non-significant. To our surprise, we found two significant correlations in the opposite direction: the correlation between demand avoidance and attentional control, $r(41) = 0.35$, $p = 0.023$, and the correlation between demand avoidance and need for cognition, $r(41) = 0.39$, $p = 0.011$. The correlation between demand avoidance and intelligence (Raven) was also positive but non-significant, $r(39) = 0.15$, $p = 0.34$. These positive correlations are surprising because the attentional control scale is presumably measuring the effortful control of attention (Derryberry & Reed, 2002) and the need for cognition scale measures trait cognitive engagement (Cacioppo et al., 1986). Thus, the correlation should be negative, not positive. To better understand these surprising correlations we inspected their scatterplots and observed that, on average, the so-called demand indifferent participants tended to be lower on attentional control and need for cognition than the demand avoidant participants. To check for this new hypothesis, we divided the participants in two groups based on their demand indifference: those who showed and those who did not show demand indifference in at least one of the DST variants. We found that on average the so-called demand indifferent participants had lower scores on need-for-cognition, $t(38.1) = 1.97$, $p = 0.056$ and attentional control, $t(33.3) = 1.21$, $p = 0.234$, even though the latter is non-significant. Thus, returning to the surprising positive correlations, they seem to be driven by the so-called demand indifferent participants, who do not appear to be indifferent with regard to their willingness to expend cognitive effort. A point can be made that these participants could not detect the demand manipulation because they did not put enough effort into this task. Under this assumption, they should be characterized as extremely demand avoidant rather than demand indifferent. These findings suggest that the demand detection process itself is a cognitively demanding task and the effort the participants are willing to put into detecting demand differences should also be considered in the measure of demand avoidance.

A new measure of demand avoidance

As mentioned above in section 1.3, Kool et al.'s (2010; 2013) measure of demand avoidance (i.e., the proportion of low-demand choices) classifies a large number of participants as demand indifferent. This would be an issue in and of itself for the so-called "law" of less work that is supposed to be universal. However, there is a more serious validity issue here. In our studies presented above (and in line with Dunn and Risko, submitted), we found that, when detection of demand differences is made easier, the rate of demand avoidance increases and the rate of demand indifference decreases. Thus, what Kool et al.' measure of demand avoidance captured was not necessarily demand indifference, but rather (at least in some cases) inability to detect the demand manipulation or unwillingness to expend the effort that would be required for successful detection. These participants seem to be extremely demand avoidant, so reluctant to exert effortful cognitive control that they fail to detect the demand manipulation. Under this assumption, it is not surprising that their choice behavior hovers around the indifference point (0.5): they cannot prefer one of the two options because they don't know which option is preferable; as a result, they keep sampling from both options, which keeps their choice rates around 0.5. Thus, the bigger problem of the Kool et al.'s measure is that it classifies a large number of participants as non-avoidant, when they really are very avoidant. This is reflected in the surprising positive correlations of demand avoidance with attentional control and need for cognition.

Here we describe how we turn this problem into an opportunity. We assume that the demand detection process requires effortful cognitive control, for example, it requires keeping track of the amount of task switches in the trial sequence, or monitoring the amount of stimulus incongruence in both options. This assumption is supported by a theoretical consensus on what tasks qualify as cognitive control tasks (see Dunn & Risko, submitted, for a more detailed exposition of this argument) and our findings showing that the so-called demand indifferent participants are (marginally) lower than the demand avoidant participants on attentional control and need for cognition. Based on this assumption, we postulate that whether and when the detection process is successful can be used as a measure of cognitive demand avoidance.

The new measure of demand avoidance can be computed based on the following formula: New demand avoidance = DDP – CAD, where DDP (demand detection point) is the trial number where demand detection most likely occurred and CAD (choice after detection) is the rate of high-demand choices in the trials that followed the detection point. Both DDP and CAD are normalized to range from 0 to 1; thus, the new demand avoidance measure ranges theoretically from -1 to 1, but practically from slightly below 0 to 1 in our pooled dataset. The distribution appears clearly skewed, meaning that most of the participants are demand avoidant, which is now consistent with the proposition that demand avoidance is a "law" in the sense that most people appear to "obey" it and only a few "violate" it.

The demand detection point (DDP) was computed based on the following procedure. A sliding window of size n was set for each DST variant. For each participant i, for each trial $j >= n$, a Wilcoxon sign test (*alpha* = 0.05) was used to determine whether the participant i's choice rate in the window $[j-n, j]$ was significantly different than 0.5. If a significant test was found for trial j' and the test remained significant for all $j > j'$, the detection point was set to be equal to j'. If the Wilcoxon test turned non-significant for any $j > j'$, the old j' was discarded and a search for a new j' was initiated. If a detection point was never found it was set to the highest trial number. To normalize the detection points, they were divided by the total number of trials for each participant and each DST variant. Thus, a detection point close to zero represents a very early detection and a detection point equal to 1 represents a detection that never occurred. The value of the detection point depends on the size of the moving window (n). Thus, a very low n might give a lot of false early detection points while a very high n might miss some late detection points. We searched for an n value that was able to pick some early detectors while minimizing the number of participants who were classified as unable to detect the demand manipulation. This search was done separately for each DST variant because the detection process was assumed to be different in the two variants. The best n was found to be 30 for DST-S and 5 for DST-GL.

This procedure to determine the detection point comes with some degree of uncertainty. We did not collect the data required to fully validate this procedure. However, two arguments can be brought in support of the validity of this procedure: (1) the participants who reported to have detected the demand manipulation have on average significantly lower (i.e., earlier) detection points (0.80) than the participants who reported that they were not aware of the demand manipulation (0.93) ($F(1,70) = 11.62$, $p = 0.001$); and (2) the correlation between detection point and task performance (a composite of accuracy and latency) is significant and negative, $r(110) = -0.19$, $p = 0.047$, meaning that the earlier the detection the higher the performance and vice versa. This would be expected if the detection point truly indicated demand detection: early detectors would be able to get higher accuracies and lower response times by choosing the low-demand option more frequently.

Once detection is successful, do all participants choose the low demand option exclusively? The data on choice after detection and the self-reports indicate that some of the participants deliberately select the high-demand option, because it is more challenging or interesting.

The new demand avoidance measure shows within-subject consistency across variants in all three studies (study 1: Spearman's *rho* = 0.30, $p = 0.057$; study 2: *rho* = 0.45, $p = 0.006$; study 3: *rho* = 0.38, $p = 0.022$). This suggests that the new measure is somewhat invariant with regard to how difficult to detect the demand manipulation is.

Next, we computed the correlations of the new measure of demand avoidance with the trait measures of executive control mentioned above (self control: $r(112) = -0.19$, $p = 0.04$; attentional control: $r(41) = -0.37$, $p = 0.01$; need for cognition: $r(41) = -0.37$, $p = 0.01$; grit: $r(41) = -0.15$, $p = 0.31$; Raven: $r(39) = -0.19$, $p = 0.23$). All these correlations are now in the expected direction (i.e., negative), even though two of them are non-significant. The correlations of the new demand avoidance measure with attentional control and need for cognition, respectively, were flipped from positive to negative. These correlations are now consistent with the theory of demand avoidance and cognitive control.

General discussion and conclusion

In accord with previous studies, our studies presented here show that participants manifest a tendency to avoid cognitive effort after they learn which option is less effortful. This learning could be implicit as suggested by Kool et al. (2010); however, more often than not, this learning must be explicit and requires executive control processes like exploration, self-monitoring, and self-evaluation, which themselves are effortful. The measure of demand avoidance used by Kool et al. (2010; 2013) and others (Dunn & Risko, submitted; Gold et al., 2014) is very attractive to researchers, not only because of its simplicity, but also because of its assumption of implicitness. An implicit measure of demand avoidance would be a very valuable tool in controlling for motivational effects in cognition and perception research as well as in survey-based research. Our previous modeling work (Larue & Juvina, 2016) suggested that, in principle, demand avoidance could occur implicitly. In the work reported here, we put the assumption of implicitness to an empirical test and the results seem to suggest that this assumption is not (entirely) tenable. This is consistent with other findings suggesting that demand detection is a key variable in demand selection (Dunn & Risko, submitted). Even when the demand manipulation was explicit in the instructions (as in Gold et al, 2014), detection was not 100%. However, we find the idea of completely revealing the demand manipulation to the participants (or using a forced familiarization stage as in Dunn & Risko, submitted) to be unattractive, because it renders DST as useful as a questionnaire asking the participants whether they would prefer the easier of two options. For our envisioned use of DST, it is not desirable to explicitly reveal the demand manipulation in the instruction. This would make DST more like a self-report measure: if the participants already know which option is easier, the decision to select one of the options may be influenced not only by effort-related preferences but also by many other factors such as social desirability. In our view, the strength of DST lies in its impenetrability: it requires cognitive effort to detect demand differences, which makes it harder to "game" by the participants. We suggest keeping a somewhat demanding demand detection process, and measuring how much effort the participants are willing to put into detecting. We also put Kool et al.' measure of demand avoidance measure to a test of external validity, which it does not seem to pass, because it creates the situation in which someone can be truly demand avoidant and yet appear as demand indifferent. As a consequence, it (surprisingly) shows positive correlations with attentional control and need for cognition. Our proposed demand avoidance measure does better in this respect: it flips these two correlations in the expected direction and shows a consistent pattern of correlations with other trait measures of executive control. The new measure of demand avoidance that we propose here is able to characterize most individuals in the studied sample as demand avoidant, as a "law of minimum cognitive effort" would predict. Even though an "indifference" point still exists (around 0.4 in our data), it does not capture the bulk of the data. When the old measure of demand avoidance is used, the results seem to largely fluctuate depending on a number of factors such as the subject population, the task paradigm, and the instruction (Gold et al, 2014; Dunn & Risko, submitted; Kool et al., 2010, 2013). We expect that the new measure can accommodate variations in some of these factors. For example, as we showed above, two different task paradigms (i.e., DST-S and DST-GL) yield relatively consistent demand avoidance scores.

In conclusion, we suggest a new measure of demand avoidance that compiles demand avoidance from both demand detection and demand selection. This measure shows within-subject consistency across two different task paradigms and correlates in the expected direction with a number of personality measures of executive control. Therefore, we propose it to the research community as a performance-based, objective, and unbiased measure of the motivational component of executive control.

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