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Trait Intellect Predicts Cognitive Engagement: Evidence from a Resource Allocation Perspective*†

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ABSTRACT

Trait Intellect, one of the two ‘aspects’ of the broader Openness/Intellect ‘domain’, predicts performance on a range of cognitive tasks including tests of intelligence and working memory. This has been explained in terms of the tendency for high-Intellect individuals to explore, or engage more effortfully with, abstract information (DeYoung, 2013). This theoretical perspective can be framed in the language of Resource Allocation Theory (Kanfer & Ackerman, 1989), in terms of high-Intellect individuals allocating more of their available cognitive resources to abstract cognitive tasks. In two experiments (total N = 160), we examined the relation between Intellect and cognitive engagement during a primary word-search task under conditions of both high and low secondary cognitive load. Both experiments revealed that high-Intellect individuals were more vulnerable to the impact of the secondary cognitive load on primary task performance. This suggests that, under low secondary load, such individuals were indeed allocating more of their available cognitive resources to the primary task. In experiment two, these results held after controlling for trait Industriousness (an aspect of Conscientiousness) and a measure of working memory capacity (N-back task). Our findings provide novel support for the cognitive mechanisms proposed to underlie trait Intellect.

Key Words: Intellect; Openness; Cognitive Engagement; Cognitive Capacity; Resource Allocation Theory

Trait Intellect Predicts Cognitive Engagement: Evidence from a Resource Allocation Perspective

Openness/Intellect (O/I) is one of the five empirically-derived trait 'domains' of personality (along with Extraversion, Neuroticism, Conscientiousness, and Agreeableness – i.e., the 'Big Five'; Goldberg, 1993; John, Naumann & Soto, 2008). The compound label O/I reflects an early debate regarding the most salient characteristics of this domain: While Costa and McCrae (1985, 1992) preferred the label 'Openness to experience', emphasizing propensities toward aesthetic appreciation and fantasy, Goldberg (1990, 1993) preferred the label 'Intellect', emphasizing Intellectual curiosity. It was subsequently shown that both of these conceptualizations are relevant for describing the patterns of behavior and experience captured by this domain (Johnson, 1994; Saucier, 1994), and correspond to two correlated 'aspects' located below the O/I domain within the hierarchical structure of personality traits (DeYoung, Quilty & Peterson, 2007). O/I has therefore been conceptualized as a broad tendency toward *cognitive exploration*, reflecting engagement with abstract or 'intellectual' information (Intellect), as well as perceptual and sensory information (Openness) (DeYoung, 2013, 2014, see also McCrae & Costa, 1997).

Unique among the Big Five domains, O/I predicts higher performance on various cognitive tasks, including tests of general intelligence, executive functions, and working memory (e.g., Ackerman & Heggestadt, 1997; Chamorro-Premuzic, Moutafi & Furnham, 2005; DeYoung, Peterson, & Higgins, 2005; McCrae & Costa, 1997; von Stumm & Ackerman, 2013). More recently, these relations have been shown to be restricted to the Intellect aspect of O/I (e.g., DeYoung, Quilty, Peterson, & Gray, 2014; DeYoung, Shamosh, Green, Braver & Gray, 2009; Nusbaum & Silvia, 2011; Kaufman et al., 2015). These findings are aligned with the perspective that Intellect is underpinned by *cognitive engagement* with abstract information (e.g., DeYoung, 2013). That is, high-Intellect individuals may perform well on challenging cognitive tasks because they are more motivated to explore the abstract and Intellectual information within such tasks — they "become *more involved in* tasks that require flexible and fluent thought" (McCrae & Costa, 1997, p. 834, emphasis by present authors).

On the other hand, these associations might also stem from individual differences in ability or *cognitive capacity* captured by measures of Intellect. Some have suggested that Intellect provides a proxy measure of self-assessed intelligence, which is moderately related to actual intelligence (Chamorro-Premuzic et al., 2005). Others have argued that intelligence itself can be represented within the personality trait hierarchy as a facet of Intellect (DeYoung, 2011, 2013). Either of these perspectives allows for the possibility that the link between Intellect and cognitive performance is driven by individual differences in cognitive capacity. Intellect-related differences in cognitive engagement might also be difficult to disentangle from cognitive capacity. Indeed, one theory posits that interest — an emotion reflecting curiosity and information seeking (Silvia, 2008a), and therefore a potential marker of cognitive engagement — results in part from one's capacity to understand or interpret the information being processed (Silvia, 2005, 2008b). That is, engagement may be partly underpinned by capacity. In line with this theory, it was recently shown that appraised understanding mediated the relation between Intellect and ratings of interest in abstract, intellectual stimuli (literary quotations; Fayn et al., 2015). However, these authors also noted the challenge for future research to examine the relation between Intellect and cognitive engagement, *distinct from* cognitive capacity (p. 51).

A study by DeYoung and colleagues (2009) comes close to meeting this challenge. Here, participants underwent a functional Magnetic Resonance Imaging (fMRI) scan while performing a working memory (WM) task. Using facets from the O/I domain of the NEO-PI-R (Costa & McCrae, 1992), the authors showed that Intellect but not Openness was associated with WM performance, and also with WM-related activity in the left anterior Prefrontal Cortex and posterior Medial Frontal Cortex. Activity in these regions explained over 75% of the association between Intellect and WM task accuracy, and one of these indirect pathways (via activity in the posterior Medial Frontal Cortex) remained significant after statistically controlling for intelligence. DeYoung et al. (2009) concluded from this finding that the association between Intellect and activity in this region may be partly explained in terms of cognitive engagement. However, their study does not provide *direct* support for this view: One must infer that, because the performance of high-Intellect individuals could not be fully explained in terms of cognitive capacity, it must be at least partly explained in terms of cognitive engagement. Of course, it could also be explained by extraneous factors, such as sampling or measurement error, or by other variables not assessed in this study.

Disentangling Cognitive Engagement from Cognitive Capacity

The distinction between cognitive engagement and cognitive capacity can be brought into sharp focus through the lens of Resource Allocation Theory (Hocky, 1997; Kanfer & Ackerman, 1989). This framework postulates that task performance is dependent upon cognitive resources of limited availability. The finite nature of these resources represents an individual's cognitive capacity, and accounts for their standing on measures of intelligence and cognitive abilities. However, the availability of cognitive resources during task performance will also be influenced by a 'resource allocation policy', which describes how individuals *selectively allocate* differing proportions of their total cognitive resources to a given task. In terms of the relation between Intellect and cognitive performance, high-Intellect individuals might tend to outperform their low-Intellect counterparts either because they have more cognitive resources available for allocation to any task, or because they tend to selectively allocate more of those resources to cognitive tasks. Metaphorically, high-Intellect individuals might *'have'* a greater number of cognitive resources available for allocation (i.e., higher capacity), but they might also *'use'* those resources according to a different resource allocation policy – whereby more resources are devoted to the task at hand (i.e., more effortful cognitive engagement).

Individual differences in resource allocation policy can be examined using a dual-task paradigm, in which a secondary task limits the resources that can be allocated to a primary task (e.g., DeShon, Brown, & Greenis, 1996; Lavie, Hirst, de Fockert, & Viding, 2004; O'Donnell & Eggemeier, 1986). By comparing primary task performance across high and low secondary cognitive load, one can infer to what extent performance can be attributed to resource allocation policy. For instance, if high-Intellect individuals perform better than their low-Intellect counterparts on the primary task as a result of high cognitive capacity, these individuals should better withstand the resource-demands of the secondary task. That is, Intellect should predict a *shallower* decline in primary task performance under high secondary load. Conversely, if high-Intellect individuals perform well by allocating more cognitive resources to the primary task, these individuals should be more vulnerable to the resource-consuming impact of a secondary task. That is, Intellect should predict a *steeper* decline in primary task performance under high secondary load. This is because the high secondary load would consume the cognitive resources required to sustain high-Intellect individuals' performance on the primary task.

The Present Research

Our aim in this paper was to examine the relation between trait Intellect and cognitive engagement from a resource allocation perspective. Specifically, we sought to examine the relation between Intellect and cognitive engagement, conceptualized in terms of an individual's resource allocation policy. To achieve this, we used the dual-task paradigm described by Avery, Smillie, and de Fockert (2013). Here, participants complete a primary, word-search task involving the construction of English words from a random letter grid. This task is similar to well-known puzzles and games, such as Boggle™, and contains exactly the kind of abstract information with which high-Intellect individuals are thought to engage. This primary task is interleaved with a simple digit recall task, restricting the cognitive resources that participants can allocate to the word-search task.

Building on theory (DeYoung, 2013, 2014; McCrae & Costa, 1997) and research (DeYoung et al., 2009; Fayn et al., 2015) suggesting that Intellect is characterized by motivated cognitive engagement, we hypothesized that the deleterious impact of a secondary load on primary task performance would be stronger for high-Intellect individuals. That is, we predicted that there would be an interaction between Intellect and secondary load, such that the decline in primary task performance under a high relative to low secondary load would be *steeper* for high-Intellect individuals (because the higher load directly compromises cognitive engagement). Support for an alterative hypothesis, whereby Intellect is only related to higher cognitive capacity, would also require an interaction between Intellect and secondary load. But in this instance we would expect the decline in primary task performance under a high relative to low secondary load to be *shallower* for high-Intellect individuals (because their superior capacity buffers the effects of the higher cognitive load). Given the abstract nature of the task — a word-search game

— we also expected any effects of O/I on task performance to be specific to Intellect, with no associations anticipated for Openness.

Experiment 1

Method

Participants

Seventy-nine University of Surrey psychology students (59 females, aged 18-45) participated in this experiment in exchange for course credit. As the primary task in this study involved constructing English language words (see below), only fluent English language speakers were recruited. According to Fraley and Marks (2007), the average effect size in psychology equates to a correlation of $r \sim .25$. In this experiment, our sample size provided 74% power to detect such an effect.

Materials and Design

Openness/Intellect (O/I) scales. Measures of Openness and Intellect were derived from two well-validated and widely-used Big Five questionnaires. The first was the O/I scale from the Big Five Aspects Scales (BFAS; DeYoung et al., 2007), which was constructed using items from the International Personality Item Pool (IPIP; Goldberg, 1999), and is the only measure developed specifically to distinguish aspects of the Big Five. The Intellect and Openness aspects are each assessed by ten statements (e.g., *"like to solve complex problems"* [Intellect], *"get deeply immersed in music"* [Openness]) that participants rate in terms of how strongly they agree that each statement describes them personally (using 5-point

Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*). The second was the Openness facet scales from an open-source alternative to the NEO Personality Inventory (NEO PI-R; Costa & McCrae, 1992) derived from the International Personality Item Pool (IPIP; Goldberg, 1999). These are each assessed using 10 descriptive statements, and were responded to using the same 5-point Likert scale described for the BFAS. The Intellect scale is the only clear marker of Intellect within the NEO-IPIP (e.g., *"enjoy thinking about things"*), and was highly correlated with BFAS-Intellect in this study (r = .73). Conversely, the Imagination (e.g., "*love to daydream*") and Artistic (e.g., "*enjoy the beauty of nature*") scales provide particularly good markers of Openness, and were highly correlated with BFAS-Openness in this study (rs = .65 and .76).

Because BFAS and NEO-IPIP were both derived from the same pool of IPIP items there is considerable item overlap between these questionnaires (e.g., six of the ten BFAS Intellect items also appear on the ten-item NEO-IPIP Intellect scale). To address this redundancy, and potentially increase measurement precision, we averaged across responses to all 14 non-redundant items from the two measures of Intellect to create an overall Intellect composite. Similarly, we averaged across responses to all 24 non-redundant items from the BFAS Openness scale and the NEO-IPIP Imagination and Artistic scales. These composite measures yielded high internal consistency (αs = .84 and .89).

Interleaved dual-task paradigm. Our dual-task paradigm was previously described by Avery et al. (2013), and programmed by the third author of this paper using

E-prime™ (Schneider, Eschman, & Zuccolotto, 2002). The primary task was a word-search game in which WM is thought to play a critical role by facilitating retrieval of verbal information from long-term memory (Avery et al., 2013; Halpern & Wai, 2007). On each trial, participants were presented with 4 × 4 letter matrix (see middle box of trial sequence depicted in Figure 1) and allowed 20s to type as many words as possible using letters contained in the matrix. Only English words with three or more letters were allowed. Letters could only be used once, and did not need to be adjacently located. Each 16-letter matrix comprised at least two vowels, with the remaining 14 letters selected randomly with replacement from the 21 consonants of the alphabet. Each trial presented a unique matrix.

The secondary task was a simple digit-recall task, which has been successfully shown to load WM resources when interleaved with a primary task (e.g., Avery et al., 2013; Lavie et al., 2004). On each trial, participants were presented with a five-digit sequence to memorize (e.g., *0-1-2-3-4*), which was displayed for 1,500ms prior to a 1,500ms interval, after which the primary task was completed (see Figure 1). Then, at the end of each trial, one of the digits from the five-digit sequence reappeared, requiring participants to correctly identify and type the subsequent number in the sequence within 3,000ms (e.g., if shown "*2 _ ?*", the correct response for the sequence shown in Figure 1 is '*3*'). Sequences varied in complexity, with complex sequences placing greater demand (or load) on WM resources. All low load trial sequences were *0-1-2-3-4*. On high load trials, 0 always remained in first position, whereas digits 1-4 randomly varied in order (e.g., *0-4-2-1-3*).

[Figure 1 Here]

Following task instructions and an 8-trial practice block under low secondary load, participants completed 64 trials of the interleaved dual-task paradigm. These were divided into four blocks of 16 trials each, two of which applied a *high* secondary load and two of which applied a *low* secondary load (presented in counterbalanced order). On each trial, a primary task letter-matrix was randomly selected (without replacement) from a pre-constructed pool of 64 matrices of equivalent difficulty. Word game performance was calculated in terms of the number and length of generated words (one point per three letter word, plus one point per letter thereafter). Only valid words were included (i.e., real English words formed using letters from the letter-matrix shown in that trial). Trials were only included for analysis if the response to the secondary task was correct (see Table 2 for accuracy data). We summed the total points obtained in each load condition to create a single performance measure, *Game Points,* per load condition. A secondary measure, *Points Decline*, was computed by subtracting low from high load *Game Points* to provide a single index of the impact of the secondary load on primary task performance. Finally, as a measure of *Secondary Task Accuracy* we used the total number of correct responses to the interleaved digit-recall task for both the high and low load blocks.

Procedure

Participants attended a 45-minute experimental session in a soundproof computer lab and were seated in front of a desktop computer. After providing informed consent, they completed the O/I scales, along with some other questionnaires that were not related to our hypotheses. Participants were then advised that the main experimental task would last approximately 20 minutes and would be cognitively challenging. Between the 8-trial practice block and the 4 experimental blocks, they were instructed to challenge themselves throughout the task by maximizing their points (i.e., by detecting long words whenever possible). To minimize fatigue, participants were encouraged to take a short break between each block. After completing the task, participants were fully debriefed and thanked for their time.

Results and Discussion

Preliminary Analyses

Descriptive statistics and intercorrelations for all variables are presented in Table 1. Our composite measures of Intellect and Openness were moderately intercorrelated, reflecting their shared location within the O/I trait domain. Intellect tended to have positive associations with task performance variables, while Openness did not.

[Table 1 here]

As reflected by the means displayed in Table 1, an ANOVA confirmed that the secondary task had a strong impact on *Game Points*: Participants performed much more poorly under high secondary load relative to low load, $F(1,78) = 300.34$, $p < .001$, $\eta_p^2 = .79$, indicating that the load manipulation was effective. Additionally, *Secondary Task Accuracy* was reduced under high load relative to low load, $F(1,78) = 284.18$, $p < .001$, $\eta_p^2 = .79$, suggesting that the effect of the secondary task on primary task performance was not a trivial result of secondary task prioritization. Lastly, counterbalance load order did not affect either *Game Points* or *Secondary Task Accuracy* (all *p*s > .25 for all main effects and interactions involving counterbalance order).

Does Intellect Reflect Cognitive Engagement?

To evaluate our stated predictions for this experiment, we re-examined the within-subjects effect of secondary load on *Game Points*, this time including Openness and Intellect as continuous predictors (standardized, so as to not alter the *Game Points* main effect; Delaney & Maxwell, 1981) within an ANCOVA. It is essential to include both trait measures in the same model (bearing in mind their close statistical overlap, see Table 1) in order to assess their *unique* associations with performance on the primary task. Results again revealed a main effect of secondary load, $F(1,76) = 299.74$, $p < .001$, $\eta_p^2 = .80$, along with main effects of both Intellect, $F(1,76) = 17.80$, $p < .001$, $\eta_p^2 = .19$, and Openness, $F(1,76) = 7.47$, $p = .008$, $\eta_p^2 = .09$. This first main effect mirrors the significant, positive zero-order correlations between Intellect and *Game Points* shown in Table 1. Conversely, the second main effect was unexpected, and, given the near-zero correlations between Openness and *Game Points*, seems likely to reflect a suppression effect. Of most relevance to our predictions for this experiment, there was a marginally significant interaction between Intellect and secondary WM load, $F(1,76) = 3.91$, $p = .052$, $\eta_p^2 = .05$. The pattern of this interaction indicates that high-Intellect participants were more adversely affected by the high secondary load in terms of primary task performance: This can be seen in Figure 2, which plots *Game Points* under low and high secondary load for participants scoring above the 66th percentile ($n = 24$) or below the 33rd percentile ($n = 26$) on Intellect. This also accords with the significant, positive zero-order correlation between intellect and *Points Decline* (see Table 1)[1]. Finally, the Openness × load interaction was not significant, $F(1,76) = 0.24$, $p = .970$, $\eta_p^2 < .01$, which accords with the lack of a significant association between Openness and *Points Decline* (see Table 1).

[Figure 2 here]

Summary

In this experiment we found that Intellect predicted better performance on our primary WM-dependent task, which is consistent with extensive research linking O/I in general (e.g., Ackerman & Heggestadt, 1997; DeYoung et al., 2005, von Stumm & Ackerman, 2013), and Intellect in particular (e.g., DeYoung et al., 2009; Kaufman et al., 2015), with higher cognitive performance. In line with our focal hypothesis, the negative effect that our secondary digit-recall task had on word game performance was stronger for high-Intellect participants. That is, although individuals with higher Intellect scores generally performed

[1] Note: Supplementary analyses revealed similar interactive patterns for both the NEO-IPIP and BFAS Intellect scales when analyzed separately ($\eta_p^2 = .06$ and $.03$, respectively), although the interaction with BFAS Intellect fell short of significance.

better on our primary task, their performance *declined* to a greater extent than lower-Intellect individuals when burdened by a secondary executive load. This pattern of results did not emerge for our measure of Openness, suggesting that it is unique to the Intellect aspect of the broader O/I domain.

The nature of the interaction between Intellect and cognitive load provides novel support for the relation between Intellect and cognitive engagement — as distinct from cognitive capacity. Specifically, if the task performance of high-Intellect individuals stemmed only from their higher cognitive capacity, we would expect these individuals to have better withstood the executive load applied by our interleaved digit-recall task. Instead, our results revealed the opposite pattern: Under the more burdensome executive load, the performance of high-Intellect participants deteriorated to a *greater* extent than their low-Intellect counterparts. From a resource-allocation perspective, this suggests that high-Intellect individuals 'use' more of their available cognitive resources when completing a challenging cognitive task. That is, participants in our study with higher Intellect appear to have allocated more cognitive resources to our demanding primary task, and thus their performance was greatly impaired when the availability of their cognitive resources was constrained by the interleaved secondary task. This supports the view that the relation between Intellect and various tests of cognitive performance can be at least partly attributed to individual differences in cognitive engagement — as dictated by one's 'resource allocation policy' (Kanfer & Ackerman, 1989). Note, however, that this does not rule out a role for cognitive capacity. In fact, the main effect of Intellect, which was significant after accounting for cognitive engagement (represented by the Intellect × load interaction term), could be plausibly explained in terms of capacity-related differences. Our finding is therefore aligned with DeYoung et al's (2009) conclusion that Intellect relates both to cognitive capacity and cognitive engagement.

There are two noteworthy caveats to these findings. First, and most importantly, our predicted Intellect × load interaction reached only marginal levels of significance. This may indicate that the true effect is smaller than we anticipated. Second, the significant main effect of Openness on task performance was unexpected, and is difficult to reconcile with the fact that Openness had no zero-order association with task performance under either low (r = -.03) or high (r = -.13) secondary load. This finding may be spurious, or it may indicate a complex relation between Openness and word game performance. To examine these issues further we provide a second experiment comprising a direct replication of the first. Beyond meeting the valuable and increasingly emphasized goal of direct replication (e.g., Open Science Collaboration, 2015), we also attempt to improve on our first experiment by controlling for additional relevant individual difference variables that may have influenced the present findings.

Experiment 2

Method

Participants

Eighty-one University of Melbourne psychology students (58 females, aged 18-48) participated for course credit. Only fluent English speakers were recruited. This sample size provides 75% power to detect a typical effect size in personality psychology (r ~ .25, Fraley & Marks, 2007).

Materials and Design

Openness/Intellect (O/I) scales. As in experiment 1, Intellect and Openness were assessed using composites formed from the BFAS and NEO-IPIP (see experiment 1 for full description), which were again highly internally consistent (αs = .87 and .86). In this experiment, the full 100-item BFAS was administered to participants. While we continue to restrict our focus to the O/I scales, as only these are related to our stated hypotheses, we considered that the Industriousness aspect of trait Conscientiousness could provide a valuable control measure. This is because Intellect tends to correlate moderately (r > .30) with Industriousness — i.e., propensities toward persistence, diligence, and task-focus — which might plausibly influence task performance. We therefore controlled for Industriousness as well at its interactions with secondary WM load in all of our main analyses. This will allow us to confirm that any effects we observe for Intellect cannot be attributed to its overlap with Industriousness.

Working memory capacity. As a second control measure, we also administered the widely-known N-back assessment of WM capacity (Gevins & Cutillo, 1993; Owen, McMillan, Laird, & Bullmore, 2005). The N-back is a complex-span task that presents a sequential stream of single letters on a computer screen to be monitored by participants. Each letter remains on screen for 1,000ms (central location, black text, white background), and is preceded by a 1,500ms inter-stimulus interval. While each letter is on screen, participants must indicate whether or not it matches that presented *n* positions previously in the stream of letters. That is, on 1-back trials participants indicate whether each letter matched that presented immediately before it (e.g., given *P* – *B* – *A* – *C* – *C*, the second *C* is a match and all others are non-matches). Conversely, on 2-back trials, participants indicate whether each letter matched that presented two positions previously (e.g., given *P* – *B* – *A* – *C* – *A*, the second *A* is a match and all others are non-matches). Participants use the '1' key on a QWERTY keyboard to indicate a match, and the '2' key to indicate a non-match. In this experiment, participants completed 30 1-back trials and a further 30 2-back trials as practice, followed by three blocks of the moderately demanding 2-back trials, comprising 10 matches and 20 non-matches per block. A single measure of *N-back Accuracy* was calculated across all three blocks using response sensitivity (or d-prime) from Signal Detection Theory (Wickens, 2002). This provides an unbiased measure of an individual's ability to correctly discriminate matches from non-matches.

Interleaved dual-task paradigm. The experimental task was identical to that described in experiment 1, and again yielded measures of primary *Game Points*, *Secondary Task Accuracy*, and *Points Decline*.

Procedure

Participants attended a 1-hour session in an equivalent environment to experiment 1. After providing informed consent, they completed the questionnaires described above, along with other questionnaires that were not related to the aims of this paper. They then completed the interleaved dual-task, during which they were encouraged to find as many long words as possible, and also to take a short rest between each block. Finally, they completed the N-back, and short breaks were again encouraged between the practice and experimental trials, and between the three experimental blocks. Participants were then fully debriefed and thanked for their time.

Results and Discussion

Preliminary Analyses

Descriptive statistics for all measures are presented in Table 2. Our Openness and Intellect measures were again positively correlated, and Intellect (but not Openness) showed a sizable correlation with Industriousness. Unlike in experiment 1, neither measure of Intellect tended to show any association with task performance, with the exception of positive correlations with *Points Decline*. In light of previous research (e.g., DeYoung et al., 2009), it was also surprising that neither Intellect nor Openness showed any relation with *N-back Accuracy*.

[Table 3 here]

Consistent with experiment 1, ANOVA revealed a main effect of secondary load on *Game Points*, reflecting poorer primary task performance under high secondary load, $F(1,80) = 220.53$, $p < .001$, $\eta_p^2 = .73$. *Secondary Task Accuracy* was also reduced under high relative to low load, $F(1,80) = 202.59$, $p < .001$, $\eta_p^2 = .72$. *Game Points* was somewhat higher for both high and low secondary loads in this sample, relative to our sample in experiment 1 ($ps < .05$). However, the samples did not differ in terms of *Secondary Task Accuracy* ($ps > .19$), suggesting that the superior performance of participants in the present study on the word game was not due to primary task prioritization. Finally, the order in which participants completed the four blocks of the interleaved dual-task did not impact on either *Game Points* or *Secondary Task Accuracy* (all $ps > .05$ for all main effects and interactions involving counterbalance order).

[Table 2 here]

Does Intellect Reflect Cognitive Engagement?

As in experiment 1, we re-examined the within-subjects effect of secondary load on *Game Points* using ANCOVA, with Openness and Intellect included as continuous predictors in the factorial design. As covariates, we also included Industriousness and *N-back Accuracy*, along with their interactions with task load. All continuous variables were first standardized (Delaney & Maxwell, 1981). Results from this analysis, being somewhat detailed, are relegated to Table 3. There was again a main effect of secondary load along with a main effect of *N-back Accuracy,* indicating — unsurprisingly — that individuals who performed well on the N-back assessment of WM also tended to perform well on our WM-dependent word game task. Contrary to experiment 1, there was no main effect of Intellect or Openness on *Game Points*. On the other hand, we again observed our predicted interaction between Intellect and secondary WM load. As in experiment 1, it appears that high-Intellect participants were more adversely affected by the high secondary load in terms of primary task performance: This can be seen in Figure 3a, which depicts *Game Points* under low and high secondary load for participants scoring above the 66th percentile (n = 24) or below the 33rd percentile (n = 25) on Intellect. The vulnerability of high-Intellect individuals to the high executive load is also shown in the correlation between intellect and *Points Decline* (see Table 2)[2]. As in experiment 1 the Openness × load interaction was not significant, F(1,76) = 0.24, p = .970, η_p^2 < .01, which probably means that the significant zero-order association between Openness and *Points Decline* in this experiment (see Table 2) was accounted for by Intellect.

Although the N-back was only intended as a control variable in this study, the significant interaction between *N-back Accuracy* and secondary load was also of interest. As the N-back is a widely-used measure of WM capacity, one might expect high scorers to have

[2] Note: Supplementary analyses revealed identical, significant interactions for both the BFAS and NEO-IPIP Intellect scales when analyzed separately (η_p^2 = .05 for both interaction terms).

fared better under the more demanding executive load. However, Figure 3b shows that the opposite was in fact the case: High scorers on the N-back — like high-Intellect individuals — exhibited a sharper decline in *Game Points* under high secondary load. This is also reflected in the significant positive association between *N-back Accuracy* and *Points Decline*. While counterintuitive at first, this finding is actually in line with the theorizing that motivated this paper: Just as it is difficult to attribute the generally superior cognitive performance of high-Intellect individuals either to cognitive capacity or cognitive engagement, the superior performance of *any* individual on *any* cognitive task, including the N-back, might be owing to either capacity, or engagement, or both. Again, our dual-task paradigm enables us to resolve this ambiguity: The N-back × load interaction depicted in Figure 3b can be interpreted in terms of cognitive engagement — i.e., individuals who performed well on the N-back allocated a greater proportion of available cognitive resources to the word game task under low load, but were unable to do so under the more demanding executive load. Conversely, the main effect of N-back on *Game Points* can be interpreted in terms of cognitive capacity — i.e., after accounting for differences in engagement, high scorers on the N-back had more cognitive resources available for allocation to the primary task.

Pooled Sample Analysis

Given that participants in our second experiment completed the same dual task paradigm and O/I measures as participants in our first experiment, we combined the two samples in order to maximize statistical power (i.e., N = 160 provides 89% power to detect a typical effect size in personality psychology, r = .25), and re-examined our focal hypothesis. A one-way ANCOVA with Openness and Intellect (standardized) included as continuous predictors in the full design yielded a highly-significant main effect of secondary load, $F(1,157) = 516.76$, $p < .001$, $\eta_p^2 = .77$, along with a significant main effect of Intellect, $F(1,157) = 5.33$, $p = .02$, $\eta_p^2 = .03$, on *Game Points*. These effects were both qualified by the predicted Intellect × load interaction, $F(1,157) = 8.11$, $p = .005$, $\eta_p^2 = .05$. The pattern of this interaction matches that found separately in both samples (depicted in figures 2 and 3a), and is reflected in a positive relation between Intellect and *Points Decline*, r (158) = .29, $p < .001$. Again, despite performing somewhat better overall, the task performance of high-Intellect individuals was more adversely affected by secondary cognitive load. Finally, there was no main effect of Openness, $F(1,157) = 0.49$, $p = .484$, $\eta_p^2 < .01$, and no Openness × load interaction, $F(1,157) = 0.67$, $p = .414$, $\eta_p^2 < .01$.[3]

Summary

The results of our second experiment provide further support for our focal hypothesis. Specifically, the performance-impairing effect of our secondary digit-recall task was more pronounced for high-Intellect individuals. This effect was again distinct from the

[3] We also conducted a pooled analysis employing two novel measures of Intellect — one comprising Intellect items that appear to reflect cognitive engagement (e.g., *"like to solve complex problems"*) and the other comprising items that appear to reflect cognitive capacity (e.g., *"think quickly"*). Against expectations, these scales showed closely converging relations with primary task performance, each replicating the pooled analyses we have presented here. For the reader's interest, we include a short report of these analyses, including the construction of the 'Intellect-engagement' and 'Intellect-capacity' scales, in the Appendix.

Openness aspect of O/I, which was unrelated to task performance — both in this sample and when pooling the samples from both of our experiments. Our predicted Intellect × load interaction was further shown to be independent of the Industriousness aspect of Conscientiousness and a measure of WM capacity — two potentially confounding factors. From a resource allocation perspective, the steeper decline in word game performance experienced by high-Intellect individuals under high relative to low secondary load suggests that these individuals depended more heavily on the cognitive resources that were consumed by the secondary task in order to perform well on the primary task. That is, it appears that high-Intellect individuals 'use' more of their cognitive resources when completing our mentally challenging word-search task. Due to the finite nature of these resources, such individuals experience a sharp drop in performance when the availability of these resources is constrained by a secondary task. Taken together, our two experiments provide novel and robust support for the relation between Intellect and cognitive engagement, distinct from cognitive capacity.

Because the pattern of the Intellect × load interaction observed in this research appears to reflect Intellect-related differences in cognitive engagement, we suggest that a significant main effect of Intellect emerging independently of this interaction might be plausibly explained in terms of capacity-related differences in task performance. This main effect was observed in experiment 1, but was not replicated in experiment 2. (When we pooled the samples from our two experiments a modest main effect of Intellect reemerged.) Accordingly, our two experiments appear to provide consistent support for the relation between Intellect and cognitive engagement, but more mixed support for the relation between Intellect and cognitive capacity.

A particularly surprising finding in our second experiment was the lack of any association between Intellect and performance on the N-back. This contrasts with many previous studies that have found a relation between O/I and various tests of cognitive performance (e.g., von Stumm & Ackerman, 2013). The size of these previously observed associations is typically around r = .30, which our sample of N = 81 was reasonably well-powered to detect (i.e., we had 80% power to detect an effect of this size, or 87% allowing for a one-tailed test). A potential explanation for the null relation between Intellect and N-back scores is the apparent restriction of range in N-back scores in this study: Ancillary analyses revealed substantial positive skew in N-back, with 50% of participants attaining accuracy levels of 90% or more. In future research, a more fine-grained measure of cognitive capacity could be used — for example, an N-back task including both 2-back and 3-back blocks. On a related note, given that our primary task requires verbal performance, a measure of verbal ability might have been a more relevant control variable than the (numeric) N-back, and would be a useful addition to similar future studies. Overall, our results surrounding the N-back should be treated with caution; in any case, they are of secondary relevance to our main focus on Intellect and cognitive engagement.

General Discussion and Conclusion

While personality is sometimes misleadingly described as a 'non-cognitive' phenomenon (e.g., Heckman & Rubenstein, 2006), cognition has long been considered the defining feature of the basic trait domain Openness/Intellect (e.g., McCrae & Costa, 1997). This is readily apparent in the item content of O/I scales (Pytlik Zillig, Hemenover & Dienstbier, 2002), and in the consistent empirical associations such scales have with measures of intelligence and working memory, along with other tests of cognitive performance (e.g., Ackerman & Heggerstadt, 1997; DeYoung et al., 2005; Furnham et al., 2007; Kaufman et al., 2015; von Stumm & Ackerman, 2013). Recent research shows that this relation is restricted to the Intellect aspect of O/I (DeYoung et al., 2009, 2014), and has been interpreted in terms of a tendency for high-Intellect individuals to more deeply explore or engage with abstract or semantic information (DeYoung, 2013; Fayn et al., 2015). The experiments reported in this paper provide novel support suggesting that Intellect does indeed reflect individual differences in cognitive engagement. In terms of Resource Allocation Theory (Hockey, 1997; Kanfer & Ackerman, 1989), our two experiments show that Intellect captures individual differences in resource allocation policy: High-Intellect individuals appear to allocate more cognitive resources to a challenging task, relative to their low Intellect counterparts.

Beyond supporting the theorized link between Intellect and cognitive engagement, these findings speak to a number of broader issues of importance in this area. First, they build on recent demonstrations that Intellect and Openness often sharply diverge in their association with variables formerly linked with the broader O/I domain, including creative achievement (e.g., Kaufman et al., 2015), well-being (e.g., Lavigne, Hofman, Ring & Ryder, 2013), and political ideology (e.g., Perry & Sibley, 2013). This implies that each Big Five domain subsumes multiple, related-but-distinct processes — and is therefore likely to be underpinned by multiple causal mechanisms, as has been argued elsewhere (e.g., Jang et al., 2002; Zuckerman, 2005). Second, our findings suggest that deeper cognitive engagement may benefit learning and performance, but only if the task at hand can be prioritized or completed in the absence of competing demands. This may have important implications for achievement settings that attempt to foster intellectual engagement as a means to enhance performance (e.g., Paunesku, et al. 2015; Senko, Hama & Belmonte, 2013). Third, they demonstrate how Resource Allocation Theory can be used to formalize the somewhat abstract distinction between cognitive engagement and cognitive capacity. Because numerous learning and performance outcomes are likely to depend upon the *motivation* to engage with the task at hand, as well as the *ability* to do so (e.g., Kruglanski & Sheveland, 2012), the utility of clearly distinguishing these processes therefore likely extends well beyond the realm of personality theory.

It is also worth highlighting the relevance of the present research, which focused on the O/I domain within the Big Five framework, to a range of other closely related constructs. Examples of these include Need for Cognition (Cacioppo & Petty, 1982), Typical Intellectual Engagement (Goff & Ackerman, 1992), and Epistemic Curiosity (Litman, 2008), which are all potentially subsumed within the Intellect aspect of O/I (DeYoung, 2014). Judging from the item content of scales used to measure these constructs (e.g., "*I enjoy exploring new ideas*", Litman, 2008; "*The notion of thinking abstractly is appealing to me*"; Cacioppo & Petty, 1982), they seem especially likely to relate to cognitive engagement rather than cognitive capacity. However, we offer this suggestion cautiously given our supplementary analyses reported in the Appendix, which demonstrate the difficulty of clearly distinguishing between engagement and capacity based on face validity of questionnaire items. Replications and extensions of the present research could directly examine this issue by assessing convergent relations among Epistemic Curiosity, Need for Cognition, Typical Intellectual Engagement — and other markers of Intellect — in relation to resource allocation policy. This would help to clarify the scope and generality of the present findings, and their implications for the broader personality literature.

The cognitive processes we have studied in this paper may also be relevant to personality traits lying beyond the O/I domain. For instance, Big Five Conscientiousness is a robust predictor of scholastic achievement (Poropat, 2009), and this association may be explained in terms of deeper versus more superficial study strategies (Corker, Oswald & Donnellan, 2012). Similarly, numerous studies have linked Anxiety (a facet of Big Five Neuroticism; Costa & McCrae, 1985) with visual attention bias for negative stimuli (see Mathews & MacLeod, 2005), reflecting both increased attentional capture by, as well as decreased shifts in attention from, such stimuli (Rudaizkya, Basanovic & MacLeod, 2014).

While such findings tend to be conceptualized in terms of tendencies or preferences, some have suggested that they might also reflect capacities and abilities, whereby, for instance: “Conscientiousness encompasses the *ability* to resist distraction.... and [low] Neuroticism the *ability* to remain calm under stress” (DeYoung, 2015, p. 44, emphasis by present authors). Just as previous research had not clearly distinguished cognitive capacity from cognitive engagement in relation to Intellect, there may be similar distinctions of relevance to other personality traits that remain to be clearly disentangled in future research at the interface of personality psychology and cognitive science.

A number of limitations to our experiments should be noted and improved upon in further investigations. First, because our second experiment provided a direct replication of our first experiment, we do not know whether our findings generalize to tasks beyond our word-search game. Further research could employ alternative primary tasks containing abstract or semantic information, such as arithmetic problems (e.g., Avery et al., 2013, study 2) or literary quotations (e.g., Fayn et al., 2015). Indeed, high-Intellect individuals may potentially engage even more strongly with such stimuli in comparison to our simple word-search task. Second, because our present findings hinge upon our interpretation of the decline in primary task performance under secondary load, it would be of value to corroborate our findings using an alternative operationalization of cognitive engagement. For example, our word-search task might be ideally combined with eye-tracking to determine whether high-Intellect individuals visually explore the letter matrix more thoroughly than their low-Intellect counterparts (see Yarbus, 1967). Finally, our two experiments demonstrate only a *single* dissociation between Intellect and Openness – the former predicted cognitive engagement while the latter did not. This was expected, as Openness has been linked only to engagement with aesthetic or perceptual stimuli (DeYoung, 2013). Nevertheless, worthwhile extensions of this research could attempt to provide a *double* dissociation by showing that Intellect predicts cognitive engagement with abstract/intellectual stimuli while Openness predicts cognitive engagement with aesthetic/perceptual stimuli (cf. Fayn, MacCann, Tiliopoulos & Silvia, 2015).

In conclusion, we have provided novel support for the perspective that the personality trait Intellect (distinct from Openness) reflects individual differences in cognitive engagement. We distinguished cognitive engagement from cognitive capacity by drawing on Resource Allocation Theory and through the use of a dual-task paradigm. From a resource allocation perspective, it appears that high-Intellect individuals allocate more of their available cognitive resources to a challenging abstract task. This may help to explain why such individuals perform well on a range of cognitive tasks.

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Table 1

Means, Standard Deviations, and Correlations for All Variables in Experiment 1

		1	2	3	4	5	6	7
O/I	1. Intellect	—						
	2. Openness	.48***	—					
Task	3. Game Points (L)	.37**	-.03	—				
	4. Game Points (H)	.26*	-.14	.78***	—			
	5. Points Decline	.25*	.13	.58***	-.05	—		
	6. Secondary Task (L)	.22	.05	.07	.07	.01	—	
	7. Secondary Task (H)	.08	-.24*	.21	.66***	-.53***	.16	—
Means		3.56	3.75	80.73	44.27	36.46	98.77	65.17
Standard Deviations		0.56	0.54	30.05	24.44	18.70	2.03	17.92

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; L = low secondary load, H = high secondary load.

Table 2

Means, Standard Deviations, and Correlations for All Variables in Experiment 2

		1	2	3	4	5	6	7	8	9
O/I	1. Intellect	—								
	2. Openness	.54***	—							
Task	3. Game Points (L)	.14	.14	—						
	4. Game Points (H)	-.08	-.01	.77***	—					
	5. Points Decline	.31**	.23*	.66***	.03	—				
	6. Secondary Task (L)	-.16	-.20	.07	.05	.03	—			
	7. Secondary Task (H)	-.19	-.11	.23*	.68***	-.44***	-.02	—		
Controls	8. Industriousness	.42***	-.05	-.10	-.17	.05	.07	-.06	—	
	9. N-back (d-prime)	.01	-.01	.41**	.24*	.36**	.01	-.03	.11	—
Means		3.63	3.94	96.60	52.68	43.96	97.75	64.21	3.02	1.08
Standard Deviations		0.54	0.43	41.86	31.49	26.64	5.83	20.25	0.52	0.23

Note: * $p < .05$; ** $p < .01$; *** $p < .001$; L = low secondary load, H = high secondary load

Table 3

ANCOVA results from Experiment 2

Variables in Model	Significance Test	Effect Size (η_p^2)
Secondary load	**$F(1,76) = 253.96, p < .001$**	**.77**
Intellect	$F(1,76) = 0.95, p = .332$	.01
Intellect × Load	**$F(1,76) = 6.18, p = .015$**	**.08**
Openness	$F(1,76) = 0.01, p = .977$	< .01
Openness × Load	$F(1,76) = 0.08, p = .784$	< .01
Industriousness	$F(1,76) = 3.68, p = .069$	< .01
Industriousness × Load	$F(1,76) = 1.34, p = .250$	.04
N-back performance	**$F(1,76) = 12.89, p = .001$**	**.15**
N-back performance × Load	**$F(1,76) = 13.90, p < .001$**	**.16**

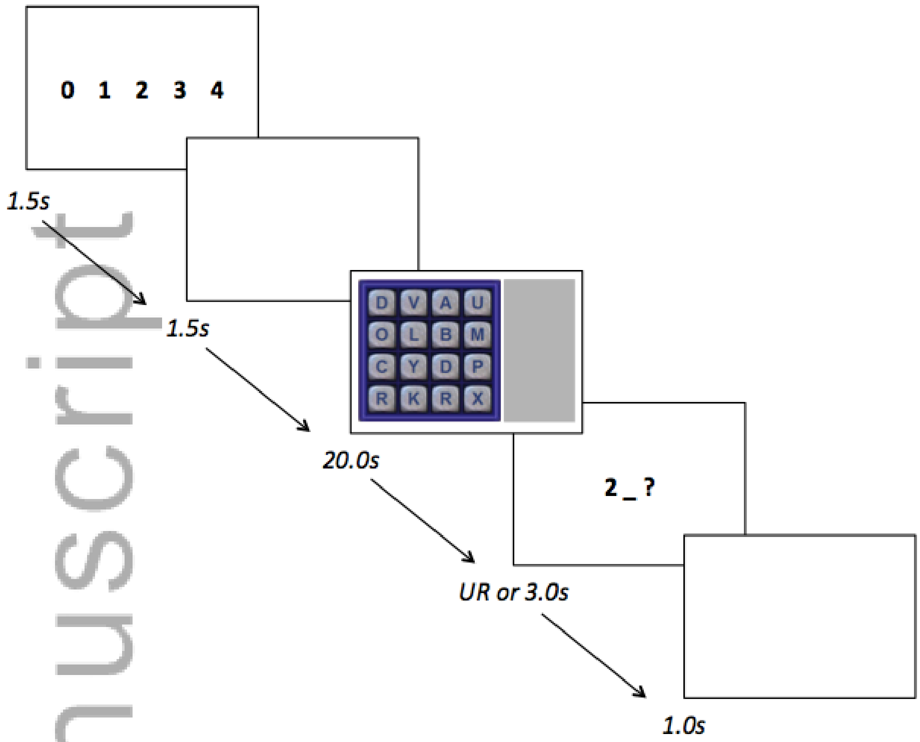

Figure 1. Example trial sequence from the dual-task paradigm (low secondary load), displaying one of the 64 possible 16-letter matrices used for the primary task. *Note.* UR = until response.

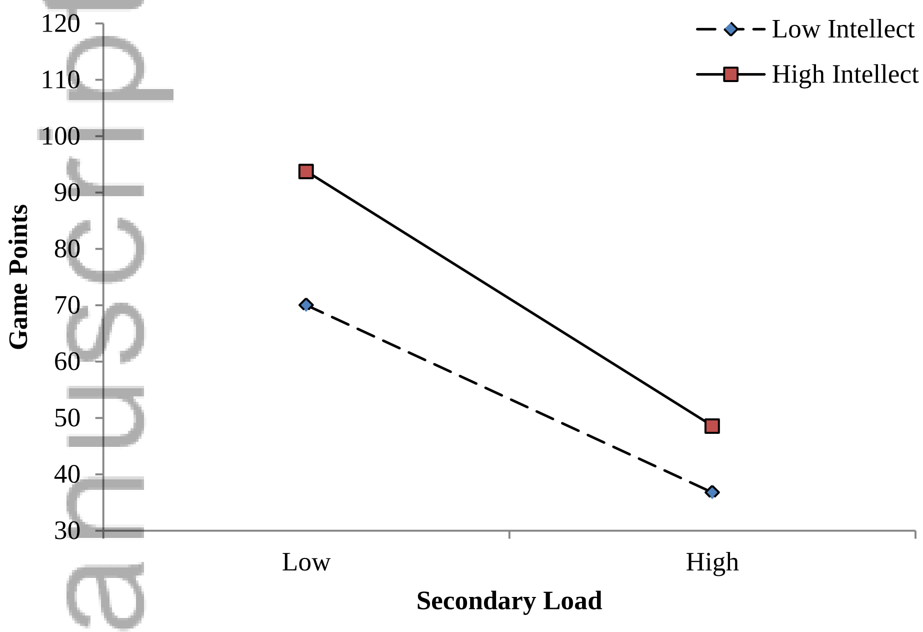

Figure 2. Plot from Experiment 1 depicting primary task performance (Game Points), under low and high secondary load, for individuals scoring in the top and bottom third of scores on a composite measure of Intellect (derived from the BFAS and NEO-IPIP). The decline in primary task performance under high (versus low) secondary load was steeper for high-Intellect individuals (effect size: η_p^2 = .76) compared to low-Intellect individuals (effect size: η_p^2 = .64).

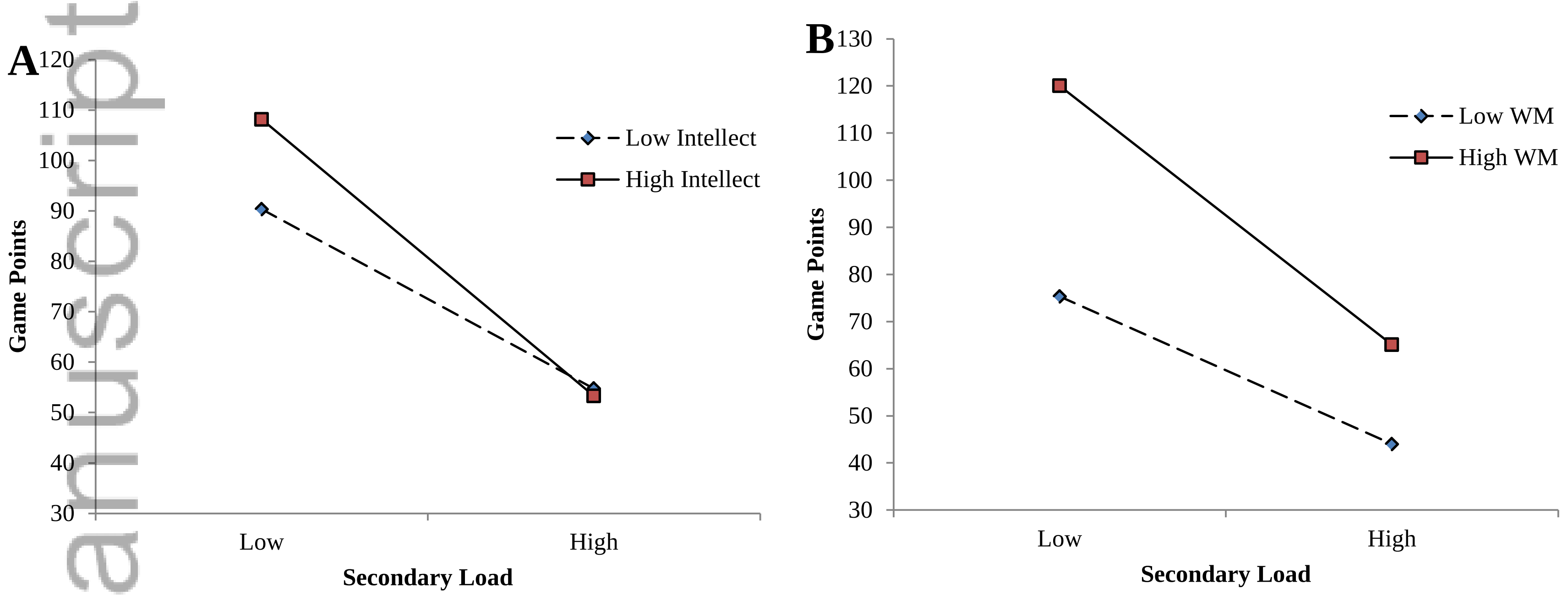

Figure 3. Plot from Experiment 2 depicting primary task performance (Game Points), under low and high secondary load, for (**A**) individuals scoring in the top and bottom third of scores on a composite measure of Intellect (derived from the BFAS and NEO-IPIP), and (**B**) individuals scoring in the top and bottom third of scores on a 2-back Working Memory (WM) task. The decline in primary task performance under high (versus low) secondary load was steeper for high-Intellect individuals (effect size: η_p^2 = .71) compared to low-Intellect individuals (effect size: η_p^2 = .50). Similarly, the decline in primary task performance under high

(versus low) secondary load was steeper for high-WM individuals (effect size: η_p^2 = .72) compared to low-WM individuals (effect size: η_p^2 = .45).

APPENDIX A

Cognitive Engagement versus Capacity as Facets of Intellect?

Given the focus of this paper on the relation between Intellect and cognitive engagement, distinct from cognitive capacity, we were intrigued to discover that the items from both the NEO-IPIP and BFAS Intellect scales appear, at face value, to divide neatly between these two concepts. As shown in Table A1, the NEO-IPIP Intellect scale appears weighted more toward cognitive engagement while the BFAS-IPIP scale appears weighted more toward cognitive capacity — though both scales span both concepts. We averaged across the 7 non-redundant items in the top half of Table A1 to create an 'Intellect-Engagement' scale, and across the 7 non-redundant items in the bottom half of Table A1 to create an 'Intellect-Capacity' scale. Potentially, each scale could be considered a facet-level measure of Intellect. Pooling across the 160 participants from our two experiments, we then examined the reliability and structure of these novel measures of Intellect, as well as their relation to performance on our dual task paradigm.

The internal consistency of the Intellect-Capacity scale (α = .82) and Intellect-Engagement scale (α = .78) were both high — which is of course unsurprising given that they were derived from an already internally consistent pool of items. The correlation between these scales was also high (r = .53, p < .001), though comparable to that between the Intellect and Openness aspect scales from the BFAS (see Tables 1 and 2 of main article). We then extracted two factors from the pool of Intellect items via an exploratory factor analysis (principle axis factoring, direct oblimin rotation), and found that these were clearly aligned with the apparent division between capacity-related and

Table A1

Items from the NEO-IPIP- and BFAS-Intellect scales that appear to reflect the concepts of cognitive engagement (uper panel) and cognitive capacity (lower panel).

	NEO-IPIP-Intellect	BFAS-Intellect
1. Cognitive Engagement	Like to solve complex problems.	Like to solve complex problems.
	Avoid philosophical discussions. [R]	Avoid philosophical discussions. [R]
	Avoid difficult reading material. [R]	Avoid difficult reading material. [R]
	Enjoy thinking about things.	
	Love to read challenging material.	
	Am not interested in abstract ideas. [R]	
	Am not interested in theoretical discussions. [R]	
2. Cognitive Capacity	Have difficulty understanding abstract ideas. [R]	Have difficulty understanding abstract ideas. [R]
	Can handle a lot of information.	Can handle a lot of information.
	Have a rich vocabulary.	Have a rich vocabulary.
		Think quickly.
		Learn things slowly. [R]
		Formulate ideas clearly.
		Am quick to understand things.

engagement-related items in table A1. (The first five eigenvalues were 5.08, 1.68, 1.27, 0.95, and 0.83.) Factor loadings depicted in table A2 show that each item loaded > .30 on one factor only, with the exception of one cross-loading item, *"Have a rich vocabulary"*. The correlation between these two factors (r = .54) was almost identical to the inter-scale correlation reported above

Table A2

Pattern loading matrix

	F1	F2
Am quick to understand things	.82	
Think quickly	.80	
Learn things slowly [R]	.68	
Can handle a lot of information	.65	
Have difficulty understanding abstract ideas [R]	.58	
Formulate ideas quickly	.51	
Have a rich vocabulary	.33	.24
Love to read challenging material		.79
Like to solve complex problems		.62
Avoid difficult reading material [R]		.61
Am not interested in theoretical discussions [R]		.53
Am not interested in abstract ideas [R]		.47
Enjoy thinking about things		.46
Avoid philosophical discussions [R]		.46

NB: Loadings below .20 are not shown.

We then repeated the last analysis reported in experiment two, in which we examined the interaction between secondary load and Intellect in the prediction of primary task performance, separately for the Intellect-Engagement and Intellect-Capacity scales. We anticipated that that the former analysis would reveal a significant interaction with secondary load, in line with our reasoning that this is indicative of differences in cognitive engagement, while the latter would reveal a main effect, in line with our reasoning that this is indicative of differences in cognitive capacity. (For a recapitulation of this logic see the summary section of experiment 1.) However, findings revealed both a main effect and interaction with load for Intellect-capacity, as well as similar, though more marginal, effects for Intellect-engagement. Note that the apparent differences in degree of significance of these effects contrast with the fact that the effect sizes associated with each of these scales were nearly identical.

The overall lack of divergent validity for these two putative Intellect facets may simply remind us that face validity is a poor guide to actual validity, and that disentangling cognitive capacity from cognitive engagement is particularly difficult. Nevertheless, it may prove fruitful for follow-up studies to further explore the feasibility of assessing Intellect-related differences in engagement versus capacity as distinct facets of the O/I domain.

Table A3

ANCOVA results

Variables in Model	'Intellect-Engagement'		'Intellect-Capacity'	
	Significance Test	Effect Size (η_p^2)	Significance Test	Effect Size (η_p^2)
Secondary load	**F(1,157) = 501.72, p < .001**	**.76**	**F(1,157) = 517.39, p < .001**	**.77**
Intellect	F(1,157) = 2.68, p = .103	.02	**F(1,157) = 4.77, p = .030**	**.03**
Intellect × Load	**F(1,157) = 3.31, p = .071**	**.03**	**F(1,157) = 8.31, p = .004**	**.05**
Openness	F(1,157) = 0.14, p = .714	< .01	F(1,157) = 0.11, p = .747	< .01
Openness × Load	F(1,157) =1.69, p = .195	.01	F(1,157) = 1.78, p = .182	.01