Supplementary tables

Supplementary Table 1: Neuroscience in Psychiatry consortium author list and affiliations.

Supplementary Table 2: Bivariate relationships of task variables with confirmed predictors. Bivariate relationships were selected in the discovery sample at an alpha level of p < .001. A joint model including all bivariately significant task measures per predictor variable was then confirmed without re-fitting in the hold-out sample (permutation test p < .05 after Holmes-Bonferroni correction for 9 comparisons). See figures S2-4 for the confirmation tests. In this table, p-values for the bivariate relationships serve for illustration purposes and are not corrected for multiple comparison. 95%-CI: 95% parametric confidence interval. For confidence intervals on correlation coefficients that include zero, an upper limit for R2 is given.

Supplementary Table 3. Child and Adolescent Disposition Scale 'Daringness' (the other CADS items are omitted for convenience).

These questions are of your personality. When you answer these questions, please think about the last 12 months and tick the box that you feel best describes you.

Supplementary Table 4. Extract from Barratt Impulsivity Scale extract, including the full Cognitive Complexity subscale, which is boxed in bold. The rest of the BIS is omitted for convenience.

People differ in the ways they act and think in different situations. This is a test to measure some of the ways in which you act and think. Read each statement and put and tick in the appropriate box. Do not spend too much time on any statement. Answer quickly and honestly.

Supplementary results

1. Psychometric properties of the task

Supplementary figure 1. Correlation matrix of the 38 task variables at BSL, for the combined sample. Variables appear in systematic order.

Supplementary Figure 2. Correlation matrix of the 38 task variables at BSL, for the combined sample. This is the same as Supplementary Figure 1 but with variables ordered by hierarchical clustering for better visualisation.

Supplementary Table 5: Consistency (Cronbach's alpha) at BSL, and test-retest reliability from baseline to FU-1 (over 11- 32 months). Cronbach's alpha is for linear adaptation in the 7 time-dependent measures at baseline. Factor scores for discovery and confirmation samples are based on factor analysis of discovery sample. Factor scores for the combined sample are based on a factor analysis of the combined sample.

Linear adaptation in the 7 previously reported task measures showed a high internal consistency as indexed by Cronbach's alpha = .86 in the combined sample (see Supplementary Table 5). Nevertheless, parallel analysis suggested a 2-factor solution for these 7 measures. After varimax rotation, 4 measures loaded dominantly onto one factor, and three on the other (see Supplementary Figure 3A). This factor analysis replicated between discovery and confirmation sample (see Supplementary Figure 4A). In parallel analysis using 34 task measures (excluding the 4 collinear sum scores), a 6-factor solution was preferred. The first 3 factors could meaningfully be interpreted and replicated over partitions of the discovery sample (see Supplementary Figure 3B). These three factors replicated between the discovery and confirmation sample (see Supplementary Figure 4B).

Test-retest reliability between BSL and FU-1 (e.g. over 1-3 years) was larger than $r_{tt} = .40$ for most measures unrelated to the predator differences, and was high as $r_{tt} = .70$ for some measures related to performance (see Supplementary Table 5, see Supplementary Figure 5 for measures with $r_{tt} > .50$ in the combined sample). Overall, although not designed to do so, it appears that the task quantifies traits that are stable over time, particularly the case for those measures predicted by sex, IQ, and self-report variables.

Supplementary Figure 3: Exploratory factor analysis (EFA) with varimax rotation in the combined sample. A: EFA on linear adaptation in 7 previously reported time-sensitive measures. B: EFA on all 34 independent task measures (excluding 4 linearly dependent sum scores). See Supplementary Figure 4 for comparison between discovery and confirmation sample.

Supplementary Figure 4: Factor loadings from two exploratory factor analyses (EFA) on discovery and confirmation samples with varimax rotation. Positive loadings are in red shades, negative in blue. The factor loadings almost perfectly replicated between discovery and confirmation data set. Specifically, we computed factor scores in the confirmation data set, either using loadings derived from the discovery data set or loadings derived from the confirmation data set. For both EFAs, the two factor scores were highly correlated. EFA with 7 measures: Factor $1, r > 0.99$ (0.99-1.00, 95% parametric confidence interval; t(287) = 364.8; p < .001); Factor 2, r = 0.99 (0.99-1.00, 95% parametric confidence interval; t(287) = 162.7; p < .001). EFA with 34 measures: Factor 1, r > 0.99 (0.99-1.00, 95% parametric confidence interval; t(287) = 211.0; p < .001); Factor 2, r > 0.99 (0.99-1.00, 95% parametric confidence interval; t(287) = 234.6.8; p < .001), Factor 3, r > 0.99 (0.99-1.00, 95% parametric confidence interval; $t(287) = 139.6$; $p < .001$). To further confirm the factor structure of the 34-measure EFA, we defined a confirmatory factor model as structural equation model that included only factor loadings above 0.2. However, this model did not converge.

Supplementary Figure 5: Test-retest-reliability from BSL to FU-1 for the combined sample, showing all measures for which rtt > 0.50 . See Supplementary Table 5 for a full list split into discovery and confirmation sample.

2. Mediation analysis

Here we report effect sizes (but, following journal policy, no inference statistics) from posthoc mediation analysis across the combined sample. For each predictor, we constrained this mediation analysis to task variables that were related to this predictor, and other predictor variables that were themselves related to task variables, namely sex, IQ, CADS daringness, and BIS cognitive complexity.

Sex difference in performance - mediation by task variables

Average token collection mediated the largest proportion of the performance difference between sexes (82%; 75%-90%; 95% bootstrap confidence interval). After accounting for this variable, the rate of decrease in token collection (as the epoch progressed) carried the next highest proportion of mediation (13%; 8%-19%). After accounting for both these variables, estimated proportion of mediation was 0% (-2%-0%) for minimum distance, 0% (-2%-1%) for decrease in speed, 0% (-2%-1%) for average speed, and -2% (-5%-1%) for decrease in wall distance. At the request of a reviewer, we analysed whether the slope of the trial-by-trial performance trajectory mediated the sex effect on performance. This variable mediated 3% (1%-6%). After accounting for average token collection, which mediated a much higher proportion of variance, the individual performance slope mediated 0% (0%-1%).

Sex difference in performance - mediation by other variables related to performance

Among the variables considered, self-reported daringness mediated the highest proportion of the sex effect $(5\%, 0\% - 11\%)$, while IQ mediated 4% $(1\% - 7\%)$, and BIS cognitive complexity 3% (1%-6%). Because of the relatively small proportion of mediation, we did not investigate the unique contribution of these covariates.

CADS daringness effect on performance - mediation by task variables and by other

variables related to performance

Average token collection mediated the greatest proportion of a daringness effect on performance (87%; 70%-107%), similar to the sex effect on performance. After accounting for this variable, the rate of decrease in token collection (as the epoch progressed) carried the next highest proportion of mediation (2%; -1%-6%), while average speed mediated 0% (-1%- 1%). Regarding other predictor variables, IQ mediated -1% (-1%-5%) and BIS cognitive complexity mediated 3% (-2%-10%) of the daringness effect on performance.

IQ effect on performance - mediation by task variables and by other variables related to

performance

Decrease in token collection mediated 80% of an IQ effect on performance (80%; 62%-104). No other task variables were related to IQ. Self-reported daringness mediated -2% (-12%-6%) and self-reported cognitive complexity mediated 13% (3%-30%) of the IQ effect on performance

BIS cognitive complexity effect on performance - mediation by task variables and by other variables related to performance

Decrease in token collection mediated 94% of a BIS cognitive complexity effect on performance (68%-151%). No other task variables were related to cognitive complexity. Selfreported daringness mediated 6% (-4%-19%) and IQ mediated 33% (17%-73%) of a BIS cognitive complexity on performance. Thus, both IQ and BIS cognitive complexity may have a separate impact on task performance. The proportion of cognitive complexity variance mediated by IQ was descriptively higher than vice versa (13%, see above).

3. Analysis of performance trajectory over trials (H2)

Under a hypothesis that males performed better because they had more experience with computer game, we expected that females may improve their performance more over trials than male. We first determined the curvature of the performance trajectory across both sexes and all conditions. Model evidence indicated that a logarithmic trajectory fitted the data decisively better than a linear, quadratic, or square root trajectory (LBF -44 with respect to the linear model). We then computed a threat level \times task \times trial \times sex linear effects model with trial as logarithmic predictor across all conditions. This model revealed a significant trial \times sex interaction (F(1, 30982) = 9.66; $p < .001$), but in the opposite direction than expected, i.e. male participant increased their performance over time more than females. However, this exploratory finding was not replicated in the confirmation sample $(H2, F(1, 18193) = 0.2; p$ $= .65$). Instead, we found a significant threat level \times trial \times sex interaction (F(1, 18193.1) = 10.46; $p < .001$), implying that males increase their performance more than females only in the high threat probability condition. Across the entire sample, both the trial \times sex (F(1, 49189) = 9.79; p = .002 uncorrected) and the threat level \times trial \times sex (F(1, 49541) = 4.15; p < .042 uncorrected) interactions were significant.

4. Analysis of maturation effects

A subsample of $n = 63$ participants, distributed across discovery and confirmation sample, returned 6 months after the first visit (BSL) and played the game again (visit FU-R). $N = 55$ of these participants also came back 11-32 months after visit 1 for another session (FU-1). Many task measures changed in the 6 months between BSL and FU-R, while over a much longer (5-26-month) interval between FU-R and FU-1, only four measures changed systematically, indicating practice as opposed to maturation effects. A full list of changes is found in Supplementary Table 6 below.

To address further whether observed systematic changes between visits were due to maturation or practice, we capitalised on the variable interval between BSL and FU-1, availing of the larger number of participants who took part in BSL and FU-1 (after 11-32 months), but not necessarily in FU-R. Thus, in the discovery sample $(N = 357)$ we computed a model that included task measures at visits BSL and FU-1 as dependent variables, and repetition and time interval between BSL and FU-1 as predictors. We observed an effect of repetition in many measures, but for no variable was this effect better explained by the time elapsed between the two visits. For each of the 38 task measures, Bayesian model comparison favoured a model with repetition but without time effects ($LBF > 3$ in favour of the simpler model). This finding was corroborated in both the confirmation sample $(N = 210)$ and the combined sample ($N = 567$). Overall, we found no evidence for any effects of maturation on task behaviour.

Finally, at the request of a reviewer, we computed, for each task variable, an age \times (repetition + time interval) linear mixed effects model across the combined sample, and contrasted this with an age \times repetition model. There were no significant age \times time interval interactions at our alpha threshold of $p < .001$. Even at $p < .05$, there was only one significant finding, but here the simpler model explained the data better than the more complex one (BF difference \geq 700 in favour of the simpler model). Thus, we did not find any evidence that age moderates the impact of maturation in this sample. The impact of age on repetition of the task is illustrated in Supplementary Figure 11 below.

Supplementary Table 6. Effect of maturation: change in 38 task measures between BSL and FU-R, or FU-R and FU-1.

95%-CI: 95% parametric confidence interval.

Supplementary Figure 6. Distribution of performance (tokens retained) split by sex and age group, for BSL and FU-1. White lines show mean and standard error of the mean.

5. Relation of task variables and parameters from an economic lottery

Supplementary table 7. Post-hoc analysis of bivariate relationships of the task variables that related to predictors to paramters from the economic lottery task. In line with journal policy, we state effect sizes but no inference statistics. 95%-CI: 95% parametric confidence interval. For confidence intervals on correlation coefficients that include zero, an upper limit for R2 is given.

6. Analysis of the task parameter extraction method

Because the epochs had variable duration, fewer data points were available later in the epoch compared to early in the epoch. In previous publications we had used mean imputation, i.e. we ignored missing data points when computing the average over trials for each time bin. The same strategy was used in the current analysis of trajectory similarity. To compute regression coefficients for these averaged trajectories however, it may be appropriate to take into account the different number of available data points per time bin, for example using weighted linear squares regressions with estimated coefficients

$$
\hat{\beta} = (X^TWX)^{-1}X^TWy;
$$

where y is the vector of data per time bin (averaged over trials), X the design matrix, and W a diagonal matrix that contains, for each time bin, the proportion of available observations out of all trials.

Due to a coding error that was detected after pre-registration, we had instead used zero imputation before averaging trajectories over trials, followed by ordinary least squares regression. Using this method, the resulting coefficients are of the form

$$
\hat{\beta} = (X^T X)^{-1} X^T W y;
$$

where y is the averaged trajectory one would have obtained using mean imputation. It is easy to see that these coefficients span the same space as the ones obtained in the aforementioned WLS approach, such that they do not contain different information.

However, we note that the discrete criterion for inclusion of any task measure into our predictive models may results in different predictive accuracy, and that the interpretation of the coefficients in these models may be different. This is why we replicated the original analysis, using mean imputation and WLS regression. First, we refitted the preregistered predictive models in the discovery sample, using the same nominal task variables, and tested their predictive performance in the confirmation sample (Supplementary Table 8). All models were confirmed, such that our key findings can be seen as independent from the method of task variable extraction. Second, we used the same approach of including task variables into the predictive models at an alpha threshold of $p < .001$ for the bivariate relationship. The confirmed models from this set related to the same predictor variables as in our original analysis. We note that fewer task variables were included and that the predictive performance was descriptively lower than in the original analysis. Third, we summarise all bivariate relationships relating to our original models in Supplementary Table 9.

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Supplementary Table 8: Joint predictive models and their performance when using WLS-derived task parameters instead of OLS parameters with zero imputation. Further models predicting CADS subscale "prosocial behaviour", RCMAS, and SPQ subscale "odd or eccentric behaviour" in the discovery sample were not confirmed and are not shown here. Notably, the procedure of deriving confidence intervals is unrelated to the permutation test; they are included due to journal requirements and do not reflect the posterior plausibility of true parameter values 65 .

Supplementary Table 9: Bivariate relationships of task variables extracted with WLS regression with confirmed predictors. Bivariate relationships are shown if they were included in the preregistered analysis; no new task variables were included in the discovery analysis with WLS regression. In this table, p-values for the bivariate relationships serve for illustration purposes and are not corrected for multiple comparison. 95%-CI: 95% parametric confidence interval. For confidence intervals on correlation coefficients that include zero, an upper limit for R2 is given.

