Individual differences in information demand have a low dimensional structure predicted by some curiosity personality traits

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Authors list & Affiliations

Hayley K. Jach*: hayley.jach@uni-tuebingen.de [University of Tübingen, Hector Research Institute of Education Sciences and Psychology], **Roshan Cools** [Radboudumc, Dept of Psychiatry & Donders Institute for Brain, Cognition and Behaviour], **Alex Frisvold** [University of Arizona, Psychology Department], **Michael Grubb** [Trinity College, Department of Psychology], **Catherine A. Hartley** [New York University, Department of Psychology], **Jochen Hartman** [Hartaki LLC], **Laura Hunter** [Columbia University, Neuroscience Department, Mortimer B. Zuckerman Mind Brain Behavior Institute], **Ruonan Jia** [Yale University, Interdepartmental Neuroscience Program and Department of Comparative Medicine], **Floris P de Lange** [Donders Institute for Brain, Cognition and Behaviour], **Ruby Larisch** [Yale University, Department of Comparative Medicine], **Rosa Ellen Lavelle-Hill** [University of Tübingen, Hector Research Institute of Education Sciences and Psychology][University of Copenhagen at both the Department of Psychology and SODAS], **Ifat Levy** [Yale University, Departments of Comparative Medicine, Neuroscience, and Psychology, and Wu-Tsai Institute], **Yutong Li** [Yale University, Department of Psychiatry], **Lieke van Lieshout** [Donders Institute for Brain, Cognition and Behaviour], **Kate Nussenbaum** [New York University, Department of Psychology], **Silvio Ravaioli** [Columbia University, Economics Department], **Siyu Wang** [University of Arizona], **Robert Wilson** [University of Arizona, Psychology Department and Cognitive Science Program], **Michael Woodford** [Columbia University, Economics Department], **Kou Murayama** [University of Tübingen, Hector Research Institute of Education Sciences and Psychology], & **Jacqueline Gottlieb** [Columbia University, Neuroscience Department, Mortimer B. Zuckerman Mind Brain Behavior Institute.]

*corresponding author

Abstract

To understand human learning and progress, it is crucial to understand curiosity. But what is curiosity, and how consistent is its conception and assessment across scientific research disciplines? We present the results of a large collaborative project assessing the correspondence between curiosity measures in personality psychology and cognitive science. 820 participants completed 15 personality trait measures and 9 cognitive tasks that tested multiple aspects of information demand. We show that shared variance across the cognitive tasks was captured by a dimension reflecting directed (uncertainty-driven) versus random (stochasticity-driven) exploration and individual differences along this axis were significantly and consistently predicted by personality traits. However, the personality metrics that best predicted information demand were not the central curiosity traits of openness to experience, deprivation sensitivity, and joyous exploration, but instead included more peripheral curiosity traits (need for cognition, thrill seeking, and stress tolerance) and measures not traditionally associated with curiosity (extraversion and behavioral inhibition). The results suggest that the umbrella term "curiosity" reflects a constellation of cognitive and emotional processes, only some of which are shared between personality measures and cognitive tasks. The results reflect the distinct methods that are used in these fields, indicating a need for caution in comparing results across fields and for future interdisciplinary collaborations to strengthen our emerging understanding of curiosity.

Significance Statement

The importance of curiosity for learning is becoming evident in multiple disciplines, but it is unclear how definitions of curiosity are related across disciplines. Here we compared perspectives from cognitive science and personality psychology by testing a large participant sample on 9 tasks of information demand and 15 personality traits. We found that inter-individual variability across tasks of information demand was captured by a dimension reflecting directed versus random exploration. Importantly, this dimension was predicted by personality constructs that index appraisals of reward and uncertainty and are part of the broader curiosity nomological network, but was not predicted by core curiosity constructs of openness to experience, deprivation sensitivity, and joyous exploration, identifying areas of overlap and divergence between the definitions of curiosity across the two fields.

Introduction

Humans are both curious and intelligent, and curiosity motivates humans to use their intelligence to learn and create. To understand human learning, then, it is crucial to understand curiosity. But what is curiosity? Different fields of research have investigated curiosity in unique ways, and it is currently unclear how well they can be synthesized[1]. In this study, we investigate this question from the dual perspectives of personality psychology and cognitive science.

Although both personality psychology and cognitive science define curiosity as *the desire to know*[2,3], they operationalize curiosity distinctly. Personality psychologists consider curiosity to be a constellation of personality traits that are relatively stable over the lifespan, are present to differing degrees in different individuals, and are measured via self-report questionnaires[4,5]. In this view, trait curiosity includes one's tendency to experience emotions, cognitions, and behaviors related to possible information gain, such as joy and interest in learning and exploring (called *joyous exploration*) and frustrated deprivation related to not knowing something (called *deprivation sensitivity*)[6]. Curiosity is also considered to be part of the broad Big Five personality dimension *openness to experience*, which describes individual differences in imagination, creativity, and aesthetic sensitivity. Trait curiosity and related constructs predict important life outcomes including learning and academic achievement, choices of occupation (e.g., investigative vs artistic), creative and scientific achievement, subjective well-being, and a sense of meaning in life[5,7–10].

By contrast, cognitive scientists investigate curiosity as a cognitive/emotional state measured via a decision to seek information or attend to specific features of a situation[2,11,12]. Investigations using these methods describe curiosity as a constellation of drives that combine in different proportions across individuals and produce different information gathering styles. Two motives described in this literature include the desire to reduce uncertainty—thus increasing the accuracy of one's beliefs and predictions about future events[2,11,13–17]—and the desire to regulate anticipatory emotions, savoring the anticipation of positive outcomes but avoiding the dread inherent in anticipating negative outcomes[18,19]. In addition, studies recognize the key role of behavioral randomness or stochasticity, which can be deployed strategically as a function of the exploration horizon (i.e., time available to explore) and allows individuals to learn about lower-value options they would not approach otherwise[20]. Stochasticity generates random (or *diversive*) exploration, which contrasts with directed (or *specific*) exploration focused on specific sources of information (i.e., those which reduce uncertainty)[21].

An additional important feature of curiosity is that it is *intrinsically motivated*—i.e., indicates a desire for information as a good in itself. This is operationalized in the laboratory in tasks of *non-instrumental* information demand in which participants cannot exploit the information they gather to obtain external (instrumental) rewards[18,22,23]. However, emerging evidence suggests that uncertainty reduction, anticipatory emotions, and stochasticity also affect behavior under instrumental conditions, suggesting that information gathering shares similar drives regardless whether participants can or cannot act on the information to obtain future rewards[24–26].

Together, the results from personality questionnaires and cognitive tasks raise two critical questions.

First, within cognitive science multiple tasks have been devised to measure information demand (e.g., in instrumental, non-instrumental, and attentional contexts[12]) but these tasks have been siloed in individual laboratories, raising the question of whether they tap into common or distinct aspects of information gathering. Understanding the specific constructs that are tapped across tasks will benefit theory development and help researchers select the appropriate paradigm/s for their particular question. A second question pertains to the correspondence between cognitive and personality studies: how well do curiosity states measured in cognitive tasks overlap with trait curiosity measured in personality psychology? Theoretical and empirical studies suggest that personality traits can be considered density distributions of psychological states[1,27,28], but the proposed mechanisms for information demand in cognitive tasks—such as dreading threats or savoring rewards—appear to share little resemblance with the states assumed to underpin trait curiosity—for example, joyous exploration's joy in learning and exploring the unknown. If curiosity as a trait cannot predict curiosity as a behavior, then the two fields may fall prey to the jingle fallacy, studying different constructs that share a label[29]. In an increasingly interdisciplinary research landscape, it is vital to avoid this pitfall.

Here we examined both questions by testing a large sample of participants ($N = 820$) on multiple tasks of information demand and personality questionnaires. The 9 cognitive tasks we selected spanned the range of tasks recently proposed in the literature, in which participants gathered instrumental or non-instrumental information using attention or explicit decisions (a press of a button), rated their curiosity, or expressed their risk/ambiguity attitudes. The questionnaires were likewise broad and indexed 15 personality traits, including those considered core curiosity traits (joyous exploration, deprivation sensitivity, openness to experience), as well as traits considered part of the broader curiosity nomological network (need for cognition, thrill seeking, stress tolerance) and non-curiosity traits (e.g., other Big Five personality traits) which were important for assessing divergent validity.

Using principal component analysis, we show that inter-individual variability across the cognitive tasks was captured by an axis corresponding to the distinction between random versus directed exploration—that is, seeking information stochastically or specifically to minimize uncertainty. Second, individual variability along this axis was well predicted by personality traits, reflecting a degree of convergence between cognitive and personality literatures. Third and surprisingly, the best predictors of information demand did not include the core curiosity constructs of joyous exploration, deprivation sensitivity, or openness to experience but, rather, more peripheral constructs indexing attitudes to uncertainty and cognitive styles (thrill seeking, stress tolerance and need for cognition) as well as constructs not classically associated with curiosity like extraversion and behavioral inhibition. The findings identify a low-dimensional structure that underlies a diverse set of cognitive tasks, and point to areas of overlap and divergence between the definitions of curiosity in cognitive science and personality research.

Results

Tasks and analytical pipeline

Eight-hundred and twenty (820) participants were recruited via Amazon Mechanical Turk and completed an online battery of 9 cognitive tasks and 15 personality traits presented in randomized order across several days (*Methods*). The cognitive tasks spanned the range of those that have been recently used to test information gathering or related cognitive constructs and are described in detail in **Supplement A** and in following sections. The results from the cognitive tasks and personality scales were submitted to a 2-step data analysis pipeline that is summarized in **Fig. 1**. In the first analysis step (**Fig. 1A**), we combined the 35 parameters characterizing performance on the cognitive tasks (**Table 1** and **Supplement A**) and subjected them to principal component (PC) analysis to extract lower-dimensional variance that was shared across tasks (**Fig. 1A** and **Supplement B**). In a second step, we used machine learning methods to test the extent to which the PC scores from the cognitive tasks were predicted by personality metrics (**Fig. 1B**). We chose to apply PC analysis to the cognitive tasks but not personality metrics because, while the cognitive tasks are relatively recent and have never been tested together, the nomological network of personality traits is well understood from decades of factor analytic evidence[30]. Thus, this approach is well-suited to addressing our questions about the extent to which diverse cognitive tasks may tap into a few general constructs and *which* personality traits best align with these constructs. We describe the principal component analyses followed by the machine learning results.

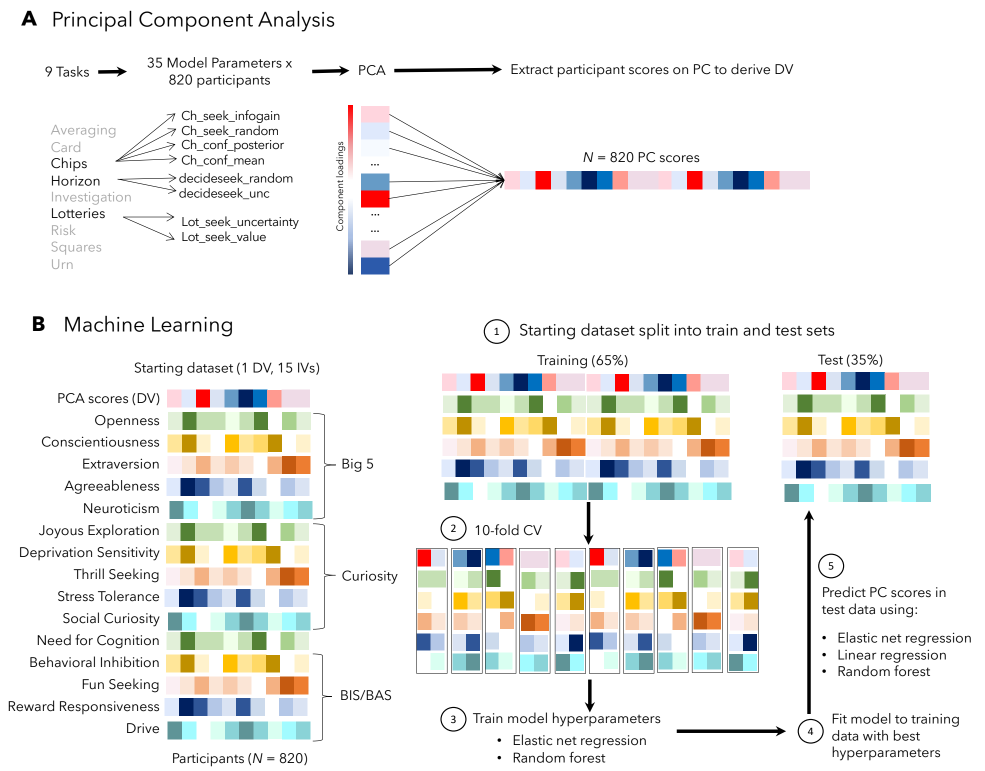

Figure 1. Study analysis pipeline. **(A) Dimensionality reduction.** For each participant, performance on the cognitive tasks was characterized by thirty-five model parameters (**Table 1**) which were then subjected to principal component (PC) analysis. This produced component loadings (i.e., weights) corresponding to each parameter's contribution to the PC. Each participant's parameter weights were then linearly combined to produce a PC score indicating the participant's PC loading across all the tasks. **(B) Machine learning.** Participant-level PC scores were the dependent variable (DV) predicted by personality traits (independent variables, IVs). To test prediction performance, we split the full dataset into a training and test set. We then used ten-fold cross-validation in the training dataset to train model hyper-parameters for elastic net regression and random forest (*Methods*). Models were fit in the training set for linear regression and, using the selected hyperparameters, for elastic net and random forest; and then test PC scores were predicted with the prediction model from the training data.

Cognitive tasks of information demand share a low-dimensional structure

The cognitive tasks were chosen to span a range of approaches that have been recently devised to assess information demand. The approaches differed in whether they used instrumental or non-instrumental conditions and in whether they had explicit requirements for requesting or rating information versus testing related constructs like attention and risk attitudes.

In 5 of the 9 cognitive tasks, participants explicitly indicated their preferences for information. In the *Lotteries* task, participants chose which source of information to inspect to infer the sum of two randomly drawn values[22,23]. In the *Investigation* task, participants chose which source of information to inspect to make a categorization decision (about which of two suspects was guilty). In the *Squares* task, participants chose whether to inspect information about reward probability or magnitude before choosing one of two distinctly valued options[31]. In the *Chips* tasks, participants chose which node in a circuit to probe to infer the connectivity of the circuit[32,33]. Finally, in the *Urn* task, participants rated their confidence and desire to obtain advance information about a probabilistic reward (gain or loss)[34]. Most of these tasks were instrumental, with participants using information to guide an incentivized choice; the *Urn* task and one version of the *Lotteries* task were non-instrumental, as participants could not use the information to alter their reward gains.

Two additional tasks used exploration/exploitation scenarios in which participants explored in advance of an economic decision. The *Horizon Task* used an exploration/exploitation scenario in which participants had to trade off the relative benefits of exploring lesser-known options for information versus exploiting known options for a more certain reward. In this task, the key manipulation is the time horizon, which changes the relative value of exploration and exploitation—favoring exploration when the horizon is long and exploitation when the horizon is short[20]. The *Card* task used a stopping scenario similar to the "secretary problem[35]," in which participants had to decide when to stop drawing cards to stick with the card they currently had to maximize their rewards[36].

The final two tasks did not involve overt information seeking decisions but examined cognitive constructs proposed to be closely related to these choices. The *Averaging* task tested attentional prioritization, examining how participants weight individual numbers in a number stream when attempting to calculate a running average of the stream[37]. Because attention and active sensing behaviors are natural information gathering actions[38], this task was included to test whether and how covert weighting of competing information relates to explicit information demand. The *Risk* task required participants to choose between deterministic versus risky or ambiguous lotteries and parametrized their tendency to seek or avoid risk and ambiguity[39]. This task was included to test whether and how information demand, which has a close mathematical relationship with risk and uncertainty, is related to risk and ambiguity attitudes.

Each task was analyzed with bespoke models that parametrized aspects of the information-seeking decisions, as well as aspects of the final decisions and confidence ratings. Individual parameters are described in detail in **Supplement A** and **Table 1** and descriptive statistics are in **Supplementary Table B1**. After accounting for outliers and poor-quality/missing data (*Methods;* **Supplementary Figure B1**), the resulting 35 parameters were pooled and submitted to a principal component analysis (*Methods*; **Fig. 1A**).

The scree plots from this analysis showed that the fraction of variance explained declined slowly over the principal components (PCs; **Supplementary Figure B2**). The lack of a clear "elbow" pattern in the plot suggests that the tasks we considered were non-redundant and tapped into distinct constructs that required multiple dimensions to explain. However, the 1st PC (which, in a 1-component model accounted for 10% of the variance in the data) captured meaningful variance for information demand (**Fig. 2A**). This PC showed strong positive or negative loadings from the *Horizon, Cards, Chips, Lotteries, Urn,* and *Investigation* tasks, but much smaller loadings, at the center of the axis, from the *Averaging*, *Risk,* and *Squares* tasks (**Fig. 2A**). Moreover, the two poles of the PC seemed to clearly distinguish information demand based on reducing uncertainty from strategies based on randomness or stochasticity[20,40]. The two parameters with the highest loadings at one pole of the PC came from the *Chips* task and described, respectively, the tendency to investigate based on expected information gain (Chips_seek_infogain) and report confidence based on posterior uncertainty (Chips_conf_posterior). The next four strongest-loading parameters described, in order, the demand for uncertainty-minimizing observations in the *Lottery* tasks, the dependence of curiosity ratings on uncertainty in the *Urn* task, the tendency to continue investigation as a function of uncertainty in the *Investigations* task, and the preference for the uncertain option in the *Horizon* task. In contrast, the three parameters that loaded most strongly on the opposite (negative) pole of the PC captured random exploration in the *Horizon*, *Card,* and *Chips* tasks. This is unlikely to have merely reflected disengaged or inattentive behaviors, as these were screened out based on independent criteria at the pre-processing stage (*Methods*) and some parameters measuring stochasticity lacked strong negative loadings (e.g., from the *Squares* task). Thus, as we elaborate in the *Discussion*, this PC seems to have captured a continuum of exploration that corresponds loosely with the distinction between directed versus random exploration—that is, a cognitive-heavy information seeking style focused on uncertainty-reduction versus a simpler strategy focused on the regulation of stochastic or random behavior[20]. Importantly, the directed-random exploration distinction was shown by both instrumental and non-instrumental tasks (*Urn* and *Lotteries)* tasks (**Fig. 2A**), suggesting it is at least partially independent of instrumental incentives.

To verify that these results are robust to model specification, we compared models containing 1, 2 or 3 PCs (**Supplementary Table B3**). The 2nd and 3rd PC, which captured additional ~6% of the variance each, had no obvious interpretation in terms of information gathering. The 2nd PC in both models showed heavy loadings on parameters from only the *Squares* task, while the 3rd PC included a scattered mix of parameters from the *Squares*, *Averaging* and *Risk* tasks. Most importantly, adding these PCs to the model had minimal effects on the 1st PC loadings (**Supplementary Table B3**), supporting our conclusion that the 1st PC captures shared variance across information gathering tasks that is distinct from related cognitive tasks.

Finally, the results were confirmed with a network graph visualizing the statistically significant zero-order parameter correlations ($p < .05$, Bonferroni-corrected**; Fig. 2B;** see also **Supplementary Fig. B4** for exact correlation matrix between parameters). Consistent with the PC loadings, the graph revealed a core region of strongly interconnected parameters from the information-seeking tasks, and more peripheral, weakly connected locations for parameters from the *Averaging*, *Risk* and *Squares* tasks (**Fig. 2B**). This structure can also be observed via metrics of network centrality (**Supplementary Fig. B5**). In sum, dimensionality reduction analyses capture features that are specific to information seeking/exploration decisions across multiple contexts in which these decisions unfold.

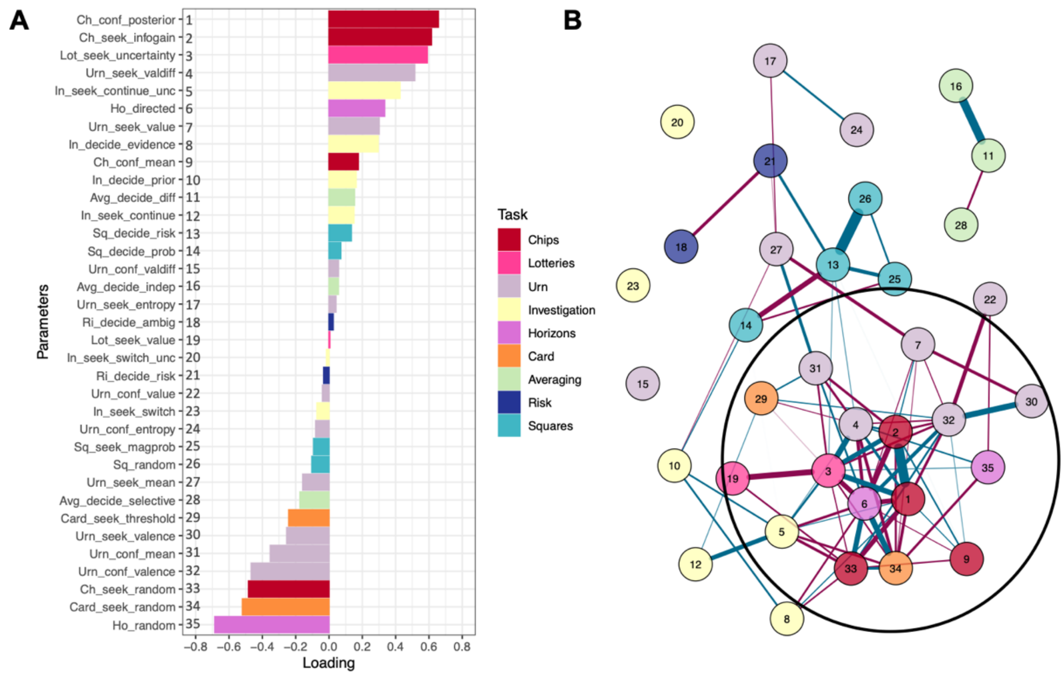

Figure 2. Relationship between parameters of cognitive tasks. For **A** and **B**, variables are color-coded by task according to the legend in the center of the figure. **(A) Principal component loadings from a 1-component model,** ordered by the sign and magnitude of the loading. The parameter labels are the same as in **Table 1**. The color coding indicates the task as specified by the legend. **(B) A network graph displaying zero-order correlations between task variables**. Nodes (colored circles) refer to variables and lines indicate correlations between variables. Red and blue lines indicate, respectively, positive and negative correlations and line thickness corresponds to correlation strength. Only significant correlations are shown (p < .05, Bonferroni corrected for multiple comparisons). The color coding by task and the numbering of the nodes correspond to those in **A** to facilitate cross-comparison between graphs. The black circle superimposed over the graph facilitates visualization of the center area of the network.

Predicting Information Demand from Personality Traits

Given our identification of a low dimensional structure in information demand, we next asked whether this structure was associated with personality traits. To this end, we computed for each participant an "information demand" score as a linear combination of their parameter values multiplied by loadings on the PC. Thus, participants with more positive PC scores were more likely to use uncertainty-reducing strategies, while those with less positive scores were more likely to use stochasticity-based strategies across multiple information-gathering tasks. We then analyzed if these scores could be predicted by a set of 15 measures of personality traits that were derived from 4 personality scales. Five of the traits came from the *Big Five Inventory* and included openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism[30]. Five additional traits came from the *Five Dimensional Curiosity Inventory* and included joyous exploration, deprivation sensitivity, social curiosity, thrill seeking, and stress tolerance[5]. Four traits came from the *BIS/BAS* questionnaire and included the behavioral inhibition system and the fun seeking, reward responsiveness, and drive sub-scales of behavioral activation system[41]. The final trait was *need for cognition*, which measured the preference for complex thinking — e.g., *I prefer my life to be filled with puzzles that I must solve*[42]. Descriptive statistics for all 15 measures are given in in **Supplementary Table C1**).

We used a machine learning approach to assess the joint contribution of many personality traits, with regularization and cross-validation procedures to minimize the chance of overfitting and incorrectly inferring signal from noise[43,44]. Specifically, we *a priori* split the dataset into a 65/35 train/test set, imputed missing data, used 10-fold cross-validation to train model hyperparameters on the train set, and assessed prediction accuracy in the held-out test set (**Fig. 1B** and *Methods*). Finally, we applied these methods to 3 alternative methods: elastic net, linear regression, and random forest. This was beneficial both as a robustness check and as a clue to possible underlying structure of the data (for example, if a nonlinear model outperforms linear models, this could indicate that the underlying structure of the data is nonlinear). All models performed similarly, providing no evidence that the findings reflect the idiosyncrasies of a particular algorithm

(**Fig. 3B**). For simplicity, we focus primarily on the results from elastic net regression, which has the advantage of being similar to linear regression and thus easily interpretable, while including penalties for model complexity to reduce the risk of false positives (**Supplementary Tables C2 and C3** provides the elastic net and random forest model tuning grids, respectively).

Individual participants' PC scores of information demand were significantly predicted by personality metrics, as shown by the high correlation coefficients between predicted and actual scores ($r = .44$, $p < .001$ for the elastic net model, **Fig. 3A**; $r = .43$ $p < .001$ and $r = .44$ $p < .001$ for, respectively, linear regression and random forest models). Prediction R^2 values showed that the models predicted 15-20% of the variance in the data, with R^2 values (mean across 5 imputations, $n = 279$ in the test set) .19 for elastic net regression; .16 for linear regression, and .20 for random forest. Analysis of the mean absolute errors between observed and predicted results showed that all 3 personality-based models were superior to a null model in which information demand was set to the average across all participants in the train data (**Fig. 3B**; Wilcox signed rank test relative to the null model: elastic net regression $p = .010$, linear regression $p = .030$, random forest $p = .002$).

Examination of individual weights showed that predictive capacity was associated with a small subset of traits (**Fig. 3C**). Significant positive predictors of PC scores were need for cognition (the preference for deep thinking), stress tolerance (the tendency to be comfortable with uncertainty), and behavioral inhibition, while significant negative predictors were extraversion and thrill seeking. These results were consistent in the elastic net (**Fig. 3C**) and alternative models (**Supplementary Fig. C1; Supplementary Table C4**). Although social curiosity was also a positive predictor of PC scores for elastic net (**Fig. 3C**), this trait failed to be a significant predictor in linear regression (**Supplementary Table C4**) and produced low feature importance scores in random forest (**Supplementary Fig. C1**); given the lack of consistency across models, we do not further interpret social curiosity scores. Overall, participants who adopted more uncertainty-focused information demand tended to have higher scores on need for cognition, stress tolerance, and behavioral inhibition, and lower scores on thrill seeking and extraversion.

To verify these results, we constructed alternative models in which personality traits predicted individual parameter values rather than the aggregate PC score (**Supplementary Figure C2**). These models rarely outperformed the null model, supporting our conclusion that the PC captures meaningful variability that enhances statistical power in detecting associations with personality traits. While the results must thus be interpreted with caution, their trends support our conclusion. Prediction accuracy tended to peak for the personality metrics that showed high predictive power for the aggregate PC score, with parameters indicating directed versus random exploration tending to show opposite weights (respectively, positive/negative associations with need for cognition, stress tolerance, and behavioral inhibition and negative/positive associations with thrill-seeking and extraversion).

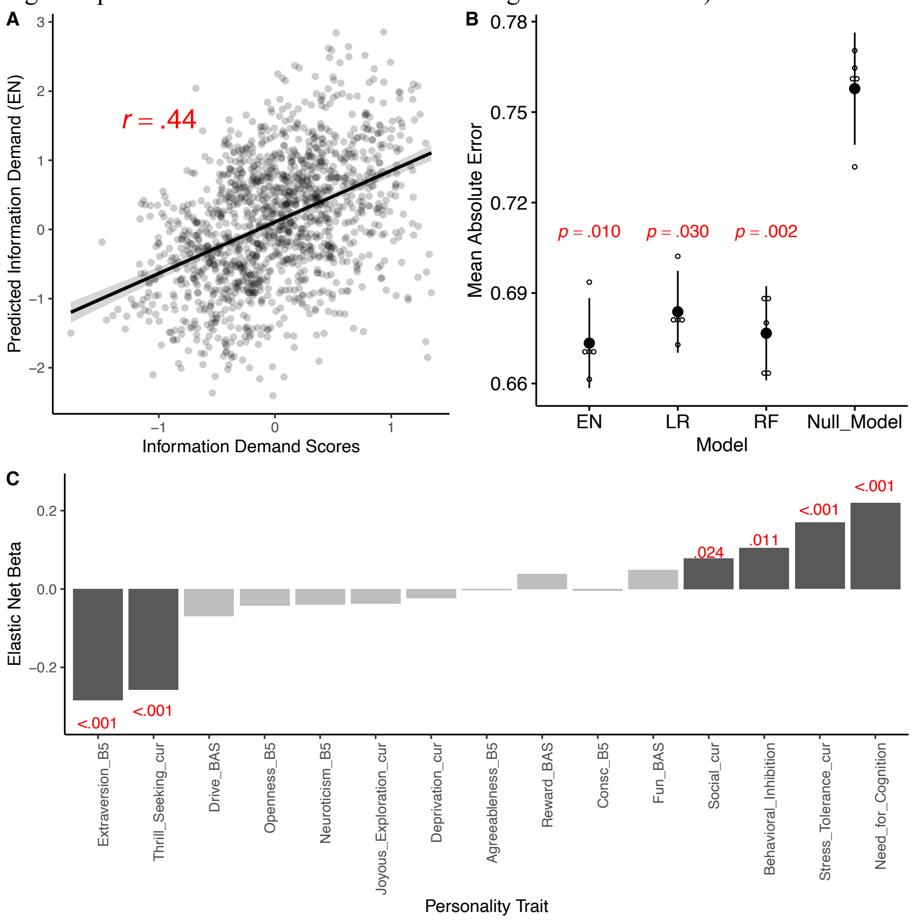

Figure 3. Predicting PC scores from personality traits. **(A) Correlation between predicted and observed information demand for the elastic net model in the test dataset (N = 279)**. Each participant has 5 points corresponding to 5 multiple imputations, but the *r* value is the Pearson correlation derived by integrating across imputations and applying Rubin's rules for combining technical replicates[45]. **(B) Comparison with a null model** where PC scores were set to the mean. The filled circles show the Mean Absolute Errors (mean and 95% confidence intervals across 5 imputations), for each model, and the open circles show the Mean Absolute Error for each imputation. **(C) Predictive power of each personality trait.** The bars show the regression beta weights from the training dataset (N = 541 participants) in the elastic net model. The black bars and numbers show the weights that were statistically significant at p < .05, and gray bars show non-significant weights (significance assessed via permutation test, 1000 permutations x 5 multiple imputations for each trait; *Methods*).

A striking aspect of these findings is that the core measures of trait curiosity—joyous exploration, deprivation sensitivity, and openness to experience—did not emerge as significant predictors in our analyses. A possible explanation was that the effects of these traits were masked by need for cognition, which was a significant predictor of information demand and was significantly correlated with these and additional traits (**Supplementary Fig. C3**). However, repeating the analyses after removing need for cognition scores replicated the findings, leaving overall predictive power intact while failing to increase the weights of the curiosity traits (**Supplementary Fig. C4**). Thus, need for cognition was not unduly skewing the findings or suppressing other curiosity traits.

Importantly, the association with personality metrics did not seem to be affected by instrumental incentives. Parameters from the non-instrumental Urn task followed the same associations with personality scores as those from the instrumental tasks (**Supplementary Fig. C2**). To verify this result, we compared the 3 versions of the *Lottery tasks*, which had identical information-sampling steps and differed only in the presence or absence of instrumental incentives (**Supplementary Fig. C5**). Parameters extracting value and uncertainty-sensitive sampling were highly correlated across the instrumental and non-instrumental tasks (**Supplementary Fig. C5A**), confirming the conclusion from the PC analysis above. Importantly, these parameters showed similar associations with personality traits in the instrumental and non-instrumental conditions (**Supplementary Fig. C5B**), supporting the view that personality traits predicted the tendency for uncertainty-focused exploration independently of instrumental incentives.

Discussion

Curiosity drives human innovation and development, but how well do we understand this construct? In this study, we demonstrate that inter-individual variability across diverse tasks of information demand can be captured by an axis which resembles the distinction between directed versus random exploration[20,21]. Second, we show that this axis is predicted by curiosity traits in personality research, consistent with literature describing a correspondence between traits and states[1,27,28]. Third and most remarkably, we show that personality predictors of uncertainty-driven information demand are not the central curiosity personality traits of openness to experience, deprivation sensitivity, and joyous exploration, but instead include more peripheral curiosity traits (need for cognition, thrill seeking, and stress tolerance), and measures not traditionally associated with curiosity (extraversion and behavioral inhibition). We discuss the significance of these findings for cognitive studies of information demand and their relation with research on personality traits.

Uncertainty-Driven Information Demand

Our findings suggest that diverse tasks of information demand tap into a common low-dimensional structure that distinguishes between information demand based primarily on uncertainty versus randomness or stochasticity. The PC describing this structure did not trivially reflect engaged versus disengaged/inattentive behavior, as shown by our use of multiple task design features, attention checks, and analyses to ensure performance quality (**Methods**) and by the fact that the highest loading parameter indicating stochasticity came from the Horizon task in which randomness is controlled strategically based on the exploration horizon[20].

The low dimensional structure we found is remarkable given the vast differences between the tasks we included – which required participants to guess the causal structures of electrical circuits (*Chips*), investigate a suspect (*Inspector Bayes*), explore for an economic decision (*Horizon*), report curiosity about a probabilistic outcome (*Urn*) or guess the sum of two prizes (*Lotteries*). Importantly, the random vs directed exploration distinction cut across tasks in which the information was instrumental for obtaining external rewards (*Chips, Inspector Bayes, Horizon,* and some of the *Lotteries tasks*) or was intrinsically valued as a good in itself (*Urn* and other versions of the *Lotteries* task). Detailed comparisons of the instrumental and non-instrumental *Lotteries* tasks confirmed that uncertainty-bound information demand clustered together regardless of instrumental incentives (**Fig. 2**, **Supplementary Fig. C5**) consistent with previous evidence from behavior[25] and neural activity[38,46] that uncertainty drives are independent of specific incentives. These findings suggest that random versus directed exploration are fundamental strategies that are recruited across a wide range of conditions – whether information serves instrumental incentives or is valued as a good in itself, bolstering previous findings that these strategies develop differently over the lifespan[47–49], are differentially altered in anxiety[50] and schizophrenia[51], and have dissociable neural substrates[52–57].

It is important to note that a substantive set of our parameters did *not* show strong loadings on our PC. This establishes the specificity of the construct that was identified by the PC and suggests processes that are likely to fall outside its confines. One class of parameters that had only weak loadings on our PC were those reflecting valence-driven information demand (**Fig. 2**; **Supplementary Table B2**). Given the robust evidence for the importance of anticipatory emotions in information gathering[18,58], we believe this finding reflects the fact that only two of our tasks measured valence effects (the *Lotteries* and *Urn* tasks), and these tasks pitted valence against uncertainty-driven information demand, biasing the analyses to capture valence as stochasticity (i.e., 2 of 3 valence parameters had moderate negative loadings). Thus, better understanding anticipatory emotions and their relation to personality traits will require a wider range of cognitive tasks that specifically focus on valence effects.

A second class of parameters with weak PC loadings were those describing risk and ambiguity preferences in the *Risk* task (**Fig. 2**). This result is noteworthy because it suggests that, despite the fact that information, risk and uncertainty have very similar mathematical operationalizations, they involve dissociable neural and psychological mechanisms[59],[22]. A third and final set of weakly-loading parameters were those indexing selective attention in the *Squares* and *Averaging* tasks. This finding seems puzzling given the prominent role of attention and active sensing behaviors in sensory information gathering[21,25,38, 63, 66], and is likely to reflect the specific ways in which attention was parametrized in our tasks. In the *Squares* task, the parameters measured the participants' relative preference for observing an option's reward magnitude versus probability but did not reflect the information gains of each feature. In the *Averaging* task, the parameters measured the weight of a stimulus in the economic decision rather than on covert attention *per se*. These considerations reflect the multiple ways in which attention can be operationalized and suggest that metrics that specifically measure the focusing of attention to reduce uncertainty are needed to characterize the relation of attention to exploratory strategies.

Together, these findings highlight the benefit of assessing multiple tasks simultaneously for understanding the common and unique components measured by the tasks. Both the common axis of uncertainty-driven and random exploration, and the fact that some constructs related to information gathering do not load strongly on this axis because of differences in contexts and/or parametrizations, would have been missed if a single task was selected and assumed to be representative of information demand.

Convergence and Divergence Between Curiosity Literatures

The second key result we report is that, while the low dimensional structure in information demand was predicted by personality traits, predictive power came from traits that were peripherally or not closely associated with curiosity. We interpret this result as indicating methodological distinctions between cognitive psychology and personality research, which lead the two fields to emphasize different aspects of curiosity.

Turning first to the traits that did predict information demand, some showed positive associations with uncertainty-driven strategies (need for cognition, stress tolerance, and behavioral inhibition) while others predicted more stochasticity-driven strategies (thrill seeking and extraversion). The positive association between uncertainty-driven exploration and need for cognition is consistent with the fact that estimating the expected reduction in uncertainty (information gain) is a complex operation, and suggests that individuals who choose to adopt this strategy tend to prefer deep and complex thinking as indexed by this personality trait[32]. The relationship between uncertainty-driven exploration and higher stress tolerance suggests that the willingness to search for informative options can benefit from a higher capacity to tolerate uncertainty-related stress. We note that stress tolerance correlates highly with uncertainty intolerance in empirical studies ($r \sim -.85$[60]) and thus we expect that our findings would replicate had we used other scales reflecting attitudes to uncertainty (i.e., on the Intolerance of Uncertainty scale[61], more tolerance of uncertainty would predict greater directed exploration). Finally, the relationship with behavioral inhibition—the tendency to experience fear and anxiety when expecting potential punishment—suggests that individuals who are more sensitive to punishments may be more willing to adopt costly discriminatory strategies to avoid errors (consistent with findings that excessive information demand is related to traits including obsessive compulsive disorder and neuroticism that are similar to behavioral inhibition[62,63]).

Conversely, we found that thrill seeking, which measures risk taking, avoidance of boredom, and novelty preference [5,64,65] predicts less uncertainty-driven and more random exploration. This suggests that some participants who used random exploration—i.e., did not gather the best information for accurately predicting an outcome—may have done so in order to experience the thrill or novelty of receiving an unpredictable outcome, or perhaps to alleviate boredom while performing the task[47,66]. Last but not least, more random exploration was robustly predicted by higher extraversion, a result we attribute to the breadth of this personality metric. Extraversion is related to greater risk taking[67] and may act through similar mechanisms as thrill-seeking; in addition, extraversion is linked to optimism and positive affect[68], suggesting that a more optimistic attitude may reduce the salience of potential errors and the consequent motivation to employ mentally costly information-gathering strategies to avoid errors.

Together, these findings suggest that preferences for random versus directed exploration are associated with a suite of cognitive and emotional strategies that are relatively stable across contexts and time and are measurable as personality traits. The traits we identified index how an individual appraises various aspects of uncertainty—namely, how one weights the stress that uncertainty may provoke, the surprises or errors it produces, or the cognitive effort needed to resolve uncertainty through information gathering[69]. Our results suggest that tendencies to use directed versus random information gathering strategies result from different constellations of traits in different individuals, such as a general preference to think deeply (need for cognition) in some individuals and, in others, an attempt to avoid boredom (thrill seeking) or, conversely, to avoid making mistakes (behavioral inhibition).

In contrast with the predictive power of the constructs above, information demand strategies in the cognitive tasks were not well predicted by the core constructs of curiosity (**Fig. 3**). These include joyous exploration, reflecting interest in exploring and learning, deprivation sensitivity, reflecting a need to eliminate a specific information gap, and openness to experience, encompassing broader differences in curiosity, creativity, and aesthetic sensitivity. One possibility is that this negative finding is explained by task implementation details, like the fact that our tasks required participants to express curiosity as a behavior rather than a subjective experience (i.e., act on the information rather than report their curiosity for it). However, this is refuted by our analysis of individual tasks (**Supplementary Fig. C2**) which showed that parameters from the Urn task—in which participants did report their subjective curiosity states—were not better predicted by curiosity traits relative to other tasks in which participants expressed curiosity as a behavior.

A more plausible explanation may lie in broader differences in the *type* of information that is assessed in cognitive versus personality research. Following the longstanding tradition in cognitive science, the tasks we included involved highly simplified information about a reward (a payment that may arrive later on) or, at most, information about highly simplified abstract situations that would not be mistaken for natural exploratory behavior—e.g., a fictitious circuit in the *Chips* task, a number stream in the *Averaging* task, or a highly stylized "investigation" in the *Inspector Bayes* task. This reflects the deliberate practice in cognitive studies to use controlled situations that avoid tapping into participants' natural and personal knowledge, which would add undesirable variability to the results. However, this practice may explain the null relationships we report with respect to core curiosity traits. Indeed, recent results show that openness to experience, joyous exploration, and deprivation sensitivity were robustly related to curiosity about trivia questions that tap into the participants' rich personal knowledge (e.g., "What is the height of the Eiffel tower?")[6,70,71].

We propose, therefore, that cognitive tasks and personality studies are optimized for revealing different aspects of curiosity. Cognitive tasks are designed to facilitate computational analyses and the dissection of neural and psychological reactions to uncertainty and, as we have shown, correlate with important personality metrics indexing reactions to uncertainty. However, these tasks do not sufficiently tap the core curiosity traits that index emotions such as desire to know, the joy of finding the answer, as well as imagination, creativity or aesthetic sensibility—processes that may be best unmasked when participants interact with their rich personal knowledge banks[70] and/or explore their environment in more naturalistic contexts. Thus, an important challenge for future research is to design tasks that maintain computational tractability and analytical depth and also permit more naturalistic exploration and/or tap into personal knowledge banks, as recently attempted by several authors[17,72–76].

In sum, our findings suggest that cognitive tasks of information demand evoke reliable reactions to and appraisals of uncertainty, which generalize across contexts and are predicted by personality traits. However, these tasks do not yet capture the full range of cognitions and emotions that form the core curiosity traits, indicating a need for caution in comparing results across fields, as noted previously with respect to curiosity[22,70,77] and self-regulation[78,79]. Although no field has primacy on the "correct" definition, it is crucial to identify the relationships between conceptualizations and avoid jingle fallacies whereby different constructs hide under the same name[29] particularly for a term that has such salience in the popular mindset as curiosity[80]. Multidisciplinary collaborations are highly beneficial for this aim.

Methods

Participants

The study was approved by the Institutional Review Board of Columbia University. Participants (N = 820) were recruited online on Amazon Mechanical Turk between August and December 2020. After registering for the study and providing informed consent, participants completed up to 10 tasks implemented in custom software (Haratki LLC) as described further below. Meta-analytic evidence suggests that inter individual correlations stabilize at a sample size of $N \sim 250$[81]; a sample size of 820 participants meets this criterion as, assuming a 65/35 test/train split, it provides 279 participants in the test set.

Procedure

Once participants registered for the study they provided (optional) demographic information about age, sex and education and embarked on the sequence of tasks. The sequence started with an automated email inviting the participant to perform one of the tasks; after completing the task, the participant received the next invitation, and so on until they completed all tasks or disengaged from the sequence. Each task was randomly selected without replacement, so that each participant performed the tasks in randomized order and performed each task only once. A new invitation was issued 2 hours after completion of the previous task, preventing participants from rushing through all the tasks in one setting. However, once issued, an invitation remained active indefinitely and participants could complete the task at a time of their choice.

Participants received payment after completing each task and, as an incentive to complete the full sequence, an additional bonus for completing all tasks within a 3-week timeframe. The payment for each task consistent of a base pay ($1 - $2) and a performance-based bonus of up to $11 (average $3 across tasks), and the bonus at the end of the sequence was $5. These rates translated to approximate hourly compensation of $5-$8 (depending on the participants' time on task) which, in 2020, was nearly double the mean and median of workers on mTurk ($2-$4[82]).

Demographic data were offered by 704 participants and showed that participants' modal age (collected in categories) was 26-30 years old (range, 18-75 years old), 44% were women (56% men, 2 identified as "other"), and highest educational attainments were college (59%), post graduate degree (23%), high school (17%) or vocational school (1%).

Measures to ensure data quality

Testing on online platforms like Amazon Turk is widely used in psychology and social science research, and a considerable literature shows that it produces results comparable to those obtained in in-lab research both in terms of specific findings and reliability[83–85]. However, online testing raises special concerns related to bots, the potential for poor task comprehension and inattentive behaviour, which can be minimized through careful task design and analysis methods. Thomas and Clifford[86] offer a comprehensive meta-analysis and list of best-practices to ensure data reliability, and we implemented these practices carefully in our task design and analyses.

A core recommendation of Thomas and Clifford is to embed in each task multiple screeners for identifying poor quality or inattentive performance, including screeners for bots and screeners that are novel and specific to individual tasks[86]. Following these recommendations, we implemented a two-level screening procedure across all our tasks. The first-level (technical) check relied on two features: to register for the task, participants had to be adults over 18 years of age, live in the United States, and have completed more than 100 prior Amazon Turk tasks with an approval rate of over 80%; in addition, while performing each task, participants had to correctly answer 2-3 randomly interspersed questions designed to detect bots (e.g., "What is the color of the sky on a sunny day?", with two choices of "red" or "blue"). The second-level, performance quality check relied on task-specific "catch" trials that were randomly interspersed in each task. The catch trials were identical to the other trials in the task but were trivially easy to solve; for example, the risk preference task presented some trials where options differed greatly in value and the (obvious) correct choice should be selected on 100% of the trials by an attentive participant. Finally, as recommended by Thomas and Clifford[86], we ensured transparency by clearly informing participants about the registration requirements, that a task would be terminated without payment if they failed a bot question, and that task trials would vary in difficulty.

As an additional precaution against rushed responding or interruptions, we imposed reaction time limits, including a minimum reaction time to prevent participants from speeding through the task and a maximum reaction time to ensure they did not take breaks in the midst of a trial. Because each task had different requirements, the limits were adjusted for each task based on the individual investigators' recommendations as explained in **Supplement A**. Responses with reaction times outside of this range produced immediate feedback of "Too slow", or "Too fast" and caused the trial to be discarded and be repeated later in the block. Participants were informed about the allowed reaction time range, ensuring transparency.

To ensure adequate comprehension, we paid particular attention to designing instructions that were clear and easy to follow. Before starting each task, participants read extensive instructions that explained the purpose of the task, followed by detailed explanations and screenshots of the displays they would see at each step of a trial. Participants then completed comprehension tests with 3-4 multiple-choice questions about the instructions; in case of an incorrect answer, they were returned to the instructions to read them again. Finally, participants completed 3-5 practice trials before proceeding to the full task. At all steps of this process, participants could navigate back to reread any part of the instructions for as long as they wished.

Further details on these screeners and their use for data analysis are provided in the **Supplementary Materials** as follows: **Supplement A** describes the task-specific screeners and quality scales for each task; the **Data Preparation and Preprocessing** section below describes the exclusion criteria; **Supplementary Table A2-1** gives a tally of the excluded/included participants, datasets, and parameters for each task; **Supplementary Table B1 and Supplementary Figure B1** give details on the parameter distributions and outlier exclusions. Finally, **Supplementary Figures C6, C7 and C8** show that all our results are replicated, albeit more noisily, before task-level exclusions above, showing that our screening procedures did not distort the results.

Last but not least, we note that, although we could not provide an in-lab replication of this extensive dataset, the majority of the tasks we included had been previously validated in laboratory settings, often multiple times[20,22,23,31–34,36,37,39,47,50,51,87–93]. In **Supplement A**, we provide references relevant to each task, showing that our results confirm previous findings from individual tasks. Similarly, we used well-established personality questionnaires and, in **Supplementary Table C1** we provide detailed descriptive statistics for each set of results and references documenting comparable reliability to prior published results.

Behavioral Tasks and Model Parameters

The cognitive tasks we employed assessed processes involved in information demand (*Chips, Investigation, Lotteries, Horizon, Urn,* and *Card*) or behavior conceptually related to information demand (*Averaging, Squares,* and *Risk*). Of the tasks, *Urn* and one condition of the *Lotteries* task assessed non-instrumental information seeking; the remaining tasks were instrumental. A detailed description of each task, the model used to assess it, and the model parameters we extracted can be found in **Supplement A**. We provide a summary in the current section.

The six tasks of information demand required participants to seek information in diverse contexts. In *Chips*[32,33], participants attempted to discover the structure of a toy 3-node or 4-node causal system (described to the participant as a computer chip). Participants could select causal interventions that would elicit confirmatory information in favor of a single hypothesis or discriminatory information that would disambiguate between competing hypotheses. In *Investigation*, participants tried to guess which suspect (Red or Blue) was guilty of a crime by *enquiring* (i.e., seeking information) about the suspect; they could choose to pay a cost from their initial endowment to enquire. In the *Lotteries* task (based on a prior study[22], with some instrumental variants of the task added), participants received random payoffs from the sum of two lotteries that differed in their expected value and variance. On each trial, they had the option to seek advance information about one of two lotteries. The *Horizon* task[20] is a variation on the classic Bandit task. Participants could choose between two slot machines that paid out random rewards from two Gaussian distributions with fixed variance and different means. There was either one opportunity or six opportunities to sample from these bandits (i.e., seek information), reflecting differing levels of "time horizon". Prior to making their free choice, participants are given four forced choices, allowing experimenters to manipulate the information participants have about the bandits' distributions. In the *Urn* task[34], participants see a jar (i.e., urn) with red and blue marbles in different quantities, where both marbles are associated with a monetary gain or loss (i.e., when the marble is virtually chosen from the urn). Participants rate how *curious* they are to learn the outcome and how *confident* they are that they will gain or lose the highest possible absolute value. Trials vary by valence (i.e., winning or losing money), expected value, uncertainty (the difference between the two monetary values associated with the marbles) and entropy. At the end of the trial, participants either see which colored marble was selected for them and how much money they gained or lost in that trial, or they see a black marble that does not provide information about this outcome. The *Card* task[36] assesses information demand in the context of a stopping problem. In this task, playing cards are flipped over one-by-one (between 2 and 5 cards total per trial), revealing a number from 1 to 100 randomly sampled from a uniform distribution. The participants' aim is to select the card with the highest number on each trial: once they "stop" the search, no more cards will be flipped over and that will be their final trial payout. Thus, participants need to decide if they want to stop their search early or continue to seek information and risk obtaining a worse reward on a later trial.

The remaining tasks (*Averaging, Squares,* and *Risk*) assess theoretically-related concepts to information-seeking. The *Squares* task[31] characterizes decision-making under risk (uncertain situation, where outcome probabilities are fully known) for different monetary values and probabilities of success. Participants make choices between a constant 5 points and a risky lottery under various probabilities of payout and reward magnitudes. The *Risk* task[39] similarly assesses decision-making under uncertainty (again, making a choice between a certain 5 points and an uncertain number of points, which were then translated into money), but investigates both risky decisions and decisions that vary in ambiguity (participants do not know the precise probability of obtaining the reward). Given that exploratory behavior is often taking place in environments where the probability structure of the world is fundamentally uncertain, these tasks were considered valuable additions to gain a comprehensive assessment of information demand. Finally, in the *Averaging* task[37], participants view six values presented in two groups and guess which group has the highest average value, with rewards for being accurate. This paradigm is designed to assess processes related to integrating information for the purposes of decision-making. This paradigm was included in the group of paradigms because of the putative link between attention and curiosity described in prior literature[11,38].

Computational models describing choice behavior were fit to all tasks; descriptions of these models can be found in Supplement A alongside each task description. Participant-level model parameters were extracted from computational models and these parameters (or derivations/composites thereof) formed behavioral variables which we compared to one-another and to personality traits. Parameters were diverse, reflecting the variety of models of choice behavior and variety of behavioral tasks employed. Table 1 summarizes all parameters used in this study.

Personality Traits

Fifteen personality traits were measured from four personality trait scales, with the presentation order of each scale randomized. Personality traits were chosen to provide good coverage over those reflecting curiosity/information demand (i.e., five facets of the Five Dimensional Curiosity Inventory, the Big Five trait openness to experience, and need for cognition, which describes the related tendency to enjoy complex thinking) as well as well-established personality measures that are not thought to reflect curiosity/information demand. Descriptive statistics and internal consistency are reported in Supplement D. Internal consistency α was above .73 for all traits except for BAS fun-seeking (α = .62). All traits were relatively normally distributed, with skew and kurtosis values of less than 1, with the exception of BAS-reward (skew = -1.17, kurtosis = 1.56). Across all personality traits, we excluded participants' data if we observed timing issues (i.e., 3 or more trials with response time below 500ms) and/or little variation in answers (i.e., at least one of the four questionnaires contained *all* the same answers). This quality check led to the removal of 17 participants' questionnaire data.

Curiosity. The 25-item Five Dimensional Curiosity Inventory[5] was used to measure five facets of curiosity: *joyous exploration* (describing the pure joy and love of learning; e.g., "I find it fascinating to learn new information.") *deprivation sensitivity* (describing a drive or "need" to know, e.g., "Thinking about solutions to difficult conceptual problems can keep me awake at night."), *stress tolerance* (describing the ability to deal with the stress of unknown situations; e.g., "I cannot function well if I am unsure whether a new experience is safe."), *social curiosity* (describing the interest in social interaction and other people, e.g., "When people quarrel, I like to know what's going on.") and *thrill-seeking* (describing the tendency to find novelty and new, potentially-dangerous experiences exciting, e.g., "Risk-taking is exciting to me."). All items were reported on a 7-point Likert scale from 1 (*Does not describe me at all*) to 7 (*Completely describes me*).

Big Five. The Big Five Inventory[30] is a 44-item scale that was used to measure the Big Five personality traits: *Extraversion* (describing the tendency to be assertive, enthusiastic, and sociable; e.g., "Is talkative"; "Has an assertive personality"), *Neuroticism* (describing the tendency to be anxious, volatile, and express negative emotionality; e.g., "Can be moody"; "Worries a lot"), *Conscientiousness* (describing the tendency to persevere, to be achievement-oriented, and to be neat and organized, e.g., "Does a thorough job"; "Does things efficiently"), *Agreeableness* (describing the tendency to be compassionate, polite, and altruistic; e.g., "Has a forgiving nature"; "Likes to cooperate with others") and *Openness to Experience* (describing the tendency to be imaginative, intellectual, and artistic, e.g., "Is curious about many different things"; "Is inventive"). Responses were scored on a 5-point Likert scale from *Disagree strongly* to *Agree strongly.*

Need for Cognition. This 18-item scale measures the preference for putting in mental effort[42] (e.g., "I find satisfaction in deliberating hard and for long hours."; (reversed) "Thinking is not my idea of fun"). Responses were scored on a 5-point Likert scale from *Extremely uncharacteristic* to *Extremely characteristic.*

Behavioral avoidance/inhibition (BIS/BAS) scales. A scale measuring reward sensitivity was important to include because curiosity is considered an intrinsic reward, many cognitive tasks involve information about rewards, and uncertainty could lead to either punishments or rewards (positive and negative outcomes). The BIS/BAS scale was best suited for this role as it compactly indexes sensitivity to punishments and rewards. Theoretically, cues of reward are proposed to activate the Behavioral Activation System (BAS), whereas cues of punishment activate the Behavioral Inhibition System (BIS). People with higher BAS sensitivity are thought to be more affected by signals of upcoming reward and should consequently experience a stronger drive to seek rewards. Conversely, people with higher BIS-sensitivity are thought to be more impacted by signals of threat and punishment[41]. The 24-item BIS/BAS scale was designed to measure individual differences in the responses to these cues of reward and punishment. Responses were scored on a 4-point Likert scale from 1 = *very true for me* to 4 = *very false for me.* To bring scoring for the BIS/BAS scale in line with the other trait measures, responses were reverse scored prior to analyses such that higher scores reflected greater assent.

Data Preparation and Preprocessing

Data cleaning and quality checks. We removed poor-quality data in three sequential steps. In Step 1, datasets that failed the first level (technical) screening—that is, failed a bot test or had duplicate or missing Amazon Turk IDs—were discarded and not advanced to the analysis stage. In Step 2, from the remaining datasets we removed those that failed task-specific screening criteria (described in the **Measures to Ensure Data Quality** section above). In Step 3, we fit the datasets passing Step 2 to task-specific computational models (described in **Supplement A**) and removed outlier parameter values falling within the 2.5% of either tail of the parameter distributions. Step 2 was applied at the level of task and Step 3 was applied at the level of parameter. That is, if data from a participant were removed from one task at Step 2, they were not automatically removed from the other tasks the participant performed; similarly, if a specific parameter was removed for a participant at Step 3, that participant's parameter values were not automatically removed in all tasks. These procedures ensured that our exclusion criteria were clearly defined for each individual dataset and parameter.

Supplementary Table A2-1 provides details of the datasets and parameters that were excluded at each step for each task, and **Supplementary Table B1** shows descriptive statistics for parameters after Step 3. All data exclusion steps were decided and implemented prior to analyses.

Four lines of evidence confirm the quality of the resulting body of data. First, across the tasks only 2% - 17% datasets were eliminated at Step 2 (median = 8.4%), suggesting that inattentiveness was not pervasive in our study. Second, results were similar (albeit noisier) if analyses were applied before Step 2 (i.e., including the data sets deemed to have poor quality at Step 2; **Supplementary Figs. C6-C8**). Third, six of the 9 cognitive tasks had been previously tested in the laboratory (*Lotteries, Urn, Risk, Horizon, Chips, Squares*), and in each case our results reproduce those obtained in the laboratory as is described for each task in **Supplement A**. Finally, reliability (alpha internal consistency) for personality traits were comparable to those in the original studies introducing these questionnaires, as is documented in **Supplementary Table C1**. Together, these measures validate our use of online testing and the reliability of our data relative to previous research.

Factor scores of personality traits. Latent measures of personality traits are superior to a simple mean- or sum-score of scale items, as latent scores account for measurement error and provide less biased estimates[94]. However, it was not feasible to integrate formal structural equation modeling alongside a complex machine-learning pipeline with multiple-imputation. Thus, we employed a "middle-way" approach by conducting an exploratory factor analysis with one factor requested per trait/facet (employing ordinary least squares with a direct Oblimin rotation) and saving latent factor scores with the correlation-preserving (''ten Berge") method[95]. These saved scores were used in the inferential analyses described below.

Imputation of missing data. Because each variable had missing values due to differential rates of completion and the results of the quality checks (**Supplementary Table A2-1**) we used multiple imputation (MI) to provide 820 datasets for each task. MI is a principled method that provides efficient and unbiased estimates across many situations, including when data are not missing completely at random[96]. Alongside Full Information Maximum Likelihood methods, MI is considered best practice in scientific research with missing data[45,97]. Employing MI allowed us to achieve a total sample size of 820 participants, which is substantially more than had we limited our analyses to complete cases.

Briefly, this method accounts for missing data by creating n versions of a given dataset (we used n = 5), where missing values are imputed with different values in each dataset according to a particular algorithm. This study employs the *predicted mean matching* algorithm within the R package *mice*[98]. Predictive mean matching employs linear regression to predict a target variable Y from other variables in the dataset. The regression model is then used to predict both observed and missing values of Y, and missing value Y_i is assigned a number of possible "candidate" values of Y based on the closeness between predicted $\hat{Y}_i$ and other values of $\hat{Y}$. One value is randomly chosen from these candidate values, and that is assigned to Y_i. This process is then repeated several times to create n multiply-imputed datasets[99,100]. Note that when multiple imputed datasets were created, we created imputed data on the training set and used those results to create imputed test sets.

After multiple datasets are created, the next step is to conduct desired statistical analyses on each dataset and then pool analyses to derive an estimate that accounts for the uncertainty of missing values. Multiple imputation includes well-developed procedures for pooling results of some analyses (correlation, regression) using Rubin's rules[45]. Unless otherwise mentioned, all results are presented on multiply imputed data.

Analysis Strategy

Dimension reduction. Fig. 1 provides a visual depiction of our analysis strategy. Variables were subjected to a one-factor principal component (PC) analysis for the purpose of dimension reduction across 35 model parameters (component loadings **Fig. 2A**). We then extracted the component scores for each participant; these component scores were our key dependent variable that we predicted from personality traits (**Fig. 1A**). For comparison with PC results, we additionally performed network analysis on zero-order correlations between model parameters (**Fig. 2B**) and computed measures of network centrality (**Supplementary Fig. B4**). Finally, we conducted additional analyses predicting each of our model parameters as separate DVs (**Fig. D2**) to compare with overall results predicting PC scores.

Machine Learning. The *R* package *caret*[101] was used for all machine learning analyses. We predicted PC scores (i.e., information demand) with three supervised learning models: two linear models (elastic net regression and linear regression) and one nonlinear model (random forest). In the manuscript body we present results from the elastic net regression; results from the linear regression and random forest can be found in Supplement C.

Linear regression was chosen as it is the most familiar to researchers without prior experience in machine learning, and hence is a good baseline model with easily interpretable coefficients. Elastic net regression was chosen as it is an extension of linear regression (and thus, is easily comparable) that employs regularization to penalize the size of regression coefficients. Regularization results in more parsimonious models compared to linear regression and reduces the chance of models overfitting to the training data[44]. More specifically, elastic net regression combines the *ridge regression* and *lasso regression* by reducing the impact of coefficients in different ways: via a mixture of setting some coefficients to zero (*L1* regularization; similar to lasso regression) and shrinking the size of coefficients (*L2 regularization;* similar to ridge regression). Finally, random forest was chosen as a popular nonlinear model for comparison to linear models. The random forest model[102] was chosen as our non-linear modelling option. Random forests are an assortment of decision trees which produce powerful predictions by capturing the non-linearities, interactions, and subgroup effects within data, without becoming too sculpted (or "overfitting") to a particular sample or data frame. Feature selection occurs intrinsically in random forests as trees only use the features to split the data that are the most optimal. This is a very different method to linear models, and thus evidence of similar variables' importance across both linear and nonlinear models provides stronger evidence than considering one model in isolation.

Data were split into a training set (65%) and test set (35%). To tune model hyperparameters for the elastic net regression and random forest**,** we conducted 10-fold cross validation on the training set (**Fig. 1B** and see **Supplementary Table C2/C3** for hyperparameter tuning grids). The best hyperparameters were selected from this process and the training set was fit with these values. The fit model from the training set was then applied to the held-out test set to predict scores.

We assessed model performance (comparison between predicted PC values and actual PC values) with the Mean Absolute Error and prediction R^2. We computed Mean Absolute Error for each of the three models, as well as for a null model that was computed by setting each participant's score to the average PC value. We compared the null model to each of the non-null models with a Wilcox signed rank test to account for the non-normality of the error distributions. Prediction R^2 is an alternative calculation of R^2 that is more appropriate for machine learning analyses than the typical squared-correlation computation[43]. In this calculation, R^2 values can be negative, which indicates that the model used to predict scores is worse than a baseline "null" model in which scores were set to the mean. The Prediction R^2 is calculated as 1 minus the Normalized Mean Squared Error (see equations in Section 4.2 in [43]).

To assess which personality traits were most important in deriving model performance, we assessed the statistical significance of beta weights (elastic net **Fig. 3C**, linear regression **Supplementary Table C1**) and variable importance (Random Forest; Supplementary **Fig. C1**). To test the statistical significance of beta weights for the elastic net model, we conducted a permutation test, randomly swapping the PC scores (1000 permutation orders) and then predicting 5 (multiple imputations) x 1000 (permutation orders) = 5000 models. From this we could extract a null distribution and compare our observed elastic net regression scores; the *p* value was the proportion of the distribution that exceeded our observed beta score. Variable importance is a common metric from Machine Learning to select which are the most important features in a given model, and is calculated from the mean squared error on the out-of-bag data for each tree, and the same is computed after permuting a variable. Scores are scaled to have a maximum value of 100.

Table 1
Summary of task parameters used in the current study

Task	Parameter Label	Description	Equation, parameter name in supp. info
Chips	Ch_seek_infogain	Favored a discriminatory (EIG) over a confirmatory strategy	Eq. 5, θ
	Ch_seek_random	Information seeking was not well-captured by either strategy	Eq. 6, τ
	Ch_conf_posterior	Confidence ratings tracked the true posterior probability	N/A, Evidence sensitivity
	Ch_conf_mean	Average confidence ratings	N/A, Confidence mean
Investigation	In_seek_continue	Tendency to seek more information	Eq. 7, $\beta_{continue}$
	In_seek_continue_unc	Tendency to seek more information under higher uncertainty	Eq. 7, $\beta_{uncertainty}$
	In_seek_switch	Tendency to switch investigation focus	Eq. 8 β_{switch}
	In_seek_switch_unc	Tendency to switch investigation focus under higher uncertainty	Eq. 8 $\beta_{uncertainty}$
	In_decide_prior	Weight of the prior information in the final decision	Eq. 9, β_{prior}
	In_decide_evidence	Weight of the new evidence in the final decision	Eq. 9, $\beta_{evidence}$
Lotteries	Lot_seek_uncertainty	Dependence of information demand on uncertainty	N/A, α
	Lot_seek_value	Dependence of information demand on value	N/A, β
Horizon	Ho_seek_unc	Investigate the option with the higher uncertainty	N/A, P High Info
	Ho_seek_random	Investigate the option with the lower mean	N/A, P Low Mean
Urn	Urn_conf_mean	Average confidence rating	Eq. 10, intercept
	Urn_conf_valence	Dependence of confidence ratings on valence (win vs. loss)	Eq. 10, valence
	Urn_conf_valdiff	Dependence of confidence ratings on uncertainty	Eq. 10, diffValue
	Urn_conf_value	Dependence of confidence ratings on expected value	Eq. 10, EV
	Urn_conf_entropy	Dependence of confidence ratings on entropy	Eq. 10, entropy
	Urn_seek_mean	Average curiosity rating	Eq. 11, intercept
	Urn_seek_valence	Dependence of curiosity ratings on valence (win vs. loss)	Eq. 11, valence
	Urn_seek_valdiff	Dependence of curiosity ratings on uncertainty	Eq. 11, diffValue
	Urn_seek_value	Dependence of curiosity ratings on expected value	Eq. 11, EV
	Urn_seek_entropy	Dependence of curiosity ratings on entropy	Eq. 11, entropy
Averaging	Avg_decide_indep	Dependence of decision weight on individual numerical values	Eq. 12, γ
	Avg_decide_diff	Dependence of decision weights on the number difference	Eq. 13, γ
	Avg_decide_selective	Dependence of decision weights on the largest of two numbers	Eq. 14, γ
Squares	Sq_seek_magprob	Attentional bias to probability or magnitude information	N/A, Feature-based attention index
	Sq_decide_risk	Distortion of magnitude estimate implied by choices	Eq. 16, α
	Sq_decide_prob	Distortion of probability estimate implied by choices	Eq. 16, γ
	Sq_decide_random	Randomness in decisions	Eq. 15, σ
Risk	Ri_decide_risk	Risk attitude	Eq. 17, $\alpha - 1$
	Ri_decide_ambig	Ambiguity attitude	Eq. 17, $-\beta$

Card	Card_seek_threshold	Threshold level of earnings at which to stop searching	Eq. 19, θ_H
	Card_seek_random	Decision noise	Eq. 19, σ_H

Note. Paradigms are described in more detail in Supplement A.

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Supplementary Materials

Supplement A: Description of Tasks and Task Variables

A1: Summary of Tasks

The following section includes descriptions of all tasks and variables used in the current study. Each task has the same four headings:

1 Overview of the Task and Variables

2. Model/s of Behavior

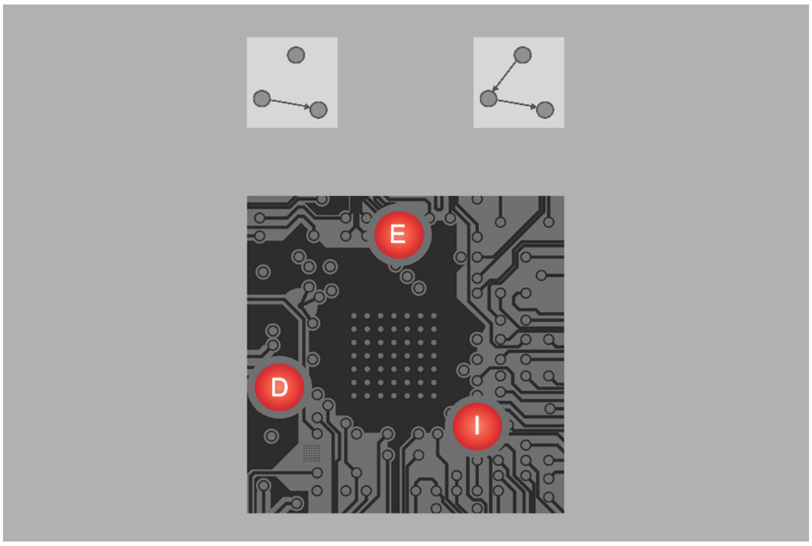
3. Variables used for the current study.

4. Data quality.

5. Comparisons with lab data (if applicable)

To facilitate comparisons across studies, we include the original parameter label given by the researchers who designed each study (under "Variables used for the current study"), with the variable label employed by the current study included in parentheses.

1. Chips



Overview of the Task and Variables

Manuscripts that have used this task in the past include[32,33]. In this task, participants try to discover the causal structure of 3- and 4-node systems described as *computer chips* by making causal interventions. On each trial, participants view a computer chip with all of its nodes turned 'off' as well as two possible configurations of the chip's hidden wires. To determine the chip's configuration, participants make a single causal intervention by selecting a node to activate. The activation of a parent node causes each of its immediate (direct) descendants to activate with 80% probability. Any activated node also activates *its* direct descendant nodes with 80% probability, such that indirect descendants can be activated via direct descendants. There are no background causes; nodes only turn on if they are directly selected or activated by a parent node. Nodes in 3-node chips could have between 0 and 2 direct descendants and nodes in 4-node chips could have between 0 and 3 direct descendants.

On each trial, after participants make their initial node selection, the selected node is always immediately activated, as indicated by it turning green. After a brief delay, participants view the final state of the computer chip and must select the configuration they believe reflects the true configuration of its hidden wires. Participants then rate their confidence in their selection on a scale from 1 (not at all sure) to 9 (completely sure). Participants complete 40 experimental trials in a pseudo-random order such that within each block of 10 trials, participants always active five 3-node chips and five 4-node chips.

Behavior is modeled with a mixed-strategy model whereby participants are thought to either adopt a confirmatory strategy — here a Positive Test Strategy (PTS), in which they test nodes with high causal centrality that are likely to activate a high proportion of causal links (i.e., confirming their prior hypothesis) — or a discriminatory, Expected Information Gain (EIG) strategy in which they select interventions that will maximize information gain by leading to the largest reduction in uncertainty. The degree to which participants use either strategy is indexed by the extracted model parameter (Ch_seek_infogain), where higher scores reflect the more discriminatory strategy, and lower scores reflect the more confirmatory strategy. Further, the degree to which decisions were not well-captured by either strategy or were random is reflected in the τ parameter (Ch_seek_random), with higher values reflecting more decision noise. Finally, participants' meta-cognitive accuracy (i.e., how sensitive they are to the quality of evidence that they have elicited) is indexed by the correlation between their confidence ratings and the posterior probability of the structure they selected given the elicited evidence on each trial. This is represented by the parameter *evidence sensitivity* (Ch_conf_posterior).

Model of Behavior

Bayesian mixture model

To characterize intervention choices, we fit a mixture model which assumes that participants linearly combine a confirmatory intervention strategy (PTS) with a discriminatory intervention strategy (EIG)[32]. The trial data file already includes the PTS and EIG 'values' of each node for each problem. To derive these values, we used the following equations:

Positive testing strategy

PTS assumes that participants prefer interventions with high causal centrality, meaning they are likely to elicit a large number of effects under a single hypothesis. The PTS 'value' of each node is determined by:

$$1.\quad PTS(n) = \left(\frac{DescendantLinks_{n,g}}{TotalLinks_g}\right) \tag{1}$$

where "DescendantLinks" refers to the number of links originating at a particular node and "TotalLinks" refers to the total number of links within a particular causal graph.

Expected information gain

EIG assumes that individuals have a set of hypotheses about the structure of a particular causal system, with each system represented as a causal graphical model. A learner's uncertainty about which graph (g) is most likely the source of their current observations is represented as the Shannon entropy over the graphs within their hypothesis set (G):

$$2.\quad H(G) = \sum_{g \in G} P(g) log_2 \frac{1}{P(g)} \tag{2}$$

Learners maximizing information gain should select the intervention that will cause the largest reduction in their uncertainty. This can be computed by considering the amount of information gained by each possible outcome (o) of intervening on each node (n), weighted by their probability:

$$3.\quad EIG(n) = H(G) - \sum_{o \in O} P(n)H(n,o) \tag{3}$$

where $H\ (G|n,\ o)$ is the new uncertainty after an intervention:

$$4.\quad H(n,o) = \sum_{g \in G} P(n,o) log_2 \frac{1}{P(n,o)} \tag{4}$$

Combining strategies

Once we have derived the PTS and EIG 'values' of each node for each problem, we can examine how participants combine the strategies to select interventions through our mixture model. The mixture model assumes that participants linearly combine strategies with weight θ where $\theta = 0$ indicates a pure PTS strategy and $\theta = 1$ indicates a pure EIG strategy. The 'value' of a given intervention (n) can be described as:

$$5.\quad V(n) = \theta * EIG(n) + (1 - \theta) * PTS(n) \tag{5}$$

We further assume that participants' choices are noisy such that the probability of selecting each node is:

$$6. \quad P(n) = \frac{exp\left(\frac{V(n)}{\tau}\right)}{\sum_{i} exp(V(n_i)/\tau)} \qquad (6)$$

where τ is a noise parameter.

Model-fitting. We estimate θ and τ separately for each participant by using the brms package for R. We estimate posterior distributions over the parameters using Markov chain Monte Carlo sampling (4 chains of 4,000 iterations, 2,000 per chain discarded as warm-up; 8,0000 total samples per parameter). We use a noninformative prior for θ : β (1, 1) and a weakly information prior for τ : γ (1, .1).

Evidence sensitivity. Finally, for each participant, we can determine the extent to which their confidence ratings tracked the posterior probability of the structure they selected. We can do this by computing, for each participant, the correlation between the posterior probability of the structure they selected given the evidence they observed (post_prob_selected) and their confidence ratings on every trial (conf_rating).

Variables used for the current study

For the current study, we utilize three parameters that capture participant behavior on the task:

- **Seeking strategy mixture weight (**θ; Ch_seek_infogain**)**, which captures the extent to which participants used a confirmatory (θ = 0) or discriminatory (θ = 1) intervention strategy.
- **Seeking strategy randomness (**τ ; Ch_seek_random**)**, which captures the extent to which decisions were random or not well-captured by either strategy (higher values = more noise).
- **Confidence evidence sensitivity** (Ch_conf_posterior), which captures the extent to which participants' confidence ratings tracked the posterior probability of the structure they selected.
- **Confidence mean (**Ch_conf_mean**)**: Average confidence ratings per person.

Data quality

We used four criteria to determine data quality:

- Participants who made their intervention choice in less than 500ms on more than 10 out of 40 intervention trials are flagged with "A".
- Participants who chose either the left or right structure on more than 35 out of 40 intervention trials are flagged with "B".
- Participants who chose the same node on all 3-node or all 4-node problems are flagged with "C."
- Participants who gave the same confidence rating on all 40 trials are flagged with "D."

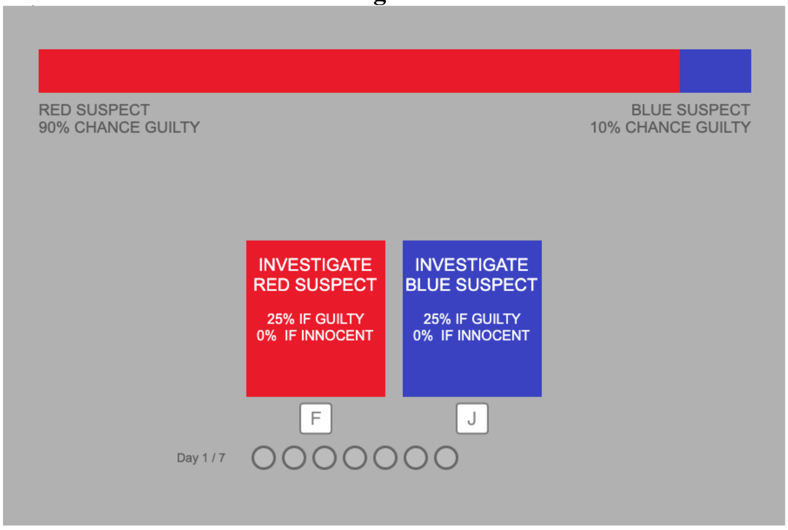
Some participants have more than one flag (e.g., "A_C") if they met multiple criteria.

We removed participants who fulfilled any of these quality ratings. This resulted in 41 people being removed from this task.

Comparisons with lab data

- The Chips task has been tested in an in-person study[33] as an adaptation of the original version of the task run on mTurk[32]. In both prior studies, participants' choices were well captured by the model above, which posits a mix of confirmatory and discriminatory information-seeking strategies, and parameter estimates were comparable with those from the present Amazon Turk sample[36,33].

2. Investigation



Overview of the Task and Variables

On each trial, participants try to guess which out of two suspects (Red [R] or Blue [B]) is guilty of a crime. One of the suspects is guilty, and the other is innocent. On each trial, they can choose to (1) investigate one of the two suspects [investigation decision] — either R or B — or (2) stop and accuse a suspect [stopping decision] — again, either R or B. At the beginning of each trial, participants receive an initial piece of information about the likelihood of each suspect being guilty (prior π_0). After, participants can use their "investigation attempts" to further investigate the suspects and collect evidence before accusing one of them. The investigation can provide either conclusive evidence ("the murderer's weapon") or inconclusive evidence (no final proof). Investigating the innocent suspect always return inconclusive evidence. Investigating the guilty suspects returns a conclusive piece of evidence in 25% of the investigations, and inconclusive evidence in 75% of the investigations, with independent probabilities for each investigation attempt. The task has three blocks, that differ in how participants can decide whether to collect additional evidence. In Block 1, the number of investigation attempts in each trial is fixed and known. In Blocks 2 and 3, the number of investigation attempts in each trial depends on the participant, as at any point they can stop and accuse one of the suspects, or collect additional evidence for a fixed cost deducted from their initial endowment. In Block 2 the cost is symmetric across the two suspects, while in Block 3 investigating one suspect is more expensive than the other.

The likelihood of the suspect being guilty, and therefore the degree of uncertainty about the correct answer, changes based on the evidence collected. For example, the initial information might suggest that Red is guilty with probability 0.9, but after several observations the perceived state may shift to a probability 0.4, making Blue the most likely suspect. Note that the true state does not change here, only the participants' beliefs over the state of the world.

Three different candidate models were created to describe behavior in this task. Each model includes two extracted parameters which we included in analyses.

Model of Behavior

We use three main logit regressions to capture relevant stylized features of the behavior of the task: (1) when participants stop, (2) if they search, whether they maintain or change search strategy (direction of search), and (3) if they stop, how they integrate the stream of information collected.

Stopping decision: when to stop

In each decision node, participants face some uncertainty about the outcome and decide whether to stop or continue the search process. Some participants might decide to stop earlier or later based on individual preferences. We consider the regression:

$$Logit[Pr\ (continue)\ ] = \beta_{continue} + \beta_{uncertainty} \cdot H(p) \qquad (7)$$

where we consider the binary decision (continue or stop) based on the current uncertainty $H(p)$ and a constant $\beta_{continue}$. To capture uncertainty about the correct answer, we use Shannon entropy, $H(p) = -[p \cdot (p) + (1-p) \cdot (1-p)]$, where $p = Pr\ (Red\ is\ guilty)$ is the current (updated) probability that the correct state is Red. In this way, $H(p)$ ranges between 1 (for $p = 0.5$, maximal uncertainty) and 0 (for $p \sim 0$ or $p \sim$

1, minimal uncertainty). For the stopping regression, we use only observations from Blocks 2 and 3, and remove observations from Block 1 in which stopping time is exogenous.

Search decision: which hypothesis to test

During each round, participants can make several search decisions. After observing the outcome of a search action at time t, they have the chance to investigate the same suspect as they did at time $t+1$, or switch to the other suspect. We can consider whether this behavior differs across participants:

$$Logit[Pr\ (switch)\ ] = \beta_{switch} + \beta_{uncertainty} \cdot H(p) \tag{8}$$

where we consider the binary decision (repeat or switch based on current uncertainty $H(p)$ (defined as above) and a constant β_{switch}. From previous analysis, we know that switches occur more often in trials with larger uncertainty (in particular, when the initial prior $\pi_0 = \frac{1}{2}$. For the search switch regression, we use only search observations (no stopping), from the second period onward (no period 1, that contain the first search and therefore switching is not defined), and only when no conclusive evidence has been observed yet (once the state is revealed, there is nothing to learn).

Guessing decision: how to integrate different information

We consider how participants combine the prior (initial information available even before searching) and subsequent evidence (accumulated through search) when they make a guess about the correct answer:

$$Logit[Pr\ (guess\ Red)\ ] = \beta_{prior} \cdot z^{prior} + \beta_{evidence} \cdot LL(evidence) \tag{9}$$

where $z^{prior} := log\left(\frac{\pi_0}{1-\pi_0}\right)$ is the log-odds ratio for the initial probability π_0 (probability that Red is the correct state), and $LL(evidence) := log\left(\frac{p(evidence|Red\ guilty)}{p(evidence|Blue\ guilty)}\right)$ is the log-ratio for the subsequent evidence accumulated in the search process (one or multiple observations, regardless of the order in which these are obtained). For the guessing regression, we use only guessing observations (stopping only, no search), and only when no conclusive evidence has been observed yet (once the state is revealed, there is nothing to learn).

Variables used for the current study.

The estimated coefficients βs of the different regressions capture the heterogeneity across participants in their information acquisition and integration behavior.

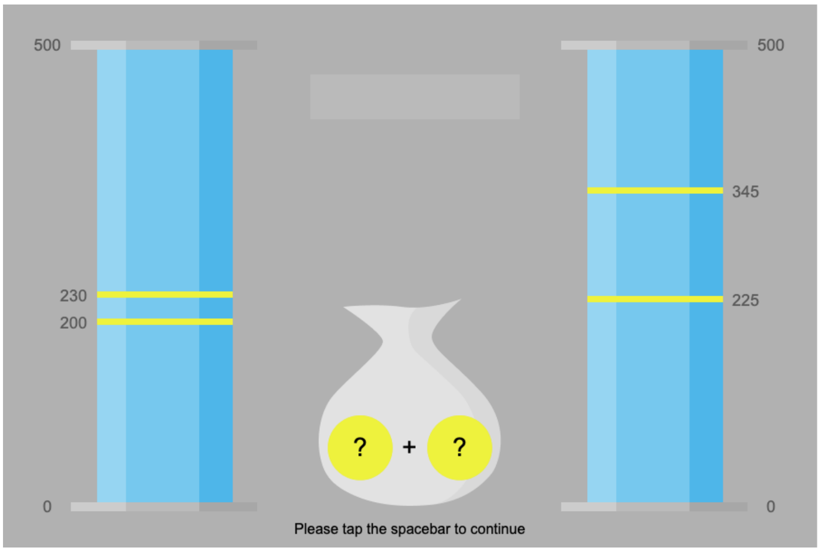
- In (7), larger $\beta_{continue}$ (In_seek_continue) indicates a higher willingness to search to acquire information before stopping (can be interpreted as more intense "curiosity" regardless of the current uncertainty), and $\beta_{uncertainty}$ (In_seek_continue_unc) captures the degree to which participants continue to search as a function of uncertainty (greater values describe more searching/enquiring about suspects when uncertainty is higher).
- In (8), larger β_{switch} (In_seek_switch) indicates a higher likelihood to review own search strategy (can be interpreted as a more "exploratory" search approach) and $\beta_{uncertainty}$ (In_seek_switch_unc) captures the degree to which participants switch the suspect they enquire about as a function of uncertainty (greater values indicate more switching between suspects when uncertainty is higher).
- In (9), larger β_{prior} (In_decide_prior) indicates a relatively greater reliance on the information initially provided, and higher values of $\beta_{evidence}$ (In_decide_evidence) indicate more weight on new evidence obtained during the trial.

Data quality

Participants are given a "mistake category" mark: 0 = few or no mistakes, 1 = some, 2 = many. Participants are placed into these categories based on the number of "hard mistakes" in the first task, using the threshold 0.2 and 0.4. These hard mistakes occur if (1) the final evidence is collected (e.g., the suspect red is certainly guilty), but (2) the participant accused the wrong suspect (accuse blue instead). These mistakes can be due to erratic behavior, not understanding the instructions, or testing what are the consequences of a mistake (that they should already know from the instructions).

Using this criterion, 78% of participants belong to category 0 (few or no mistakes), 11% to category 1, and 11% to category 2. Note that 61% of the participants made zero mistakes. We removed participants in Category 2 from the dataset (*n* = 69 participants removed).

3. Lotteries



Overview of the Task and Variables

In this task, participants performed an identical information sampling step in 3 contexts—one non-instrumental condition ("Observe") and two instrumental conditions ("Estimate" and "Intervene") as described in Rischall et al.[23] (see also[22]). On each trial, participants saw two lotteries as depicted above, and were told that one value would be randomly drawn from each lottery and the two values would be summed. The random draws were kept hidden, but participants chose one value they wished to reveal with precision. In the non-instrumental, *observe* condition, participants could not act on the information their revealed. In the *Intervene* condition, people could intervene in the lottery they inquired about: after seeing the precise prize that they drew from this lottery, they could choose to keep this prize or switch to receive the expected value (average) of the lottery, whichever was higher. In the *Estimate* condition, the decision-makers did not receive payoffs directly from the lottery; instead, after revealing one draw, they had to guess whether the sum of the two random draws was higher or lower than a criterion value, and receive payoffs for a correct guess. In both conditions, the clear instrumental incentive is to inquire strictly about the high variance lottery.

Each of these three conditions (observe, intervene, estimate) has an extracted model parameter reflecting the bias to sample from the high-variance lottery, α (Lot_seek_uncertainty) and a parameter reflecting bias to sample from the high-value lottery, β (Lot_seek_value), leading to a total of six parameters.

Model of Behavior

Behavior can be described with two parameters of the psychometric choice function relating the % observing choices to the difference in expected value (dEV) between the two lotteries. Parameters w_var and w_EV capture the extent to which participants' curiosity increases as a function of, respectively, the uncertainty and expected value of the component lottery.

Each person's data is fit with one of two models:

- A bi-variate sigmoid model in which parameter α indicates the baseline and parameter β indicates the slope.
- A uni-variate model in which parameter α indicates the baseline and parameter β is null (no slope)

Each participant is represented by the model that provides a better fit (according to BIC). For people who are better fit by the univariate model, parameter β is set to zero. In both models, parameter α corresponds to the overall bias to sample the high variance lottery. Parameter β indicates the sensitivity to relative value (deltaEV)

Variables used for the current study

In the current study we extracted the α and β parameters for each task version, for a total of 6 parameters. Because both α and β parameters were very highly correlated across the Observe, Intervene and Estimate tasks, we avoided multicollinearity by entering only their average values in the main analyses. For follow-up analyses of differences between instrumental and non-instrumental conditions, we used individual-task parameters as described in Supplementary material.

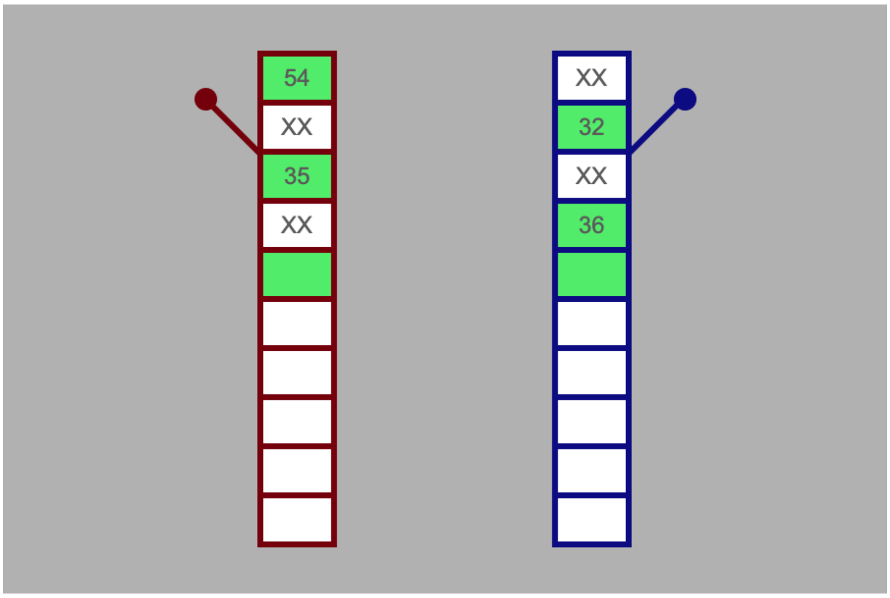
Data quality

Participants who made more than 30% of incorrect responses in the intervene condition were excluded from this task. "Incorrect" means that in the intervene condition, the participant chose the lower reward option, which they should only do if they're not attending to the task. Using this criteria, $N = 69$ participants were removed from this task's dataset.

5. Comparisons with lab data

Two previous studies using the 2-Lotteries tasks showed that participants tested on Amazon Turk and in-lab produced comparable findings[22,23] and both sets of results were comparable to the present results with respect to the distributions of α and β parameters[22,23] and their correspondence with personality scores[23].

4. Horizon



Overview of the Task and Variables

In this variation on the classic Bandit task[20], participants choose between two slot machines that pay out random rewards from two Gaussian distributions with equal variance and different means. In this version, there are differing levels of "horizon" (i.e., how many trials participants have to investigate either bandit before they reach the end of the bandit). Participants first have four forced choices that make them sample from the bandits and gain some information about their distributions. Following their forced choices, participants make either one or six free choices where they can investigate either bandit (i.e., Horizon levels 1 and 6). They are awarded the result of the most recent bandit that they sample from, making the final choice also a decision about which lottery to obtain.

This paradigm can distinguish between *directed exploration* and *random exploration*[20]. Directed vs. random exploration can be distinguished by varying the amount of information revealed about either bandit before participants make choices to seek information. Directed exploration can be assessed in situations where participants were forced to see one choice about one bandit and three choices from the other. Here, a high information (directed information) choice is selecting from the bandit where only one choice has been shown. Random information can be assessed in the situation where participants were forced to see two choices about each bandit. Here, a decision indexing random exploration can be seen when participants choose the low mean option (which is sub-optimal). This is called the "low-mean" choice. The model parameters in this task are designed to distinguish between these two forms of information in differing levels of horizon.

Model/s of Behavior

P Low Mean: Fraction of the time that participants chose to enquire about the low mean option in the 2,2 condition. These were games where the forced trials revealed 2 outcomes from each bandit.

P High Info: Fraction of the time that participants chose the high information option in the 1,3 condition. These were games where the forced trials revealed 1 outcome about a bandit and 3 outcomes from the other. The P High Info choice is selecting from the bandit from which only one outcome has been revealed.

The equations can compare how participants' choices of P Low Mean and P High Info change with horizon condition.

Variables used for the current study.

pHi1: Model predictions for the probability of choosing the high-information option in Horizon 1 games (directed exploration)

pHi6: Model predictions for the probability of choosing the high-information option in Horizon 6 games (directed exploration)

pLo1: Model predictions for the probability of choosing the low mean in Horizon 1 games (Random exploration)

pLo6: Model predictions for the probability of choosing the low mean in Horizon 6 games (Random exploration).

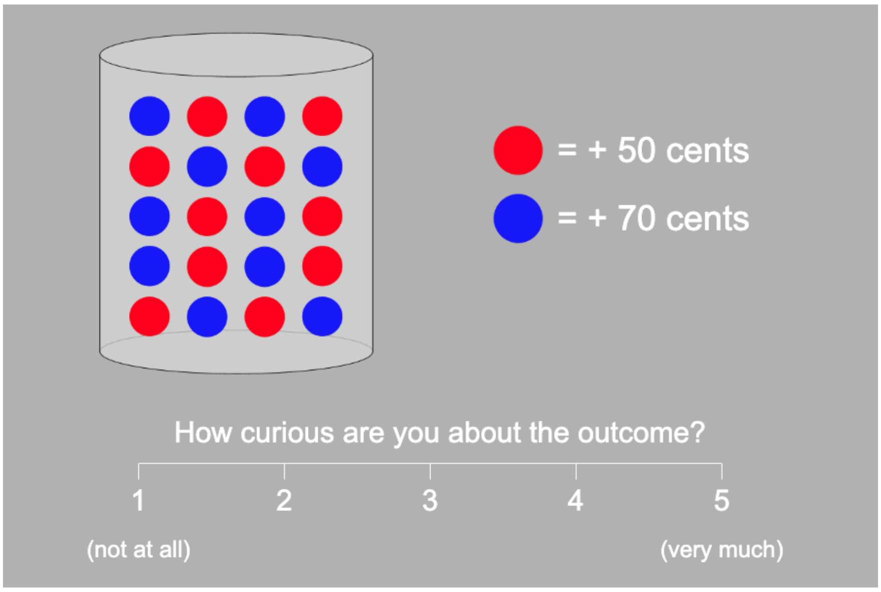
The two random exploration parameters were very highly correlated to one-another, as were the two variables that indexed directed exploration. To avoid multicollinearity issues, these were averaged prior to principal component analyses, meaning that two parameters were employed for PCA: directed exploration and random exploration. However, for machine learning analyses of individual behavioral variables, these four parameters were analyzed separately.

Data quality. The exclusion criteria for this data set were based on performance on the last trial of horizon 6. By the last trial participants should be able to select the optimal option so participants with less than a 70% accuracy on the last trial of horizon 6 games were dropped. Thirty-five participants were excluded by this criterion.

Comparisons with lab data

The Horizon task has been tested in multiple in-lab studies, which showed that the time horizon produces increases in both directed exploration (p(high info) and information bonus) and random exploration (p(low mean) and decision noise) [20,47,50,51,55] – and this classic pattern was replicated in the current results.

5. Urn



Overview of the Task and Variables

In this paradigm[34], participants see a lottery on every trial that consists of a vase containing blue and red marbles. Each color of marble is associated with a win or loss (counterbalanced across participants). The experiment varies on several dimensions: (a) whether participants can gain or lose their reward, (b) how much will be gained or lost, and (c) how uncertain it is which marble will be picked from the trial (i.e., outcome uncertainty). Participants cannot intervene in this task, nor can they make a choice to seek information; they instead probabilistically view advance information about their upcoming result. On each trial, participants rate how *curious* they are to learn the outcome, and how *confident* they are that they will gain or lose the highest possible absolute value (e.g., if the possible outcomes on a trial are 90c or 10c, they are asked "How confident are you that you will receive 90 cents?", and for a trial with possible outcomes of -50c or -20c, they would be asked "How confident are you that you will lose 50 cents?").

Model/s of Behavior

For each person, the following models were fit and parameters saved.

Model 1 predicting confidence

$$Confidence \sim intercept + valence + diffValue + EV + entropy \tag{10}$$

Model 2 predicting curiosity

$$Curiosity \sim intercept + valence + diffValue + EV + entropy \tag{11}$$

Where:

- *valence* is the valence ("loss" or "gain"), effect-coded ("LOSS" = -1, "GAIN" = 1)
- *diffValue* is difference in value, where diffValue = $|value_{blue} - value_{red}|$, centered and scaled
- *EV* is expected value, where EV = $(prop_{blue} * value_{blue}) + (prop_{red} * value_{red})$, centered and scaled
- *Entropy* is Shannon entropy, centered and scaled

This produces 10 parameters: for each model, intercept and beta weights for each of the predictors.

Variables used for the current study.

Urn_seek_mean*:* Mean (intercept) of curiosity ratings
Urn_seek_valence: Beta weight of valence_c predicting curiosity
Urn_seek_valdiff: Beta weight of diff_value_c predicting curiosity
Urn_seek_value: Beta weight of ev_c predicting curiosity
Urn_seek_entropy: Beta weight of entropy_c predicting curiosity
Urn_conf_mean: Mean (intercept) of confidence ratings
Urn_conf_valence: Beta weight of valence_c predicting confidence
Urn_conf_valdiff: Beta weight of diff_value_c predicting confidence
Urn_conf_value: Beta weight of ev_c predicting confidence
Urn_conf_entropy: Beta weight of entropy_c predicting confidence

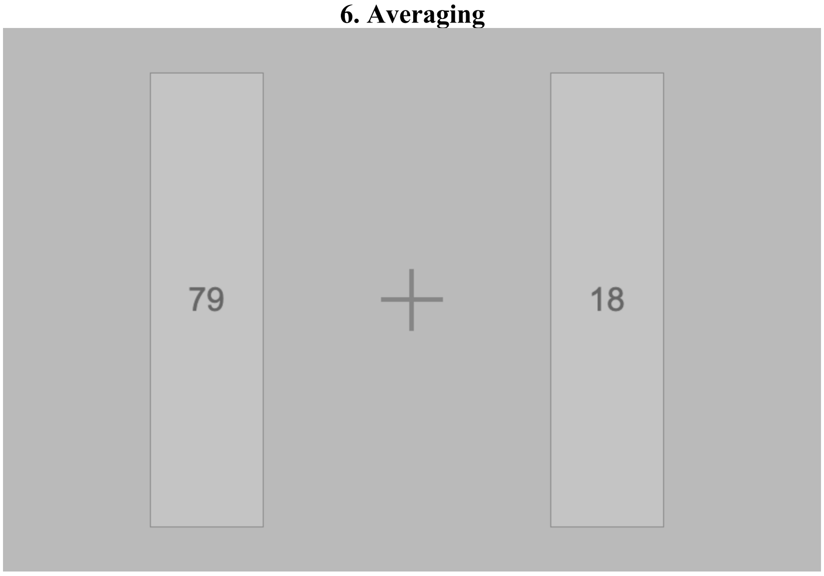
Data quality

Participants who used one of the five response bins on more than 80% of the trials for either the curiosity or confidence ratings are marked "0" under "quality" (*N* = 72) in the dataframe and excluded from analysis.

5. Comparisons with lab data

The urn task has been used in multiple lab studies that showed that curiosity is a function of both outcome uncertainty (i.e. a combination of "entropy" and "difference in value"), as well as valence [34,103]. This is consistent with the pattern of results shown in the current study.

6. Averaging



Overview of the Task and Variables

Participants view two groups of values and guess which group has the highest average value making a binary choice. Participants are awarded for being accurate. This paradigm has been used previously to look at violations of choice preference[37,88]. This paradigm assesses processes related to integrating information for the purposes of decision-making, and the weighting of specific stimuli/evidence streams can be considered a form of information seeking[11,38].

The experiment has 6 blocks that differ in the way values are presented (Arabic numerals or bar heights) and the order of appearance of the two groups (simultaneous, sequential, or alternate) with 30 trials in each block (180 trials overall). Each option (left/right) is represented by a vector of six values shown in separate frames. For example, v_t^i indicates the value that was shown at time t in the screen position $i \in \{L, R\}$ (left/right). In the simultaneous trials, there are 6 different frames: in frame t the participant is simultaneously presented two values: v_t^L on the left and v_t^R on the right-hand side of the screen. In the sequential and alternate trials, there are 12 different frames, each with one single value presented. The values on the L (left) and R (right) are presented in different orders in the sequential (LLLLLL-RRRRRR or RRRRRR-LLLLLL) and in the alternate conditions (LRLRLRLRLRLR or RLRLRLRLRLRL). Participants are randomly assigned to one among two possible treatments (up/down, between-subject randomization), that indicate the overall distribution of values (upward/downward triangular distribution), with different values being more frequent based on the treatment. However, these treatments are not relevant for the current study.

Model of Behavior

The three models used to describe behavior in this paradigm capture different ways in which people can integrate information in their decision-making. Each model includes a γ parameter that captures the distortion of values in the evaluation process.

For Model 1, we consider all the trials (180 observations per participant). For Models 2 and 3, we focus on the "simultaneous appearance" trials (60 observations per participant).

Transformation of independent values (Model 1)

We consider a baseline model in which each value is considered, and possibly transformed, independently from the other value on the screen, differently from Models 2 and 3 in which values were considered jointly:

$$Pr\ (choose\ R)\ = \frac{1}{1+\ e^{-\Delta V/\theta}},\quad \Delta V =\ \Sigma_t[(v_t^R)^\gamma -\ (v_t^L)^\gamma] \tag{12}$$

where v_t^i is the value displayed in position i at time t, $\gamma \geq 0$ is the distortion parameter and θ is a noise parameter.

Transformation of value differences (Model 2)

We consider a family of models in which the decision maker encodes the *differences* between values displayed on the right and left, possibly after a monotonic transformation:

$$Pr\ (choose\ R)\ = \frac{1}{1+\ e^{-\Delta V/\theta}},\quad \Delta V =\ \Sigma_t[(v_t^R - v_t^L)\cdot\ |v_t^R - v_t^L|^\gamma] \tag{13}$$

where v_t^i is the value displayed in position i at time t, γ is the distortion parameter and θ is a noise parameter.

Selective integration (Model 3)

We consider a simplified version of the selective integration model introduced in[88]. The highest value in each frame is encoded with weight 1, while the lowest value is encoded with a lower weight $\gamma\ \leq 1$.

$$Pr\ (choose\ R)\ = \frac{1}{1+\ e^{-\Delta W/\theta}},\qquad \text{with}\ \ \Delta W =\ \Sigma_t[f(v_t^R, v_t^L)\ -\ f(v_t^L, v_t^R)]$$

$$f(v_A, v_B) = \begin{cases} v_A \cdot 1\ if\ v_A \geq v_B \\ v_A \cdot \gamma\ if\ v_A < v_B \end{cases} \tag{14}$$

where v_t^i is the value displayed in position i at time t, $0\ \leq \gamma\ \leq 1$ is the selective gating parameter and θ is a noise parameter.

Variables used for the current study.

The three γ parameters are used for the current study:

Model 1: A parameter $\gamma < 1$ characterizes a concave function (diminishing sensitivity, Weber's law). $\gamma > 1$ instead captures a convex function (consistent with a salience or regret model).

Model 2: A parameter $\gamma < 0$ characterizes a concave odd function (diminishing sensitivity to differences, analogous to Weber's law for differences), $\gamma > 0$ instead captures a convex function (consistent with a salience or regret model).

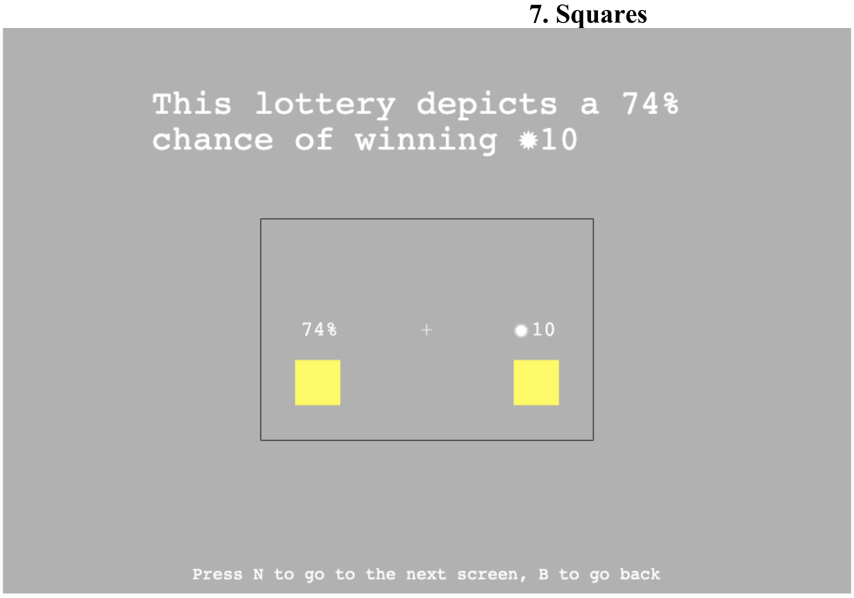
Model 3: A parameter $\gamma < 1$ characterizes a distortion of the values in favor of the "local winner" (i.e., the highest value in the frame), with $\gamma = 0$ indicating that only the local winner value is encoded.

Data Quality

Participants are classified based on the frequency of "hard mistakes" across all the tasks, using the accuracy thresholds 0.95 and 0.8. In this way, 75% of the participant belong to category 0 (few or no mistakes), 18% to category 1, and 7% to category 2. Note that 56% of the participants make zero of these mistakes.

These hard mistakes occur if (1) the value difference between the two options is very large (100 points or more) and consequently the choice should be very simple for an attentive participant, but (2) the participant chose the wrong option. On average, a difference of 100 or more points occurs in 14% of the trials (about 25 times in a session) and the overall accuracy is 95% (to have a measure to compare, the overall accuracy in the whole dataset is 80%, and for differences above 50 points is 90%). These mistakes can be due to inattention, erratic behavior, not understanding the instructions, or testing what are the consequences of a mistake (that they should already know from the instructions). Using these criteria, 40 participants were removed from this task's dataset.

7. Squares



Overview of the Task and Variables

This paradigm[31] characterizes decision-making under risk (uncertainty) for different monetary values and probabilities of success. Specifically, participants make choices between a constant 5-points reward and a risky lottery, where the probability of payout varies from .20 to .80, and the magnitude of possible reward varies between 5 points and 80 points. Participants were randomly assigned to one of two choice sets: in the magnitude-diverse choice set there are 21 unique magnitudes and 5 unique probabilities; in the probability-diverse choice set there are 21 unique probabilities and 5 unique magnitudes. Both choice sets spanned the ranges detailed in the previous sentence. Exploration and reward-seeking in uncertain environments are hallmarks of information seeking in neuroscience, thus these tasks are important to include alongside other more direct information-seeking paradigms to gain a comprehensive assessment of the construct.

Model of Behavior

The model for this task is a variation of a classic subjective utility model; it assesses how sensitivity to the magnitude and probability of reward relates to probability distortions (i.e., the tendency for low probabilities to be overweighted and high probabilities to be underweighted; a key part of risk aversion and a feature of prospect theory). In addition to probability distortion, the parameters included in the current study index factors including one's risk tolerance, variance in response, and attentional bias toward reward magnitude information.

For each participant, we use maximum likelihood to estimate three parameters (alpha, gamma, sigma), fitting the model below to individual choice data.

The probability of choosing the lottery on each trial was given by the following logistic choice function:

$$P_{lotto} = \frac{1}{1 + e^{-(SU_{lotto} - SU_{ref})/\sigma}} \qquad (15)$$

The subjective utility (*SU*) of each option was modeled using the functional form:

$$SU(p, m) = e^{-(-\ln p)^{\gamma}} \cdot m^{\alpha} \qquad (16)$$

where *p* and *m* denote the probability and magnitude of the gain on offer in each lottery, respectively.

Variables used for the current study

α : The weight on the magnitude; controls the curvature of the utility function. This reflects risk tolerance, with higher alpha indicating more risk tolerance.

γ: Indicates the degree of distortion in the probability weighting function.

σ: Slope of the logistic function, indicating choice stochasticity

Feature-based attention index (FBAI): Indexes attentional bias toward magnitude information after controlling for reaction time and total viewing time (specifically, proportion of time spent attending magnitude minus proportion of time spent attending probability, averaged across trials). Larger values indicate a greater bias to magnitude.

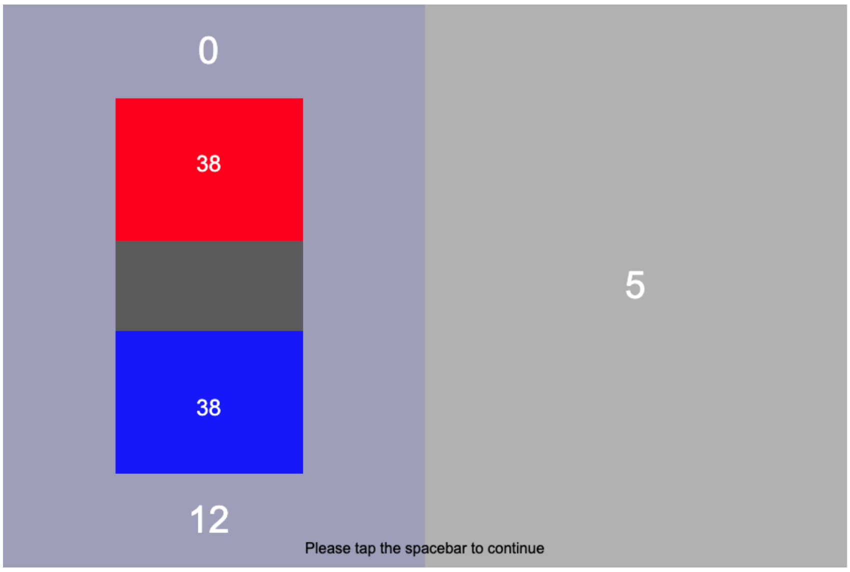
Data quality.

96 participants were excluded due to excessive first-order stochastic dominance violations, choosing a chance of 5 points over 5 points for sure on half or more of the trials.

Comparisons with lab data

A recent study has been published with this task that included an mTurk dataset along with a lab-based study that was identical in most respects[31]. These authors found that (1) the proportion of lottery choices was ordered in the expected direction (i.e., people choose the lottery more often when it has a higher probability of payout and when it has a higher potential magnitude of payout), (2) model fitting produced evidence of risk aversion (alpha < 1) in both the lab-based study and the web-based study, replicating the classic pattern of risk aversion in the literature, (3) when experimentally manipulating the amount of probability weighting, this manipulation was effective in both the lab-based and web-based study (people in the "probability-diverse" environment made choices that evidenced less probability distortion).

8. Risk



Overview of the Task and Variables

In this paradigm[39], participants make choices between a certain 5-point reward and an uncertain reward. This uncertain reward is either risky (participants know the probability of obtaining the reward; 50% of trials) or ambiguous (participants do not know the precise probability of obtaining the reward; 50% of trials). This task is therefore conceptually similar to the *Squares* paradigm but extends that paradigm by also assessing ambiguity preferences. Given that exploratory behavior is often taking place in environments where the probability structure of the world is fundamentally uncertain, this task is also appropriate to use in assessing information seeking behavior. The model describing choice preference in this experiment includes two parameters of interest: α, which describes risk attitudes, with higher values indicating more risk-seeking; and β, which describes ambiguity attitudes, with higher values indicating more ambiguity *aversion*.

Model-based analysis:

In this analysis, choices are fitted by a behavioral model based on[39] (https://www.physiology.org/doi/full/10.1152/jn.00853.2009). The model separates the decision process into two steps: valuation and choice. In the valuation step, the subjective value (SV) of each option is modelled by equation,

$$SV = \left[P - \beta\left(\frac{A}{2}\right)\right] \times V^{\alpha} \tag{17}$$

where P is the outcome probability (0.25, 0.50, or 0.75 for risky lotteries, 0.5 for ambiguous lotteries, and 1 for the certain option); A is the ambiguity level (0.24, 0.5, or 0.74 for ambiguous lotteries; 0 for risky lotteries and the certain amount); V is the non-zero outcome magnitude of the lottery or the certain option. Risk attitude is modeled by discounting the objective outcome magnitude by a participant-specific parameter, α. A participant is risk averse when $\alpha < 1$, and is risk seeking when $\alpha > 1$. Ambiguity attitude is modeled by discounting the lottery probability linearly by the ambiguity level, weighted by a second participant-specific parameter, β. A participant is averse to ambiguity when $\beta > 0$, and is ambiguity seeking when $\beta < 0$.

The choice process is modeled by a standard soft-max function (Equation 18),

$$P_V = \frac{1}{1 + e^{\gamma(SV_F - SV_V)}} \tag{18}$$

where P_V is the probability of choosing the lottery option, SV_F and SV_V are the subjective values of the fixed certain option and the lottery respectively, calculated by equation (1); γ is a participant-specific noise parameter. For consistency, we transformed risk and ambiguity attitudes in way below such that negative values indicate aversion and positive values indicate seeking. By model-fitting, we get three parameters for each participant:

- Model-based risk attitude: $\alpha - 1$
- Model-based ambiguity attitude: $-\beta$
- Stochasticity: γ

Analysis of risk and ambiguity attitudes:

After model-based risk and ambiguity attitudes are calculated as above, pair-wise correlations can be calculated between these attitudes. Relationship between attitudes with other measures of participant characteristics can also be investigated.

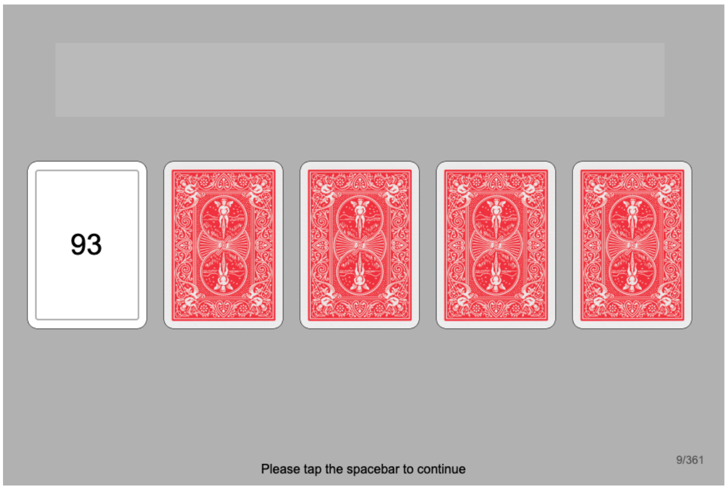
Data Quality

Quality mark is based on trials in which the choice was between 5 points for sure and a lottery that offered an uncertain chance for 5 points. On those trials, participants should choose the certain option, regardless of their risk and ambiguity attitudes. Choosing the lottery indicates either lack of understanding of the task, or that the participant did not aim to maximize their earnings. Data from participants who chose the inferior option on more than 50% of those trials were excluded, resulting in 60 participants being removed from this task.

Comparisons with lab data

Behavior on the Risk task was similar to behavior in our previous research using similar tasks in the lab[89–92] and in fMRI[39,93]. First, a similar proportion of participants passed the quality-assurance criterion. Our main measure for decision quality is what is known as violations of “first-order stochastic dominance”. These are trials in which participants prefer an uncertain prospect of gaining $5 over a sure bet of the same magnitude ($5). In the current study, 60 out of 619 participants (10%) committed such violations in more than half the trials of this type. This is similar to a recent fMRI study from our lab[93] in which 10 out of 68 participants (15%) committed a similar number of violations. Second, the distributions for model parameters for risk and ambiguity attitudes for participants included in the analysis were also similar to in-lab studies. Specifically, most participants exhibited both risk aversion (alpha < 1) and ambiguity aversion (beta > 0), and the ranges of the parameters were similar to previous studies.

9. Card



In this task[36], a series of playing cards are flipped over one-by-one, and on each card is a number from 1 to 100, where the number is drawn from a uniform distribution. The sequence of cards to flip over varies from two cards to five cards on each trial. The participants’ aim is to select the card with the highest number on each trial. Participants must choose where to “stop” in the trial, and they will claim the points that are included on that particular card. However, they cannot go backwards in their search. Thus, participants need to decide if they want to stop their search early or continue to search and take the chance that they will obtain a worse reward on a later trial. There is an optimal solution for this task that has been previously outlined[36]. The model describing participant behavior includes *threshold* parameters, which describes the threshold (number on card) where participants stop their search and claim their reward; and *noise* parameters which indexes decision noise.

Model/s of Behavior
Probability of choosing to STOP on

$$P_H = \frac{1}{1 + e^{-\frac{V-\theta_H}{\sigma_H}}} \tag{19}$$

Observed variables:
H: Number of cards remaining, the Horizon
V: Current card value
Parameters for each subject:
θ_H: Participant’s stopping threshold for each horizon
σ_H: Decision noise for each horizon
Model is fit using maximum likelihood method.

Variables used for the current study.
There are four threshold and four noise parameters corresponding to each of the conditions in the task (2 cards to 5 cards). As the four threshold variables and four noise variables were very highly correlated, and

each formed unambiguous 1-factor solutions, factor scores were extracted across each of the variables. This led to two variables related to the Card paradigm: one *threshold* variable and one *noise* variable.

Data quality

Participants were excluded based on the average number of points earned per game. Ten (10) participants who scored 50 or fewer points per game—the number that would be expected from purely random performance—were considered to be disengaged from the task and excluded from the analysis.

Comparisons with lab data

In previous work in the lab, it has been shown that in the Card task, as the horizon decreases, participants' stopping thresholds decrease while their decision noises increase[36]. The change of both threshold and decision noise has the same trend in both samples. The main findings of the parameters hold across samples. Overall, behavior in the online version of the task in this paper is similar.

Supplement A2: Task Participant Exclusion Details

Supplementary Table A2-1

	# of Datasets Passing Step 1 (technical quality checks)	# of Datasets Removed at Step 2 (performance quality checks)	# of parameter values removed at Step 3 (outlier parameters)	# of parameter values included in the analyses before multiple imputation
Questionnaires	623	17	0	606
Chips	580	41	28-29	510-511
Investigations	606	69	15-28	509-522
Lotteries	578	69	13-26	483-496
Horizons	605	35	28	542-557
Urn	568	72	25	471
Averaging	593	40	13-28	525-540
Squares	561	96	24	441
Risk	619	60	28	531
Card	615	10	55-67	538-550
Total all tasks	**5,948**	**509**	**-**	**-**

Note. The 1st column shows the number of datasets that were available for analysis after passing technical quality checks at Step 1 (i.e., for bots or participant ID irregularities; see **Methods**). The 2nd column shows the number of datasets removed for each task after performance quality checks at Step 2 (see **Supplement A** for the criteria used for each task). The last row shows the totals of these numbers across all the tasks. Of 5,948 datasets analyzed for all tasks, 509 were removed at Step 2, showing that 91% of the datasets passed criteria for attentive behavior. The 3rd column shows the number of participant values per parameter that were removed because of outlier status at Step 3 (note: for Card, additional participants are removed at this step due to the dimension reduction procedure required from highly correlated parameters as described in Supplement A) and the 4th column shows the number of participants per parameter/s retained for final analysis.

Supplement B: Principal Component Analyses

Supplementary Table B1

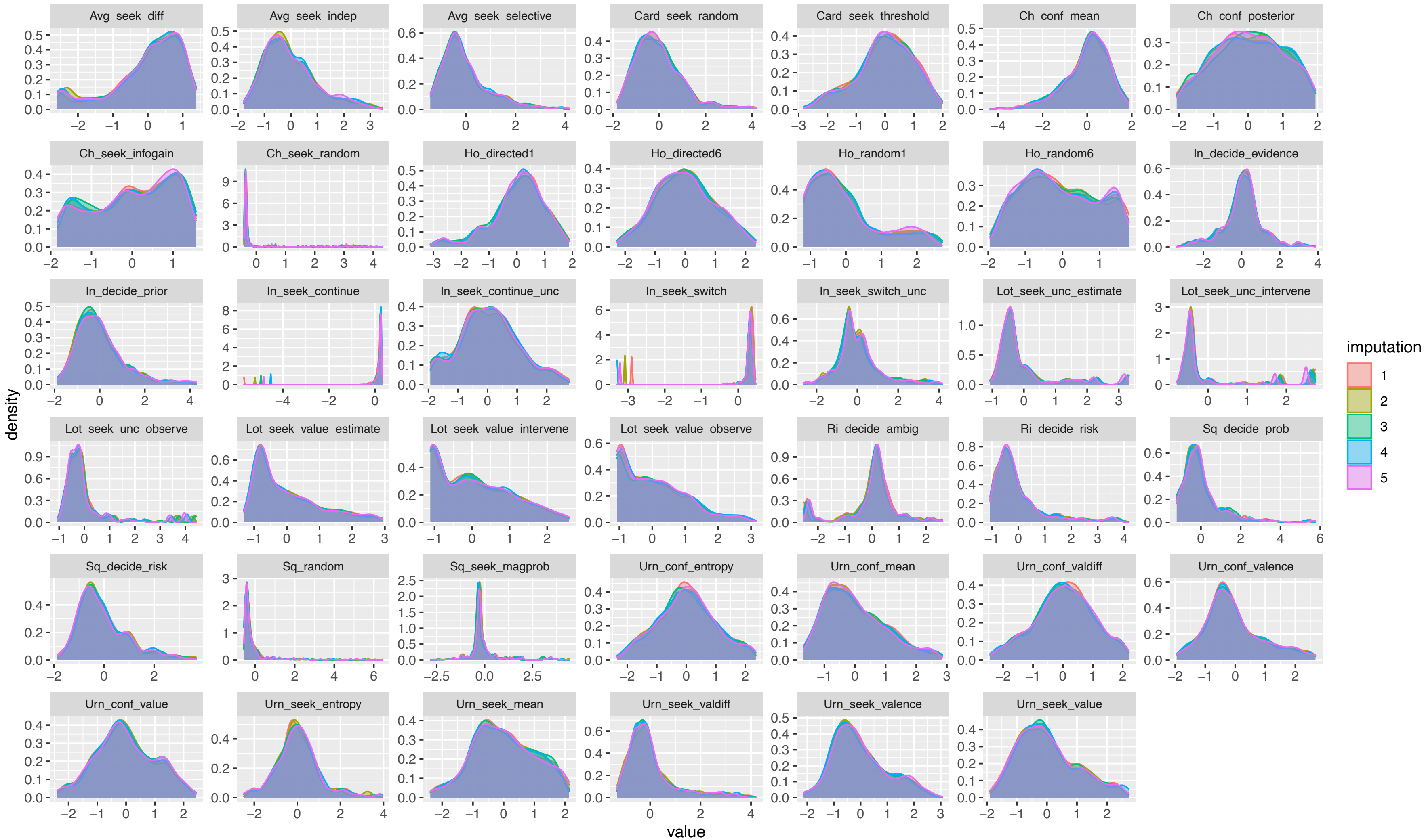
Descriptive Statistics for Behavioral Variables Following Outlier/Poor Data Removal, Prior to Multiple Imputation, Standardizing and Scaling

Variable	n	mean	sd	min	max	skew	kurtosis
Ch_seek_infogain	511	0.55	0.26	0.04	0.93	-0.45	-1.02
Ch_seek_random	511	0.69	1.7	0.07	9.27	3.67	12.4
Ch_conf_posterior	510	0.48	0.25	-0.07	0.93	-0.16	-0.84
Sq_decide_risk	441	0.56	0.37	-0.14	1.95	1.12	1.45
Sq_decide_prob	441	1.15	0.97	0	6.35	2.27	7.01
Sq_random	441	0.76	1.42	0.01	10.88	4.4	22.23
Sq_seek_magprob	441	0.01	0.05	-0.15	0.27	2.3	8.58
Avg_decide_indep	525	-0.12	0.52	-1.05	1.73	0.94	0.79
Avg_decide_diff	540	0.78	0.3	0	1.19	-1.16	0.66
Avg_decide_selective	525	2.25	1.55	0	8.93	1.38	2.25
In_seek_continue	520	-5.48	20.02	-102.57	1.04	-4.59	19.33
In_seek_continue_unc	509	6.05	3.15	-0.2	14.26	0.19	-0.2
In_seek_switch	522	-10.69	27.33	-102.57	1.48	-3.03	7.28
In_seek_switch_unc	509	0.99	2.31	-4.71	9.5	0.92	1.81
In_decide_prior	509	1.14	0.45	0.37	2.86	1.25	2.02
In_decide_evidence	509	0.99	0.96	-2.19	4.42	0.1	1.79
Ri_decide_risk	531	0.61	0.55	0.03	3.19	2.19	5.48
Ri_decide_ambig	531	-0.04	1.53	-4.03	4.17	-0.86	1.98
Lot_seek_unc_observe	484	0.6	1.06	-0.47	4.66	2.57	6.18
Lot_seek_value_observe	484	2.64	2.46	0	10.28	0.72	-0.21
Lot_seek_unc_estimate	496	1.18	1.75	-0.59	6.22	1.79	2.08
Lot_seek_value_estimate	483	2.33	2.83	-1.33	10.67	1.14	0.41

Lot_seek_unc_intervene	496	1.32	1.96	-0.28	6.22	1.68	1.22
Lot_seek_value_intervene	484	3.75	3.47	0	12.4	0.57	-0.73
Card_seek_threshold	550	-0.03	0.95	-2.7	1.91	-0.37	-0.3
Card_seek_random	538	0	0.87	-1.49	3.51	1.23	2.21
Ho_directed1	542	0.44	0.08	0.16	0.6	-0.79	0.84
Ho_directed6	542	0.58	0.13	0.28	0.87	0.11	-0.53
Ho_random1	557	0.12	0.11	0	0.42	1.17	0.63
Ho_random6	542	0.22	0.11	0.02	0.43	0.23	-1.05
Urn_conf_mean	471	3.3	0.3	2.77	4.16	0.66	-0.09
Urn_conf_valence	471	0.15	0.44	-0.73	1.43	0.74	0.4
Urn_conf_valdiff	471	0	0.08	-0.22	0.19	-0.15	-0.28
Urn_conf_value	471	0.06	0.25	-0.53	0.66	0.14	-0.49
Urn_conf_entropy	471	-0.02	0.1	-0.26	0.23	0.08	-0.29
Urn_seek_mean	471	3.45	0.49	2.29	4.49	0.1	-0.59
Urn_seek_valence	471	0.25	0.45	-0.69	1.68	0.67	0.08
Urn_seek_valdiff	471	0.11	0.21	-0.18	0.96	1.75	3.29
Urn_seek_value	471	0.25	0.36	-0.46	1.21	0.6	-0.21
Urn_seek_entropy	471	0	0.14	-0.35	0.53	0.62	1.58
Ch_conf_mean	539	7.26	0.95	3.3	8.97	-0.95	1.22

Supplementary Fig. B1.

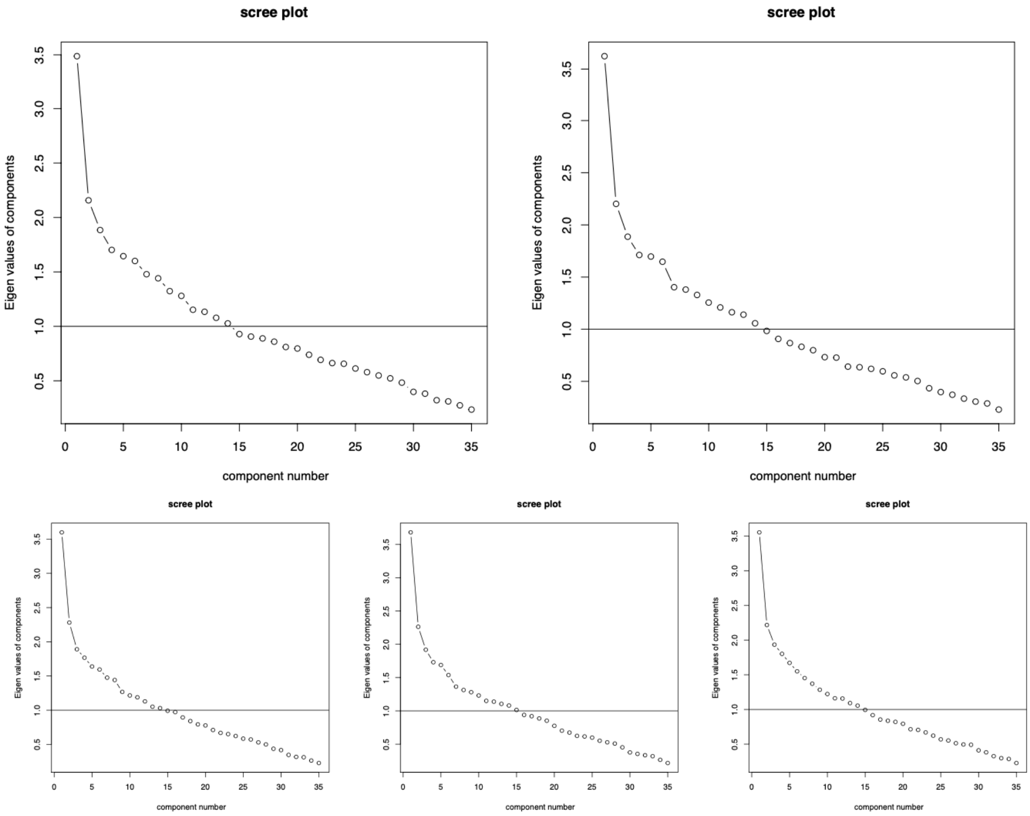
Distributions of behavioral parameters after multiple imputation.



Note. Distributions of individual parameters entered in the analyses (after Step 3, i.e., removal of outliers and poor-quality data). Variables are centered and scaled. Colors display results across the five multiply imputed datasets, permitting visualization of what is similar or different across dataset.

Supplementary Fig. B2

Scree plot



Note. Scree plots across the full dataset (train + test) for each of the five multiply imputed datasets, assessing the dimensionality of the structure.

Supplementary Table B2

Comparison of 1-, 2-, and 3-Component Model Loadings

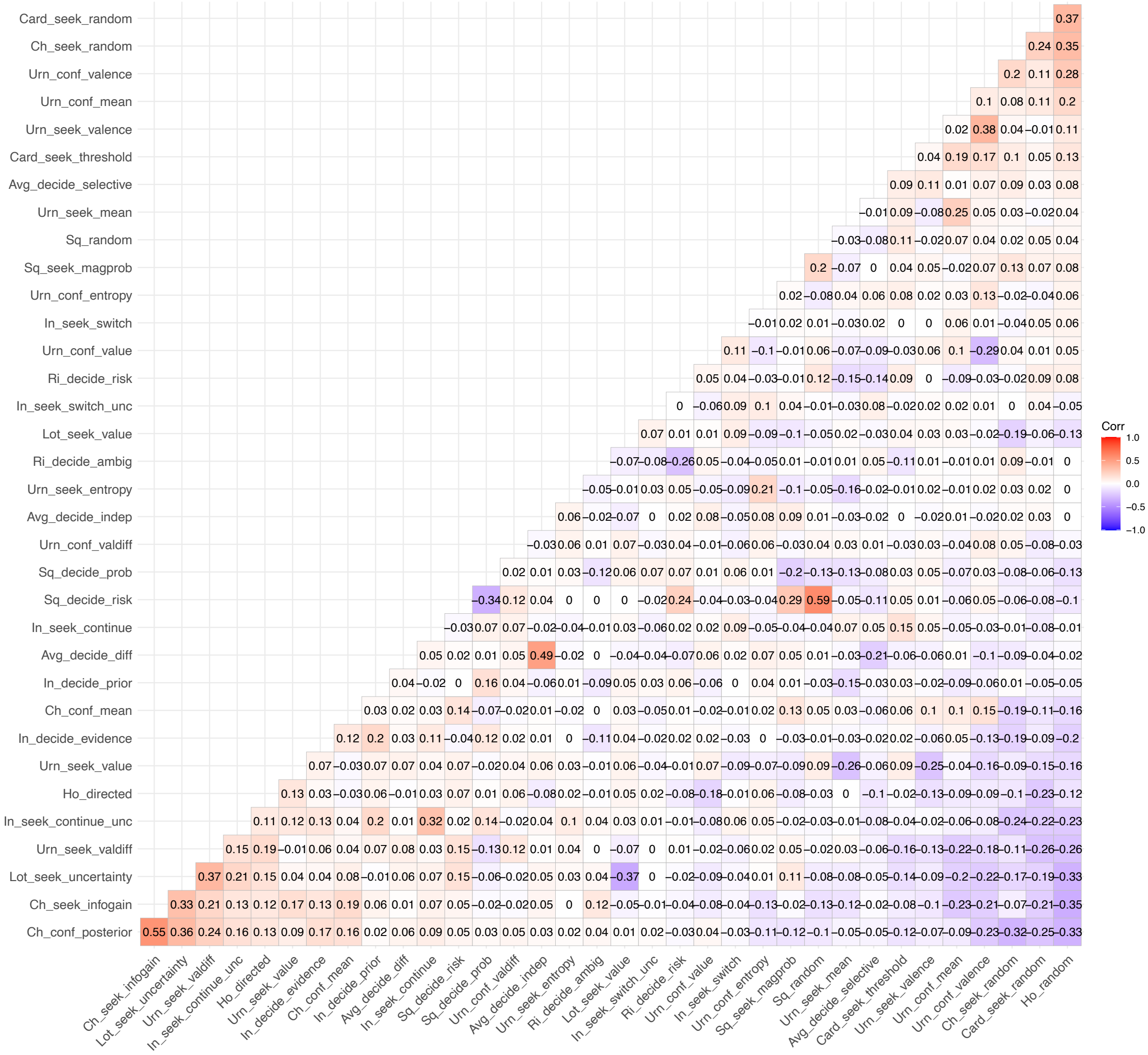
	1PC	2PC		3PC		
	PC1	PC1	PC2	PC1	PC2	PC3
Ch_conf_posterior	**0.66**	**0.66**	0.01	**0.65**	0.02	0.15
Ch_seek_infogain	**0.61**	**0.61**	0.07	**0.65**	0.01	0.01
Lot_seek_uncertainty	**0.59**	**0.57**	0.29	**0.67**	0.13	-0.2
Urn_seek_valdiff	**0.51**	**0.5**	0.26	**0.55**	0.17	-0.11
In_seek_continue_unc	**0.43**	**0.44**	-0.11	**0.32**	0.06	**0.38**
Ho_directed	**0.33**	**0.34**	0	**0.31**	0.03	0.12
Urn_seek_value	**0.3**	**0.3**	0.06	0.21	0.19	0.25
In_decide_evidence	0.29	**0.31**	-0.13	0.17	0.08	**0.42**
Ch_conf_mean	0.18	0.16	0.21	0.12	0.28	0.08
In_decide_prior	0.16	0.17	-0.13	0.04	0.07	**0.38**
Avg_decide_diff	0.15	0.14	0.14	0.14	0.14	-0.01
In_seek_continue	0.15	0.16	-0.12	0.08	0	0.25
Sq_decide_risk	0.13	0.07	**0.81**	0.06	**0.84**	-0.16
Sq_decide_prob	0.07	0.11	**-0.54**	-0.05	**-0.3**	**0.55**
Urn_conf_valdiff	0.06	0.05	0.07	0.02	0.13	0.07
Avg_decide_indep	0.06	0.04	0.17	0.06	0.14	-0.09
Urn_seek_entropy	0.04	0.05	-0.06	0.01	-0.01	0.11
Ri_decide_ambig	0.02	0.02	0.08	0.18	-0.17	**-0.4**
Lot_seek_value	0	0.02	-0.26	-0.14	0	**0.48**
In_seek_switch_unc	-0.01	-0.01	-0.1	-0.04	-0.05	0.1
Ri_decide_risk	-0.03	-0.05	0.19	-0.18	**0.4**	0.25
Urn_conf_value	-0.04	-0.04	0	-0.06	0.03	0.03
In_seek_switch	-0.07	-0.06	-0.1	-0.12	-0.01	0.15
Urn_conf_entropy	-0.08	-0.08	-0.06	-0.08	-0.04	0.02
Sq_seek_magprob	-0.09	-0.13	**0.54**	-0.06	**0.44**	**-0.34**
Sq_random	-0.1	-0.15	**0.64**	-0.19	**0.71**	-0.09
Urn_seek_mean	-0.16	-0.15	-0.05	-0.09	-0.15	-0.18
Avg_decide_selective	-0.17	-0.16	-0.15	-0.1	-0.25	-0.15
Card_seek_threshold	-0.24	-0.24	0.02	**-0.35**	0.19	0.19
Urn_seek_valence	-0.25	-0.25	-0.04	-0.27	-0.02	0

Urn_conf_mean	**-0.35**	**-0.35**	-0.06	**-0.37**	-0.03	-0.01
Urn_conf_valence	**-0.47**	**-0.47**	0.04	**-0.47**	0.04	-0.1
Ch_seek_random	**-0.48**	**-0.49**	0.09	**-0.36**	-0.1	**-0.42**
Card_seek_random	**-0.52**	**-0.52**	0.01	**-0.47**	-0.07	-0.23
Ho_random	**-0.68**	**-0.69**	0.01	**-0.62**	-0.08	-0.29

Note. Each number shows the PC loading of individual task parameters, ordered as in **Fig. 2A**. The leftmost column shows the 1 PC model used in **Fig. 2A**, and successive columns show the 1st and 2nd PC from a 2-PC model, and the 1st, 2nd, and 3rd PCs from the 3-PC model. Positive loadings are shown in red, negative loadings in blue, and loadings with absolute values greater than .30 are in **bold** font.

Supplementary Figure B3

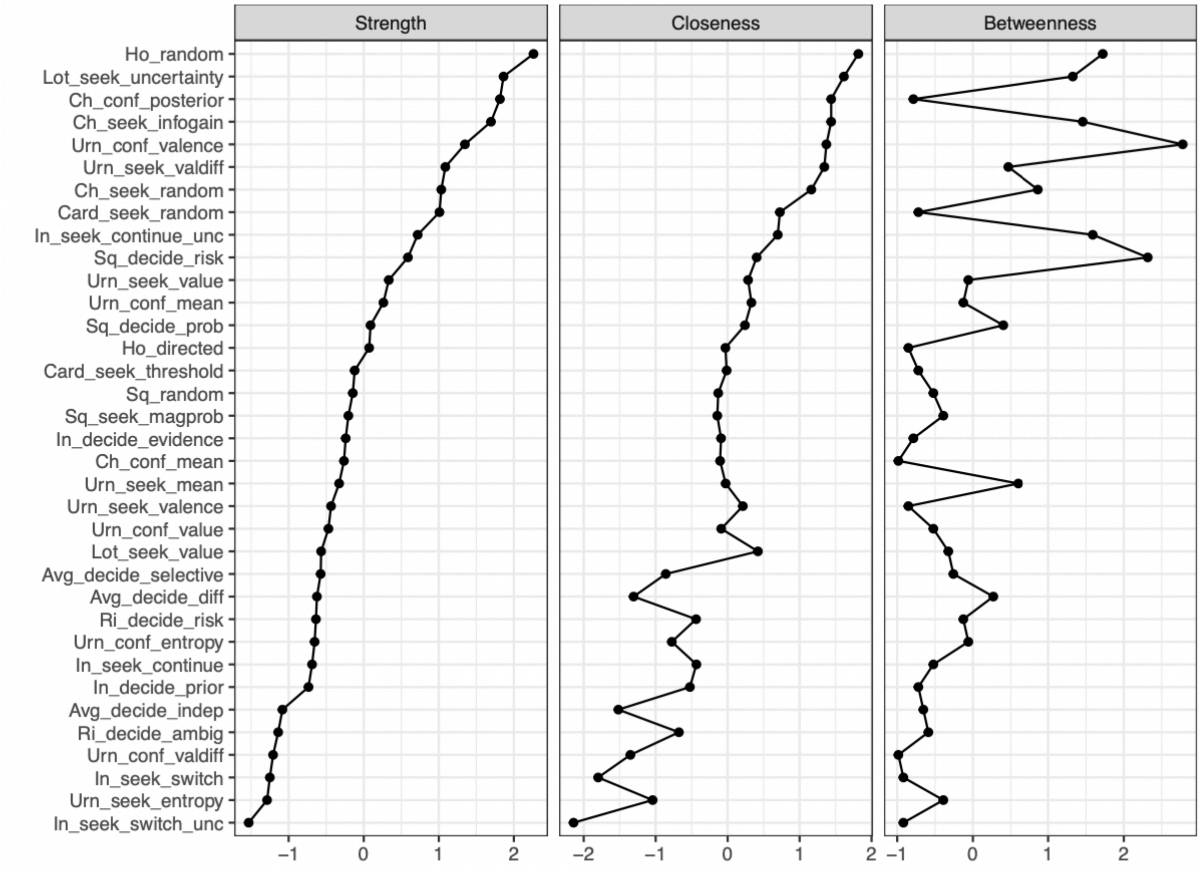
Correlations between model parameters



Note. Correlations are performed in the full dataset (N = 820), following imputation and aggregated via Rubin's rules. The variables are ordered according to PC loadings as in **Fig. 2A**. The numbers show the Pearson correlation coefficients and shadings indicate the correlation signs.

Supplementary Figure B4

Centrality indices for network model in Fig. 2B



Note. Network centrality can be conceived of as operationalizations of a node's importance based on the pattern of the connections in which the node plays a role. *Strength* is the number of immediate connections to the node. *Closeness* is the inverse of the sum of the distances of the node from all the other nodes in the network. *Betweenness* is the number of connections between any other two nodes that pass through the node of interest. The *y*-axis is ordered by greatest strength to weakest strength. Taken together, the graphs demonstrate that the same variables that appear to cluster together in **Fig. 2B** tend also to have the highest strength, closeness, and betweenness, and thus be the most "central" when employing statistical measures of network centrality.

Supplement C: Relationship Between PC and Personality Metrics

Supplementary Table C1

Descriptive Statistics for Personality Traits

Trait	α	*N*	mean	SD	min	max	skew	kurtosis	α Original study	Citation original study
Extraversion_B5	.84	606	3.01	0.88	1	5	-0.17	-0.67	.88	[104]
Agreeableness_B5	.77	606	3.83	0.68	1.67	5	-0.16	-0.64	.79	[104]
Consc_B5	.82	606	3.82	0.72	1.33	5	-0.27	-0.41	.82	[104]
Neuroticism_B5	.85	606	2.76	0.88	1	5	0.12	-0.54	.84	[104]
Openness_B5	.76	606	3.63	0.63	1.2	5	-0.45	0.73	.81	[104]
Need_for_Cognition	.87	606	3.43	0.67	1.17	5	-0.25	0.22	.90	[105]
Joyous Exploration_cur	.82	606	5.31	1.10	1.2	7	-0.75	0.36	.90/.87	[5]
Deprivation_cur	.81	606	4.77	1.26	1	7	-0.47	-0.20	.83/.81	[5]
Stress_Tolerance_cur	.83	606	4.22	1.39	1	7	-0.04	-0.67	.90/.87	[5]
Social_cur	.81	606	4.60	1.34	1	7	-0.43	-0.34	.84/.86	[5]
Thrill_Seeking_cur	.82	606	3.79	1.38	1	7	-0.04	-0.69	.86/.85	[5]
Drive_BAS	.74	606	2.69	0.68	1	4	-0.18	-0.31	.76	[41]
Fun_BAS	.62	606	2.73	0.61	1	4	-0.27	-0.24	.66	[41]
Reward_BAS	.74	606	3.37	0.54	1	4	-1.17	1.56	.73	[41]
Behavioral Inhibition	.74	606	2.89	0.59	1	4	-0.23	-0.22	.74	[41]

Note. Descriptive statistics for questionnaire scores from the full dataset used (606 participants) prior to imputations. For each trait, the columns show, from left to right, alpha internal consistency, number of participants, mean, standard deviation, minimum value, maximum value, and assessments of normality (skew and kurtosis). The final two columns list the alpha internal consistency of the original study where this scale was introduced and citation for that study, respectively.

Supplementary Table C2

Hyperparameter Tuning Grid (Alpha and Lambda), Elastic Net Model

Imputation 1			Imputation 2			Imputation 3			Imputation 4			Imputation 5		
alpha	lambda	RMSE	alpha	lambda	RMSE	alpha	lambda	RMSE	alpha	lambda	RMSE	alpha	lambda	RMSE
0.1	0	0.846	0.1	0	0.848	0.1	0	0.885	0.1	0	0.879	0.1	0	0.861
0.1	0.001	0.846	0.1	0.001	0.848	0.1	0.001	0.885	0.1	0.001	0.879	0.1	0.001	0.861
0.1	0.002	0.846	0.1	0.002	0.848	0.1	0.002	0.885	0.1	0.002	0.879	0.1	0.002	0.861
0.1	0.006	0.846	0.1	0.005	0.848	0.1	0.005	0.884	0.1	0.005	0.879	0.1	0.005	0.861
0.1	0.013	0.846	0.1	0.012	0.847	0.1	0.012	0.884	0.1	0.012	0.879	0.1	0.013	0.861
0.1	0.029	0.846	0.1	0.028	0.847	0.1	0.028	0.883	0.1	0.028	0.878	0.1	0.029	0.86
0.1	0.068	0.846	0.1	0.065	0.846	0.1	0.065	0.882	0.1	0.064	0.876	0.1	0.068	0.86
0.1	0.157	0.85	0.1	0.151	0.849	0.1	0.151	0.884	0.1	0.148	0.878	0.1	0.156	0.862
0.1	0.363	0.866	0.1	0.349	0.864	0.1	0.348	0.894	0.1	0.343	0.891	0.1	0.36	0.876
0.2	0	0.846	0.2	0	0.848	0.2	0	0.885	0.2	0	0.879	0.2	0	0.861
0.2	0.001	0.846	0.2	0.001	0.848	0.2	0.001	0.885	0.2	0.001	0.879	0.2	0.001	0.861
0.2	0.002	0.846	0.2	0.002	0.848	0.2	0.002	0.885	0.2	0.002	0.879	0.2	0.002	0.861
0.2	0.006	0.846	0.2	0.005	0.848	0.2	0.005	0.884	0.2	0.005	0.879	0.2	0.005	0.861
0.2	0.013	0.846	0.2	0.012	0.847	0.2	0.012	0.884	0.2	0.012	0.878	0.2	0.013	0.861
0.2	0.029	0.846	0.2	0.028	0.847	0.2	0.028	0.883	0.2	0.028	0.877	0.2	0.029	0.86
0.2	0.068	0.847	0.2	0.065	0.846	0.2	0.065	0.883	0.2	0.064	0.876	0.2	0.068	0.861
0.2	0.157	0.854	0.2	0.151	0.853	0.2	0.151	0.887	0.2	0.148	0.882	0.2	0.156	0.866
0.2	0.363	0.879	0.2	0.349	0.875	0.2	0.348	0.907	0.2	0.343	0.903	0.2	0.36	0.889
0.3	0	0.846	0.3	0	0.848	0.3	0	0.885	0.3	0	0.879	0.3	0	0.861
0.3	0.001	0.846	0.3	0.001	0.848	0.3	0.001	0.885	0.3	0.001	0.879	0.3	0.001	0.861
0.3	0.002	0.846	0.3	0.002	0.848	0.3	0.002	0.885	0.3	0.002	0.879	0.3	0.002	0.861
0.3	0.006	0.846	0.3	0.005	0.848	0.3	0.005	0.884	0.3	0.005	0.879	0.3	0.005	0.861
0.3	0.013	0.846	0.3	0.012	0.847	0.3	0.012	0.884	0.3	0.012	0.878	0.3	0.013	0.861
0.3	0.029	0.847	0.3	0.028	0.846	0.3	0.028	0.883	0.3	0.028	0.876	0.3	0.029	0.861

0.3	0.068	0.848	0.3	0.065	0.848	0.3	0.065	0.883	0.3	0.064	0.877	0.3	0.068	0.862
0.3	0.157	0.859	0.3	0.151	0.858	0.3	0.151	0.891	0.3	0.148	0.888	0.3	0.156	0.87
0.3	0.363	0.893	0.3	0.349	0.889	0.3	0.348	0.921	0.3	0.343	0.915	0.3	0.36	0.903
0.4	0	0.846	0.4	0	0.848	0.4	0	0.885	0.4	0	0.879	0.4	0	0.861
0.4	0.001	0.846	0.4	0.001	0.848	0.4	0.001	0.885	0.4	0.001	0.879	0.4	0.001	0.861
0.4	0.002	0.846	0.4	0.002	0.848	0.4	0.002	0.884	0.4	0.002	0.879	0.4	0.002	0.861
0.4	0.006	0.846	0.4	0.005	0.848	0.4	0.005	0.884	0.4	0.005	0.879	0.4	0.005	0.861
0.4	0.013	0.846	0.4	0.012	0.847	0.4	0.012	0.883	0.4	0.012	0.877	0.4	0.013	0.861
0.4	0.029	0.847	0.4	0.028	0.846	0.4	0.028	0.883	0.4	0.028	0.876	0.4	0.029	0.861
0.4	0.068	0.849	0.4	0.065	0.85	0.4	0.065	0.884	0.4	0.064	0.879	0.4	0.068	0.863
0.4	0.157	0.865	0.4	0.151	0.861	0.4	0.151	0.896	0.4	0.148	0.893	0.4	0.156	0.875
0.4	0.363	0.908	0.4	0.349	0.906	0.4	0.348	0.939	0.4	0.343	0.928	0.4	0.36	0.922
0.5	0	0.846	0.5	0	0.848	0.5	0	0.885	0.5	0	0.879	0.5	0	0.861
0.5	0.001	0.846	0.5	0.001	0.848	0.5	0.001	0.885	0.5	0.001	0.879	0.5	0.001	0.861
0.5	0.002	0.846	0.5	0.002	0.848	0.5	0.002	0.884	0.5	0.002	0.879	0.5	0.002	0.861
0.5	0.006	0.846	0.5	0.005	0.847	0.5	0.005	0.884	0.5	0.005	0.878	0.5	0.005	0.861
0.5	0.013	0.847	0.5	0.012	0.847	0.5	0.012	0.883	0.5	0.012	0.877	0.5	0.013	0.861
0.5	0.029	0.847	0.5	0.028	0.846	0.5	0.028	0.883	0.5	0.028	0.876	0.5	0.029	0.861
0.5	0.068	0.85	0.5	0.065	0.852	0.5	0.065	0.885	0.5	0.064	0.881	0.5	0.068	0.865
0.5	0.157	0.871	0.5	0.151	0.865	0.5	0.151	0.901	0.5	0.148	0.897	0.5	0.156	0.881
0.5	0.363	0.923	0.5	0.349	0.924	0.5	0.348	0.955	0.5	0.343	0.942	0.5	0.36	0.937
0.6	0	0.846	0.6	0	0.848	0.6	0	0.885	0.6	0	0.879	0.6	0	0.861
0.6	0.001	0.846	0.6	0.001	0.848	0.6	0.001	0.885	0.6	0.001	0.879	0.6	0.001	0.861
0.6	0.002	0.846	0.6	0.002	0.848	0.6	0.002	0.884	0.6	0.002	0.879	0.6	0.002	0.861
0.6	0.006	0.846	0.6	0.005	0.847	0.6	0.005	0.884	0.6	0.005	0.878	0.6	0.005	0.861
0.6	0.013	0.847	0.6	0.012	0.847	0.6	0.012	0.883	0.6	0.012	0.877	0.6	0.013	0.861
0.6	0.029	0.847	0.6	0.028	0.847	0.6	0.028	0.883	0.6	0.028	0.876	0.6	0.029	0.861
0.6	0.068	0.852	0.6	0.065	0.854	0.6	0.065	0.887	0.6	0.064	0.884	0.6	0.068	0.866

0.6	0.157	0.876	0.6	0.151	0.871	0.6	0.151	0.907	0.6	0.148	0.902	0.6	0.156	0.887
0.6	0.363	0.942	0.6	0.349	0.945	0.6	0.348	0.97	0.6	0.343	0.958	0.6	0.36	0.955
0.7	0	0.846	0.7	0	0.848	0.7	0	0.885	0.7	0	0.879	0.7	0	0.861
0.7	0.001	0.846	0.7	0.001	0.848	0.7	0.001	0.885	0.7	0.001	0.879	0.7	0.001	0.861
0.7	0.002	0.846	0.7	0.002	0.848	0.7	0.002	0.884	0.7	0.002	0.879	0.7	0.002	0.861
0.7	0.006	0.846	0.7	0.005	0.847	0.7	0.005	0.884	0.7	0.005	0.878	0.7	0.005	0.861
0.7	0.013	0.847	0.7	0.012	0.847	0.7	0.012	0.883	0.7	0.012	0.876	0.7	0.013	0.861
0.7	0.029	0.848	0.7	0.028	0.847	0.7	0.028	0.883	0.7	0.028	0.877	0.7	0.029	0.862
0.7	0.068	0.855	0.7	0.065	0.855	0.7	0.065	0.889	0.7	0.064	0.887	0.7	0.068	0.867
0.7	0.157	0.881	0.7	0.151	0.877	0.7	0.151	0.914	0.7	0.148	0.907	0.7	0.156	0.894
0.7	0.363	0.962	0.7	0.349	0.961	0.7	0.348	0.987	0.7	0.343	0.971	0.7	0.36	0.97
0.8	0	0.846	0.8	0	0.848	0.8	0	0.885	0.8	0	0.879	0.8	0	0.861
0.8	0.001	0.846	0.8	0.001	0.848	0.8	0.001	0.885	0.8	0.001	0.879	0.8	0.001	0.861
0.8	0.002	0.846	0.8	0.002	0.848	0.8	0.002	0.884	0.8	0.002	0.879	0.8	0.002	0.861
0.8	0.006	0.846	0.8	0.005	0.847	0.8	0.005	0.884	0.8	0.005	0.878	0.8	0.005	0.861
0.8	0.013	0.847	0.8	0.012	0.847	0.8	0.012	0.883	0.8	0.012	0.876	0.8	0.013	0.861
0.8	0.029	0.848	0.8	0.028	0.848	0.8	0.028	0.883	0.8	0.028	0.877	0.8	0.029	0.862
0.8	0.068	0.858	0.8	0.065	0.856	0.8	0.065	0.891	0.8	0.064	0.889	0.8	0.068	0.868
0.8	0.157	0.887	0.8	0.151	0.885	0.8	0.151	0.921	0.8	0.148	0.912	0.8	0.156	0.901
0.8	0.363	0.977	0.8	0.349	0.975	0.8	0.348	1.001	0.8	0.343	0.984	0.8	0.36	0.984
0.9	0	0.846	0.9	0	0.848	0.9	0	0.885	0.9	0	0.879	0.9	0	0.861
0.9	0.001	0.846	0.9	0.001	0.848	0.9	0.001	0.885	0.9	0.001	0.879	0.9	0.001	0.861
0.9	0.002	0.846	0.9	0.002	0.848	0.9	0.002	0.884	0.9	0.002	0.879	0.9	0.002	0.861
0.9	0.006	0.847	0.9	0.005	0.847	0.9	0.005	0.884	0.9	0.005	0.878	0.9	0.005	0.861
0.9	0.013	0.847	0.9	0.012	0.847	0.9	0.012	0.883	0.9	0.012	0.876	0.9	0.013	0.861
0.9	0.029	0.848	0.9	0.028	0.849	0.9	0.028	0.884	0.9	0.028	0.878	0.9	0.029	0.863
0.9	0.068	0.86	0.9	0.065	0.856	0.9	0.065	0.893	0.9	0.064	0.89	0.9	0.068	0.87
0.9	0.157	0.893	0.9	0.151	0.892	0.9	0.151	0.929	0.9	0.148	0.917	0.9	0.156	0.909

0.9	0.363	0.993	0.9	0.349	0.99	0.9	0.348	1.014	0.9	0.343	0.997	0.9	0.36	1
1	0	0.846	1	0	0.848	1	0	0.885	1	0	0.879	1	0	0.861
1	0.001	0.846	1	0.001	0.848	1	0.001	0.885	1	0.001	0.879	1	0.001	0.861
1	0.002	0.846	1	0.002	0.848	1	0.002	0.884	1	0.002	0.879	1	0.002	0.861
1	0.006	0.847	1	0.005	0.847	1	0.005	0.884	1	0.005	0.877	1	0.005	0.861
1	0.013	0.847	1	0.012	0.846	1	0.012	0.883	1	0.012	0.876	1	0.013	0.861
1	0.029	0.848	1	0.028	0.849	1	0.028	0.884	1	0.028	0.879	1	0.029	0.863
1	0.068	0.863	1	0.065	0.858	1	0.065	0.895	1	0.064	0.892	1	0.068	0.873
1	0.157	0.899	1	0.151	0.899	1	0.151	0.936	1	0.148	0.923	1	0.156	0.916
1	0.363	1.008	1	0.349	1.007	1	0.348	1.025	1	0.343	1.012	1	0.36	1.014

Note. This model includes two hyperparameters: alpha and lambda. Alpha decides the degree to which regularization is based on the L1 penalty term (setting coefficients to zero) or L2 penalty term (shrinking the size of the coefficients), while lambda controls the degree of shrinkage in the L2 penalty term. The level of detail in the tuning parameter grid was set to 10, meaning that 10 values of alpha were chosen (.1 to 1 in .1 increments).

Supplementary Table C3

Hyperparameter Tuning Grid (mtry), Random Forest model

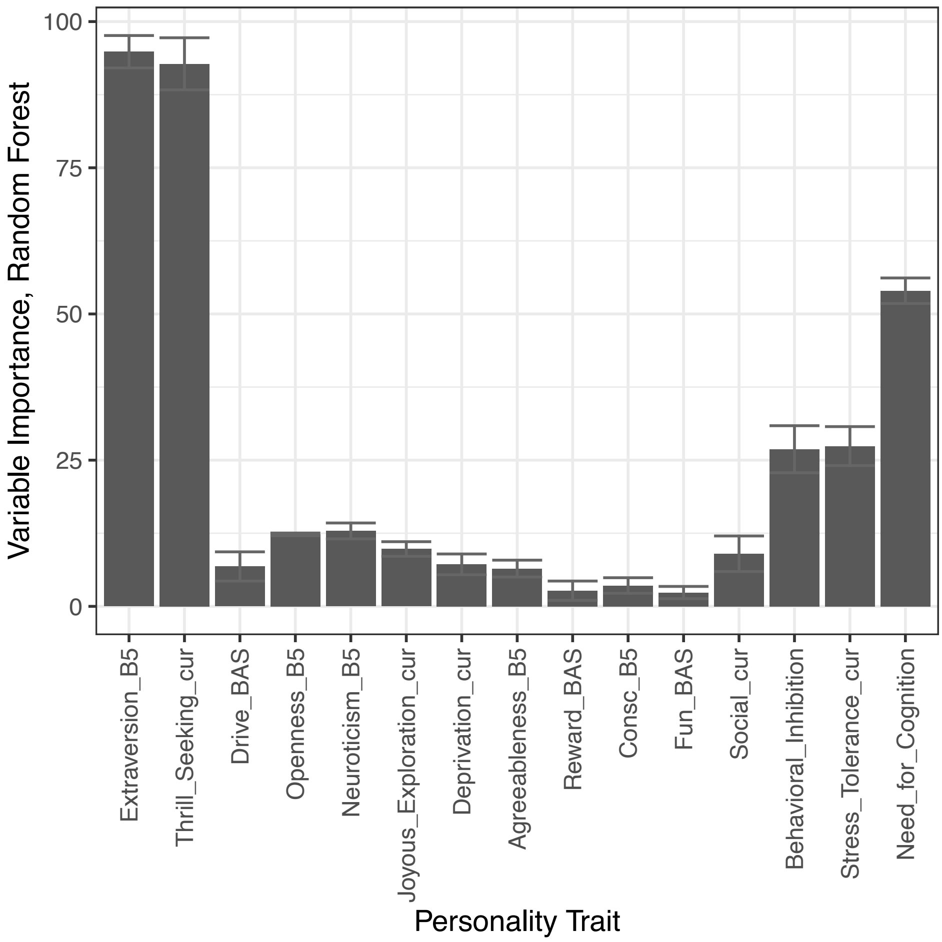
Imputation 1			Imputation 2			Imputation 3			Imputation 4			Imputation 5		
mtry	RMSE	R^2	mtry	RMSE	R^2	mtry	RMSE	R^2	mtry	RMSE	R^2	mtry	RMSE	R^2
2	0.879	0.296	2	0.886	0.288	2	0.911	0.258	2	0.894	0.271	2	0.883	0.291
3	0.872	0.3	3	0.881	0.289	3	0.904	0.266	3	0.89	0.27	3	0.88	0.289
4	0.87	0.299	4	0.883	0.285	4	0.906	0.26	4	0.888	0.271	4	0.88	0.286
6	0.869	0.298	6	0.882	0.284	6	0.906	0.259	6	0.891	0.264	6	0.881	0.284
7	0.871	0.295	7	0.883	0.283	7	0.908	0.256	7	0.896	0.256	7	0.888	0.273
9	0.875	0.287	9	0.885	0.279	9	0.908	0.256	9	0.891	0.263	9	0.886	0.276
10	0.874	0.291	10	0.886	0.279	10	0.912	0.249	10	0.896	0.256	10	0.887	0.274

12	0.875	0.29	12	0.888	0.275	12	0.908	0.256	12	0.894	0.261	12	0.891	0.27
13	0.876	0.287	13	0.89	0.274	13	0.909	0.254	13	0.896	0.258	13	0.892	0.267
15	0.879	0.283	15	0.887	0.277	15	0.911	0.251	15	0.896	0.256	15	0.89	0.27

Note. Random forest models are created by combining the predictions of many independently-trained models called decision trees. The *mtry* parameter controls how many features a decision tree can incorporate at a given point of time.

Supplementary Figure C1

Random Forest variable importance values



Note. Variable importance is a common Machine Learning metric to select which features are the most important in a given model. For Random Forest, variable importance is calculated from the mean squared error on the out-of-bag data for each tree, and then the same computed after permuting a variable. Note that this measure of variable importance doesn't show the direction in which personality traits predict the PC; instead, it demonstrates that some traits (here extraversion, need for cognition, thrill seeking, behavioral inhibition, and stress tolerance — are important to the predictions of the model.

Supplementary Table C4.

Linear regression predicting principal component scores

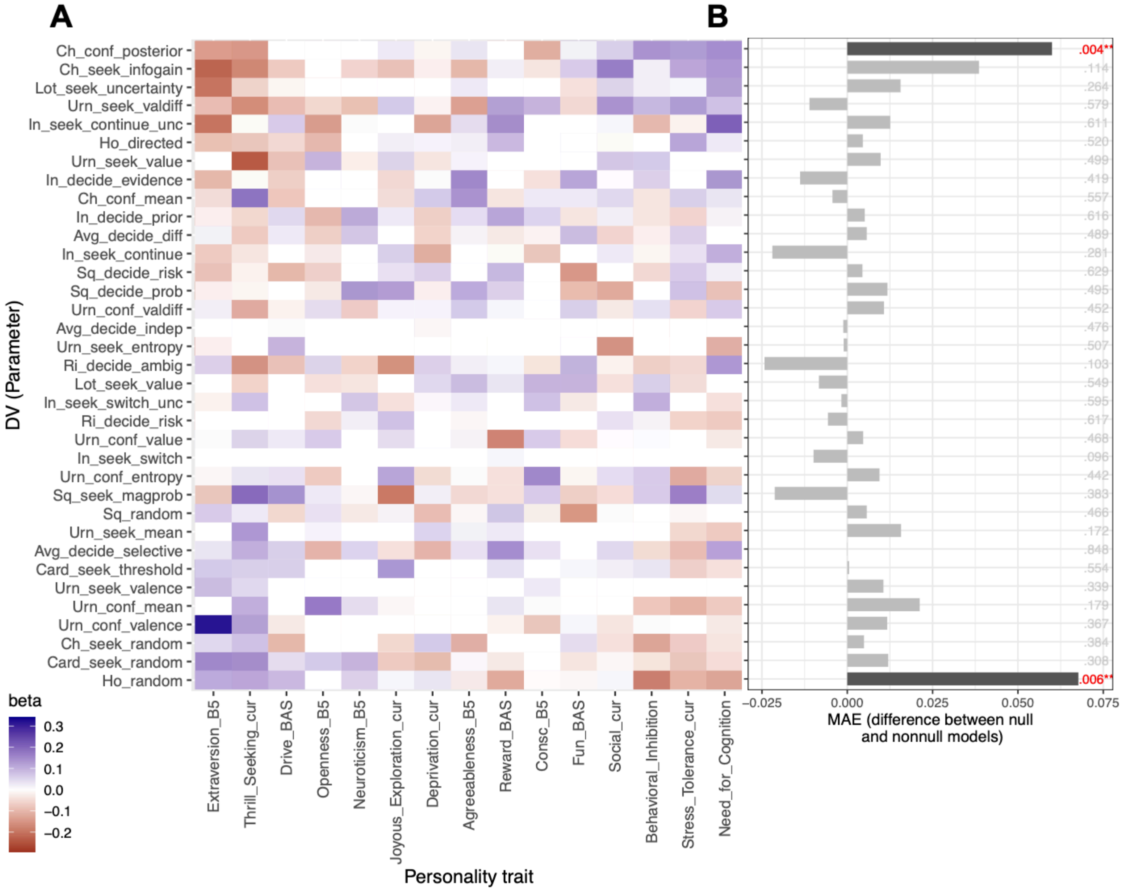
Predictor	*b*	*SE*	*t*	*DF*	*p*-value	*p*-value (corrected)
Stress_Tolerance_cur	0.21	0.05	4.20	22.36	<.001	.003
Need_for_Cognition	0.21	0.05	3.85	17.81	.001	.005
Behavioral_Inhibition	0.16	0.04	3.63	49.22	.001	.004
Social_cur	0.07	0.04	1.98	72.77	.051	.103
Fun_BAS	0.08	0.05	1.75	31.44	.090	.161
Agreeableness_B5	0.03	0.06	0.45	10.71	.661	.814
Reward_BAS	0.01	0.05	0.30	29.01	.764	.855
Consc_B5	0.01	0.05	0.25	64.04	.802	.855
Deprivation_cur	0.00	0.05	0.09	18.42	.927	.927
Drive_BAS	-0.04	0.05	-0.74	12.51	.473	.631

Neuroticism_B5	-0.05	0.05	-1.08	82.02	.285	.455
Joyous_Exploration_cur	-0.10	0.05	-2.08	63.87	.042	.096
Openness_B5	-0.12	0.04	-2.66	50.14	.010	.028
Thrill_Seeking_cur	-0.21	0.06	-3.65	13.59	.003	.009
Extraversion_B5	-0.30	0.05	-6.00	14.09	<.001	.001

Note. Beta weights and p-values (corrected and uncorrected) for linear regression model predicting principal component scores. Scores are computed on the full sample (N = 820) and corrected for multiple comparisons with false discovery rate at p <.05 (Benjamini-Hochberg procedure). Results are ordered by *t*-value.

Supplementary Figure. C2

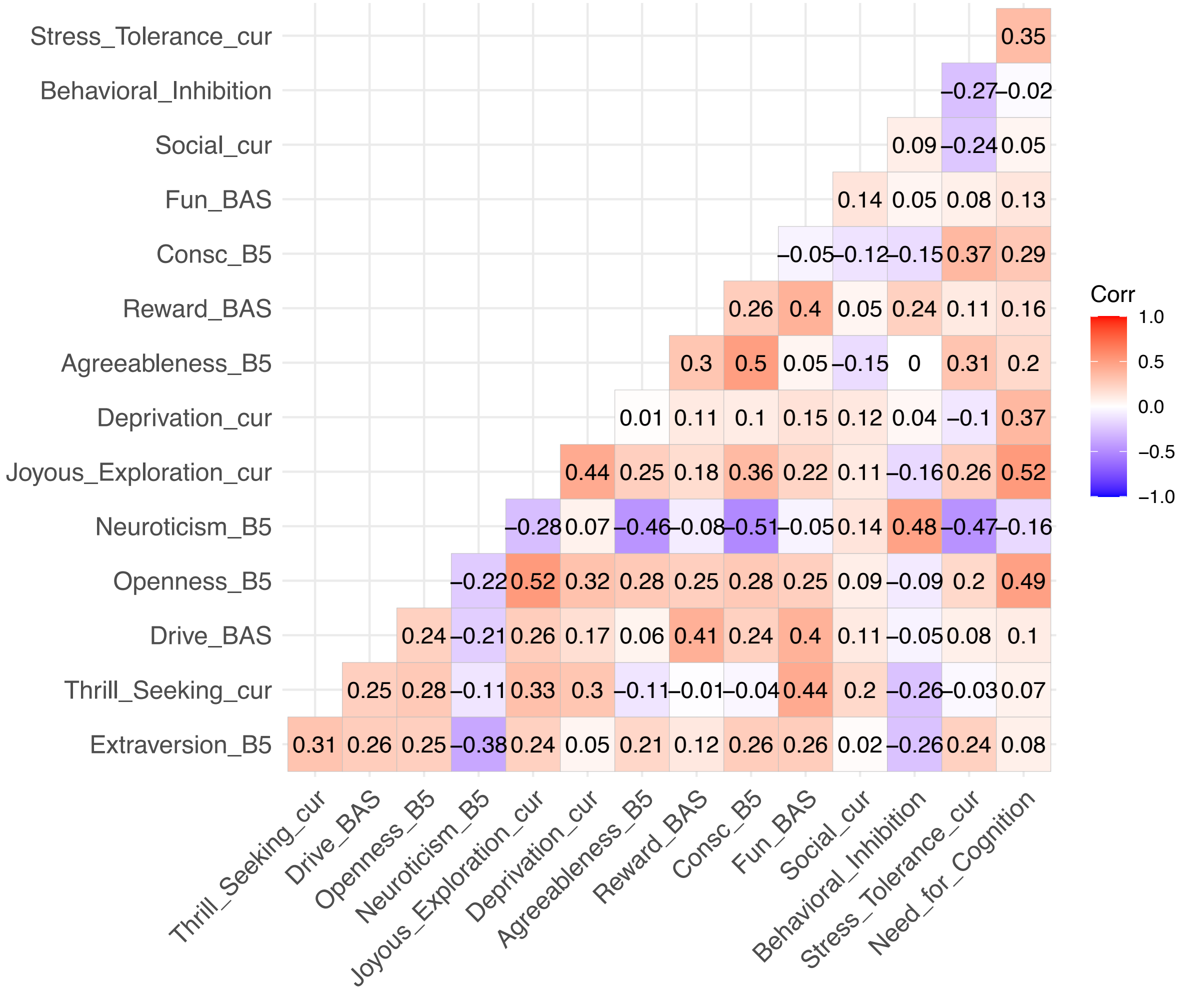
Prediction of individual parameters of information demand by personality traits



Note. **(A) Elastic net regression beta weights**. Colors represent the sign and strength of the beta weights according to the legend. Parameters are ordered by PC loading as in **Fig. 2A** (rows). Personality scores are ordered by overall predictive power as in **Fig. 3C** (columns). **(B) Comparison with the null model** The bars show the difference in the mean absolute error between the personality-based and null models for each parameter. Numbers show p-values relative to the null model (Wilcoxon test). Only the top positive and negative parameters (Ch_conf_posterior and Ho_random) were significantly better predicted by personality traits relative to the null model (black bars, red p-values) while the other parameters were not significantly predicted (gray), indicating that the PC analysis extracts meaningful variance that enhances statistical power in detecting associations with personality traits. Nevertheless, the trends are consistent with those from the aggregate PC score. The strongest predictors were consistent with those emerging from the aggregate PC score and prediction weights tended to have opposite signs for parameters indicating uncertainty-based versus random exploration (darker red/purple colors at opposite corners of the matrix).

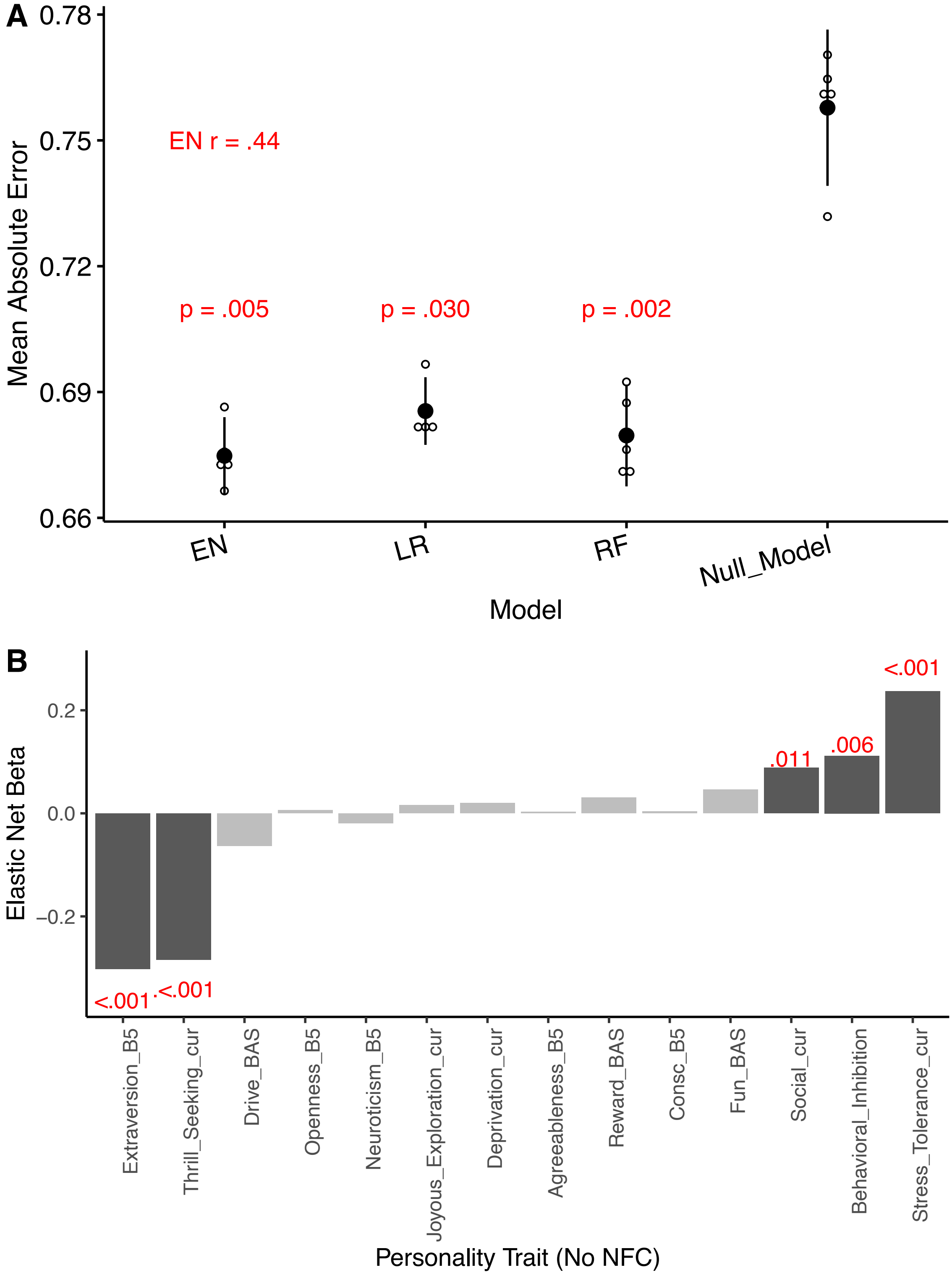
Supplementary Figure C3

Correlations among personality predictors



Note. Pearson correlations are performed in the full dataset ($N = 820$), following imputation and aggregated via Rubin's rules. The numbers and shading of each entry show the Pearson correlations between personality trait measures with traits ordered according to predictive weight as in Fig. 3C. Frames show correlations between need for cognition and the core curiosity traits joyous exploration, deprivation sensitivity, and openness to experience (all *ps* <.001).

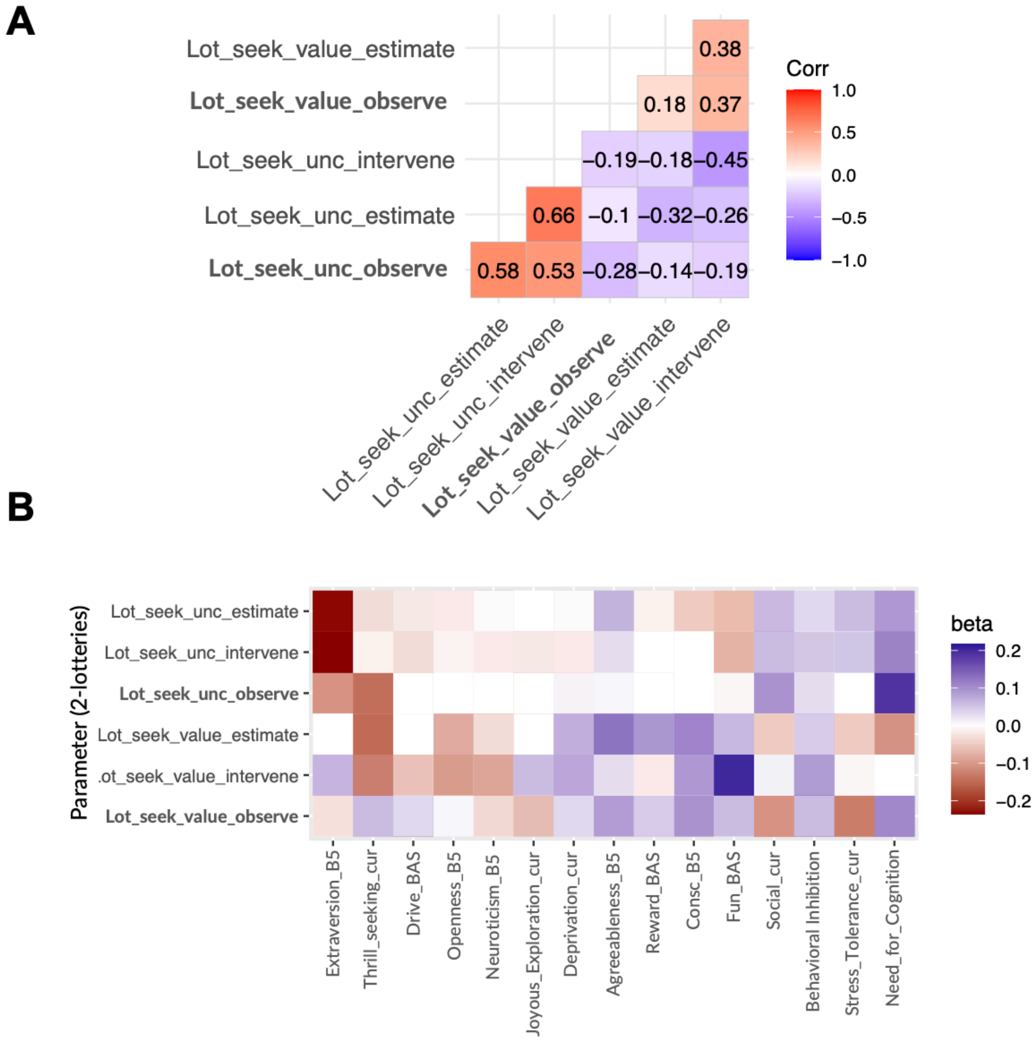
Supplementary Figure C4
Predicting PC scores from all personality traits except need for cognition



Note. Predictions excluding need for cognition replicated those in the entire dataset. **(A)** Mean absolute errors (same format as in **Fig. 3B**). **(B)** Prediction weights from the elastic net model (same format as in **Fig. 3C**).

Supplementary Figure C5

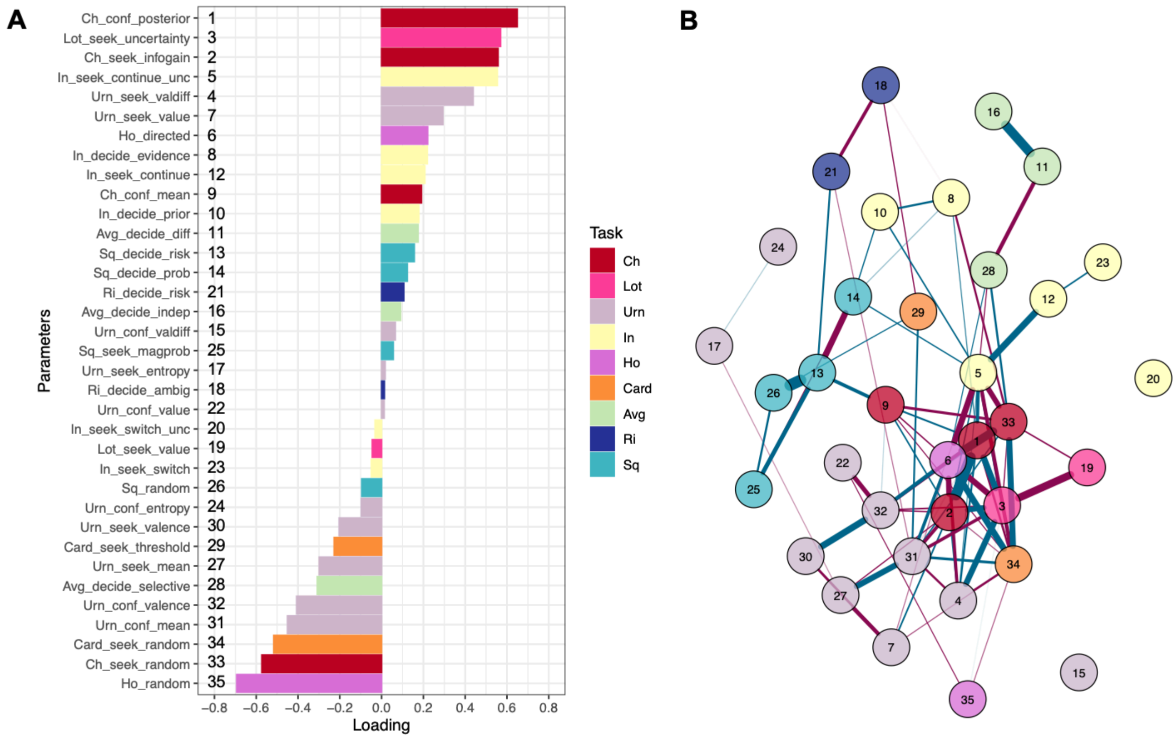
Comparisons of Instrumental and Non-Instrumental 2-lottery tasks



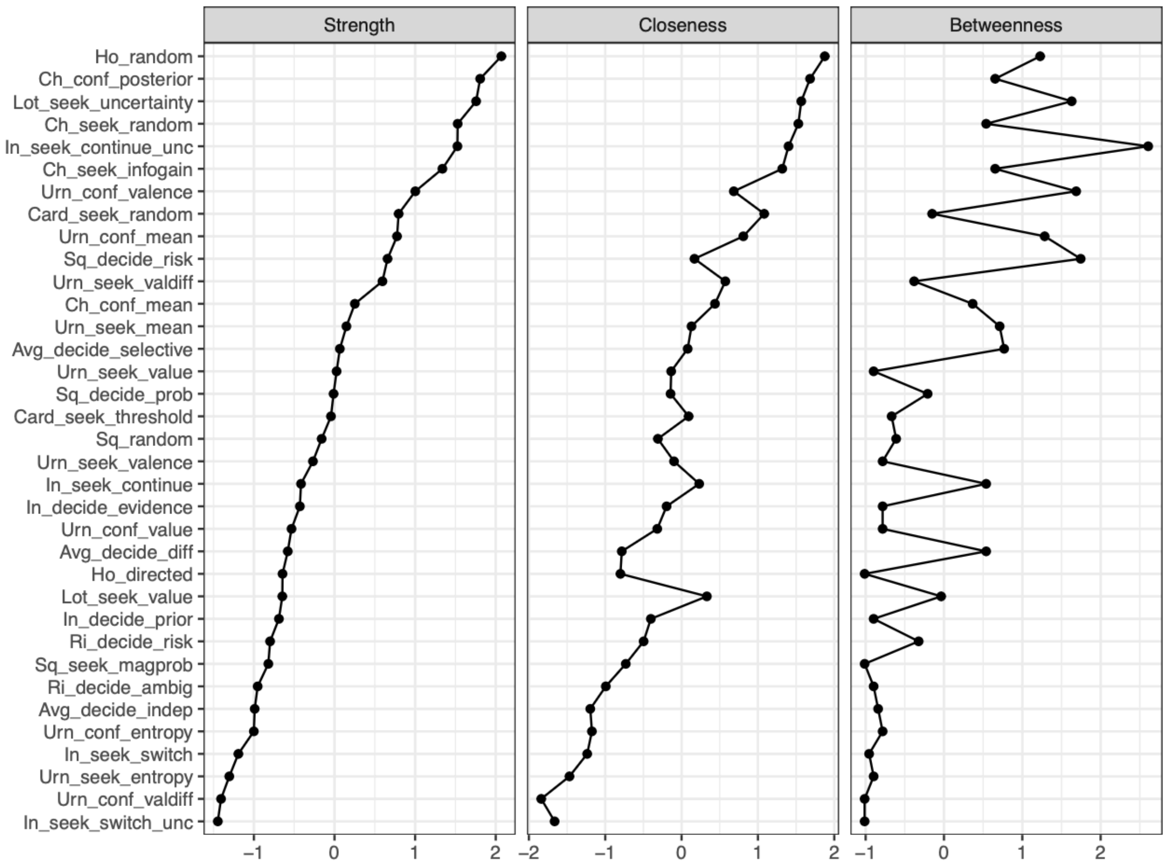
Note. **(A) Correlations between parameters on instrumental and non-instrumental 2-Lotteries tasks**. Uncertainty and value parameters from the non-instrumental version of the task (Observe) showed positive correlations with the corresponding parameters and negative correlations with the non-corresponding parameters from the instrumental versions of the task (Estimate and Intervene). This pattern corresponded to that shown across the two instrumental tasks. **(B) Elastic net beta weights showing the extent to which a personality trait predicted each parameter in instrumental and non-instrumental tasks.** Although no parameter was predicted significantly above the null model, the sign and magnitude of the beta weights showed similar trends for the instrumental and non instrumental tasks. As in the main analysis (**Fig. 3C**), uncertainty parameters tended to show positive weights for need for cognition, stress tolerance and BIS, and negative weights for thrill-seeking and extraversion. Value parameters showed a more mixed pattern.

Supplementary Figure C6

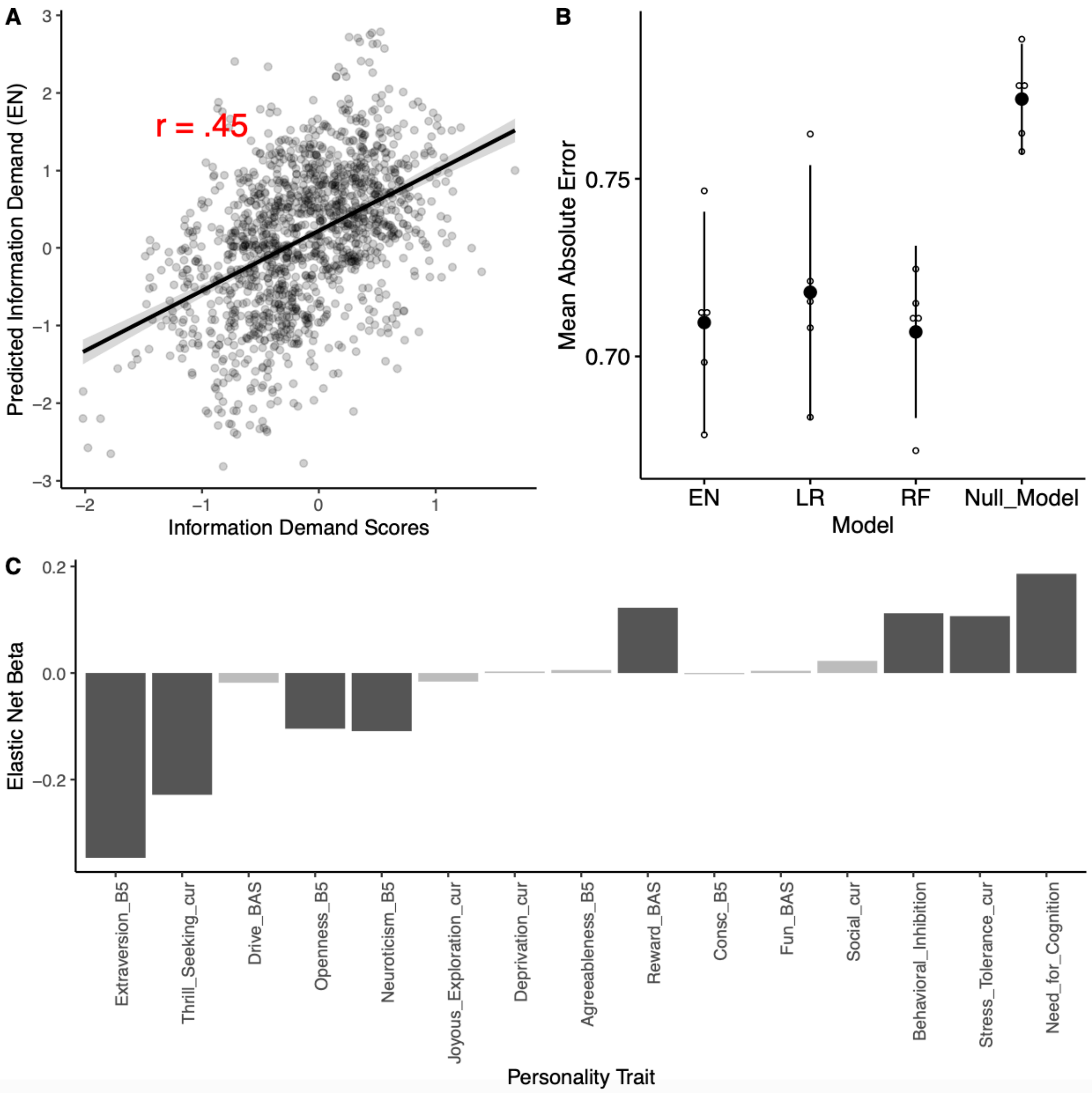
Replication without removal of poor-quality data



Supplementary Fig. C6. Equivalent of manuscript body Figure 2, displaying relationships between parameters of cognitive tasks, but including all datasets that were removed for poor quality data at Step 2 (see Supplementary Table A2-1). Variables are color-coded by task according to the legend in the center of the figure. **(A) Principal component loadings from a 1-component model**, ordered by manuscript body Figure 2, demonstrating close convergence to Figure 2's order and magnitude of the loading. Ch = Chips, Lot = Lotteries, In = Investigation, Ho = Horizons, Avg = Averaging, Ri = Risk, Sq = Squares. **(B) A network graph displaying zero-order correlations between task variables.** Nodes (colored circles) refer to variables and lines indicate correlations between variables. Red and blue lines indicate, respectively, positive and negative correlations and line thickness corresponds to correlation strength. Only significant correlations are shown ($p < .05$, Bonferroni corrected for multiple comparisons).



Supplementary Fig. C7. Centrality indices for model parameters. Equivalent of Supplementary Figure B4, but including all datasets that were removed for poor quality data at Step 2 (see Supplementary Table A2-1). See figure caption of Supplementary Figure B4 for description of centrality, closeness, and betweenness.



Supplementary Figure C8. Predicting PC scores from personality traits; equivalent of Figure 3 in the main manuscript, but including all datasets that were removed for poor quality data at Step 2 (see Supplementary Table A2-1). Results are broadly similar, albeit somewhat noisier. (A) Correlation between predicted and observed information demand for the elastic net model in the test dataset (N = 280). Each participant has 5 points corresponding to 5 multiple imputations, but the *r* value is the Pearson correlation derived by integrating across imputations and applying Rubin's rules for combining technical replicates[45]. (B) Comparison with a null model where PC scores were set to the mean. The filled circles show the Mean Absolute Errors (mean and 95% confidence intervals across 5 imputations), for each model, and the open circles show the Mean Absolute Error for each imputation. (C) Predictive power of each personality trait. The bars show the regression beta weights from the training dataset (N = 541 participants) in the elastic net model. The black bars show the weights that were statistically significant at $p < .05$, and gray bars show non-significant weights (significance assessed via permutation test, 1000 permutations x 5 multiple imputations for each trait; *Methods*).