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

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To understand human learning and progress, it is crucial to understand curiosity. But how consistent is curiosity's 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. A total of 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.

curiosity | information seeking | personality traits | individual differences | machine learning

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, and decades of psychological and neuroscientific research have made large strides toward this goal (1–3). These expansive efforts, however, produced different operationalizations of curiosity across fields of research, raising the question of how these operationalizations align and what that means for our understanding of curiosity (4). In this study, we investigate the convergence of curiosity constructs across personality psychology and cognitive science.

Although both personality psychology and cognitive science define curiosity as the desire to know (1, 5), they operationalize curiosity distinctly. Personality psychologists generally operationalize curiosity via scores on participant-rated trait curiosity personality scales (6, 7). Like other personality traits, curiosity traits are considered to be relatively stable over the lifespan and to be present to differing degrees in different individuals. In this view, trait curiosity includes one's tendency to experience emotions, cognitions, and behaviors related to possible information gain, which can be described by the core curiosity facets of joy and interest in learning and exploring (called *joyous exploration*) and frustrated deprivation related to not knowing something (called *deprivation sensitivity*) (5, 7–10) as well as more peripheral facets related to the ability to tolerate the stress associated with the unknown (*stress tolerance*), the willingness and appreciation to take risks (*thrill seeking*), and interest in understanding the motivations of others (*social curiosity*) (7, 11). 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 (7, 12–16), and even the propensity for aggression in interpersonal relationships (17).

Significance

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. Interindividual variability across tasks 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 openness to experience, deprivation sensitivity, and joyous exploration, identifying areas of overlap and divergence between definitions of curiosity across the two fields.

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By contrast, cognitive scientists typically operationalize curiosity as the desire or decision to request information—often referred to as "information seeking" or "information demand" (1, 18, 19). This literature postulates that information demand reflects an intrinsic drive to reduce uncertainty (increase the accuracy of one's predictions about future events) (1, 2, 18, 20–23) alongside a desire to regulate anticipatory emotions (savor the anticipation of positive outcomes but avoid the dread inherent in anticipating negative outcomes) (24, 25). An additional curiosity drive is behavioral randomness or stochasticity, which, distinct from mere inattentiveness, can be deployed strategically as a function of the exploration horizon (i.e., time available to explore) (26). Stochasticity generates random (or *diversive*) exploration that allows individuals to learn about novel options they would not approach otherwise and contrasts with directed (or *specific*) exploration which is focused on known sources of information or stimuli (27). Finally, cognitive studies distinguish between information seeking that is *extrinsically* versus *intrinsically* motivated—studied, respectively, in *instrumental* tasks in which the information guides future actions that obtain external (instrumental) rewards versus *noninstrumental* tasks in which participants request information for its own sake (24, 28, 29). Emerging evidence suggests that, despite their distinctions, intrinsically and extrinsically motivated information demand share important similarities, as both are affected by uncertainty reduction, anticipatory emotions, and stochasticity (30–32).

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 in instrumental, noninstrumental, and attentional contexts (19), but individual labs tend to design or select a single task and use this repeatedly—a siloed approach that makes it unclear whether the different tasks 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 does curiosity measured in cognitive tasks overlap with curiosity measured in personality psychology? Several considerations suggest that the two constructs may be closely related. Theoretical and empirical studies suggest that personality traits can be considered density distributions of situation/task-specific states similar to those captured in cognitive tasks (4, 33, 34), and some studies specifically investigate state/trait relations for curiosity (35, 36) or find similar results whether curiosity is assessed via state or trait measures (17). Furthermore, both cognitive and personality studies describe curiosity as involving constellations of motives and traits, which are combined with different weights in different individuals and generate different curiosity styles or information-gathering strategies (7, 26, 28, 29, 37). However, notwithstanding this possible overlap, it is unclear to what extent proposed mechanisms for information demand in cognitive tasks resemble states assumed to underpin trait curiosity—for example, how the mechanisms of savoring an anticipated reward relate to constructs like 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 (38). 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 cognitive tasks and personality questionnaires. The 9 cognitive tasks we selected involved those testing active information-seeking behaviors (the core expression of curiosity) and used a broad range of conditions in which participants gathered instrumental versus noninstrumental information and made explicit decisions versus providing curiosity ratings—alongside additional tasks probing cognitive constructs of selective attention, probabilistic reasoning, and risk/ambiguity attitudes which, from a computational perspective, are closely related to information demand. 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 (e.g., need for cognition, thrill seeking, stress tolerance) and noncuriosity traits (e.g., other Big Five personality traits) which were important for assessing divergent validity.

Using principal component analysis, we show that interindividual 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* and *SI Appendix*, Supplement A). Data quality was ensured by means of multiple screeners and post hoc quality checks, as well as by focusing on previously investigated tasks and questionnaires and verifying that our results replicated those obtained in previous studies in-lab or online (*Methods* and *SI Appendix*, Supplement A). The results from the cognitive tasks and personality scales were submitted to a two-step data analysis pipeline that is summarized in Fig. 1. In the first analysis step (Fig. 1*A*), we combined the 35 parameters characterizing performance on the cognitive tasks (*SI Appendix*, Table SA1-1 and *SI Appendix*, Supplement A) and subjected them to principal component (PC) analysis to extract lower-dimensional variance that was shared across tasks (Fig. 1*A* and *SI Appendix*, 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. 1*B*). 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 (39). 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.

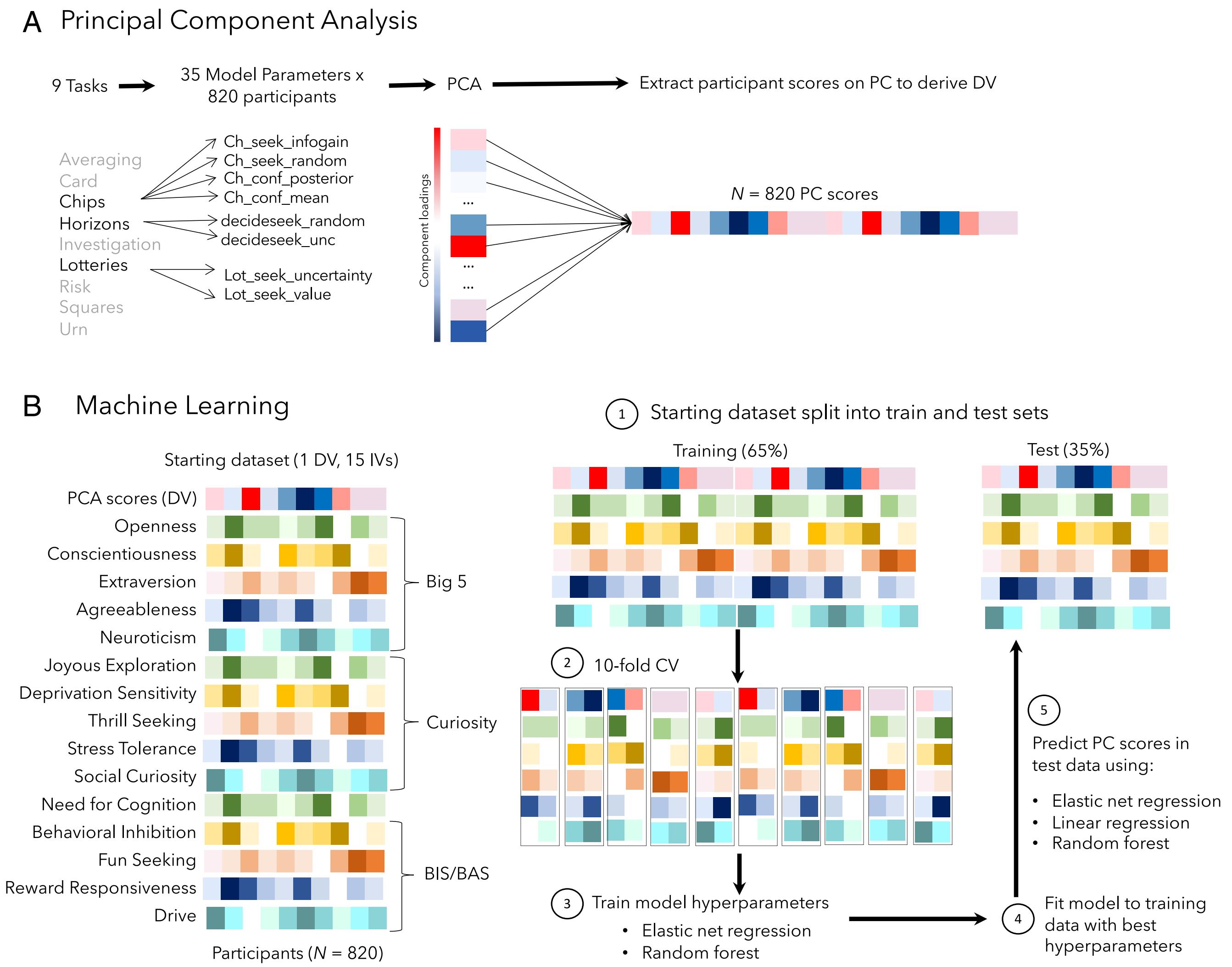

Fig. 1. Study analysis pipeline. (*A*) Dimensionality reduction. For each participant, performance on the cognitive tasks was characterized by thirty-five model parameters (*SI Appendix*, Table A1-1) which were then subjected to principal component (PC) analysis. This produced component loadings (i.e., 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 hyperparameters 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.

We describe the principal component analyses followed by the machine learning results.

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 noninstrumental 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 (28, 29). 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 (40). In the *Chips* tasks, participants chose which node in a circuit to probe to infer the connectivity of the circuit (41, 42). Finally, in the *Urn* task, participants rated their confidence and desire to obtain advance information about a probabilistic reward (gain or loss) (43). 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 noninstrumental, 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 (26). The *Card* task used a stopping scenario similar to the "secretary problem (44)," in which participants had to decide when to stop drawing cards to stick with the card they currently had to maximize their rewards (45).

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 weigh individual numbers in a number stream when attempting to calculate a running average of the stream (46). Because attention and active sensing behaviors are natural information-gathering actions (47), 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 parameterized their tendency to seek or avoid risk and ambiguity (48). 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 parameterized aspects of the information-seeking decisions, as well as aspects of the final decisions and confidence ratings. Individual parameters are described in detail in *SI Appendix*, Supplement A and descriptive statistics are in *SI Appendix*, Table SB1. After accounting for outliers and poor-quality/missing data (*Methods; SI Appendix*, Fig. B1), the resulting 35 parameters were pooled and submitted to a principal component analysis (*Methods*; Fig. 1*A*).

The scree plots from this analysis showed that the fraction of variance explained declined slowly over the principal components (PCs; *SI Appendix*, Fig. B2). The lack of a clear "elbow" pattern in the plots suggests that the tasks we considered were nonredundant 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. 2*A*). 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. 2*A*). Moreover, the two poles of the PC seemed to clearly distinguish information demand based on reducing uncertainty from strategies based on randomness or stochasticity (26, 49). The two parameters with the highest loadings at one pole of the PC came from the *Chips* task and described, respectively, the tendency to report confidence based on posterior uncertainty (Chips_conf_posterior) and investigate based on expected information gain (Chips_seek_infogain). 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 preprocessing 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 (26).

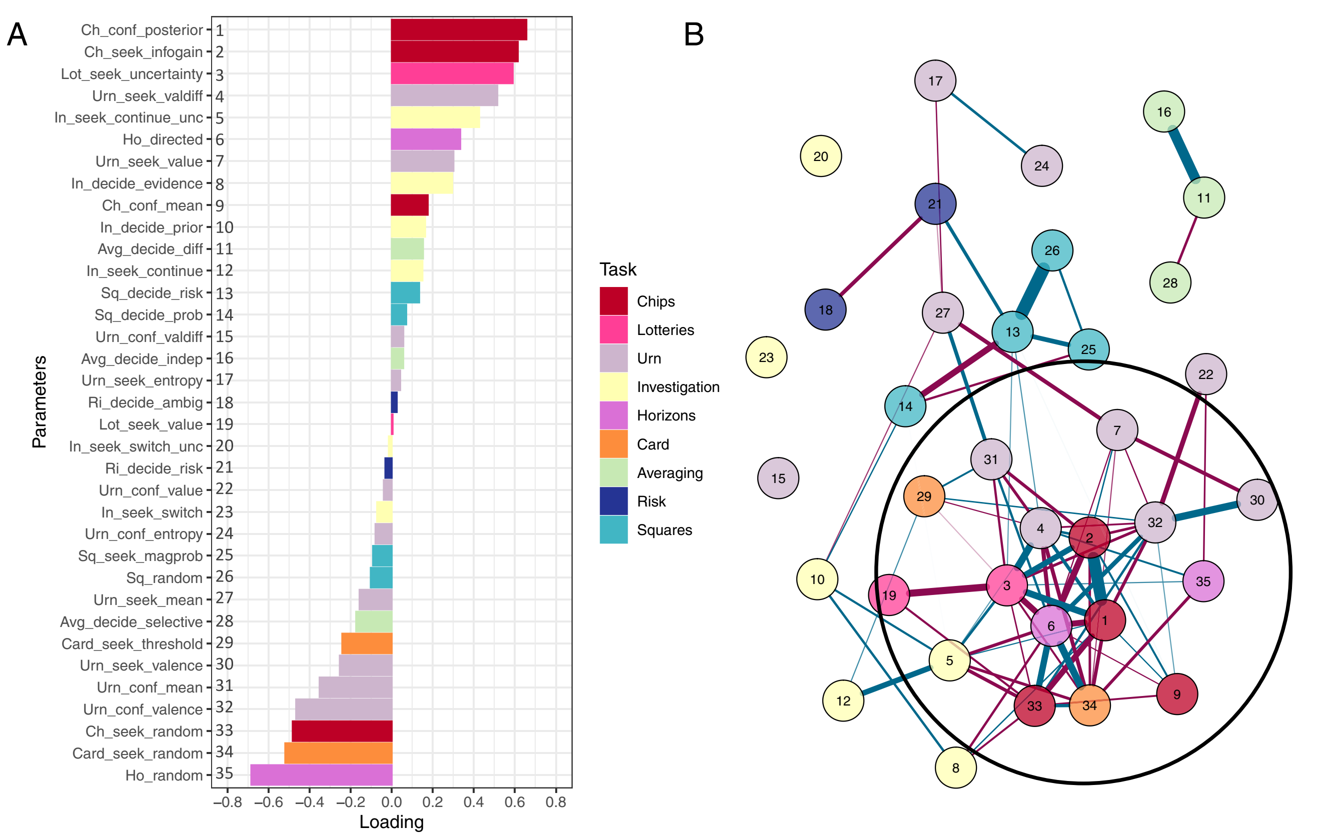

Fig. 2. Relationship between parameters of cognitive tasks. For *A* and *B*, variables are color-coded by task according to the legend in the center of the figure. (*A*) Principal component loadings from a one-component model, ordered by the sign and magnitude of the loading. The parameter labels are the same as in *SI Appendix*, Table A1-1. (*B*) A network graph displaying zero-order correlations between task variables. Nodes (colored circles) refer to variables and lines indicate correlations between variables. Blue and red lines indicate, respectively, positive and negative correlations and line thickness corresponds to correlation strength. Only significant correlations are shown ($P < 0.05$, 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.

Importantly, the directed-random exploration distinction was shown by both instrumental and noninstrumental tasks (*Urn* and *Lotteries)* (Fig. 2*A*), suggesting that 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 (*SI Appendix*, Table B2). 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 (*SI Appendix*, Table B2), 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 consistent in a network graph visualizing the statistically significant zero-order parameter correlations (P < 0.05, Bonferroni-corrected; Fig. 2*B*; see also *SI Appendix*, Fig. B3 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. 2*B*). This structure can also be observed via metrics of network centrality (*SI Appendix*, Fig. B4). In sum, dimensionality reduction analyses capture features that are specific to information-seeking/exploration decisions across multiple contexts in which these decisions unfold.

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 whether 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 (39). Five additional traits came from the *Five Dimensional Curiosity Inventory* and included joyous exploration, deprivation sensitivity, social curiosity, thrill seeking, and stress tolerance (7). Four traits came from the *BIS/BAS* questionnaire and included the behavioral inhibition system and the fun seeking, reward responsiveness, and drive subscales of behavioral activation system (50). 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* (51). Descriptive statistics for all 15 measures are given in *SI Appendix*, 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 (52, 53). 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. 1*B* 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. 3*B*). 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 (*SI Appendix*, Tables C2 and C3 provide 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 = 0.44, P < 0.001 for the elastic net model, Fig. 3*A*; r = 0.43, P < 0.001 and r = 0.44, P < 0.001 for, respectively, linear regression and random forest models). Prediction R^2 values showed that the models predicted 16 to 19% of the variance in the data, with R^2 values (mean across 5 imputations, n = 279 in the test set) 0.18 for elastic net regression; 0.16 for linear regression, and 0.19 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. 3*B*; Wilcox signed rank test relative to the null model: elastic net regression P = 0.011, linear regression P = 0.030, random forest P = 0.002).

Examination of individual weights showed that predictive capacity was associated with a small subset of traits (Fig. 3*C*). 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. 3*C*) and alternative models (*SI Appendix*, Fig. C1 and Table C4). Although social curiosity was also a positive predictor of PC scores for elastic net (Fig. 3*C*), this trait failed to be a significant predictor in linear regression (*SI Appendix*, Table C4) and produced low feature importance scores in random forest (*SI Appendix*, 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 (*SI Appendix*, Fig. 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).

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

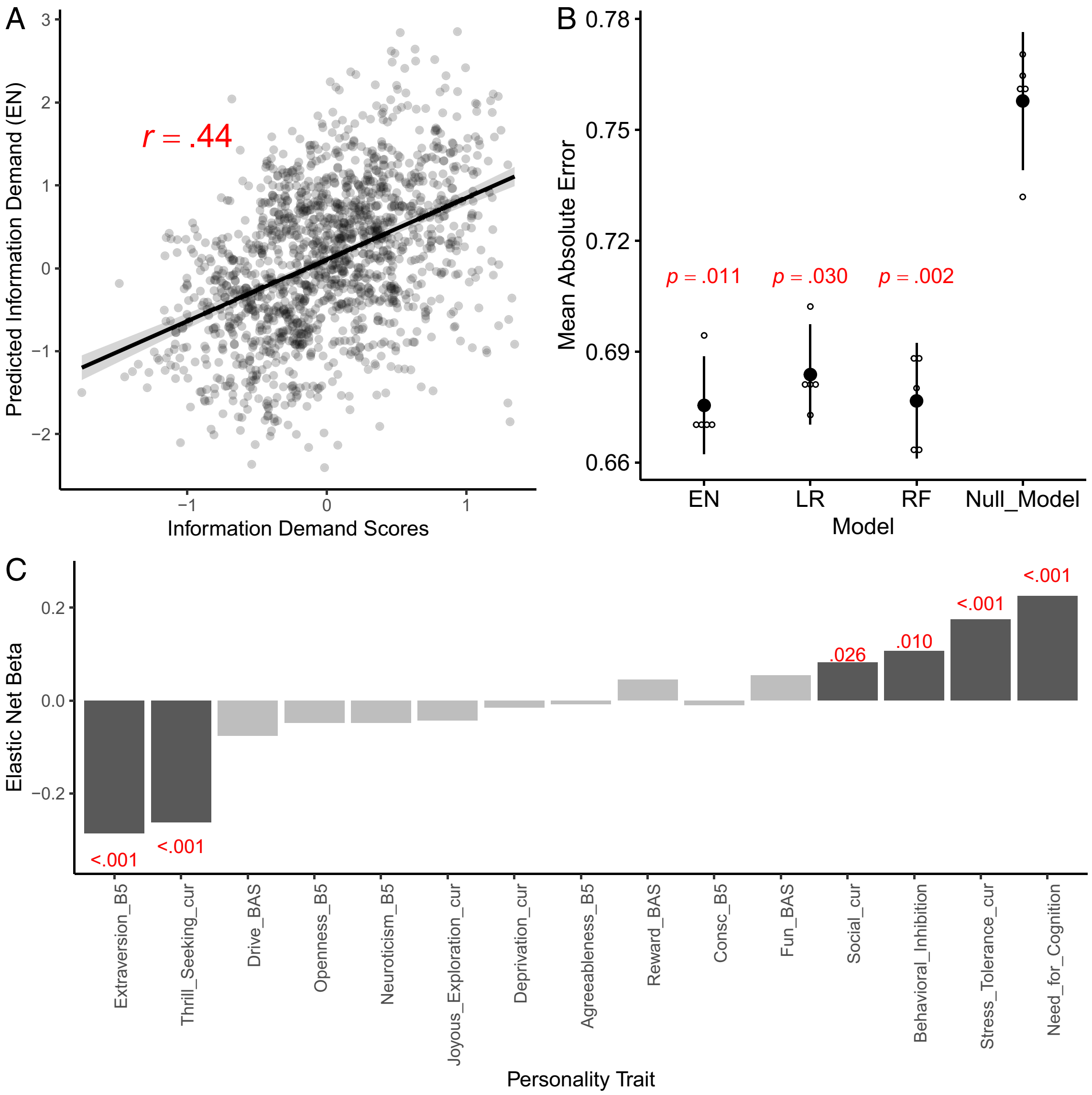

Fig. 3. Predicting PC scores from personality traits. (*A*) Correlation between predicted and observed information demand for the elastic net model in the test dataset ($N = 279$). Each participant has 5 points corresponding to 5 multiple imputations, but the r value is the Pearson correlation derived by integrating across imputations and applying Rubin's rules for combining technical replicates (54). (*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% CI across 5 imputations) for each model, and the open circles show the Mean Absolute Error for each imputation. EN = Elastic Net, LR = Linear Regression, RF = Random Forest. (*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 $P < 0.05$, and gray bars show nonsignificant weights (significance assessed via permutation test, 1,000 permutations × 5 multiple imputations for each trait; *Methods*). B5 = Big Five, cur = curiosity, BAS = behavioral activation system, Consc = conscientiousness.

with these and additional traits (*SI Appendix*, 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 (*SI Appendix*, 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 noninstrumental Urn task followed the same associations with personality scores as those from the instrumental tasks (*SI Appendix*, 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 (*SI Appendix*, Fig. C5). Parameters extracting value and uncertainty-sensitive sampling were highly correlated across the instrumental and noninstrumental tasks (*SI Appendix*, Fig. C5*A*), confirming the conclusion from the PC analysis above. Importantly, these parameters showed similar associations with personality traits in the instrumental and noninstrumental conditions (*SI Appendix*, Fig. C5*B*), 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 interindividual variability across diverse tasks of information demand can be captured by an axis which resembles the distinction between directed versus random exploration (26, 27). Second, we show that this axis is predicted by curiosity traits in personality research, consistent with literature describing a correspondence between traits and states (4, 33, 34). 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 (26).

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 noninstrumental *Lotteries* tasks confirmed that uncertainty-bound information demand clustered together regardless of instrumental incentives (*SI Appendix*, Fig. C5) consistent with previous evidence from behavior (31) and neural activity (47, 55) 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 (56–58), are differentially altered in anxiety (59) and schizophrenia (60), and have dissociable neural substrates (61–66).

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 and *SI Appendix*, Table B2). Given the robust evidence for the importance of anticipatory emotions in information-gathering (24, 67), 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*A*). 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 (68), (28). 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 (27, 31, 47, 64, 67) and may reflect the specific ways in which attention was parameterized 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 parameterizations, 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 (41). 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 [$r \sim -.85$ (69)] 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 (70), more tolerance of uncertainty would predict greater directed exploration). Finally, the relationship with behavioral inhibition—the tendency to experience 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 (71, 72)].

Conversely, we found that thrill seeking, which measures risk taking, avoidance of boredom, and novelty preference (5, 73, 74) 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 (56, 75). 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 (76) and may act through similar mechanisms as thrill-seeking; in addition, extraversion is linked to optimism and positive affect (77), 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 (78). 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*C*). 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 (*SI Appendix*, 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?") (36, 79, 80).

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 (80) 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 (23, 81–85).

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 (28, 80, 86) and self-regulation (87, 88). 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 (38) particularly for a term that has such salience in the popular mindset as curiosity (89). Multidisciplinary collaborations are highly beneficial for this aim.

Methods

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 9 tasks and 1 battery of personality questionnaires implemented in custom software (Haratki LLC). The tasks and data analyses followed best practices for online research outlined by Thomas and Clifford (2017). Demographic data were offered by 704 participants and showed that participants' modal age (collected in categories) was 26 to 30 y old (range, 18 to 75 y old), that 44% were women (56% men, 2 identified as "other"), and that highest educational attainments were college (59%), post graduate degree (23%), high school (17%) or vocational school (1%). Full details of task design, data cleaning, preprocessing, and analyses are in (*SI Appendix*, Supplement A1).

Data, Materials, and Software Availability. Anonymized Data type: .csv files, .Rdata files. Code types: R scripts, R markdown files, R Projects. (Everything is run in the R ecosystem within R studio). Data have been deposited in the open science framework (https://doi.org/10.17605/OSF.IO/KC9PB) (90).

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