Adaptive information seeking is critical for goal-directed behavior. Growing evidence suggests the importance of intrinsic motives such as curiosity or need for novelty, mediated through dopaminergic valuation systems, in driving information-seeking behavior. However, valuing information for its own sake can be highly suboptimal when agents need to evaluate instrumental benefit of information in a forward-looking manner. Here we show that information-seeking behavior in humans is driven by subjective value that is shaped by both instrumental and noninstrumental motives, and that this subjective value of information (SVOI) shares a common neural code with more basic reward value. Specifically, using a task where subjects could purchase information to reduce uncertainty about outcomes of a monetary lottery, we found information purchase decisions could be captured by a computational model of SVOI incorporating utility of anticipation, a form of noninstrumental motive for information seeking, in addition to instrumental benefits. Neurally, trial-by-trial variation in SVOI was correlated with activity in striatum and ventromedial prefrontal cortex. Furthermore, cross-categorical decoding revealed that, within these regions, SVOI and expected utility of lotteries were represented using a common code. These findings provide support for the common currency hypothesis and shed insight on neurocognitive mechanisms underlying information-seeking behavior.

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Significance

It is more important than ever to seek information adaptively. While it is optimal to acquire information based solely on its instrumental benefit, humans also often acquire useless information because of psychological motives, such as curiosity and pleasure of anticipation. Here we show that instrumental and noninstrumental motives are multiplexed in subjective value of information (SVOI) signals in human brains. Subjects’ information seeking in an economic decision-making task was captured by a model of SVOI, which reflects not only information’s instrumental benefit but also utility of anticipation it provides. SVOI was represented in traditional value regions, sharing a common code with more basic reward value. This demonstrates that valuation system combines multiple motives to drive information-seeking behavior.

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hypotheses. First, dopaminergic reward system may drive information seeking not only by encoding noninstrumental utility bonus but also instrumental benefits. While it is yet to be established whether normative VOI alone is represented or is multiplied with noninstrumental motives to constitute subjective value of information (SVOI), the reward system may represent that informational value in the same way as conventional reward signals; for example, monetary reward. Second, individual neurons may encode both informational value and conventional rewards in the same way—the neural common currency hypothesis—which is advantageous for computing trade-offs guiding choice (23, 24). Common currency may particularly provide an elegant solution to the exploration-exploitation dilemma by allowing agents to directly compare action value of respective options (4, 25). Although common currency across reward categories has been observed in humans and monkeys (24, 26–28), it has not been tested with instrumental information value.

To address these questions, we conducted an fMRI study where subjects made choices on costly, but directly actionable, information. Subjects were presented with a lottery with two monetary outcomes (a gain and a loss) and asked to choose whether to accept or reject it. The outcome probability was initially hidden and described as fair, but subjects could purchase the information to reveal the true probability. This information has direct instrumental value because subjects could change their decision based on the revealed probability. For instance, a subject may play a fair lottery with a large gain and a small loss, but reject it if the loss turns out to be more likely. Although there is a chance that the loss probability turns out to be smaller and she retains her original choice, she may purchase the information if the benefit of avoiding the loss is large enough to justify the cost.

We observed that subjects’ information-seeking behavior was indeed largely driven by instrumental benefit. Subjects’ information purchase choice was systematically sensitive to lotteries’ outcomes and possible probabilities, consistently with the normative VOI prediction. We further examined the contribution of additional noninstrumental motives. While we found no evidence for simplistic utility bonus, information-seeking choices were better explained by a SVOI model that involves anticipatory utility in addition to instrumental benefit. Next, using support vector regression (SVR) on voxel-wise BOLD signals, we tested a key prediction of the common currency hypothesis—common code between SVOI and reward values at the level of voxel-wise BOLD signals. We found that SVOI was represented in striatum and ventral piriform cortex (MPCF), traditional valuation regions. Lastly, cross-categorical decoding revealed that these representations shared a common coding scheme with more basic values, consistent with the neural common currency hypothesis.

Results

Information Seeking Is Sensitive to Instrumental Benefits. To characterize the extent to which human information seeking is sensitive to instrumental benefits, we used a two-stage task (Fig. 1A). Subjects were first asked whether to accept or reject a lottery with two outcomes (one positive outcome $x_1$ and one negative outcome $x_2$), assuming they would not receive further information (under the initial informational state $s_0$). Next, two possible probability distributions were presented, one where the positive outcome is more likely ($s_+$; $P(x_1) = \pi$) and the other where the positive outcome is less likely ($s_-$; $P(x_1) = 1 - \pi$). One of them would be true but revealed only if subjects purchased the information (Fig. 1B). Thus, $\pi$ determines information’s diagnosticity (predictability of outcome) and was randomly chosen on each trial from $\{2/3, 5/6, 1\}$. Subjects were then presented with the monetary cost of the information and indicated whether they would purchase it. VOI could change the true probability ($s_+$ or $s_-$) was not revealed during the scanning to prevent learning, subjects were instructed beforehand that they would receive the information and could change their original choices after the scanning. We verified using model-free logistic regression that subjects made information purchase decisions based on all experimental variables ($x_1$, $x_2$, $\pi$, and cost; all $P < 0.01$; SI Appendix, Figs. S1–S3).

Under normative economic accounts, agents accept the lottery if its EU under the current informational state ($u(x_1)$ or $u(x_2)$) is higher than the utility of status quo $u(0)$, and reject otherwise (Fig. 1B). Furthermore, they purchase the information if its instrumental benefit is higher than the cost, and forgo otherwise. The information provides the instrumental benefit by improving the overall EU, which happens only if EU-maximizing choices differ between informational states. Specifically, instrumental benefit is present if the lottery is preferable under $s_0$ but turns not to be preferable after unfavorable information ($s_-$), or if it is not preferable initially but changes to be preferable after favorable information ($s_+$). Instrumental benefit is nonexistent if the EU-maximizing choice would be the same irrespective of informational state (e.g., if the potential loss is extremely huge and gain is extremely small).

Normative VOI captures this marginal improvement of action utility, i.e., the difference in the expected utilities between the decision with the information and the decision without (Fig. 2A). Note that, because agents cannot predict the true probability a priori, they need to simulate their own choices under $x$ and $s$, average their EUs (i.e., overall EU of the informed choice), and compare it against EU under $s_0$. VOI computed as such is strongly sensitive to size of potential gains and losses; VOI is large if both the potential gain and loss are large, and small if the potential gain is very large and the loss is trivial (or vice versa), because the agent would not change its choice irrespective of the true probability in the latter cases.

We numerically derived instrumental normative VOI predictions based on outcomes ($x_1$, $x_2$) and diagnosticity ($\pi$) (SI Appendix, SI Methods). We then compared the predicted VOI against

Fig. 1. Experimental task. (A) Subjects were presented with lotteries with two possible monetary outcomes, gain and loss, shown as a roulette wheel. When played, a green dot appeared at a random location on the perimeter, and its position determined the outcome (left or right). Outcomes were initially described as equally likely. Subjects indicated whether to accept or reject it, assuming they would not receive any further information. Potential information was then presented as a magenta partition line; if purchased, it would reveal which side of the partition the green dot would appear. Information diagnosticity, $\pi$, was determined by the partition angle. Subjects indicated whether to purchase it given the information cost. (B) If subjects did not purchase information, they made a choice under the initial informational state ($s_0$). If subjects purchased information, it revealed which of the two possible probability distributions, $s_+$ or $s_-$, was true, based on which subjects made a choice. Because subjects could not predict the true probability ($s_+$ or $s_-$) in advance, they need to simulate their actions and EU in both states to compute instrumental benefit (VOI). Note that costless information is assumed here for illustration purposes; see SI Appendix, SI Methods for details on how our models deal with sunk cost of information.
Behavioral results. (A) Under normative VOI prediction, instrumental benefit is captured by the difference between the average EU of informed choices ($s_1, s_2$) and EU of uninformed choice ($s_0$). Note that costless information is assumed here for illustration purposes. (B) Information purchase probability was correlated with VOI predictions, but subjects over-purchased information in high-EU lotteries. Each dot represents a combination of lottery and diagnosticity, averaged over subjects and cost levels. (C) VOI with anticipatory utility deviates from VOI due to nonlinearity of the second-order utility’s aggregator function. (D) VOI model outperformed normative VOI and was able to account for over-purchase of information in high-EU lotteries. (E) Normative VOI model achieved better behavioral fit than alternative models of utility bonuses. VOI with anticipatory utility achieved even better fit, while alternative accounts that combine VOI with utility bonuses did not. ***: P < 0.001, n.s.: P > 0.5.

Coexistence of Instrumental and Noninstrumental Motives. Although we found that the instrumental benefit is a critical driver of information purchase in our task, it is possible that noninstrumental motives also contribute to the behavior. Accordingly, we tested the extent to which subjective value of information (SVOI), which would consist of instrumental VOI and noninstrumental motives, improves model fit. Specifically, we tested a prominent model of noninstrumental motives from the literature: anticipatory utility. Anticipatory utility, often referred to as savoring and dread, has been used in economics to explain people’s nonnormative preference for information, and in particular timing of information delivery (e.g., many prefer to know if they win a raffle prize earlier because of savoring, while they prefer not to know the results of their cancer diagnosis because of dread) (11, 13, 29–32).

We constructed a model of SVOI that integrates anticipatory utility VOI using a recursive utility approach (11, 33). Recursive utility, as the normative VOI theory, assumes forward-looking, utility-maximizing agents. However, it relaxes the VOI theory by allowing utility functions to change depending on the availability of information; the mere presence of information may increase or decrease the overall utility, which cannot be explained by conventional expected utility theories that assume consistency of utility functions. Specifically, the theory evaluates the lotteries in our task based on expected second-order utility, which aggregates first-order EU under the possilbe informational states ($s_0, s_1, s_2,$ and $s_3$) in a nonlinear manner (Fig. 2C). A convex (concave) aggregator function amplifies (diminishes) the difference in the overall expected second-order utility between informed and uninformed choices compared with the standard prediction. Therefore, subjects are more (less) information seeking under SVOI than normative VOI if the aggregator function is convex (concave).

We found that our subjects’ behavior was consistent with this SVOI composed of instrumental benefit and anticipatory utility. The correlation between information purchase probability and SVOI with anticipatory utility is significantly higher than the normative VOI (Kendall’s $\tau = 0.87$ vs 0.62, $P < 0.001$; Fig. 2D). Furthermore, trial-by-trial information purchase choices were predicted better by SVOI with anticipatory utility than normative VOI ($P < 0.001$; Fig. 2E and SI Appendix, Fig. S4B).

One important feature of anticipatory utility is its outcome dependence. Since the contribution of anticipatory utility depends on the convexity of the aggregator function, it is naturally allowed to be dependent on the possible outcomes, nicely echoing the widespread notions savoring on reward and dread on punishment. As a direct support for its outcome dependence, we noticed that subjects over-purchased information, compared with the normative VOI prediction, more often in higher valued lotteries than in lower valued ones (median split according to EU, $P < 10^{-3}$; Fig. 2B and SI Appendix, Fig. S4). Since VOI computation already incorporates subjects’ nonlinear utility function, this outcome-dependent over-purchase cannot be explained by factors such as risk preference (SI Appendix, SI Methods). The outcome-dependent over-purchase disappeared when the behavior was compared against the prediction of SVOI with anticipatory utility ($P > 0.05$; Fig. 2D and SI Appendix, Figs. S4B and S5).

We also tested two additional models of noninstrumental motives, in which VOI is combined with aforementioned utility bonus term (constant bonus or entropy reduction bonus), which lacks sensitivity to possible outcomes. Neither of the utility bonus models improved the normative VOI model ($P > 0.30$), and both were outperformed by SVOI with anticipatory utility ($P < 0.001$; Fig. 2E). These further support that noninstrumental motive is sensitive to possible outcomes, consistent with anticipatory utility.

Neural Representation of SVOI. The above results suggest that subjects acquired information based on SVOI, which consists of forward-looking instrumental benefit and anticipatory utility. We next sought to investigate whether SVOI shapes subjective value function at the neural level. In particular, we asked whether SVOI was represented in valuation regions, and if so, whether that representation employs a common code with more conventional
reward values. To this end, we asked subjects to make two value-based choices: whether to gamble on a lottery, and whether to purchase information regarding the said lottery, allowing us to compare encoding of the lottery EU and SVOI.

We first looked for SVOI representation during the presentation of the information’s diagnosticity. Combined with potential outcomes, which had been already presented, the diagnosticity is sufficient for subjects to compute subjective benefit of the information. We asked if we could decode trial-by-trial SVOI from voxel-wise BOLD signals in a searchlight (10-mm radius) using one-run-leave-out five-fold cross-validation and SVR (Fig. 3; see SI Appendix, SI Methods for details). Prediction accuracy was measured as a partial correlation between the predicted and actual SVOIs controlling for diagnosticity. This is to ensure that we detect regions engaged in valuation, rather than information-theoretic processing (e.g., entropy reduction) or visual processing (π was visually presented by the partition’s angle).

Consistent with the hypothesis that dopaminergic reward system is involved in value-driven information seeking, we found that SVOI was decodable from striatum and VMPFC (P < 0.05, voxel-wise FWE corrected). SVOI representation was additionally found in lateral prefrontal cortex (middle frontal gyrus; MFG), right superior frontal gyrus, posterior cingulate cortex, right angular gyrus, and cerebellum (Fig. 4A and SI Appendix, Figs. S6 and S7 and Table S1). Since we evaluated decoding accuracy while controlling for diagnosticity, this successful decoding cannot be attributed to mere representation of diagnosticity (SI Appendix, Figs. S6 and S7). Striatum and VMPFC receive dopaminergic inputs and are the two regions that are the most associated with valuation in fmri literature. Indeed, we found that lottery’s EU was represented in striatum during the presentation of lottery (P < 0.05; Fig. 4A and SI Appendix, Fig. S8 and Table S1), suggesting the involvement of traditional valuation processing in SVOI.

Since SVOI is correlated with the lottery’s EU (r = 0.62), some of our SVOI decoding performance might have been attributable to signals related to EU rather than SVOI. This issue is particularly important because our EU cluster and SVOI cluster overlapped in striatum (Fig. 4A). However, SVOI decoding could not be explained by the possible presence of EU signals; SVOI decoding accuracy in all clusters was above chance even when EU was controlled for (P < 0.05, Bonferroni corrected; Fig. 4B and SI Appendix, Figs. S6 and S7). This supports that these regions use both outcomes and information diagnosticity to calculate SVOI, as normatively predicted.

**Common Code of SVOI and EU Representations.** Having characterized representations of SVOI and EU, we next investigated their relationship, and in particular whether they are represented using a common code. Although we observed overlap of SVOI and EU clusters, this is not a strong evidence for a common code, because these representations could be distinct at a more fine-grained level. As a more direct test, we adopted cross-categorical decoding approach.

Specifically, if EU and SVOI are indeed represented on a common code in striatum at the voxel level, SVR trained based on EU in striatum should be able to predict SVOI (Fig. 3). We found that the decoder trained by EU could indeed predict SVOI above the chance level, compared with the permutation-based null-hypothesis distribution (P < 0.05; Fig. 5A and SI Appendix, Figs. S6 and S8). This holds when information diagnosticity was controlled for, and more critically, even when EU was controlled for. This provides a clear evidence that striatum did not just maintain a represent or reactivate EU representation; rather, it flexibly switched the context of representation within each trial from EU and SVOI, presumably in preparation for the upcoming choices.

Lastly, to seek for further evidence for common neural code, we examined if decoders trained by SVOI could be used to decode EU. To control for FWE over eight SVOI clusters, we constructed null-hypothesis distribution based on the highest accuracy (r-statistics) over ROIs in each permutation iteration. EU prediction accuracy was above chance in striatum, VMPFC, and right MFG (P < 0.05, Fig. 5B and SI Appendix, Fig. S9). Although EU was not decodable from VMPFC and right MFG in the within-categorical decoding analysis above, it may be because we had used a more stringent statistical threshold. Together, these results show that human brains use a common code to represent SVOI and EU.

**Discussion**

A substantial portion of our daily actions pertains to information seeking. Particularly in the digital age where a tremendous amount of information is available at our fingertips, acquiring relevant information to an appropriate degree is as important as making use of acquired information. Going back at least to Berlyne (3), psychologists studying functions, causes, and consequences of motivation and interests have hypothesized the relationship between exploratory and information-seeking behavior and reward system. More recently, since Kakade and...
Dayan’s influential proposal (15), neuroscientists have provided evidence that putative noninstrumental motives are represented in dopaminergic reward system in monkeys (16, 20) and humans (8–10, 14, 17–19), as if they shape subjective value function that favors information seeking. However, because existing studies have largely focused on instances of noninstrumental information seeking, it remains unclear how subjective preference for forward-looking, instrumental information is formed, and to what extent dopaminergic reward system is involved in that process.}

Behaviorally, our study provides evidence that subjective value of information (SVOI) consists of (at least) two motives: forward-looking instrumental benefit, consistent with normative economic VOI theories, and anticipatory utility, an example of noninstrumental motives. Other models on noninstrumental motives that are independent of reward value of outcomes, such as constant utility bonus (4), were insufficient in explaining the observed behavior. Particularly, consistent with the notion of savoring, we found outcome-dependent over-purchase of information. Our results extend the findings from the past studies on anticipatory utility, which focused mostly on noninstrumental information and did not quantitatively capture concurrent contribution of instrumental and anticipatory value for information (14, 31, 32). That both motives we identified are strongly sensitive to future possible outcomes highlight the involvement of valuation systems in information-seeking behavior in general, which is sometimes overlooked in curiosity literature.

The possibility that anticipatory utility is an important component of information seeking opens up several important questions. One particular issue concerns the effect of dread, or utility of anticipating negative outcomes (34). The effect of dread may be large enough for some people to avoid potentially negative information even when its instrumental benefit is critical, such as medical conditions, but more studies are needed to empirically quantify its relative contribution in instrumental information settings. Our study could not measure its effect quite reliably because our subjects could reject unfavorable lotteries. Second, anticipatory utility provides a possible explanation for the phenomenon of ambiguity aversion. Intuitively, the desire for information may be causally linked to aversion to the lack thereof (12). It may thus be not a coincidence that nonlinearity of the aggregator function that determines second-order utility, a critical part of recursive utility theory, is also central to some theories on ambiguity and compound lotteries (35). Future studies may be able to use our experimental paradigm to quantify anticipatory utility at the individual level and correlate with ambiguity attitude.

Neurally, if information seeking is driven by subjective value signals in dopaminergic reward system, we should expect such responses to exhibit two features; first, they should be scaled according to subjective preference for information, which would reflect both instrumental and noninstrumental motives; second, they should be on a common currency with extrinsic reward. Our results that SVOI and EU share the common code in BOLD from striatum and VMPFC are highly consistent with these predictions, because these regions receive massive dopaminergic projection (36) and represent various kinds of values (37, 38), with some evidence for common currency (24, 26–28).

In particular, our findings expand existing knowledge by showing that striatum also represents forward-looking instrumental benefits. Our decoding approach is suitable to test common code because it characterizes local linearized functional representation while typical brain mapping studies only examine spatially smoothed signals and whole-brain approaches such as elastic net examine representations distributed across the brain. Moreover, our results yield an additional prediction that, when monkeys act on forward-looking instrumental benefit of information, rather than merely receive noninstrumental information (16, 20, 39), it may also be encoded by their midbrain dopamine neurons.

We found SVOI representation in other brain regions as well, but with limited evidence for common code, where cross-categorial decoding was observed in stratum, VMPFC, and right MFG (magenta in Fig. 4A), decoders trained on SVOI-predicted EU.

Fig. 5. Evidence for common code. Cross-categorical decoding accuracies (black vertical line) are compared against permutation-based null-hypothesis distributions. (A) In striatum (green in Fig. 4A), decoders trained on EU-predicted SVOI. (B) In striatum, VMPFC, and right MFG (magenta in Fig. 4A), decoders trained on SVOI-predicted EU.
circumstances, particularly outside value-based decision-making domains. Our results raise an interesting possibility that such difference in motives may be partly caused by whether reliable SVOI signals from dopaminergic system are available, depending on factors such as the difficulty or cognitive load of model-based SVOI computation (43). Potential motives of information seeking have been long studied separately, and the current study marks an important step, both theoretically and empirically, toward integrative understanding.

Methods

All subjects provided informed consent; all protocols were approved by UC Berkeley Committee for the Protection of Human Subjects and Virginia Tech Institutional Review Board. Detailed method descriptions are available in SI Appendix, SI Methods.

Task Design. In each trial, a lottery with two outcomes ($x_1, x_2$) was presented as a roulette wheel, and subjects chose whether to play it assuming no further information ($\omega$). Then the information was presented as a magenta partition on the wheel, which defined the two possible probability distributions, $P(x) = (s_1, s_2)$, or $1 - s_1$ ($s_2$), the information’s diagnosticity, was determined by the orientation of the magenta partition; $\pi = 1, 5/6, or 2/3$ when the partition was vertical, slanted by $30^\circ$, or slanted by $60^\circ$, respectively. The cost of the information was presented after the delay, and subjects chose whether to purchase it. The purchased information was delivered after the scanning. When the information was delivered, one side of the magenta partition was brightened, indicating the posterior probability ($s_1$ or $s_2$), and subjects could change their original lottery choice. Subjects were told that the brighter side would be chosen randomly.

Behavioral Modeling. The predictions of VOI and SVOI with anticipatory utility were obtained as the sunk cost for the information at which agents that maximize EU (or expected second-order utility in the case of SVOI model) would be indifferent between informed and uninformed choices. The aggregator function that maps the first-order to second-order utility in SVOI model was estimated by likelihood maximization of information purchase choices. Models were compared by cross-subject cross validation.

fMRI Decoding Analysis. Voxel-wise activation from the two epochs in each trial, lottery presentation (for EU decoding), and information presentation (for SVOI decoding), were used as features of leave-one-run-out cross-validation SVR. Within-categorical decoding took a whole-brain searchlight approach. SVOI decoding accuracy was evaluated by Pearson partial correlation between predicted and actual SVOI labels while controlling for $\pi$. Accuracy of cross-categorical decoding was evaluated within the ROIs defined by the within-categorical decoding. Null-hypothesis distribution was obtained by permuting labels across trials while maintaining the trial-wise pairing of SVOI and EU.

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