Rational Curiosity and Information-Seeking in the COVID-19 Pandemic

Yaniv Abir[1*], Caroline B. Marvin[1], Camilla van Geen[2], Maya Leshkowitz[3], Ran R. Hassin[4†], Daphna Shohamy[1,2,5†]

[1]Department of Psychology, Columbia University, New York, NY, United States.

[2]Zuckerman Mind Brain Behavior Institute, Columbia University, New York, NY, United States.

[3]Department of Cognitive Sciences, The Hebrew University of Jerusalem, Jerusalem, Israel.

[4]Department of Psychology and The Federmann Center for the Study of Rationality, The Hebrew University of Jerusalem, Jerusalem, Israel.

[5]Kavli Institute for Brain Science, Columbia University, New York, NY, United States.

*Corresponding author**:** yaniv.abir@columbia.edu

[†]These authors contributed equally to this work.

Abstract

Curiosity is a powerful determinant of behavior. The past decade has seen a surge of scientific research on curiosity, an endeavor recently imbibed with urgency by the WHO, which set managing information-seeking as a public health goal during pandemics. And yet, a fundamental aspect of curiosity has remained unresolved: its relationship to utility. Is curiosity a drive towards information simply for the sake of obtaining that information, or is it a rational drive towards optimal learning? We leveraged people's curiosity about COVID-19 to study information-seeking and learning in a large sample (n=5376) during the spring of 2020. Our findings reveal that curiosity is goal-rational in that it maximizes the personal utility of learning. Personal utility, unlike normative economic utility, is contingent on a person's motivational state. On the basis of

these findings, we explain information-seeking during the pandemic with a rational theoretical framework for curiosity.

Curiosity is the drive that determines how we consume information in a world where information abounds[1,2]. Despite being a powerful determinant of behavior, curiosity remains poorly understood, in part due to its paradoxical relation to utility: on the one hand, curiosity is often seen as the drive for knowledge for its own sake, regardless of its utility, or even in spite of its disutility[1–5]. On the other, curiosity is the engine behind learning and development, hence clearly useful for the organism[6–10]. While there is support for each of these perspectives separately, surprisingly little is known about whether and how curiosity is shaped by utility.

The prevalent conviction that curiosity is the drive for useless information is grounded not only in a long philosophical tradition[1,2], but, more recently, also in the failure of economic models of utility to explain the extent of human curiosity, and why humans commonly overpay for information relative to an economically defined norm[1,11]. Researchers have thus been motivated to construct tasks in which only useless information is offered to participants[3,11,12]. This approach revealed that when utility cannot guide curiosity, the amount of information on offer determines information-seeking choices.

In contrast, the clear adaptive value of curiosity as an enhancer of memory and learning[9,10,13,14] and as a predictor of academic success[15] inspired the formulation of several normative theories of curiosity. These recent theoretical advances describe curiosity as a drive to maximize both information and utility[6–8,16]. However, such theories acknowledge that deriving the exact utility of an answer to a question is generally an intractable problem[16,17]. They postulate that human curiosity must instead approximate this computational goal. In what way human curiosity approximates utility maximization, however, remains unknown.

The 2020 coronavirus pandemic (COVID-19) created a unique opportunity to examine the relationship between utility and curiosity. Suddenly, many people were curious about the virus and its epidemiology, a topic they were largely ignorant about before, but which became motivationally relevant as well as intellectually interesting. Furthermore, differences in age, geography and circumstance resulted in considerable individual differences in the personal relevance of information regarding COVID-19. Thus, a rare opportunity emerged to study ecologically valid information-seeking, while measuring naturally occurring variations in utility and motivation.

Additionally, the WHO has designated the seeking and sharing of information a key area for intervention during the COVID-19 pandemic[18]. However, an understanding of information-seeking under such conditions is lacking, with conflicting views regarding the ability of humans to rationally sift through the informational deluge[19–22]. Examining the relationship between curiosity and utility addresses this pertinent gap in scientific evidence.

We therefore leveraged the conditions created by the pandemic to investigate curiosity and learning. Based on our findings, we propose a rational framework for curiosity. This framework places utility as a central driver of curiosity and learning. It suggests that curiosity is shaped by a cost-benefit analysis between the expected utility of obtaining information and the cost of seeking that information. Critically, according to this view, individuals derive their personal expected utility both from the content of information as well as from their motivational state. We show that curiosity covaries with personal utility in a manner largely consistent with normative theory, but also detail how it diverges from it.

To investigate the role of utility in curiosity we used Amazon Mechanical Turk to gather data from 5,376 participants across the United States, sampling twice a week between March 11th and May 7th, 2020. We assessed how participants' choices to seek information were affected by its usefulness and its relatedness to COVID-19, as well as by participants' expectations and concerns regarding the COVID-19 pandemic.

We measured participants' willingness to wait for information as a behavioral marker of curiosity (Fig. 1, a&b). Participants (ages 18-89) read a series of questions relating either to the coronavirus pandemic or to general trivia and everyday tips (Table S2). For each question, participants had to indicate whether they already knew the answer, would like to skip it, or were willing to wait a specified number of seconds to receive the answer. Importantly, participants knew that the entire duration of the experiment was independent of their choices and therefore were encouraged to use their own curiosity to decide whether to wait. The proportion of 'wait' versus 'skip' responses at variable waiting durations serves as our main index of curiosity[13]. One week later, we asked participants to recall the answer to each question they had waited for. Their memory performance complements our measure of curiosity, enabling us to track how curiosity drives behavior from information-seeking to learning.

To assess the personal utility of the information, three additional measures were obtained. After completing the waiting task, each participant was presented with a subset of new questions and rated each question on the expected usefulness of its answer, both for themselves and for others. Additionally, at the end of the experiment, participants completed a questionnaire assessing how concerned they were about the developing COVID-19 pandemic and the changes it could cause in their lives (henceforth "COVID-19 concern"). Prior to this, participants answered a series of

questions regarding their non-specific anxiety and affective state (henceforth "non-specific anxiety"), which allowed us to compare the effect of a domain-specific concern on curiosity with the effect of anxiety in general. Our use of these two measures is predicated on the view that affective states are motivational states[23,24].

We hypothesized that curiosity should be determined by the content of each question, which we operationalize as each question's relatedness to COVID-19, and its average usefulness judgment. However, we reasoned that just as a food reward does not have the same utility for a hungry subject and a satiated one, the same question should elicit varying expectations of utility from participants in different motivational states[25,26]. Thus, differences in participants' motivational states should result in different mappings between question content (COVID-19-related or not) and utility. We define personal utility as this interaction between motivation and content and hypothesize that it predicts curiosity-driven behavior.

Results

Cost-benefit rationality

Our findings reveal that, in accordance with a rational framework, curiosity is cost-benefit rational (Fig. 1, c&d): participants are more likely to wait for questions judged as useful, whether these are COVID-19-related or general questions b=0.66, 95% posterior interval (PI)=[0.53,0.79].

As expected from a cost-benefit analysis, willingness to wait also diminishes for longer wait durations b=-0.07, 95% PI=[-0.07,-0.06]

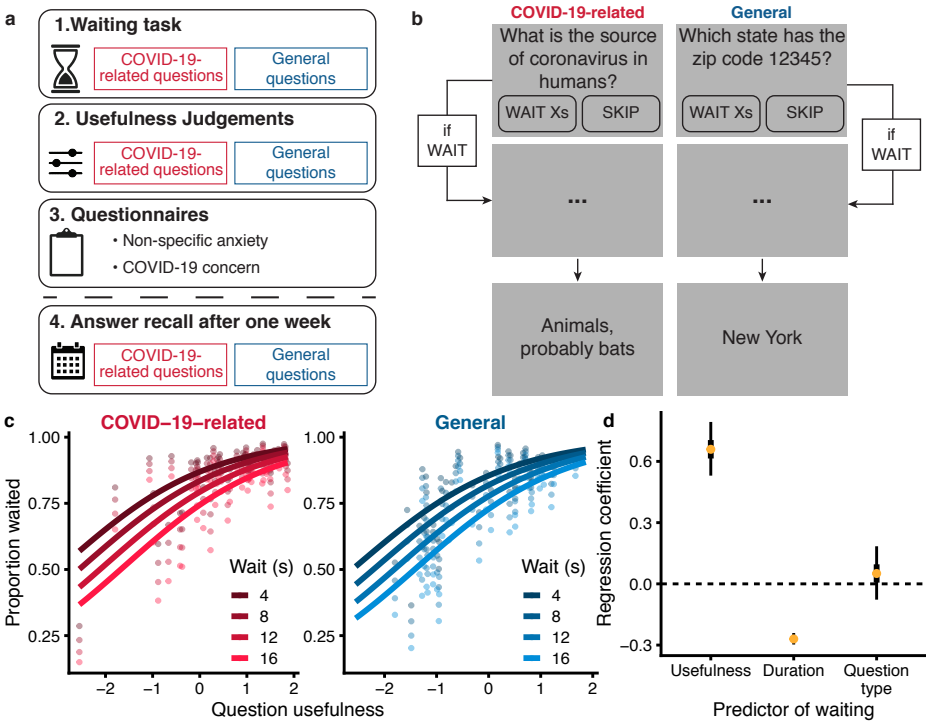

Figure 1. Curiosity is cost-benefit rational. (a) General outline of the four stages of the experiment. **(b)** On each trial of the waiting task, participants were presented with a question. If they decided to wait a specified duration, they were presented with the answer. They were then asked to rate their satisfaction with the answer and, one week later, to report their memory (not pictured). **(c)** Participants were more likely to wait for questions judged as more useful, and less likely to choose to wait long durations. These effects hold for both general and COVID-19 related questions. Lines denote predictions from a multilevel logistic regression model; dots mark marginal proportions for questions. **(d)** Coefficients from the regression model with 50% and 95% PIs.

Goal-rationality

Before addressing the role of motivational states in driving curiosity, we first verified that our two affective measures (COVID-19 concern and non-specific anxiety) were related to relevant real-world experiences. As expected, we found that both measures vary with events such as job loss,

income reduction, self-isolation, social distancing behavior in the state, and the timeline of the virus spread in the U.S. (see Methods).

Having verified the validity of our affective measures, we then tested the hypothesis that curiosity is sensitive to participants' motivation, and as such is goal-rational. First, we focused on the effect of COVID-19 concern on curiosity towards different types of questions. We found that people reporting higher COVID-19 concern were more curious about COVID-19-related questions relative to general questions b=0.11, 95% PI=[0.08,0.14] (Fig. 2a). This is in agreement with the rational framework, which predicts that a change in domain-specific motivation should impact curiosity towards information in that domain. The rational framework further posits that domain-specific motivation operates on curiosity by increasing the expected utility of questions in the relevant domain. Indeed, we find that higher COVID-19 concern is associated with higher usefulness judgments of COVID-19-related questions relative to general questions b=0.10, 95% PI = [0.07,0.12] (Fig. 2c). Furthermore, a mediation analysis revealed a significant indirect effect of the interaction of COVID-19 concern and question type (COVID-19-related/general) on waiting choices, via usefulness judgments b=0.02, 95% PI=[0.002, 0.04], 22.27% of the effect mediated, 95% PI=[1.71%, 49.86%] (Fig. 2e).

A truly normative account would predict that COVID-19 concern would only engender the changes in curiosity for COVID-19-related content, as described above. By contrast, mindset theories[27,28], as well as computational theories of motivation[25,26], predict that as COVID-19 concern changes the utility of COVID-19-related information, it should also change the average utility of information pursuit in general, leading to generalized effects on curiosity. Our results are consistent with the latter interpretation: we find that in addition to its specific effects, COVID-

19 concern has a general positive effect on curiosity and utility, as it is associated with increased waiting also for general questions b=0.28, 95% PI = [0.20,0.37] (Fig. 2a), and also with a general rise in usefulness judgments b=0.51, 95% PI = [0.47,0.55] (Fig. 2c). A mediation analysis confirmed a significant indirect effect of COVID-19 concern on waiting via usefulness judgments b=0.14, 95% PI=[0.01, 0.25], 69.27% of the effect mediated 95% PI=[5.38%, 151.16%] (Fig. 2f).

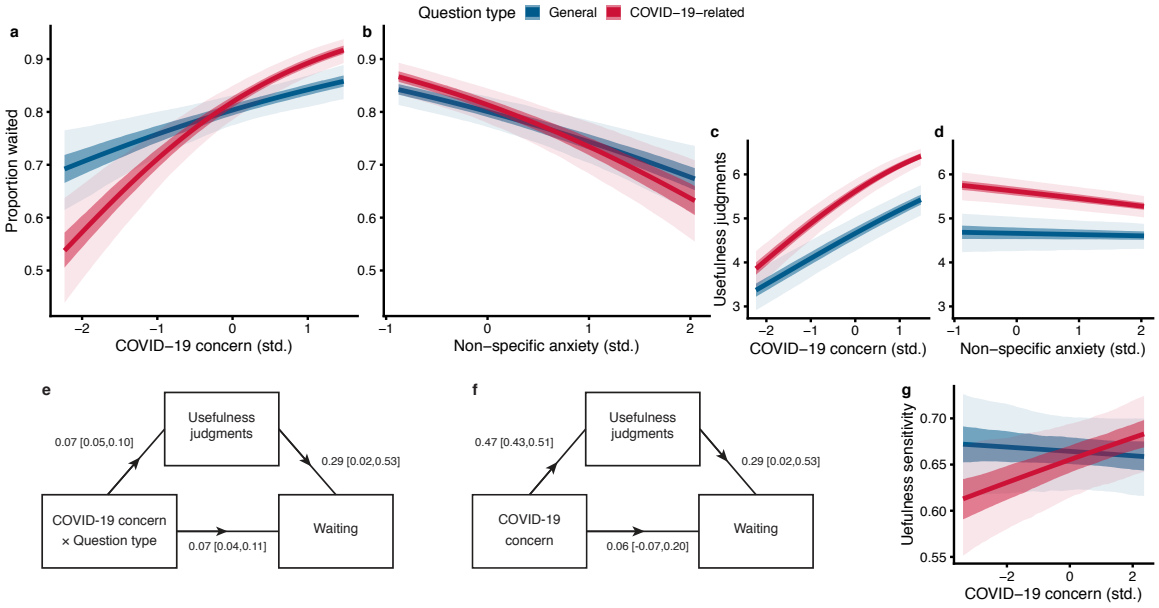

Figure 2. Motivational states modulate curiosity. (**a**) Higher COVID-19 concern is associated with more waiting for COVID-19 related questions, and also, but to a lesser degree, for general questions. (**b**) Non-specific anxiety negatively predicts waiting for all questions. (**c**) Participants reporting higher COVID-19 concern judge questions as more useful, especially COVID-19-related questions. (**d**) Participants reporting higher levels of non-specific anxiety tend to judge questions as less useful, especially COVID-19-related questions. (**e**) Consistent with a rational framework for curiosity, according to which the specific effect of COVID-19 concern on curiosity should be mediated via personal utility, we find a significant indirect effect of the interaction between COVID-19 concern and question type on waiting, mediated by judged usefulness. 95% PIs given in brackets. **(f)** We also find a significant indirect main effect of COVID-19 concern, via judged usefulness, on waiting, consistent with the motivational account of curiosity in which the generalized effect of COVID-19 concern on curiosity is mediated via personal utility. (**g**) Participants who report more COVID-19 concern have a tendency to be more sensitive to the usefulness of COVID-19-

related questions when deciding whether to wait for their answers b=0.05, 95% PI=[0.006,0.10]. COVID-19 concern, however, is not related to usefulness sensitivity for general questions b=-0.01, 95% PI=[-0.06,0.04]. Lines denote mean posterior prediction; dark shaded areas mark 50% PIs, and light areas 95% PIs.

A general effect of COVID-19 concern on curiosity could imply that people concerned with COVID-19 are just less discerning in their information-seeking. The data do not support such an account – COVID-19 concern is not associated with a reduction in sensitivity to question usefulness when making waiting choices b=0.02, 95% PI=[-0.01, 0.06]. One's personal motivation does seem to affect the extent to which one is sensitive to usefulness when seeking information in different content domains. We find that among people with higher COVID-19 concern, choices regarding COVID-19-related questions are more sensitive to usefulness, relative to choices regarding general questions b=0.03, 95% PI=[-3.45e-04,0.06] (Fig. 2g).

Importantly, the effects of COVID-19 concern on curiosity do not appear to be due to general anxiety. While COVID-19 concern and non-specific anxiety are moderately correlated, we observe that they predict curiosity in starkly different ways. Participants reporting high levels of non-specific anxiety were less likely to wait for answers of any sort b=-0.28, 95% PI=[-0.37,-0.20] (Fig. 2b). This diminished curiosity parallels previous findings of diminished pursuit of reward among people with depression[24,29,30].

Finally, we tested whether this pattern of results, supporting goal-rationality, generalize beyond the waiting task. See supplementary Information and Fig. S2 for a successful conceptual replication using a self-report measure of curiosity.

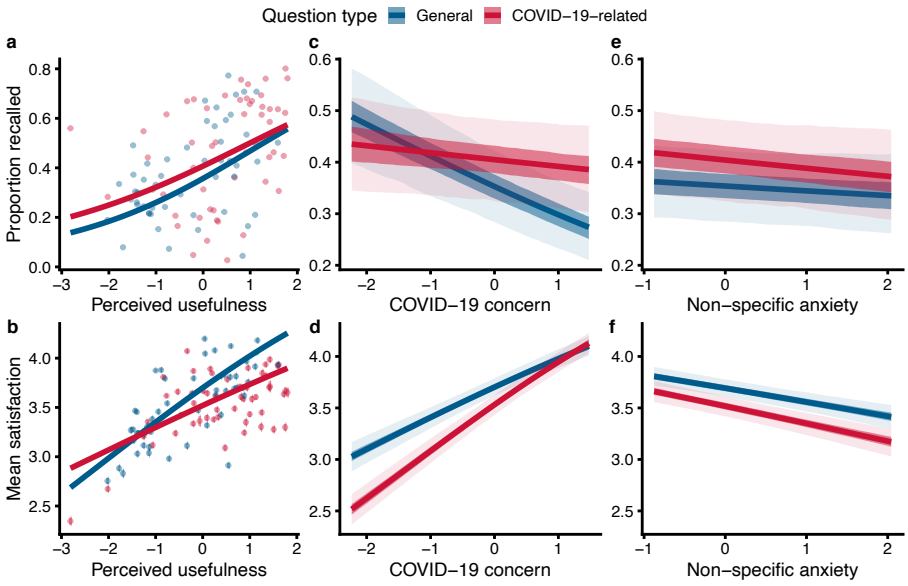

Figure 3. Motivation modulates subsequent memory for the answers to questions and subsequent satisfaction with the answers. (a) Judged usefulness is associated with better memory for the answer, assessed with a memory test one week after the waiting task. **(b)** Judged question usefulness is also positively correlated with self-reported satisfaction with answers. **(c)** COVID-19 concern is associated with poorer memory for general information, while information related to COVID-19 is spared. **(d)** Greater COVID-19 concern is associated with more self-reported satisfaction, especially for COVID-19 related questions. **(e)** Non-specific anxiety is not significantly associated with memory b=-0.04, 95% PI=[-0.08,0.003]. **(f)** Non-specific anxiety is associated with a reduction in satisfaction for both question types b=-0.20, 95% PI=[-0.25,-0.15]. Lines denote mean posterior prediction from multilevel regression models; dots mark marginal means for questions; dark shaded areas mark 50% PIs, and light areas 95% PIs.

Response to answers and subsequent learning

A role for utility in driving curiosity is rational only inasmuch as this relationship is manifested in subsequent learning. Indeed, personal utility is a central predictor not only of curiosity, but also of participants' long-term memory for the answers. We measured memory after one week and found that participants better remembered answers to questions that were judged as highly useful b=0.42, 95% PI=[0.21,0.64] (Fig. 3a). Crucially, higher COVID-19 concern predicted poorer

memory for general answers, but spared COVID-19-related answers (interaction b=0.06, 95% PI=[0.03,0.09]; Fig. 3c), a finding compatible with an adaptive forgetting account[31,32].

Similarly, we found that personal utility also affected participants' subjective reports of satisfaction, measured after each answer was shown. Like curiosity, answer satisfaction increases with question usefulness judgments b=0.53, 95% PI=[0.42,0.65] (Fig. 3b). We further found that people high in COVID-19 concern were more satisfied with all answers b=0.43, 95% PI=[0.38,0.48], but especially COVID-19-related answers (interaction b=0.08, 95% PI=[0.06,0.11]; Fig. 3d).

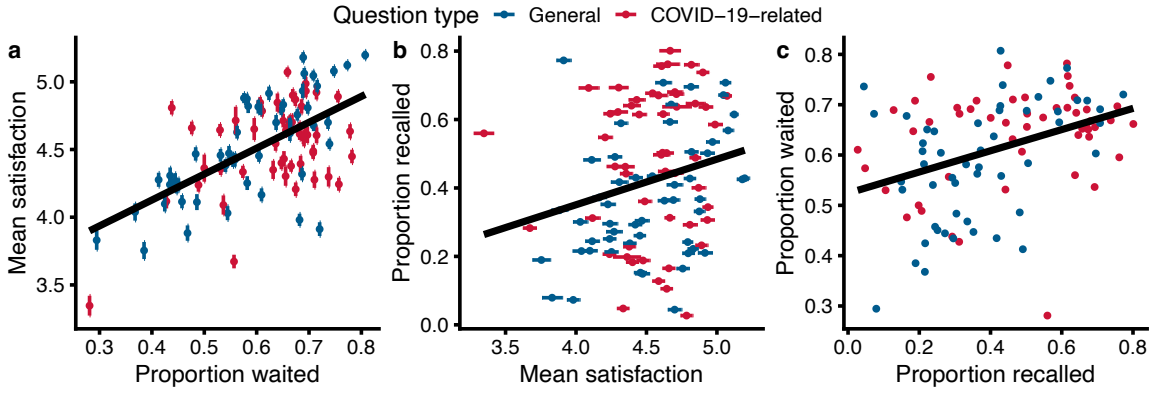

Figure. 4. Participants tend to seek information that on average would make them more satisfied, and that they are more likely to remember. (**a**) Questions for which a high proportion of participants chose to wait tend to have satisfying answers, and vice versa r=0.60, p< 0.001. (**b**) Satisfaction with answers is correlated with probability of recalling them r=0.23, p=0.02. (**c**) Proportion of participants waiting for a question is correlated with the proportion of participants recalling the answer to said question r=0.39, p< 0.001. Error bars span two standard errors. Linear regression lines are plotted for visualization purposes.

In general, we find that people tend to seek answers that they would subsequently be satisfied with and remember well (correlation between waiting and satisfaction r=0.60, p< 0.001; between

waiting and memory r=0.39, p< 0.001; Fig. 4). Taken together, these findings indicate that personal utility influences not only information seeking, but also subsequent processing of the information, with long-term consequences for learning.

Discussion

Together, these findings support the hypothesis that curiosity is the pursuit of useful information[7,8]. Moreover, these results uncover the psychological mechanisms of this process. We find that humans behave as if weighing the cost of information-seeking against the personal utility of information, which is derived from the content of a question according to the motivational state of each individual.

Deriving the exact personal utility of information based on one's motivation and goals is intractable computationally, and so must be approximated by any intelligent system[16,17]. We observe that the human cognitive system is largely rational in its approximation of personal utility. Thus, specific affective states, or motivations, bring about domain-specific changes in personal utility and curiosity – the hallmark of goal-rational behavior. However, these motivational states are also associated with general changes in curiosity towards all content domains, through the influence of motivation on the average expected utility of information. The use of average expected utility in decisions is a useful simplification from a computational perspective, but constitutes a deviation from purely normative behavior[25,26].

Our focus here was on the specific and generalized effect of COVID-19 concern. However, we also observed a generalized effect of non-specific anxiety on curiosity, whereby more anxious people tended to seek less information. This dissociation between COVID-19 concern and non-

specific anxiety was important to establish our main conclusions. However, this finding also has clinical significance in its own right, as some previous work found support for diminished curiosity[30], while other researchers postulated that anxiety might increase information-seeking, as it is associated with high intolerance for uncertainty[33–35]. Furthermore, the negative correlation between non-specific anxiety and information-seeking in our data mirrors established findings regarding diminished reward-seeking in anxiety and depression[24,29].

This rational framework of curiosity and the findings that support it strive to explain curiosity using the same computational and algorithmic principles derived from studying reward-based behavior[4,14,36]. Recently, curiosity has been implicated as a necessary core computation for natural and artificial intelligence[37,38], with information and reward postulated to be the basic fungible currencies of cognition[6,16,36]. Explaining ecological curiosity in cost-benefit terms is a step towards understanding the economy of utility and information in the brain.

Finally, our findings address key open questions about how people seek information during the COVID-19 pandemic[18]. Whether people seek information rationally, and can thus be trusted to consume useful information, is the subject of active debate in public health and political science research[e.g. 19–22]. Our findings suggest that humans are efficient information seekers, and that the measurement of affective and motivational factors as modulators of personal utility is an important tool in understanding individual information-seeking behavior during an epidemic, or other events of interest for public policy.

Methods

Data collection

Participants were recruited through Amazon Mechanical Turk, with data collection occurring twice weekly, between March 11th and May 7th 2020. A week after their participation in the first session, participants received an email inviting them to participate in session 2 of the study. Overall, 71.48% of eligible participants returned for session 2.

All subjects provided informed consent; all protocols were approved by the Columbia University Institutional Review Board. Detailed data collection descriptions are available in Supplementary Information.

Stimuli

A set of short questions and answers was used as stimuli in this experiment. 52 *COVID-19-related questions* were sourced from materials published by the World Health Organization, US Center for Disease Control and Prevention, or the New York Times. Half of these were deemed useful by the authors of the study and half non-useful. 52 *general questions* comprised the second type of questions - half of these were trivia questions drawn from previous studies[14], and half were useful household tips sourced from lists of tips on the internet. See Table S2 for list of questions.

Task Design

In the first experimental session, participants first completed the waiting task, with a block comprising COVID-19-related questions and another comprising general questions, in counterbalanced order. They then rated a held-out set of questions on the expected usefulness of answers, both for themselves and for others. At the end of the session, participants completed a questionnaire regarding their general affective state, followed by a questionnaire probing their affective concerns regarding COVID-19. This questionnaire included items regarding anxiety

about the medical, economic and social circumstances, and perceptions of severity and risk (see Table S3 for list of questions). During the second session of the experiment, held 7-8 days after the first, participants completed the answer recall task.

On each trial of the waiting task, participants were presented with a question, and three choice buttons. If they knew the answer to the question, they were instructed to press 'know'. Otherwise, they could choose to wait a specified duration for the answer by pressing 'wait Xs', or else choose to press the 'skip' button, which terminated the trial. Durations were assigned in random order from the set {4s,8s,12s,16s}. An ellipsis was presented during the waiting period, followed by the answer. Participants were asked to rate their satisfaction with each answer on a 1-5 Likert scale. The duration of each waiting task block was set to 180s, regardless of participants' choices.

On each trial of the recall task, participants were presented with a question they had chosen to wait for a week earlier. Participants indicated whether they remembered the answer to the question. If so, they had to input the answer into a text box.

Complete timing parameters are given in the Supplementary Information, see Fig. S1 for screenshots of the task.

Analysis

Data was analyzed using the R statistical environment 3.6.0, and Stan probabilistic language 2.23.0. Julia 1.4.2 scripts were used to parse raw data and model outputs for greater computational speed.

*Exclusion criteria***.** Four participants reported technical difficulties in the presentation of questions. Their data was excluded from analysis. Data from 358 participants (5.84%) reporting

less than perfect English language fluency, and 335 participants (5.46%) who interacted with other applications more than 5 times during the waiting or rating tasks were further excluded from analysis. Following previous studies with the waiting task [14], we excluded data from participants who failed to respond on more than 20% of trials (n=4, 0.07%), or whose mean response time was more than 2 standard deviations (SD) lower than the group average (n=58, 0.95%). Overall, data from 5376 participants was included in analyses (median age 36, range 18-89; 2818 female).

We separately excluded data from the second session if participants had more than 5 application interactions during the recall task (n=176, 3.27%), or inputted responses that were coded as non-compliant with instructions (e.g. non-words, n=52, 0.97%).

Scoring memory recall. Participants recollected answers were compared to the original answer they had seen. Exact matches were scored as correct by an R program. A research assistant blind to the research hypotheses and conditions scored the remaining responses as either incorrect, not recalled (e.g. "I don't remember"), partially correct, or correct. 311 responses (0.90%) were flagged as not compatible with instructions. Both partially correct and correct answers are considered as successful recollection in all subsequent analysis, while incorrect and not recalled are considered as recollection failures.

Validation of motivational state measures. Ratings for the all affective items in the experiment were subjected to a Bayesian Principal Component Analysis[39], which is robust to missingness in the data. Five-fold cross validation revealed that three was the optimal number of components in the data. The three components were rotated using the Quartimax method[40], and each item was assigned to the component on which it had the strongest loading. One group contained items

related to COVID-19, comprising the *COVID-19 concern* measure, while another contained all items measuring negative affect, which we used as the *non-specific anxiety* control. The third component contained all positive affect items. We used the unweighted means of each variable group to avoid overfitting. The relation between affective measures and curiosity are very similar when using a naive grouping of items, according to the original questionnaire they came from.

To further establish the validity of our COVID-19 concern and non-specific anxiety measures, we sought to relate them to participants' real-world circumstances. We found that ratings of COVID-19 concern were higher for participants who experienced job loss $t(1069.84)=12.49$, $p< 0.001$, a reduction in income $t(3790.22)=12.26$, $p< 0.001$, or self-isolation $t(2129.50)=7.98$, $p< 0.001$, relative to participants who did not experience these events (Fig. 5d). A similar pattern was observed for non-specific anxiety (job loss: $t(930.69)=15.42$, $p< 0.001$, income decrease: $t(3448.08)=13.94$, $p< 0.001$, self-isolation: $t(2482.32)=5.42$, $p< 0.001$; all degrees of freedom are given with the Welch correction for unequal variances).

We compared rates of COVID-19 concern and non-specific anxiety between states with different levels of social distancing, and across timepoint from mid-March to early May 2020. These effects were evaluated with a multilevel non-linear general additive model (GAM). We find a significant non-linear component in the development of COVID-19 concern over time SD=0.76, 95% PI = [0.36,1.45], but not a linear increase b=1.15, 95% PI = [-0.23,2.42]. As can be seen in Fig. 5a, COVID-19 concern rose during the last two weeks of March, before plateauing and gradually decreasing. A similar non-linear component is found for non-specific anxiety SD=0.53, 95% PI = [0.16,1.14].

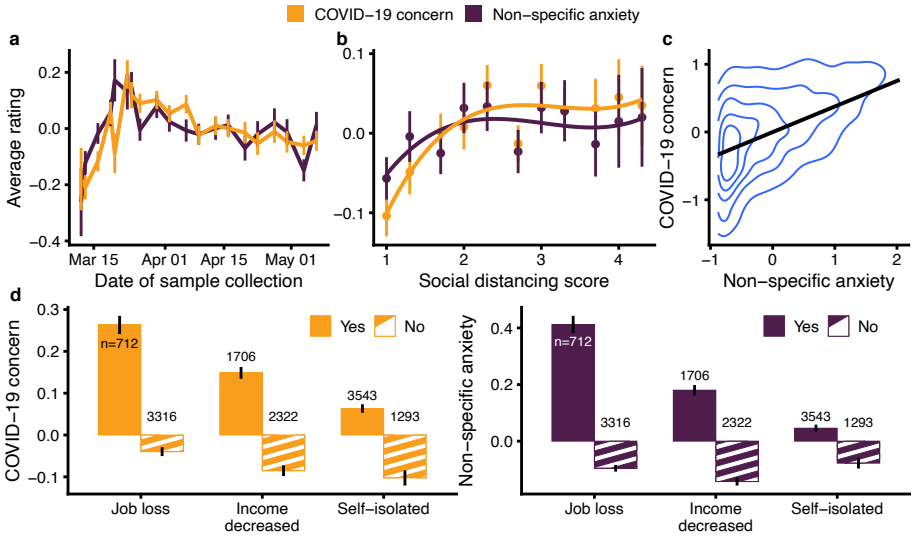

Figure 5. Motivational state metrics track with real-world circumstances. (**a**) Standardized ratings of COVID-19 concern increased sharply mid-March 2020, a similar pattern is observed for non-specific anxiety. (**b**) COVID-19 concern is higher for people in states where social distancing is practiced, as measured by Unacast via smartphone location data[44]. Lines are predictions from a general additive model. (**c**) Non-specific anxiety and COVID-19 concern are moderately correlated r=0.44, p< 0.001; black line derived from linear regression. (**d**) COVID-19 concern levels (plotted on the left) are higher among participants who had lost their jobs, had seen their income decrease, or went into self-isolation. The same was true for specific anxiety, plotted on the right. The number of participants in each group is noted near each bar. All error bars span two standard errors.

We observed a significant non-linear component in the change of COVID-19 concern with the social distancing measure SD=0.11, 95% PI = [0.02,0.28]. As can be seen in Fig. 5b, COVID-19 concern rose with social distancing behavior, and then plateaued. Between-state variance in COVID-19 concern levels was larger than zero SD=0.05, 95% PI = [0.02,0.08]. A non-linear component is significant also for non-specific anxiety SD=0.08, 95% PI = [0.003,0.31], which also varied considerably between states SD=0.06, 95% PI = [0.03,0.09].

Overall, COVID-19 concern and non-specific anxiety are moderately correlated $r=0.44$, $p< 0.001$.

Fitting regression models. Cost-benefit rationality and goal-rationality were estimated using a set of multilevel regression models, predicting waiting, satisfaction or memory from wait duration, usefulness judgements, question type, COVID-19 concern and non-specific anxiety. Logistic regression was used for waiting and memory responses and ordered-logistic regression for satisfaction ratings[41]. Models included maximal random effect structure and were fit to the data using Hamiltonian Monte Carlo sampling implemented in the Stan language. Regularizing priors were used to facilitate estimation (Table S1). All predictors were centered and scaled prior to fitting. We report coefficients for duration on the scale of the original data, and for all ratings-based predictors on a standardized scale. Four Monte-Carlo chains were run for each model, collecting 2000 samples each after a 1500 sample warmup period (for the mediation model below 3000 samples were collected due to model complexity). Convergence was assessed using the $\hat{R}$ metric, and visual inspection of trace plots. For all models mentioned in the main text, coefficients for covariates or nuisance parameters are reported in the Supplementary Information.

All models in which waiting choices were the dependent variable included usefulness judgments as a predictor. Usefulness was judged on an ordinal Likert scale with only two ratings made by each participant for each question. Thus, we first fit usefulness ratings with a two-parameter ordinal item response theory (IRT) model to extract judged usefulness estimates on a metric scale, rather than apply an averaging operation to the raw ordinal data[41,42]. The model included a term for the average usefulness of each question, and the average rating of each participant. Using R syntax, this is the IRT model fit to usefulness judgments:

```
useful_me, useful_others ~ (1 | participant) + (1 | question),
```

family = ordered(link = “logit”) Eqn. 1

We chose an ordered-logistic likelihood function for the usefulness ratings, with a separate set of threshold parameters[41] for each of the two usefulness items (useful for me / useful for others), to allow for different use of the Likert scale for these two items. The model was fit to usefulness ratings using maximum a posteriori (MAP) estimation with the Stan language[43]. We used the MAP estimates for each question's usefulness in all subsequent models in which usefulness is a predictor. These estimates are highly correlated with the raw averages of the ordinal ratings $r=0.99$, $p< 0.001$.

Assessing cost-benefit rationality. A rational account of curiosity would predict increased waiting for questions with a rise in judged usefulness, and a fall in wait duration. Satisfaction ratings and subsequent memory have been shown to follow curiosity[14], and so similar predictions can be made for these dependent variables.

In order to assess cost-benefit rationality of participants’ behavior, we constructed regression models predicting curiosity-driven behavior using judged usefulness, wait duration, the type of question (COVID-19 / general) and all of the interactions between these three factors. We used a multilevel logistic regression to predict waiting and memory from the combination of these predictors, and a multilevel ordered-logistic regression to predict satisfaction ratings. The model was fit with by-participant intercept and slope for all predictors, and by-question intercept and slope for wait duration. Using R syntax, these are the three regression models fit to the data:

```
waited ~ wait duration * usefulness * question type +
    + (wait duration * usefulness * question type | participant) + (wait duration | question),
    family = bernoulli()
```

Eqn. 2

satisfaction ~ wait duration * usefulness * question type +

+ (wait duration * usefulness * question type | participant) + (wait duration | question),

family = ordered(link = “logit”) Eqn. 3

recalled ~ wait duration * usefulness * question type +

+ (wait duration * usefulness * question type | participant) + (wait duration | question),

family = bernoulli() Eqn. 4

Assessing goal rationality. We added COVID-19 concern and non-specific anxiety as predictors to a second set of models to assess the effect of motivational state on curiosity driven behavior. Since the first set of models did not reveal any significant interaction with wait-duration in predicting waiting, and no effect of wait duration in predicting memory or satisfaction, these effects were dropped from the second set of models. Using R syntax, these are the three regression models fit to the data:

waited ~ wait duration + usefulness * question type * COVID-19 concern + usefulness *

* question type * non-specific anxiety +

+ (wait duration + usefulness * question type | participant) +

+ (wait duration + COVID-19 concern + non-specific anxiety | question),

family = bernoulli() Eqn. 5

satisfaction ~ usefulness * question type * COVID-19 concern + usefulness *

* question type * non-specific anxiety + (usefulness * question type | participant) +

+ (COVID-19 concern + non-specific anxiety | question),

family = ordered(link = “logit”) Eqn. 6

recalled ~ usefulness * question type * COVID-19 concern + usefulness *
* question type * non-specific anxiety + (usefulness * question type | participant) +
+ (COVID-19 concern + non-specific anxiety | question),
family = bernoulli() Eqn. 7

Assessing the effect of motivational states on usefulness judgments. The rational framework predicts that motivational effects on curiosity operate by changing the personal utility of questions. Hence, we were interested to see whether mean usefulness judgement levels change with motivational states, operationalized as COVID-19 concern and non-specific anxiety. We fit a multilevel ordered-logistic regression model to usefulness judgements with the goal of estimating the effect of COVID-19 concern and non-specific anxiety on usefulness judgements. Using R syntax, this is the regression model fit to the data:

useful_me, useful_others ~ question type * COVID-19 concern + question type *
* non-specific anxiety + (1 + question type | participant) +
+ (1+ COVID-19 concern + non-specific anxiety | question),
family = ordered(link = "logit") Eqn. 8

Here again we fit separate threshold parameters for each usefulness item.

Mediation model. As a further test of our rational framework of curiosity, we determined whether the data are congruent with the notion that motivational states influence curiosity by changing personal utility. While the data presented here cannot strictly support a causal account of such sort, joint statistical analysis of waiting choices and usefulness judgments can still validate whether it conforms with the predictions of the rational framework. In order to validate this

prediction, we fit a joint regression model (akin to mediation models) defined by the following two regression equations in R syntax:

useful_me, useful_others ~ 1 + question type * COVID-19 concern +
+ (1 + question type | participant) +
+ (1 + anxiety |question), family = ordered(link = "logit") Eqn. 9

waited ~ 1 + question type * COVID-19 concern + usefulness +
+ (1 + question type + usefulness | participant) +
+ (1 + anxiety + usefulness |question), family = bernoulli() Eqn. 10

The first equation defines the mediator model in mediation analysis parlance, and the second the outcome model. This joint model allowed us to estimate the extent to which both the specific and the generalized effects of COVID-19 concern on waiting are mediated by usefulness judgments.

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Author Contributions

YA, CBM, RRH and DS designed research; YA collected data; YA, CvG and ML analyzed data; YA, RRH and DS wrote the first draft; CBM, CvG and ML edited the paper; RRH and DS supervised.

Competing Interest Statement:

Authors declare no competing interests.

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