Expected information gain predicts curiosity

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EXPECTED INFORMATION GAIN PREDICTS CURIOSITY

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Curiosity has been defined as an intrinsic motivation for performing actions that result in a gain of knowledge (Berlyne, 1966; Loewenstein, 1994). As positive effects of curiosity on memorization of new knowledge were found by Kang et al., 2009, exploring the mechanisms behind curiosity can have great practical applications. Although information theoretic concepts have been linked to curiosity (Berlyne, 1966; Kang et al., 2009; Gottlieb, Oudeyer, Lopes & Baranes, 2013), this has not been tested empirically through an actual information theoretic operationalisation. This study aims to correct this by individually measuring the prior knowledge of participants and computing the expected information gain (IG) of an information rewarding action. To quantify the incentive value of curiosity a time delay was imposed on IG, forcing participants to a trade-off between maximizing information and minimizing time spent on the task. Through linear regression analysis, it is shown that curiosity is proportional to expected IG and that participants were prepared to invest 0.4 seconds per bit.

Keywords: Curiosity, information theory, information gain, prior knowledge

Nyfikenhet har definierats som en inre motivation av handlingar som resulterar i en kunskapsökning (Berlyne, 1966; Loewenstein, 1994). Då nyfikenhet har visats förbättra inlärningen av ny kunskap (Kang et al., 2009) så bör utforskadet av nyfikenhetens mekanismer vara av stort intresse och ha många praktiska tillämpningar. Även om informationsteoretiska koncept har sammankopplats med nyfikenhet tidigare (Berlyne, 1966; Kang et al., 2009; Gottlieb et al., 2013) så har denna koppling inte testats empiriskt genom en informationsteoretisk operationalisering, vilket är syftet med denna studie. Genom att göra en individuell mätning av försöksdeltagarnas förkunskap så kan den förväntade informationsvinsten (IG) av att utföra en informationsbelönande handling beräknas. För att kvantifiera det inneboende värdet hos nyfikenhet så straffas informationsvinsten med en tidskostnad, vilket tvingar försöksdeltagarna att välja mellan att maximera information och minimera tiden det tar att utföra experimentet. En linjär regressionsanalys visar att nyfikenhet är proportionell mot förväntad informationsvinst, och att försöksdeltagarna är beredda att betala 0.4 sekunder per bit.

Nyckelord: nyfikenhet, informationsteori, förväntad information, prior, förkunskap

Curiosity can be a powerful motivation for performing actions that yield information about the state of the world, even in the absence of immediate external rewards such as food or money (Berlyne, 1966; Loewenstein, 1994; Golman & Loewenstein, 2015; Gottlieb et al., 2013). The purpose of the present study is to explore the mechanisms behind curiosity. Aside from the motivational character of curiosity, it has been shown to have beneficial effects on memory and learning (Gruber, Gelman & Ranganath, 2014; Kang et al. 2009). Controlling these properties related to learning and motivation is desirable in a wide range of situations, from education to entertainment.

In previous work investigating curiosity the concept of information as defined by Shannon (1948) has been suggested as an appropriate unit of measurement (Berlyne, 1957; Gottlieb et al., 2013), yet the current literature shows a lack of the adequate operationalization and measurements needed to quantify the relationship between expected information gain (IG) and information-seeking actions. With the aim of improving on these perceived shortcomings and to demonstrate that curiosity depends on expected IG, a method is proposed which quantifies the value
of information measured at the individual level. To achieve this goal the prior knowledge of participants as well as the expected IG must be measured and controlled, and a cost must also be associated with IG. First, however, curiosity must be defined.

In this study, curiosity is defined as an intrinsic drive for learning new information that is not motivated by any external reward. Curiosity can of course lead to external reward in certain situations, but it is in that case an unexpected side effect of engaging in curious behavior. Evidence supporting the view of curiosity as an intrinsic drive for information can be found from studies in behavioral neuroscience. DeYoung (2013) linked curiosity to dopaminergic reward structures in the brain, activated by the possibility of learning new information, and Bromberg-Martin and Hikosaka (2009) found a link between activation in dopaminergic systems and environments with high information. Kang et al. (2009) and Gruber et al. (2014) found that structures related to external rewards were activated after participants had gained information that they had been curious about. Importantly, these studies also found that learning was improved for items that were rated as inducing high curiosity compared to items that were rated as inducing low curiosity. These findings show that curiosity is linked to reward mechanisms that trigger when new information is learned, and that learning can be improved when curiosity is involved.

The link between curiosity and information theory was made popular in the 1950s by Berlyne (1957), who conceptualized curiosity as a drive for gaining information and divided it into two dimensions (Berlyne, 1954, 1960), one behavioral and one motivational. The behavioral dimension concerns the goal of the curiosity driven action; specific curiosity relates to finding information that reduces uncertainty about a specific problem, while diverersive curiosity is more a general drive for stimulation, e.g. to relieve boredom (Loewenstein, 1994). On the motivational dimension we find reasons for curiosity related to the type of information that is desired. Perceptual curiosity is the basic drive in both humans and animals for exploring the surroundings, and epistemic is curiosity for information that increases knowledge. The empirical evidence for this division is not clear. Litman & Spielberger (2003) had some success in constructing a questionnaire on epistemic and perceptual curiosity, however, Mussel (2010) casts some doubt on these findings. Therefore the current study will not delve further into this matter, and remain with the more general definition given earlier.

More recently, Loewenstein (1994) proposed the information gap theory of curiosity. According to this theory, becoming aware of a gap in one’s knowledge stimulates curiosity. To illustrate what this gap is, consider your favorite author for a moment; if you learn that a new book was recently released, surely you would become curious to read it and, time and money permitting, try to procure it with haste. A gap in your knowledge was created when you became aware of the new book. According to Loewenstein, the level of curiosity sparked by an information gap is not linear, however. A small gap (small amounts of new information) instills little curiosity, but so does a gap that is too large (see Figure 1 for a visual
representation). This diminishing return on IG is a bit difficult to understand. How is it that a lot of information is less valuable than a medium amount?

A different explanation can be given for the apparent diminishing returns of information, which preserves the value of a bit within a topic. If a retrieval cost interacts with the value of information (Figure 1), all manner of relationships can be observed, and the diminishing returns proposed by Loewenstein (1994; Golman & Loewenstein, 2015) is quite likely considering that actions with a high expected IG often come at high cost. The present study will assume that the amount of curiosity instilled by information does not diminish with increased IG and is proportional to IG.

Measuring the prior knowledge on the topic being tested is crucial for an information theoretic approach. Prior knowledge will determine the probabilities that are assigned to possible outcomes of an event, and expected IG is dependent on this distribution. Observing an outcome with a high probability of occurring is less informative than observing an unlikely outcome is. This can be illustrated by imagining a coin flip with a two-headed coin versus a normal coin. Learning that the former resulted in a head is not informative at all, while the result of the latter is highly informative. Following Shannon’s (1948) information theory, uncertainty (or entropy) is the average value of information that is gained when observing repeated events with a common probability distribution (e.g., repeatedly observing the same
stimuli). Entropy is largest for uniform probability distributions, and smallest for distributions that are skewed towards one outcome. Thus, an individual should expect less IG from actions that reveal information when entropy is low, compared to when it is high. For the purpose of this study, in addition to measuring prior knowledge, the amount of IG that an individual expect from an action must be known, so that it can be compared to the cost of retrieving the information.

The method used in the present study will now be outlined. Participants were presented with a forced choice visuospatial discrimination task, which required making a judgment about the direction of a moving visual stimuli’s trajectory. Using a binary discrimination task allowed for easy approximation of each participant’s individual uncertainty regarding their performance, based on the proportion of correct answers. As it is well-known that humans are not perfect at estimating their performance level in sensory discrimination tasks, and tend to underestimate the performance on easy items, while overestimating performance on difficult items (Harvey, 1997), this method of measuring uncertainty might deviate a bit from the true values. It is not known, however, if such biases are present when no explicit confidence estimation is performed. In addition, the task was dressed up as a simple computer game with the objective of steering a space ship away from approaching meteors. The game aspect of the method was introduced simply to make participants interested in the task, something that is of importance for motivation and emotional involvement (Tobias, 1994).

Once a discrimination has been performed, curiosity about the outcome (correct or incorrect answer) should arise in the participant. This should not be a very controversial use of the term curiosity, and it seems to be in line with previous work on the topic. Golman and Loewenstein (2015) exemplifies curiosity in a similar manner, when describing a professor curious about performance ratings given by students. To quantify the value of this curiosity, two additional things must be done. First, there must be an action available which allows information to be gained, and the expected IG of performing the action must be controlled. Because a binary decision task is used, the expected IG is equal to the entropy after a decision is made, if the information only concerns a single decision and not overall performance. Moreover, to avoid confound, the IG should not allow the participant to improve performance, which could take over as the motivation behind performing the action. Therefore, the action in this study gives feedback (correct / incorrect answer) about the last decision made. Feedback about the outcome of a decision in sensory discrimination tasks has not been shown to increase performance reliably (Björkman, Juslin & Winman, 1993; Kluger & DeNisi, 1996; Olsson & Juslin, 2000) and thus safe to use for this method. In addition, analysis can be performed to see if there is any effect of feedback on performance.

Second, this action must come at a cost, to force a trade-off between satisfying curiosity and avoiding the cost. Since the cost of actions is theorized to affect the likelihood of acting to gain information, it is beneficial to use a fixed cost (i.e. every action costs the same, regardless of expected IG) when attempting to quantify curiosity with this approach. This eliminates the need for participants to learn the
cost function. For this study, a time delay of one second was added when feedback was requested. This amounted to 50% of the length of a trial (two seconds long), which should be a perceptible delay as humans have been shown to have a discrimination threshold of 5 – 10% on short time intervals (see Mauk & Buonomano, 2004 for a review). As time is used as the cost of a bit, a useful way to show the value of information will be to display it as the amount of time invested to gain a bit of information, or $s / \text{bit}$. The value of a second is of course highly individual, causing the true nature of each participants cost function to be unknown. For some this cost will be cheap enough that feedback will always be requested, while others will experience it as so punishing that it is never worth getting.

To summarize, the present study attempts to show that curiosity, defined as an intrinsic motivation for performing information seeking actions, is dependent on the expected IG from the available actions. The proposed method can quantify the value of curiosity by measuring expected IG at the individual level and adding a cost onto the available information-seeking action. Participants will be forced to make a trade-off between minimizing time spent and satisfying their curiosity, formalized as the amount of seconds invested to gain one bit, or $s / \text{bit}$. The prediction is that a significant positive $s / \text{bit}$ at the group level of analysis will be observed. As the cost is equal for information seeking actions across all trajectories, a positive proportional relationship between bits and time invested should be found.

At the individual level there are two critical elements of this trade-off method that need to be considered. First, the task must achieve a difficulty level that allows for enough variance in performance across the different stimuli to perform a regression against. Second, it is plausible, perhaps expected, that not all participants will have enough interest in the game to consider it worth investing further time, and even among those curious it is reasonable to expect large individual differences in both cost and value functions. Crucially, this study might find it difficult to distinguish whether an extremely low proportion of time investment with a flat distribution is due to disinterest or evidence for the null hypothesis that curiosity is not operating on expected IG, although exceptionally fast response times could be an indicator of disinterest. At the group level, however, finding a negative, or zero, $s / \text{bit}$ would raise serious concern about the use of expected IG as an appropriate unit of analysis when investigating curiosity.

Method

Participants
Participants were recruited through advertising on billboards around the university campus and on social media, as well as through word of mouth. 30 individuals (15 female, age 19 – 37, $M = 25.6, SD = 5.2$) with normal, or corrected to normal, eyesight participated in the experiment. Participants were paid 99 SEK as compensation for the time spent. Permission was given from the ethical board (EPN: 2014/110-31Ö) and the guidelines of the Helsinki declaration were adhered to.
**Materials**
Participants were seated on an adjustable chair and asked to adjust the height so that they were comfortably positioned while resting their chin on a SR Research Head Support device attached to a table. This setup ensured that the participants were centered in front of the screen at a distance of 75 cm. A desktop mounted EyeLink 1000 was used to track and record the subjects’ eye movements. Stimuli was presented on a 532 x 299 mm LCD screen with 1920 x 1080 resolution and a pixel size of .27 mm. Matlab R2010 32b, with Psychtoolbox (Brainard, 1997), was used to prepare and display stimuli on the screen, as well as recording trial related inputs via the left and right arrow keys on the keyboard.

**Procedure**
Participants were given a forced choice visual discrimination task, presented as a simple computer game with the objective of steering a spaceship away from approaching meteors. Figure 2 shows a trial flowchart, and Figure 3 shows the visual elements of the game. A total of 800 trials were performed, blocked into eight blocks of 100 trials. In each trial, a flare was displayed to prepare the participant for the meteor appearing. After watching the meteor appear and travel towards the cockpit for 400 ms, which constituted roughly 12% of the distance between spawn point and cockpit, participants indicated which direction they wanted to steer the ship in to avoid being hit. Correct response was to press the arrow key in the opposite direction to the meteor’s trajectory (e.g. if the meteor was headed to the right side, correct response was to press the left arrow key).

*Figure 2. Trial flowchart. A trial starts with a flare being shown for 200 ms, to prepare participants for the next meteor. The meteor appears and travels for 400 ms. Participants then have 1,400 ms to make both direction and feedback decisions. If feedback is chosen, it is shown for 1,000 ms before the next trial begins.*
After giving steering input, participants had the option of requesting feedback by looking at the cockpit element at the bottom center of the screen for 200 ms. The eyetracking camera would pick up this action and flag the MATLAB program that feedback was requested. A request for feedback paused the flow of meteors for one second, during which correct or incorrect answer was indicated using both visual and auditory cues. Each trial took two seconds to complete and there was no pause between trials. A request of feedback increased the total trial time by 50% to three seconds. For someone choosing feedback on every trial, the effective time required to complete the experiment would increase from 26.67 to 40 minutes.

Before trials started, a short background story (see Appendix) was presented, with the purpose of making participants more interested in the game. In this story, a rationale was given for why meteors were only visible for a brief duration; the ship was travelling through a fog that hampered visibility. After this, participants were given instructions on how to play the game and had to perform a short practice.

*Figure 3.* The visual elements of the game. Correct (left) and incorrect (right) feedback at the bottom. During incorrect feedback, the cockpit element moves slightly back and forth, to simulate a shaking motion.
Table 1. *The visual properties of meteor stimulus*

<table>
<thead>
<tr>
<th>Appearance</th>
<th>Trajectory $\theta$ (radians)</th>
<th>Center point $\theta$ (arcmin, arcsec)</th>
<th>Far point $\theta$ (arcmin, arcsec)</th>
<th>Near point $\theta$ (arcmin, arcsec)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.005</td>
<td>0, 29</td>
<td>8, 54</td>
<td>-7, 56</td>
</tr>
<tr>
<td></td>
<td>0.009</td>
<td>0, 52</td>
<td>9, 17</td>
<td>-7, 33</td>
</tr>
<tr>
<td></td>
<td>0.014</td>
<td>1, 21</td>
<td>9, 46</td>
<td>-7, 4</td>
</tr>
<tr>
<td></td>
<td>0.020</td>
<td>1, 56</td>
<td>10, 21</td>
<td>-6, 29</td>
</tr>
<tr>
<td></td>
<td>0.027</td>
<td>2, 37</td>
<td>11, 2</td>
<td>-5, 48</td>
</tr>
<tr>
<td></td>
<td>0.035</td>
<td>3, 23</td>
<td>11, 48</td>
<td>-5, 2</td>
</tr>
<tr>
<td></td>
<td>0.044</td>
<td>4, 15</td>
<td>12, 40</td>
<td>-4, 9</td>
</tr>
<tr>
<td></td>
<td>0.054</td>
<td>5, 13</td>
<td>13, 38</td>
<td>-3, 12</td>
</tr>
<tr>
<td></td>
<td>0.066</td>
<td>6, 23</td>
<td>14, 48</td>
<td>-2, 2</td>
</tr>
<tr>
<td></td>
<td>0.180</td>
<td>17, 19</td>
<td>25, 44</td>
<td>8, 54</td>
</tr>
</tbody>
</table>

*Note.* 1 arcmin = 1 / 60 degree. 1 arcsec = 1 / 60 arcmin. 1 radian = 180 / $\pi$ degrees.
Center point $\theta$ refers to the visual angle between the center of the stimulus and the midline.
Far point $\theta$ refers to the visual angle between the point of the stimulus furthest from the midline, and the midline.
Near point $\theta$ refers to the visual angle between the point of the stimulus furthest from the midline, and the midline.
round with the test leader present, so that it could be ensured that the instructions were understood correctly. This practice round ended after at least ten trials with feedback and ten trials without feedback were completed. On average $M = 47.97$ trials ($SD = 22.76$) were completed during the practice round.

The meteor stimuli (Table 1) consisted of ten difficulty levels, deviating from the midline by an angle ranging from .069 to 2.460 degrees (.005 to .18 radians) either to the left or right from the participant’s point of view. These angle values should produce a good variance in difficulty (Malania, Herzog & Westheimer, 2007). The following function was used to calculate the deviation from the midline (in mm) at any point in time:

$$dx = (v \cdot t) \cdot \tan(\theta) \cdot ps$$  \hspace{1cm} (1)

Where $v = 200$, $t =$ time traveled, $\theta =$ stimulus angle (see Table 1) and $ps = .27$ (pixel size in mm). Table 1 shows the visual angles that the deviation resulted in, from the view of the participant.

In addition, the meteor expanded in size as a function of time, to give the illusion of an approaching object. This expansion happened at the rate of 200% per second. The starting diameter was 4.6 mm, and the maximum diameter was 8.26 mm. Each meteor was color and texture coded according to difficulty, allowing participants to quickly discriminate between them.

![Figure 4](image1.png)  \hspace{1cm} **Figure 4.** Proportion feedback choices across all participants.

![Figure 5](image2.png)  \hspace{1cm} **Figure 5.** The Mean proportion of correct answers and feedback choices per block (100 trials).
Results

Descriptive statistics
Overall proportion of correct responses was $M = .73$, $SD = .12$ and overall proportion of feedback requests was $M = .30$, $SD = .09$. No participant chose to forgo feedback completely, as seen in Figure 4. Males performed significantly better than females but did not choose feedback at a different rate (Table 2). There was no significant difference in response times between male and female participants (Table 2). The mean proportion correct answers and feedback choices for each block are shown in Figure 5.

Table 2. Sample descriptives, with t-test for comparison of means.

<table>
<thead>
<tr>
<th></th>
<th>Male</th>
<th>Female</th>
<th>t(28)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion correct answers</td>
<td>.78 .07</td>
<td>.69 .10</td>
<td>2.85*</td>
</tr>
<tr>
<td>Proportion feedback choices</td>
<td>.31 .19</td>
<td>.29 .31</td>
<td>ns</td>
</tr>
<tr>
<td>Response time (seconds)</td>
<td>0.56 0.11</td>
<td>0.53 0.13</td>
<td>ns</td>
</tr>
<tr>
<td>Feedback request time (seconds)</td>
<td>0.33 0.12</td>
<td>0.31 0.17</td>
<td>ns</td>
</tr>
</tbody>
</table>

*p < .05.

ns = not significant

Note. M = mean. SD = standard deviation. Proportion correct answers ranges from .51 to .88. Feedback choices range from .02 to .99. Response time ranges from 0.29 to 0.77 seconds. Feedback request time ranges from 0.04 to 0.64 seconds.

Information theoretic computations
The expected IG from requesting feedback for a particular stimulus $t$ was calculated in the following way. First, the probability distribution $P(x)$ of correct and incorrect responses was calculated. The probability of correct response $c$ was calculated as the mean number of correct responses $R$, and the probability for an incorrect $\sim c$ response is the compliment to $P(c|t)$:

$$P(c|t) = \sum_{i=1}^{N} \frac{R_i}{N} \quad (2)$$

$$P(\sim c|t) = 1 - P(c|t) \quad (3)$$
Where $R_i$ is the binary response data (correct = 1) for item $i$ and $N = 80$. This distribution was then used to calculate entropy:

$$H(x) = -\sum_{i=1}^{N} P(x_i) \log_2 P(x_i)$$  \hspace{1cm} (4)

Here, $N = 2$ since it’s a binary decision task. Second, the expected IG was calculated as the difference in entropy before and after the feedback message $fb$:

$$IG(x, fb) = H(x) - H(x|fb)$$  \hspace{1cm} (5)

As $fb$ removed all uncertainty about whether the response was correct or not, $H(x|fb)$ will always equal zero. Therefore, Equation 5 can be simplified to:

$$IG(x, fb) = H(x)$$  \hspace{1cm} (6)

Which shows that any instance of requesting feedback has an expected IG equal to the entropy of the probability distribution $P(x)$.

**Group level analysis**

To investigate the main hypothesis that curiosity drives behavior as a function of the expected IG available from information seeking actions, a simple linear regression analysis was performed on the proportion of feedback requests with expected IG as the predictor (Figure 6). Expected IG significantly predicted proportion of feedback choices.

![Figure 6](image)

*Figure 6. Group level regression of proportion feedback choices on expected IG. The standard error of the mean is shown in red.*
requests, $\beta = 0.37$, $t(8) = 26.32$, $p < .05$, and explained a significant proportion of the variance, $R^2 = .99$, $F(1, 8) = 692.92$, $p < .05$. This corresponds to a predicted $0.03 + 0.37 \times IG(x, fb)$ seconds invested when $IG$ is measured in bits according to Equation 6. The average time investment was $0.40$ s / bit.

The relationship between response time and performance was investigated to support the prediction that fast response time indicates disinterest in the task. A strong positive correlation was found, $r(28) = .74$, $p < .05$. Additionally, there was a strong negative correlation between the time it took to request feedback and the proportion of requests made, $r(28) = -.67$, $p < .05$.

**Individual analysis**

Results from simple linear regression of individual proportion feedback on expected IG are shown in Table 3 and Figure 7. To better illustrate the results, the $R^2$ required for significant regression at $df = 8$, was plotted as a threshold line. As shown in the figure, for the 18 out of 30 participants above the threshold line, curiosity was significantly dependent on expected IG. One participant displayed a significant negative effect of expected IG on proportion feedback choices.

![Figure 7. Results of linear regressions of proportion feedback choices on expected IG.](image)

As a substantial proportion (12 out of 30) of participants did not show significant dependence of curiosity on expected IG, a Monte Carlo-simulation was performed to illustrate the likelihood of finding these results if feedback was randomly chosen
Table 3. Results of individual linear regressions of % Feedback choices on expected IG, and % Feedback choices on block

<table>
<thead>
<tr>
<th>Participant</th>
<th>% Feedback choices on expected IG</th>
<th>% Feedback choices on block</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( R^2 )</td>
<td>( \beta )</td>
</tr>
<tr>
<td>1</td>
<td>.92</td>
<td>.82</td>
</tr>
<tr>
<td>2</td>
<td>.88</td>
<td>0.69</td>
</tr>
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<td>3</td>
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</tr>
<tr>
<td>5</td>
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</tr>
<tr>
<td>6</td>
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<td>0.51</td>
</tr>
<tr>
<td>7</td>
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<td>0.64</td>
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</tr>
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</tr>
<tr>
<td>10</td>
<td>.74</td>
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</tr>
<tr>
<td>11</td>
<td>.01</td>
<td>0.01</td>
</tr>
<tr>
<td>12</td>
<td>.89</td>
<td>0.36</td>
</tr>
<tr>
<td>13</td>
<td>.79</td>
<td>0.49</td>
</tr>
<tr>
<td>14</td>
<td>.86</td>
<td>0.33</td>
</tr>
<tr>
<td>15</td>
<td>.26</td>
<td>0.15</td>
</tr>
<tr>
<td>16</td>
<td>.71</td>
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<tr>
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<td>&lt;0.01</td>
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<tr>
<td>18</td>
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<td>23</td>
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<tr>
<td>29</td>
<td>.33</td>
<td>0.59</td>
</tr>
<tr>
<td>30</td>
<td>&lt;.01</td>
<td>0.04</td>
</tr>
</tbody>
</table>

*Note.*

* \( p < .05 \)

** \( p < .01 \)
instead of driven by curiosity. A Monte Carlo-simulation generates large amounts of
data from variables that are randomized based on a statistical model (Chin, Marcolin & Newsted, 2003). For each participant, 100,000 data sets were generated. Each set contained artificial data from a full experiment (i.e. 80 trials / trajectory) where feedback choices were randomly performed based on the participants measured proportion of feedback choices. A linear regression was performed on each set, with the participant’s measured expected IG as the predictor. This resulted in 100,000 $R^2$ values for each participant, or 3 million in total. The actual measured results were then compared to the Monte Carlo-results (figure 8), showing that 97.99% of the artificial results explained less of the variance in feedback choices than the mean $R^2$ measured in the experiment sample.

To test if there were any changes in behavior over time, data was grouped into eight segments of 100 consecutive trials, corresponding to a block in the experiment. The group mean performance and proportion feedback choices was calculated for each block, as shown in Figure 5. Each participant’s mean performance and proportion of feedback choices was calculated for each block. Simple linear regressions of the grouped means with increasing block number as a predictor showed no significant effect of time on neither performance, $\beta = 0.005$, $t(238) = 1.823$, $p > .05$, nor proportion feedback choices, $\beta = -0.006$, $t(238) = -7.33$, $p > .05$. In addition, simple linear regressions of individual means on block number were also performed and are displayed in Table 3 and Figure 9.

*Figure 8. R^2* values from regressions of proportion feedback choices on expected IG, from the Monte Carlo-simulation.
Discussion

The main hypothesis was that curiosity can be viewed as an intrinsic motivation for performing information seeking actions, fueled by an internal representation of entropy and tempered by the associated action costs. The strong group level correlation between expected IG and investing in information seeking actions (Figure 6) supports the hypothesis. A limitation of the work done here is the narrow focus on performance in a perceptual discrimination task. It remains to be determined how the findings hold up for different topical settings and when competition between different information seeking actions are introduced.

Looking at individual data (Figure 7) we find, as expected, that there is a large variance in the effect of curiosity. At first glance the results might seem unimpressive, considering that 13 out of 30 participants did not operate under a significant positive $s / \text{bit}$. A closer look reveals that two of these individuals seem to operate under different correlations from that suggested in the hypothesis. One individual showed a significant negative correlation between bits and probability of investing time. A possible explanation for this behavior could be that the participant adopted a performance orientation (Dweck, 1986), driving the individual towards positive feedback. The second individual displayed a flat distribution of feedback.
choices \( (M = .58, \ SD = .03) \), at a surprisingly high level of investment. The rationale behind this behavior is difficult to make sense of and would likely require a detailed analysis of how and when choices were made during the experiment. The remaining eleven individuals should not be dismissed as unimportant, but all display either poor performance or extreme feedback selecting behavior, or both. As discussed, the cost function for some individuals is expected to be such that the information seeking action is always, or never, worth taking. In addition, for methodological reasons it is critical to achieve a good variance in entropy across items, as it is fruitless to perform regressions when the predictors have the same value.

Overall, participants seem to have been curious about their performance in the game, as evidenced by the proportion of feedback choices (Figure 4) made leading to an average of 14.75\% extra time spent on the task. Interestingly, there was no clear cut effect of boredom or habituation (Figure 5 and 9). Some participants (six with \( p < .05 \)) did invest significantly less time in feedback as the experiment ran its course, but a majority (21 out of 30 participants) did not show any significant effect at all.

The finding that RT correlated with performance might indicate that fast responding participants were either disinterested or misunderstood the task instructions in some way that promoted faster responses than needed. More interestingly, the negative correlation between feedback choice RT and proportion of feedback choices might pose a methodological issue where some participants did not have enough time to request feedback. Participants were asked after the practice if they understood how to use the feedback mechanism and if they experienced any problems with it, however, and no one reported having an issue with it before or after the trials. Another interpretation of this correlation is that a higher propensity towards information-seeking also facilitated faster resolution of the trade-off decision. A subjectively low cost relative to the value of IG may make the trade-off decision easy, but it must be noted that the experimental setup in the current study was not aimed at investigating curiosity and response times, which makes it difficult to draw any concise conclusions on the matter. Clarifying the relationship between curiosity and response times in decision making could be an interesting venue for future studies.

In the present study no manipulation of the cost associated with the information seeking action was performed, limiting the conclusions that can be drawn about how a cost function may interact with curiosity. As predicted by the flat cost function in this study, a strong linear relationship was observed (Figure 6). This seems like an intuitive finding; with no variation in the cost of available actions, the probability that an action is chosen should depend only on its inherent value. In more complex settings this flat cost function is likely rare, and in many cases the cost will actually increase with increased information content. For example, uncertainty about a far-away compared to a nearby stimuli is often higher due to perceptual limitations, but the cost of reaching the former is higher. Similarly, a bombastic description of the Lord of the Rings book trilogy should induce curiosity in even the most hardened
soul, but the cost associated with reading 1500 pages might seem prohibitively steep when the movies only cost ~9 hours!

An alternative interpretation of the findings is that participants investing time in feedback is not a sign of curiosity, but rather an attempt to improve performance by requesting feedback on low performance items (which correspond to high entropy items). Because performance is used to calculate expected IG this interpretation would predict similar results on the surface, making it difficult to separate the two explanations. Fortunately, there are a few counterpoints to be made against the interpretation that performance drives feedback choices. First, for an individual to determine when to invest in feedback, an internal representation of performance is required, similar to the curiosity-story. Thus, a performance oriented individual would surely notice if investing in feedback did not in fact improve performance. As neither the findings in this study nor previous research (Björkman, Juslin & Winman, 1993; Kluger & DeNisi, 1996; Olsson & Juslin, 2000) supports a significant performance improvement through feedback for this type of task, the performance interpretation seems less plausible than curiosity driving time investment.

For future studies that wish to use a similar method, it is recommended that this possible confound is kept in mind and controlled for by either dissociating performance and the measure of entropy, or ensuring that participants cannot attempt to use the information seeking action for anything immediately useful. Confidence estimation or psychophysical pretesting are possible, though slightly more cumbersome, methods available for measuring individual uncertainty. As an interesting side note, if curiosity is stimulated in situations with high uncertainty, then psychophysical testing using adaptive over constant methods might have the benefit of keeping subjects more motivated.

In conclusion, the findings presented in this work should warrant a broad and concerted effort into mapping the details of the relationships between expected IG, cost functions and curiosity. In particular, it is important to examine if similar results can be found in diverse topical settings of more interest for practical applications, such as education and entertainment. Further complicating the matter is the fact that in the world outside the lab setting, curiosity is likely to be sparked by several competing topics at once. How such competition interacts with the associated costs of available actions can shed light on ways to manage the power of curiosity to distract from more important tasks. Imagine a student who is given a long and difficult chapter to read before an exam, while simultaneously having easy to use social media applications at hand. According to the definition of curiosity put forth here, no one should be surprised if even a highly motivated and curious student finds it difficult to avoid the distraction due to the large gap in costs.
References


Appendix

Background story

You are an agent in the Rebel Intelligence Forces, fighting the good fight against the Evil Empire. In a dangerous mission on planet Starbucks, you managed to steal some important military documents that can turn the tide of the battle and help overthrow the empire once and for all. Right now you find yourself in a desperate struggle to escape the gravity of the planet so that you can activate your ship's hyperdrive. Unfortunately, a meteor shower just hit the planet, and due to heavy clouds the visibility is dangerously low! Can you muster the skill required to guide your ship to safety through the dangerous meteors? The fate of the universe is in your hands...