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Curiosity overpowers cognitive effort avoidance tendencies ☆

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ABSTRACT

Curiosity has been described as a desire to learn new information, and previous studies have demonstrated that curiosity drives peoples' decision to invest resources (e.g., time or tokens) to find out answers. It is commonly assumed that curiosity should also prompt people to invest more effort until they attain unknown answers. However, experimental evidence is lacking on whether people would be willing to exert cognitive effort — in addition to time investments — to find out answers. In three pre-registered experiments, we first asked participants to rate a set of 20 trivia questions regarding their curiosity about knowing the answers. Subsequently, participants had to perform a set of random-dot kinematograms (RDKs) to view the answer to each trivia question. We varied the motion coherence of the RDKs as a proxy for cognitive effort demands and tested whether curiosity overpowers cognitive effort avoidance tendencies. Our results provide converging evidence that curiosity outweighs peoples' tendencies to avoid cognitive effort. That is, participants avoided high-effort RDKs if they were not curious about information and when the exertion of cognitive effort did not affect the attainment of information. However, if participants were curious about questions and if no alternative low-effort option was available, they were willing to employ cognitive effort to find out answers.

1. Introduction

Curiosity can be defined as a desire for knowledge and is thought to motivate exploratory behavior to attain that knowledge (Berlyne, 1950; Jach et al., 2024; Litman, 2005; Loewenstein, 1994; van Lieshout et al., 2020), even if it is non-instrumental (i.e., not directly linked to tangible rewards, such as money or food; Gottlieb & Oudeyer, 2018). In order to satisfy their curiosity, humans (and many animals) have been found to be willing to pay a "prize" (FitzGibbon et al., 2020). Curiosity thus drives humans to seek information even if resources — such as time or tokens — have to be invested to do so (Dubey & Griffiths, 2020; Kang et al., 2009; Kidd & Hayden, 2015; Spitzer, Janz, et al., 2024). Cognitive effort can also be conceptualized as a resource, and a bulk of research has shown that humans tend to avoid spending cognitive effort when making decisions (Kool & Botvinick, 2018; Kool et al., 2010; Shenhav et al., 2017; Westbrook & Braver, 2015; Westbrook et al., 2013). However, although it has been assumed that curious people should be willing to spend more effort until they attain unknown answers (e.g., Shin & Kim, 2019), experimental evidence on the effects of curiosity on cognitive effort investments is so far largely lacking. Our work therefore contributes to the current knowledge by systematically integrating research on curiosity and cognitive effort. Specifically, we investigated whether curiosity to find out answers may not only lead to the investment of resources such as time but could also overpower peoples' tendency to avoid cognitive effort.

Kang et al. (2009) presented compelling evidence demonstrating that curiosity drives people to invest resources to acquire non-instrumental information. In their study, they first asked participants to rate a set of trivia questions regarding their curiosity about the answer to each question. Afterwards, participants were able to find out the answer to each question by investing resources (waiting 5–25 s or spending scarce tokens). Their results showed that participants were more likely to invest time, or tokens, for answers they were curious

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about (for replications and extensions, see Dubey & Griffiths, 2020; Spitzer, Janz, et al., 2024). It has also been shown that people even risk electric shocks for information they are curious about and request information that yields negative emotional consequences (e.g., Lau et al., 2020; Oosterwijk, 2017; for a review, see FitzGibbon et al., 2020). Together, these studies provide evidence that curiosity drives individuals to allocate resources toward seeking answers.

But why? Reward-learning models (Dayan & Niv, 2008; Montague & Berns, 2002) propose that behavior is guided by the rewarding value of the behavior that is computed and updated via reinforcement processes (also see FitzGibbon et al., 2020; FitzGibbon & Murayama, 2022). Whereas in traditional reward-learning models, extrinsic rewards (e.g., food, money) reinforce behaviors (e.g., Berridge, 2000), it has also been suggested that acquiring information that one is curious about is intrinsically rewarding, which strengthens information seeking and learning behaviors, even over extended periods of time (e.g., Murayama, 2022). Within this context, curiosity can be interpreted as an expected intrinsic reward associated with gaining information (Kang et al., 2009). This expected intrinsic reward can become a strong driving force, leading people to invest resources to close their knowledge gaps.

A large body of research provided converging evidence that humans tend to avoid cognitive effort (Fleming et al., 2023; Kool & Botvinick, 2018; Kool et al., 2010; Shenhav et al., 2017; Spitzer et al., 2022; Westbrook & Braver, 2015; Westbrook et al., 2013; Wisniewski et al., 2015). For instance, in a series of six experiments investigating decision-making and cognitive effort, Kool et al. (2010) found that participants consistently preferred options that required less cognitive effort across different tasks. This bias was not solely driven by concerns about avoiding errors or session duration, suggesting a *law of least cognitive effort* in that people tend to choose options involving lower cognitive effort. In addition, Kool et al. (2010) reported that providing participants with monetary rewards could overpower their cognitive effort avoidance tendencies, pointing to a trade-off between cognitive effort costs and monetary rewards.

Westbrook et al. (2013) further substantiated the results of Kool et al. (2010) by applying different levels of the N-back task, a well-established probe of working memory and cognitive effort, to examine participants cognitive effort avoidance tendencies. In particular, participants selected to perform a low-effort task for a small reward or a high-effort task for a larger reward. Participants showed greater discounting of more demanding N-back levels, indicating that they perceived cognitive effort as costly and providing further evidence that it is weight-off against monetary incentives. Importantly, this effect was independent of task performance and increased with objective cognitive load.

Building on this cognitive effort avoidance literature, cognitive control theories outline that human decisions are based on a trade-off between the costs and benefits associated with each available decision (Lieder et al., 2018; Musslick et al., 2015; Shenhav et al., 2013; Silvestrini et al., 2023). For instance, according to the expected value of control (EVC) theory, human decision-making relies on a cost–benefit arbitration (Musslick et al., 2015; Shenhav et al., 2013), where cognitive effort is costly, and these costs are typically weighted against extrinsic (monetary) rewards (for behavioral evidence see: Braun & Arrington, 2018; Spitzer, Musslick, et al., 2024). However, the EVC theory also considers intrinsic rewards in the cost–benefit arbitration (for computational modeling work, see: Masís et al., 2021; Masis et al., 2024). Given that curiosity is associated with an intrinsic value of learning (Kang et al., 2009) it may factor into a cost–benefit analysis when making decisions and may outweigh cognitive effort avoidance tendencies associated with the decision to find out answers.

1.1. The present study

In this study, we conducted three pre-registered experiments to investigate whether curiosity overpowers individuals' tendencies to avoid cognitive effort. Our experiments followed a similar procedure as reported by Kang et al. (2009), but we added a cognitive effortful task. In the first phase, participants were exposed to 20 trivia questions and rated them on a curiosity scale (1–7). In the second phase, participants had to perform six Random Dot Kinetogram (RDK) trials before seeing the answer to each trivia question. This procedure allowed us to investigate whether curiosity would lead to the investment of cognitive effort (that is otherwise avoided) to find out the answer. We selected RDK trials, as it is possible to vary the coherence of dots moving up or down and, as such, vary the difficulty and hence the cognitive effort required to perform the task accurately (Spitzer et al., 2019; Strittmatter et al., 2024, 2023).[1]

Experiments 1 and 2 were conducted to show that curiosity overpowers cognitive effort avoidance tendencies. We hypothesized that high levels of curiosity drive participants to exert cognitive effort to find out answers if the alternative would be to (a) not having to invest any effort (and not seeing the answer, and thus, not being able to satisfy one's curiosity; Experiment 1) or (b) having to invest lower effort (and not seeing the answer, and thus, not being able to satisfy one's curiosity; Experiment 2). For both experiments, we expected that curiosity would overpower cognitive effort avoidance tendencies and leading people to find out answers reflected in a positive relationship between curiosity and peoples' decision to reveal the answer.

Experiment 3 was conducted to test whether people avoid high cognitive effort and rather invest low effort if cognitive effort is not necessary to find out answers. To investigate this, participants were free to decide which of these two options (high-effort vs. low-effort) to choose prior to seeing the answer to the question,[2] (also see Fig. 1). We expected no relationship between curiosity and peoples' decision to find out answers. We also expected that participants would select the low-effort task more often than the high-effort task, as people predominantly avoid cognitive effort (Kool et al., 2010; Westbrook et al., 2013).

All data and analyses scripts can be found at the Open Science Framework https://osf.io/s3b8h/. Prior to each experiment, we conducted a pilot study to test the feasibility of the experimental settings and determine the sample size for the main experiments. The pilot studies relied on a slightly smaller number of participants than the three main experiments and showed the same effects as obtained in the main experiments, which underlines the robustness of the findings. The results from the pilot experiments are reported in the Online Supplement.

2. Experiment 1

In Experiment 1, we investigated whether participants would invest cognitive effort — in addition to time — to find out answers to questions they indicated to be curious about. Therefore, we conducted a similar procedure as applied in Kang et al. (2009) but replaced the waiting time of the second phase of the experiment with a set of RDK trials that participants had to perform accurately. We preregistered the experiment (see https://aspredicted.org/4NN_FTK).

We focused our analysis on whether people revealed the answers or not (see Online Supplement for additional analyses on the interplay between confidence, importance, and curiosity). Previous research (Dubey & Griffiths, 2020; Kang et al., 2009; Spitzer, Janz,

[1] To ensure that participants actually performed the RDK task, they were only provided with the answer if they reached a minimum accuracy of 70%.

[2] Note that participants always saw the answer to the question irrespective of their decision.

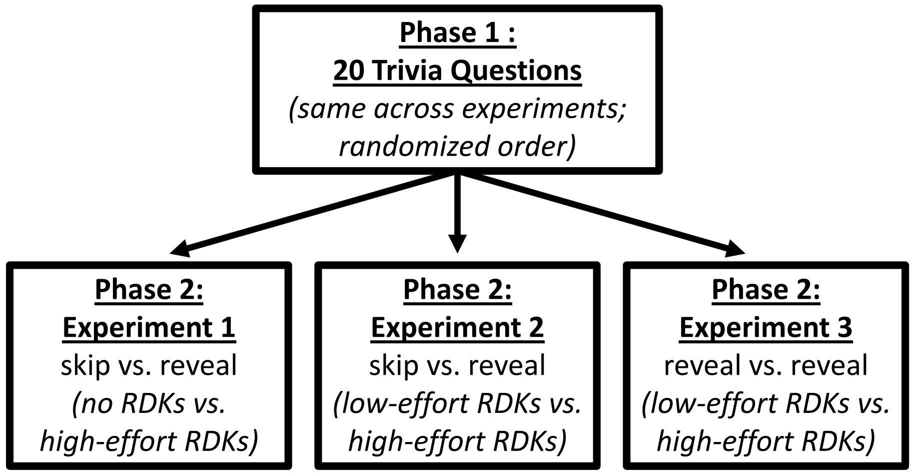

Fig. 1. Procedure of the three experiments, including the three different contrasting conditions of the second phase.

et al., 2024) involved a trade-off between time spent and curiosity. Here, we added a component that has generally been found to be avoided (i.e., cognitive effort) to the process of revealing the answer. In particular, participants not only had to spend time to perform the task but also cognitive effort to accurately do so. We expected that higher curiosity would still lead to a higher probability of revealing an answer despite having to spend cognitive effort and time.

2.1. Method

2.1.1. Participants

A total of 60 participants (30 women, 30 men, Mage = 24.32 years; range 18–40) were recruited via Prolific to participate in this online study. All participants provided informed consent prior to the onset of the study. The sample size was based on a pilot study (see Online Supplement).

2.1.2. Stimuli

The stimuli used in Experiment 1 were the same trivia questions as used in Kang et al. (2009). These questions were originally reported by Kang et al. (2009) and were designed to evoke curiosity. However, we only asked participants 20 trivia questions to keep the experiment short in time and to prevent participants from getting bored over the course of the experiment (as also reported by Spitzer, Janz, et al., 2024). These 20 questions are listed in the Online Supplement.

The RDK trials were administered with the rdk-plugin (Rajananda et al., 2017, for an extended version see Strittmatter et al., 2023). Each RDK trial comprised 500 dots, with the dot radius set to 2 and the moving distance set to 1. The moving distance is the number of pixels a dot moves per frame. Participants were instructed to respond whether the majority of the dots moved up or down as fast as possible. The coherence was set to 0.2, indicating that 20% of the dots moved in the target direction (i.e., up or down), while the remaining dots moved in random directions.

2.1.3. Procedure

After participants provided consent to participate in the study, they were instructed that the experiment consisted of two phases—a question rating phase and a find-out-answer phase (for an overview of the procedure, also see Fig. 1). They were then briefly introduced to the paradigm with one example question (“What animal can shed up to 30,000 teeth in its lifetime?”, Answer: Shark). The participants were instructed to guess the answer to this question and subsequently rated their curiosity about finding out the answer to this question (1–7).

In the first phase, we presented the questions to the participants and asked them to guess the answer to them. Subsequently, they rated their curiosity about discovering the correct answer to this question on a seven-point scale (1 = “Not curious at all”, 7 = “Very curious”) in response to the prompt: “Please indicate how curious you are to know the correct answer”. Then, they reported their confidence about their guess on an eleven-point percentage scale (0% = “Not likely at all”, 100% = “Very likely”) in response to the prompt: “How likely is it that you would answer this question correctly?”. Finally, they indicated the importance of knowing the correct answer on a seven-point scale (1 = “Not important at all”, 7 = “Very important”) in response to the prompt: “Please indicate how important it is for you to know the correct answer”. Note, that we did not consider the confidence and importance ratings for our research questions. However, we analyzed these ratings to substantiate previous findings by Kang et al. (2009). The results of this additional analysis is presented in the Online Supplement.

During the second phase, each question was again presented and participants were instructed that they could decide to either skip the answer to this question by pressing ‘A’ or find out the answer by pressing ‘K’ on their keyboard. Participants were also instructed that if they decided to find out the answer, they would need to respond to 6 to 14 RDK stimuli with an average accuracy of at least 70% to obtain the answer. Specifically, if participants decided to skip the answer, the next question was shown. However, if participants decided to view the answer and reached 70% accuracy, the answer was shown, but if they decided to view the answer but did not reach 70% accuracy a note appeared saying: “Your responses to the dot motions were not accurate enough to reveal the answer”.

We randomized and varied the number of RDK trials to mimic the original procedure by Kang et al. (2009) who randomized and varied the time the participants had to wait to receive the answer. Each RDK was presented until participants responded with a maximal duration time of 2000 ms. Afterward, a post-trial gap (black screen) of 200 ms was presented, followed by response contingent feedback presented on the screen for 400 ms (“CORRECT!” for accurate responses; “FALSE!” for inaccurate responses; “TOO SLOW!” if participants did not respond within the 2000 ms trial duration).

2.1.4. Data analysis

The data analysis was performed with the open-access software R (R Core Team et al., 2013). The lme4 package (Bates et al., 2014) was applied to run the hierarchical logistic regression models conducted to analyze the data from the find-out-answer phase. The sjPlot package (Lüdecke & Lüdecke, 2015) was applied to generate the plots and the patchwork package (Pedersen, 2019) was applied to combine a set of subplots within a figure. Before data analysis, curiosity ratings were normalized as described in Kang et al. (2009) with a z-transformation.

We examined whether curiosity ratings influenced participants' decision to seek out answers despite spending resources (cognitive effort and time) with a hierarchical logistic regression model with participants' decisions coded as 0 (skip answer) and 1 (decision to reveal the answer) as the dependent variable and their normalized curiosity as the independent variable. We additionally added a random slope term for curiosity to account for between-participant variability in the effect of curiosity on their decision and a random intercept for participants to account for overall variability in participants' decision to reveal the answer.[3]

Participants who indicated the same rating for all curiosity ratings were excluded before the statistical data analysis (as in Dubey & Griffiths, 2020; Spitzer, Janz, et al., 2024). Based on this exclusion criterion, one participant was removed. In addition, three participants aborted the experiment during data collection and were therefore excluded from data analysis. Thus, the final sample of Experiment 1 comprised 56 participants.

Furthermore, we evaluated participants' performance, by analyzing their average reaction times and average error rates on the RDK trials if they decided to perform a set of RDK trials to reveal the answer. We also calculated the average number of decisions to reveal the answer for each participant and report the results below.

Finally, we ran additional analyses on the relationship between participants' confidence ratings and their curiosity ratings of the first phase of the experiment to substantiate the findings by Kang et al. (2009). It has been repeatedly found that people are most curious about information that they have moderate knowledge about as both information that people are certain about and information that people are completely uncertain about do not evoke curiosity. Our results replicate this inverted u-shaped relationship between confidence and curiosity. We report this additional analysis in the Online Supplement as these analyses do not regard our research questions. These additional analyses also comprised a model comparison procedure showing that our curiosity model on participants' decision to reveal the answer fitted the data better than models considering participants' importance ratings or their confidence ratings as independent variables.

2.2. Results & discussion

Overall, the participants selected to skip the answer more often than to view the answer (61.3% average skipped answers), with 38 of the 56 (68%) participants selecting to reveal the answer in less than 50% of the trials (see Fig. 2B). The participants had an average reaction time of 867.56 ms (SD = 246.22 ms) on correct RDK trials and an average error rate of 32.9% (SD = 20.9) on all RDK trials. On average, the participants reached 48% of the times the threshold of a minimum accuracy of 70%. We observed a positive correlation (r = .57; p<.001) between participants' decision to reveal the answer and their average probability of reaching the 70% threshold.

The results of the hierarchical logistic regression indicated a significant main effect of curiosity on participants' decision to reveal the answer ($b = 1.11$; $z = 8.20$; $p < .001$; see Fig. 2A; see Figure S2 and the Online Supplement for the same analysis on raw curiosity ratings which show virtually the same results). This demonstrates that curiosity drove participants' decision to exert time and cognitive effort to find out the answers to questions they were curious about (please refer to the Online Supplement for an analysis of participants' raw curiosity ratings).

As such, the results of Experiment 1 show that participants would perform a set of cognitively effortful RDKs to find out answers. However, the results of Experiment 1 do not allow us to disentangle the investment of time from cognitive effort. Both resources were spent when participants decided to find out about the answer to a question and both resources were not spent when participants decided to skip the answer. Thus, we conducted Experiment 2, where participants had to spend time irrespective of their decision (skip the answer vs. find out the answer). Yet, the cognitive effort participants had to invest to accurately perform the RDKs depended on their decision.

3. Experiment 2

Experiment 2 was conducted to test whether people would be willing to exert higher levels of cognitive effort to find out the answers to a question. Therefore, participants had to decide between performing RDKs that demanded relatively low cognitive effort to skip the answer or performing RDKs that demanded relatively high cognitive effort to find out the answers to a question. Both options (high versus low effort) required the same amount of time. This experiment was preregistered (also see https://aspredicted.org/4NN_FTK).

3.1. Method

3.1.1. Participants

60 German participants (30 women, 30 men, Mage = 23.61 years; range 18–39) were recruited via Prolific to conduct the online study. All participants provided informed consent before the onset of the study. The sample size was based on a pilot study (see Online Supplement).

3.1.2. Stimuli, procedure, and data analysis

The stimuli, procedure, and data analysis[4] of Experiment 2 were the same as in Experiment 1, with the only exception being that participants were informed they would always perform RDKs; however, easy RDKs would not reveal the answer, while difficult RDKs would provide the answer to a question.

The RDK trials had the same setting as in Experiment 1 (500 dots, dot radius of 2, and a moving distance of 1), with the only difference being that we set a coherence of .8 for the low-effort task and a coherence of .25 for the high-effort task. The participants always responded to six RDK trials, irrespective of whether they selected the low-effort or the high-effort task. Finally, we ensured that participants spent the same amount of time with the task, regardless of their effort choice or response time, by adjusting the duration of the feedback. Specifically, feedback was presented for 2500 ms minus the participant's response time e.g., if a participant responded to the RDK stimuli within 700 ms, the feedback was shown for 1800 ms, and if a participant responded to the RDK stimuli within 1300 ms, the feedback was shown for 1200 ms. The maximum response time of 2000 ms and the 200 ms post-trial gap remained unchanged from Experiment 1.

In addition to reporting average reaction times and accuracies for the low-effort and high-effort trials, we ran a hierarchical linear regression with participants' reaction time as the dependent variable and the effort choice (low-effort vs. high-effort) as the independent variable. We included the effort choice as a random slope term and a random intercept for participants. Taking into account the accuracy of the participants, we ran a hierarchical logistic regression model with the dichotomous variable error (1 for errors responses and 0 for correct responses) and the same independent variable, random slope, and random intercept terms.

We ran the same additional analysis on the inverted u-shaped relationship between confidence and curiosity considering the data of phase one and report these in the Online Supplement.

[3] A model comparison procedure, evaluating the Bayesian information criterion (BIC) of this more complex model against a baseline model (decision ~ 1+(1|subject)) suggested a better model fit for our suggested model.

[4] We applied the same model comparison procedure as in Experiment 1. The results indicated that the BIC for our suggested curiosity model indicated a better model fit than the simple baseline model, an importance model, and a confidence model (see Online Supplement).

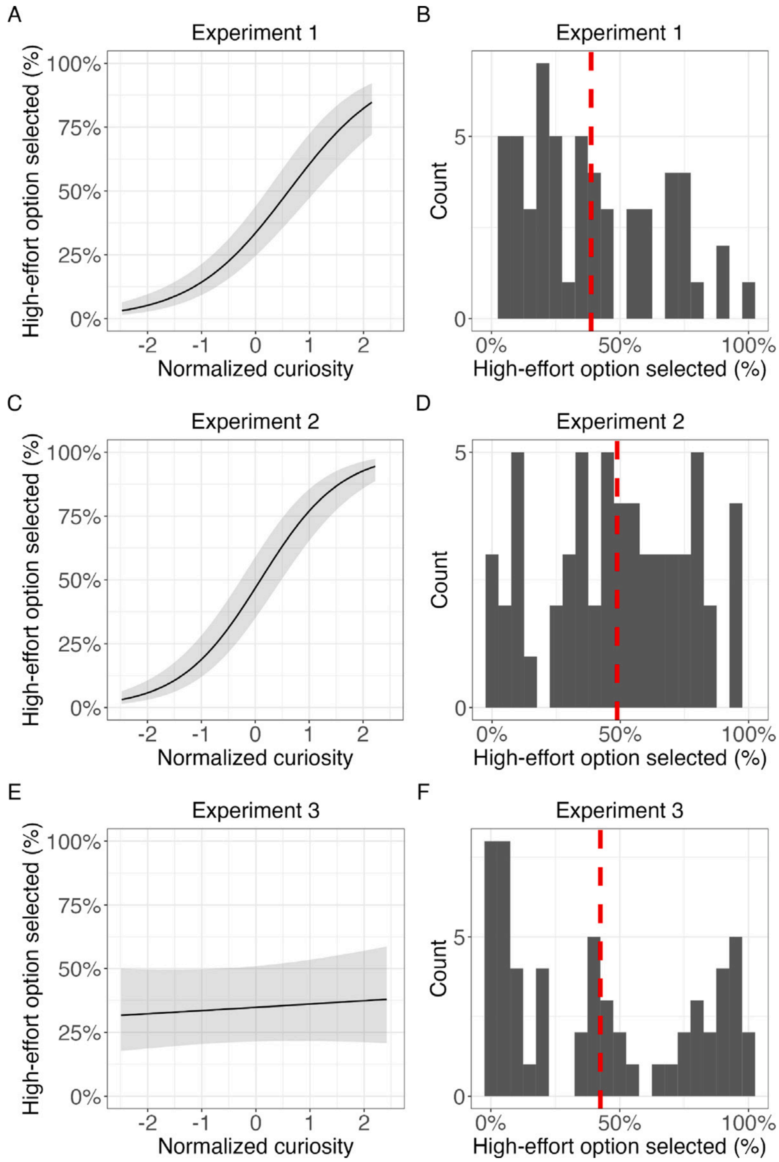

Fig. 2. Results of Experiment 1–3. A, C & D: Participants' probability to select the high-effort task as a function of their curiosity rating. The black line illustrates the fit of the logistic regression and gray shades indicate the standard error of the mean. B, D & F: A histogram showing the distribution of participants' average high-effort task selection. The red vertical dashed line indicated the average high-effort decision.

Note. The participants only saw the answer in Experiment 1–2 if they selected the high-effort option and if they accurately performed on this high-effort task. The participants always saw the answer in Experiment 3 irrespective of their effort decision and performance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Finally, we further evaluated whether participants not only avoided high effort and only selected to pay effort as a price to reveal answers but also whether participants' error rates on high-effort trials influenced their effort choice. This analysis was motivated by previous findings showing that participants not only avoid effort, but also avoid errors (Matthews et al., 2023). Participants' error aversion may be operationalized by their accumulating error rate in all previous trials. However, based on our specific procedure of only showing participants the answer if they reached 70% accuracy on high-effort trials, error aversion may also be indicated by participants' last performance on high-effort trials on performing above or below this threshold—or both variables (i.e., accumulating error rate and above threshold). We carried out three hierarchical regressions to quantify which of these two variables, or both, fit the data best. The first independent variable considered participants' accumulating error rate on high-effort trials. The second independent variable was a dichotomous variable *above threshold* indicating whether participants' performance on the previous high-effort trial was above or below the 70% threshold (i.e., whether the last high-effort selection led them to learn the answer to the trivia question). We then performed three hierarchical regressions that considered the choice of effort of the participants as the dependent variable while considering the curiosity ratings of the participants as an independent variable and: (i) considered the accumulation error rate as an independent variable, including the interaction with curiosity (model 1); (ii) considered above threshold as an independent variable, including the interaction with curiosity (model 2); and (iii) considered all three variables as independent variables, including all interactions between the three variables (model 3). Finally, we also ran a model with only curiosity as an independent variable to compare the model fit of the three described models against a model that only considered curiosity as an independent variable (model 4). Please note that we did not evaluate the first high-effort trials of participants on these analyses, as no data on previous high-effort trials was available on these trials. We then compared the BIC of these four models and reported the model with the lowest BIC in the Results section below. Note that we only considered a random intercept for participants and no random slope terms for this modeling comparison procedure to reduce the number of possible models.

We applied the same exclusion criterion as in Experiment 1. One participant did not complete the experiment and was therefore excluded from the data analysis. Thus, the regression models reported below were based on 59 participants.

3.2. Results & discussion

Overall, participants decided to skip the answer similarly often than to view it, with 28 out of 59 participants (47%) choosing to reveal the answer in fewer than 50% of the trials (see Fig. 2D). The average reaction time for correct RDK trials was 608.94 ms (SD = 189.86 ms) on low-effort trials, and 758.53 (SD = 170.60 ms) on high-effort trials. The average error rate was 13.7% (SD = 18.8%) for low-effort trials and 20.2% (SD = 19.6%) for high-effort trials. As such, participants' performance was on average less accurate and slower on high-effort trials than on low-effort trials. Similar to Experiment 1, we found a positive and significant correlation (r = .29; p = .031) between participants' decision to reveal the answer (i.e., selecting the high-effort task) and their average probability of reaching the 70% threshold.

As in Experiment 1, the result of the hierarchical logistic regression revealed a significant effect of normalized curiosity on participants' decision to reveal the answer ($b = 1.44$; $z = 10.36$; $p < .001$; see Fig. 2C; see Figure S2 and the Online Supplement for the same analysis on raw curiosity ratings). This finding indicates that participants were willing to perform a cognitively demanding task to find out answers if they were curious about the information. The results also show that people preferred to perform a task requiring relatively lower cognitive effort — which took them as long to perform as the task requiring relatively more cognitive effort — if they were not curious about finding out the answer.

The results of the hierarchical regression analysis on participants' performance indicated significantly faster reaction times on low-effort trials compared to high-effort trials (b = 76.88; t = 5.71; p < .001; see Fig. 3A). Similarly, participants made fewer errors on low-effort trials than on high-effort trials (b = −.22; t = −5.23; p < .00; (see Fig. 3B). These two analyses support the observed descriptive differences in average performance, demonstrating that participants performed worse on the high-effort task compared to the low-effort task.

Our modeling comparison procedure on error aversion effects (results from additional analyses) indicated that the second model (only considering whether participants performed above threshold in the last trial) had the lowest BIC (BIC model 1 = 896; BIC model 2 = 889; BIC model 3 = 911; BIC model 4 = 891). However, the BIC difference of model 2 did not suggest very strong evidence for a better model fit compared to model 4 that only considered curiosity as an independent variable. Note that a BIC difference of 10 indicates strong evidence for a better model fit (Kass & Raftery, 1995; Raftery, 1995). Thus, model 2 had a better model fit than model 1 but there was not strong evidence that model 2 was better than model 1. We therefore also report the results of model 1 in the Online Supplement. We, nevertheless, focus on the results of model 2 below.

The results of model 2 indicated a significant main effect for curiosity (b = 1.31; z = 8.67; p < .001), indicating a higher probability of selecting the high-effort decision when participants indicated high curiosity in finding out the answer to a question. We also observed a significant main effect for above threshold (b = 0.44; z = 2.55; p = .011), indicating an overall higher probability of selecting the high-effort option if participants performed above threshold on the last high-effort trials. Finally, we observed a significant interaction between curiosity and above threshold ($b = 0.37$; $z = 2.53$; $p = .011$), indicating that the negative effect of not reaching the threshold on participants' high-effort choice particularly affects participants' high-effort choices when they were curious about finding out the answer (see Figure S5A).

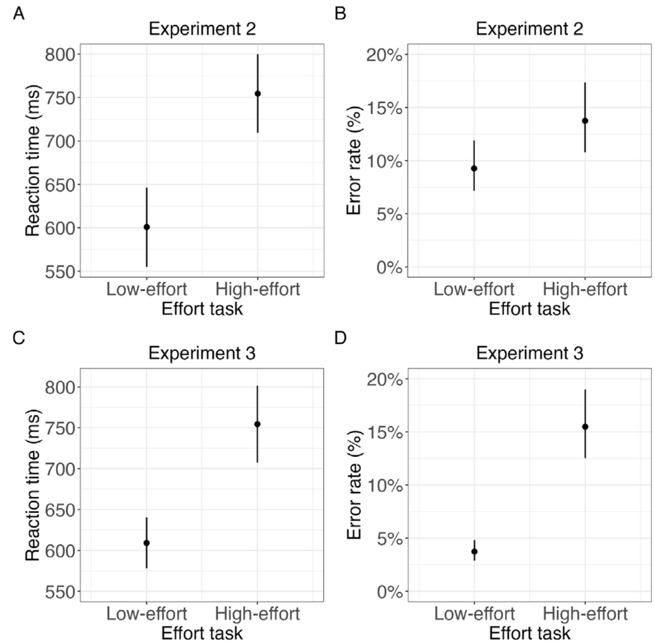

Fig. 3. The performance results of Experiment 2: Participants' reaction time (A & C) and error rate (B &D) on the low-effort and high-effort task. Black dots depict the mean and error bars indicate the standard error of the mean.

To conclude, Experiment 2 suggests that participants are willing to perform cognitively effortful tasks if they are curious about finding out answers, controlling for the time participants have to invest to perform the task as both RDK options considered the same amount of trials and thus the same amount of time. Hence, in conjunction with the findings from Experiment 1, the findings of Experiment 2 indicate that individuals are willing to invest resources in terms of cognitive effort if they have to do so in order to satisfy their curiosity. However, in both experiments, the investment of cognitive effort was tied to revealing the answer. Hence, it remains to be investigated whether people would also decide to perform a cognitively effortful task to find out answers if they could alternatively also perform a task requiring lower levels of cognitive effort. Thus, we conducted Experiment 3 to examine whether participants would avoid the high-effort RDK trials if they could also perform low-effort RDK trials to reveal the answer.

4. Experiment 3

We conducted Experiment 3 as a control experiment to demonstrate that, when free to decide and when always provided with the answer, participants would rather choose to perform low-effort RDK trials than high-effort RDK trials. The procedure was thus similar to the previous two experiments but participants had to decide between performing low-effort RDKs or high-effort RDKs. They were told that irrespective of their decision and their performance (i.e., there was no 70% threshold participants had to achieve when performing the RDK trials), they would always see the answer. As previous research has shown that humans typically avoid cognitive effort when all other factors are equal (Kool et al., 2010; Westbrook et al., 2013), we expected that participants would predominantly select the low-effort RDKs as they were also provided with the answer if they selected this low-effort option. Additionally, we expected participants' curiosity ratings to have no impact on their effort choices, as reflected by a flat regression line parallel to the x-axis. This expectation arises from the fact that participants were provided with the answer — and thus able to satisfy their curiosity — regardless of their effort decision. This experiment was also preregistered (see https://aspredicted.org/4NN_FTK).

4.1. Method

4.1.1. Participants

60 German participants (30 women, 30 men, Mage = 22.91 years; range 18–34) were recruited via Prolific to conduct the online study. All participants provided their informed consent prior to the start of the study. The sample size was based on a pilot experiment (see Online Supplement) with a lower sample size and was also based on the same sample size of the previous two experiments.

4.1.2. Stimuli, procedure, and data analysis

The stimuli, procedure, and data analysis were the same as in Experiment 2, with the only difference being that participants were always provided with the answer to each question after they performed the RDKs, irrespective of whether they decided to perform low-effort RDKs or high-effort RDKs. The participants were instructed to work on the RDKs as accurately and quickly as possible. In contrast to Experiment 1 and Experiment 2, their level of accuracy had no effect on revealing the answer. Thus, participants did not press "s" for skip answer and "v" for view answer but were instructed to press "e" for the low-effort (easy task) and "d" for the high-effort (difficult) task. We always showed participants the answer to not confound the high-effort RDKs with a lower chance of finding out the answer, compared to the low-effort RDKs. The RDK trial duration was the same, irrespective of the participants' choice as we adjusted the feedback duration according to the participants' response time (the same procedure as in Experiment 2). The RDK settings and the coherence were exactly the same as in Experiment 2.

As for Experiment 2, we report average reaction times and accuracies for the low-effort and high-effort trials. We also ran the same hierarchical linear regression to quantify differences in participants' reaction times when responding to the two effort tasks (low-effort vs. high-effort) and a hierarchical logistic regression model to quantify differences in accuracy between the two effort tasks.

Two participants did not complete the entire study and were thus excluded prior to data analysis. In addition to the hierarchical logistic regression results, we report the distribution of participants' average cognitive effort demand choice in the results section. We were interested in the proportion of participants who selected the high-effort task in less than 50% of the trials.

4.2. Results & discussion

Overall, participants selected the low-effort RDKs more often than the high-effort RDKs (57.7% average low-effort choices), with 35 of the 58 (60%) participants selecting the high-effort task in less than 50% of the trials (see Fig. 2F). The coherence of low-effort and high-effort trials was the same as in Experiment 2 and therefore participants' average performance was similar to Experiment 2 on low-effort (mean reaction time: 615.54 ms; SD = 129.07 ms; average error rate: 13.7%; SD = 18.8%) and high-effort trials (mean reaction time: 757.95 ms; SD = 189.59 ms; average error rate: 20.2%; SD = 19.6%). As such, the performance of the participants was on average less accurate and slower in high-effort trials than in low-effort trials.

Regarding the results of the hierarchical regression model, we first evaluated whether the intercept was negative and significant, as a negative and significant intercept would indicate that participants chose the low-effort task significantly more often than the high-effort task. The results indicated that the intercept was negative but not significant ($b = -.630$; $z = -1.84$; $p = .065$). While this suggests a trend towards more low-effort decisions, this trend was not significant (note that the intercept was negative and significant in the pilot study; see Online Supplement). Furthermore, we did not observe a significant effect of normalized curiosity on the decision to choose the high-effort task ($b = .06$; $z = 0.60$; $p = .548$; see Fig. 2E; see Figure S2 and the Online Supplement for the same analysis of raw curiosity ratings).

The additionally conducted hierarchical regression analysis for participants' performance revealed significantly faster reaction times on low-effort trials compared to high-effort trials ($b = 72.66$; $t = 6.51$; $p < .001$; see Fig. 3C). Similarly, participants made fewer errors on low-effort trials than in high-effort trials ($b = -.77$; $t = -13.02$; $p < .001$; see Fig. 3D). These two analyses support the observed descriptive differences in average performance, demonstrating that participants made more errors and responded slower on the high-effort task compared to the low-effort task.

Experiment 3, which can be considered a control experiment, showed that curiosity had no effect on participants' decision to select the high-effort task. In addition, the results also showed that more participants avoided high-effort RDKs and rather selected low-effort RDKs if the answer was revealed irrespective of the decision, with no effect of curiosity. Thus, overall, the results of Experiment 3 align with an existing body of literature indicating that humans tend to avoid cognitive effort when it is not necessary. Nonetheless, it is interesting to note that quite a substantial number of people still opted for high-effort RDKs sometimes, which raises the interesting possibility of further influencing factors. In particular, our pilot study painted a clearer effort avoidance picture with relatively more participants predominantly selecting the low-effort option. Both studies were identical except that we obtained data from other participants. This may suggest individual differences between participants' effort avoidance tendencies (see General discussion).

5. General discussion

The aim of this study was to integrate experimental research on curiosity and cognitive effort, which have thus far developed largely in isolation from one another. Across three preregistered experiments, we demonstrated that when people are curious about information, they are willing to expend cognitive effort to find out answers (Experiments 1 and 2). However, our results also show that people are only willing to exert high cognitive effort to find out answers to questions that sparked their curiosity when no less effortful alternatives are available (Experiment 3).

In particular, the results of Experiment 1 showed that participants were willing to exert mental effort and spend time (i.e., by completing high-effort RDK trials) only when they were curious to find out the answer. Otherwise, they chose to skip the answer, saving both time and effort, as they were directed to the next question without performing the RDK trials.

In Experiment 2, we aimed to disentangle time and effort: participants could complete low-effort RDK trials to skip the answer or high-effort trials to reveal it.[5] To ensure that participants genuinely exerted mental effort, they were required to reach an accuracy of 70% on high-effort trials in order to see the answer. We found that participants were willing to complete high-effort RDK trials when they were curious about the answer. However, additional analyses revealed that the relationship between curiosity and the choice to view an answer was moderated by subjective task difficulty, as reflected by not reaching the 70% accuracy threshold, or generally high error rates on high-effort RDK trials. Specifically, participants who performed well — those who met the accuracy threshold and/or exhibited relatively low error rates — chose to view the answer primarily when they were curious. This pattern suggests that their decision to invest effort was specifically driven by curiosity rather than by an attempt to avoid errors per se. In contrast, participants who failed to meet the accuracy threshold or who had generally high error rates on high-effort trials were less likely to choose to view the answer, particularly when they reported being curious. This indicates that people are not willing to invest effort to

[5] We controlled for time differences between low- and high-effort RDK trials by adjusting the feedback duration after each trial.

satisfy curiosity when they perceive a low likelihood that the effort will pay off (i.e., not reaching the threshold to view the answer) and/or when the task is perceived as too difficult (i.e., relatively high error rates on high-effort RDK trials). However, our experimental design does not allow to determine whether participants with relatively higher error rates on high-effort RDK trials were avoiding the possibility of failing to see the answer due to their low accuracy, or whether they were deterred by the aversiveness of making errors itself (cf. Matthews et al., 2023). We leave this question open for future research.

Experiment 3 closely mirrored the setup of Experiment 2, but with a key difference: participants always saw the answer, regardless of whether they chose the low- or high-effort RDK option or how well they performed. Thus, Experiment 3 served as a control to test whether participants would still choose the high-effort option when it did not provide any additional benefit. Our findings showed that participants predominantly avoided the high-effort option, and we found no evidence of a link between curiosity and high-effort choices in this context. Taken together, these converging findings suggest that curiosity overpowers cognitive effort avoidance tendencies.

Our study contributes to research on cognitive control theories stating that human decisions are based on a cost–benefit analysis where cognitive effort factors as a cost term and extrinsic as well as intrinsic rewards factor as benefits (Musslick et al., 2015; Shenhav et al., 2013; Silvestrini et al., 2023). We interpret our results as indicating that cognitive effort costs are weighted against the anticipated intrinsic reward of finding out answers. In other words, our results suggest that curiosity overpowers cognitive effort avoidance tendencies. Our results converge with recent modeling work revealing that the possibility to learn may be considered as a reward that feeds into cost–benefit analyses (Masís et al., 2021; Masis et al., 2024), and with reward-learning perspectives on curiosity more broadly, which conceptualize knowledge attainment as intrinsically rewarding (e.g., Bardach & Murayama, 2025; Kang et al., 2009; Murayama, 2022). In addition, our study adds to existing evidence demonstrating that people are willing to spend other resources, such as time and tokens, to find out answers and satisfy their curiosity (Dubey & Griffiths, 2020; Kang et al., 2009; Spitzer, Janz, et al., 2024).

Moreover, the findings from Experiment 3 are aligned with research demonstrating that individuals generally seek to avoid cognitive effort (Kool & Botvinick, 2018; Kool et al., 2010; Shenhav et al., 2017; Spitzer et al., 2022; Westbrook & Braver, 2015; Westbrook et al., 2013; Wisniewski et al., 2015), while extending this line of research to account for curiosity. Specifically, we find that individuals avoid higher levels of effort if they can and, most importantly, if effort avoidance does not interfere with getting access to information they are curious about. Interestingly, even though a larger proportion of participants in Experiment 3 avoided high-effort RDK trials, we also observed a considerable proportion of participants who consistently chose to perform the high-effort RDK version. This could point towards the role of individual differences in effort avoidance tendencies (see also Bustamante et al., 2023). Variability in people's decision to engage in cognitively demanding tasks can possibly be explained by individual differences. For example, prior experimental studies showed that individuals scoring higher on need for cognition were more likely to seek out cognitive effort (Westbrook et al., 2013).

Several limitations and promising directions for future research should be noted. First, even though RDK trials are well suited to manipulate cognitive effort and fit the purpose of our study, future work should ideally include a variety of tasks to test the generalizability of our findings across different cognitive effort tasks (Embrey et al., 2023) as well as across cognitive and physical effort tasks (Bustamante et al., 2023; Matthews et al., 2023). Second, considering the role of specific task characteristics could reveal further interesting insights. For example, it has previously been demonstrated that progress feedback modulates cognitive demand avoidance (Devine & Otto, 2022) and that different types of feedback play different roles in curiosity (Metcalfe et al., 2023). Hence, future studies on curiosity and effort could systematically manipulate different task characteristics (e.g., progress feedback and task difficulty; Devine & Otto, 2022; Sayali et al., 2023). Third, individuals may be curious to find out the answer to a trivia question, but they may also be curious to know whether their guess of the answer was correct. Our design does not allow disentangling these two aspects, and we believe that they are likely intertwined in many situations. Nonetheless, it may be interesting to develop designs that can separate these two aspects. Fourth, our study conceptualized cognitive effort exclusively as aversive (e.g., Kool et al., 2010). However, individuals have also been found to enjoy exerting cognitive effort in their daily lives (e.g., solving crossword puzzles; Inzlicht et al., 2018; Sakaki et al., 2023), and recent experimental evidence indicates that exerting effort can become intrinsically rewarding (Clay et al., 2022). We therefore envision future studies that look, for example, at whether repetitively coupling content that sparks individuals' curiosity and the investment of cognitive effort can lead to cognitive effort seeking behavior when individuals are curious, even in situations where cognitive effort can be avoided to obtain the same outcome. However, we caution that the setup used in our study may not be suitable for such research endeavors, as we isolated cognitive effort (performing RDKs to unlock information) from the information (i.e., participants did not need to spent substantial cognitive effort to read the information). Instead, tasks in which the effort is directly invested in pursuit of satisfying one's curiosity (e.g., cognitive effort invested to solve a crossword puzzle) and not isolated from it (as in our study, in which the RDK task was not related to the content of the trivia questions) may be more promising.

In conclusion, our findings demonstrate that individuals are willing to expend cognitive effort to find out answers to questions that pique their curiosity. This aligns with prior research indicating that people are similarly willing to invest resources, such as time or tokens, to satisfy their curiosity (e.g., Dubey & Griffiths, 2020; Kang et al., 2009; Spitzer, Janz, et al., 2024). Our results thus add to ongoing research on factors contributing to the cost–benefit analysis of human decision-making. Overall, we hope that our study prompts future research to continue reconciling curiosity and cognitive effort to better understand human decision-making and information-seeking.

CRediT authorship contribution statement

Markus W.H. Spitzer: Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Younes Strittmatter:** Writing – review & editing, Conceptualization. **Melvin Marti:** Writing – original draft, Conceptualization. **Aki Schumacher:** Writing – review & editing. **Lisa Bardach:** Writing – original draft, Conceptualization.

Appendix 1. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cognition.2025.106167.

Data availability

A link to the data and code is provided on the title page.

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