

Influence of Topic Knowledge on Curiosity

Shirlene Wade (shirlene.s.wade@gmail.com)

Department of Brain & Cognitive Sciences, University of Rochester, Meliora Hall, Rochester, NY 14627 USA
Department of Psychology, 2121 Berkeley Way, University of California—Berkeley, Berkeley, CA 94720 USA

Celeste Kidd (celestekidd@berkeley.edu)

Department of Psychology, 2121 Berkeley Way, University of California—Berkeley, Berkeley, CA 94720 USA

Abstract

Given the vast nature of information available in the world, humans must select a small subset from which to learn in a lifetime. Yet we know little about the factors that motivate learners' decisions to attend to select certain information sources over others. We investigate the role of topic knowledge on curiosity in a new domain: novel news stories. We influenced listeners' perception of their topic knowledge in these novel domains by independently varying the number of sentences they heard and the number of sentences that remained after a decision point. Listeners were most curious when they reported intermediate levels of topic knowledge. As expected, learners were less likely to switch away from content that they were curious about. This result demonstrates that topic knowledge directly impacts learners' curiosity and thus has downstream influences on their future interests and information-seeking behaviors.

Keywords: Curiosity; Information-seeking; Prior Knowledge; Learning.

Introduction

On average, American adults spend 10-48 minutes reading, 1 hour using a computer, and 2.8 hours watching television every day (Bureau of Labor Statistics, 2019). Given the sheer vastness of information available in the world, learners must select some information to attend to over others. Humans acquire breadth and/or depth of knowledge across a variety of domains across a lifetime, but it remains to be known how learners choose what information to attend to over others. Prior knowledge is one factor that has been shown to influence what we choose to attend to (e.g., Haith, 1980) and how we respond to incoming information (e.g., surprise; Itti & Baldi, 2009; belief revision; Téglás et al., 2011; Kidd, Piantadosi, & Aslin, 2012). Previous computational work also suggests that a learner's knowledge about objects is an important predictor of whether the learner should continue attending to an object or attend to a different object (e.g., Pelz, Piantadosi, Kidd, 2015). Understanding the relationship between prior knowledge, curiosity, and information-seeking has important theoretical implications and educational

applications. While there is some work investigating the role of topic knowledge on interest, no work to date investigates the mechanisms by which topic knowledge impacts information-seeking.

A large body of work suggests that topic knowledge influences interest and learning. However, variability in the measurement of topic knowledge as well as conflicting results complicate our understanding of this relationship. For example, previous studies have measured topic knowledge through unstructured open response (e.g., Reio, 2004), semi-structured open response (e.g., Alexander, Kulikowich, & Schulze, 1994), likert scales (e.g., Ainley, Hidi & Berndorff, 2002), and multiple choice questions (e.g., Alexander et al., 1994). Some studies find a positive relationship between topic knowledge, interest, and learning, where greater topic knowledge is associated with greater interest and better recall or comprehension of material (e.g., Alexander et al., 1994; Ainley et al., 2002; Wade & Kidd, 2019). Other studies support a curvilinear relationship between topic knowledge and curiosity, with higher curiosity for topics that a learner has intermediate knowledge about (e.g., Kintsch, 1980; Long, Winograd, & Bridge, 1989; Garner & Gillingham, 1991). Finally, a few others have found no relationship between topic knowledge and curiosity or interest (e.g., Baldwin, Peleg, Bruckner, & McClintock, 1985; Reio, 2004).

The challenges of quantifying topic knowledge

Examining a learner's pre-existing domain and topic knowledge is problematic from both a conceptual and practical standpoint. First, there is a chicken-and-egg problem that complicates a strong interpretation of outcomes that rely on a learner's pre-existing knowledge. Humans do not acquire domain knowledge in an indiscriminate fashion; in the absence of formal education requirements, we seek information that we are curious about (e.g., Kang et al., 2004; Wade & Kidd, 2019). In turn, a learner's curiosity is influenced by the learner's prior knowledge (estimated by the learner and estimated by a more objective rater (Wade & Kidd, 2019). This bi-directional relationship between knowledge and curiosity complicates our ability to understand *why* a learner's topic

knowledge influences curiosity. Are we curious about things we know more about because we were curious about those topics to begin with? Or, does the acquisition of knowledge itself influence our curiosity?

While a learner may acquire some of their knowledge through curiosity-driven information-seeking, there are many other ways in which a learner acquires information. For example, the information may have been learned during formal schooling or could have been incidentally acquired. Previous experimental measurements of pre-acquired knowledge are not sensitive to the manner and motivation for which the knowledge was initially acquired. This could complicate the interpretations of previous results and contribute to the variability in past study outcomes.

To circumvent these issues, we look at the role of topic knowledge on curiosity and information-seeking within the toy domain of fictional, sensational news articles. In the task, participants listen to parts of stories and decide whether or not they want to continue hearing the rest. We manipulate participant topic knowledge (about a person, place, and thing) by varying the number of sentences they hear and the length of the news stories. Through this novel domain, we attempt to minimize the chicken-and-egg problem that arises in the study of pre-existing knowledge structures.

Experiment

Methods

Stimuli We created ten fictitious news stories about popular figures for use in this experiment.¹ Each story was presented to study participants auditorily via a podcast-like format. Participants heard five of the ten fictitious news stories.

One problem with comparing the role of gained information versus remaining information on a learner's decision to engage or disengage with information content is that these two variables are often inversely related. For example, remaining information might be quantified as *I - gained information*. In our paradigm, we minimize the correlation by varying both the number of sentences participants heard prior to a decision point and the number of sentences remaining after the decision point.

Stories were 2-6 sentences long and depending on the condition, participants heard 1-5 sentences before a decision point and 1-5 sentences after the decision point. There were 15 conditions total. The condition and presentation order of the stories were randomized without replacement for each participant.

¹ Example stimuli is available at <https://github.com/shirlenewade/TopicKnowledge>

Task We tested 240 participants via Amazon Mechanical Turk. We chose the sample size of 240 given the expected effect size for curiosity on information-seeking behavior based on a previous pilot study. We collected data from 3 additional participants for a total of 243 participants due to a technical quirk in psiTurk (Gureckis et al., 2016). 27 participants were excluded from analyses for failing at least one of two audio checks in the experiment ($n = 23$ failed one, $n = 4$ failed two). 16 trials were excluded due to audio issues (a reload button was pressed), which removed an additional subject from our dataset. The remaining 215 participants were included in our analyses. Participants were compensated at a rate equivalent to \$10.00 per hour.

The instructions told participants that they would hear short story podcasts and would be asked to respond to survey questions. Each participant heard 5 out of the 10 possible stories in a randomized order. For each story, participants heard between 1 and 5 sentences prior to a decision point. A progress bar on the screen indicated how far the participant was in the story, updating after every sentence. When the participant heard the number of sentences determined by the story condition, they reached a decision point where they were asked (1) to rate their curiosity for the rest of the story on a scale of “not curious at all” (0) to “very curious” (100); (2) to rate how much of the story they thought they knew from a scale of “not much at all” (0) to “all of it” (100); (3) whether they wanted to continue to the end of the story [yes or no]. Thus, we collected two curiosity measures: (1) self-reported curiosity ratings and (2) continuation rates—whether the participants chose to listen to the rest of the story when they were under no obligation to do so.

Results

Participants in our study used the full range of curiosity ratings and provided an average rating of 48/100 ($M = 48.03$, $Mdn = 52.00$, $SD = 32.85$, range = 0-100). They also used the full scale to rate their knowledge estimates, with a mean rating of 40/100 ($M = 39.64$, $Mdn = 38.00$, $SD = 30.46$, range = 0-100). For all analyses, we normalized curiosity ratings within participants to look at how measures of topic knowledge, attended content, and remaining content might contribute to relative changes in curiosity rather than absolute changes in curiosity. On average, participants chose to continue to the end of the story 45% of the time.

Topic knowledge predicts curiosity To investigate the role of topic knowledge on curiosity, we constructed a hierarchical multiple regression²³. First, we predicted

² All predictor variables were rescaled for this analysis due to differences in scaling. While the number of sentences heard or remaining varied from 1-5, curiosity and knowledge estimates

curiosity ratings from the number of sentences heard and number of sentences remaining as fixed effects. Story and participant were included as random effects. Next, we added knowledge estimates as a linear effect. Finally, we added knowledge estimates as a quadratic effect. This hierarchical regression allowed us to test the effect of topic knowledge — how much of the story participants thought that they knew — on curiosity controlling for the number of sentences that they had heard and the number of sentences that remained. Including the quadratic effect improved the model fit to the data, $X^2(8, N = 1064) = 43.42, p < 0.001$. We evaluated the largest mixed-effects linear regression justified by the data (see Table 1). A participant’s estimate of their topic knowledge was a significant predictor of curiosity, with greatest levels of curiosity associated with intermediate estimates of topic knowledge (see Figure 1)⁴. Returning to our content manipulation, we find that participants become less curious as they hear more sentences. However, the number of sentences remaining do not have a significant impact on curiosity in our task. Collectively, these findings suggest that curiosity is greatest at intermediate levels of topic knowledge.

Curiosity predicts continuation Next, we investigated how curiosity and participant-estimated topic knowledge influenced continued attention to stories. In the task, participants were given the option of continuing to the end of each story or skipping to the next story. Continuing to the end of the story was not a required component of the task and no additional incentive was offered (participants were paid a single rate for completion of the task). However,

varied from 0-100. Thus, squared knowledge estimate values ranged from 0-10,000. all predictor variables were rescaled for our analyses, with final values lying between -1.07 and 2.75. We note that the findings are similar with or without scaling of the variables.

³ The dataset used for this analysis includes 81 trials where participants provided the same curiosity rating and knowledge estimate for a single trial. One concern is that these data points might drive the results that we observe. To determine the effects of including these data points in our analyses we conducted the same analysis on a dataset removing these data points. Removing these data points did not weaken our results and in fact strengthened them.

⁴ While the quadratic knowledge estimate term significantly improved the model fit—suggesting that the relationship between curiosity and topic knowledge is better explained by a U-shape than a line—visual inspection of the data shows the data sparsity at high levels of knowledge. Participants estimated their knowledge when they had one to five sentences left (never at the end of the story), which may have contributed to greater low- and mid-level knowledge estimates in our experiment. Follow-up work examines this aspect of the linking function to determine whether the relationship is truly quadratic.

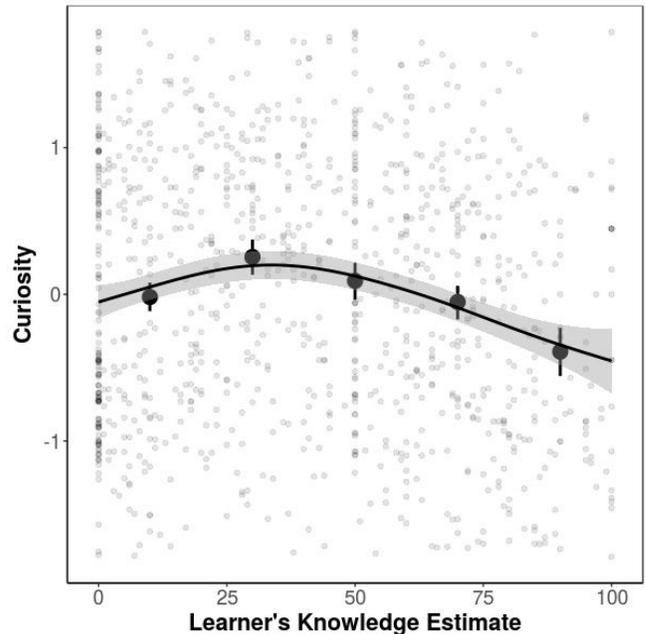


Figure 1: Average curiosity ratings binned across topic knowledge estimates. Bars denote bootstrapped 95% confidence intervals. The smoothed line and confidence interval are generated from a generalized additive model fit to the data. Note that participants evaluated their knowledge after they heard 1-5 sentences, with 1-5 sentences remaining in the story depending on the condition. Individual data points are plotted without error bars with darkness indicative of higher density. Controlling for the number of sentences heard and the number of sentences remaining in the story, curiosity is highest when learners estimate intermediate topic knowledge.

Table 1: Regression coefficients for curiosity rating analysis

Term	Coef.	SE	<i>t</i>	<i>p</i>
<i>Intercept</i>	56.04	3.57	15.70	< 0.001 ***
<i># Sentences Heard</i>	-3.10	0.76	-4.06	< 0.001 ***
<i># Sentences Remaining</i>	-0.30	0.75	-0.40	> 0.1
<i>Knowledge Estimate</i>	21.88	3.65	6.15	< 0.001 ***
<i>Knowledge Estimate (squared)</i>	-22.58	3.39	-6.66	< 0.001 ***

continuing provided participants with the rest of the information contained in the story. Participants chose to continue to the end of stories 45% of the time.

We used a mixed-effects logistic regression to predict the likelihood of a participant continuing to the rest of each story. Similar to the previous analysis, we predicted the likelihood of continuation from the number of sentences heard, the number of sentences remaining in the story, *z*-scored curiosity ratings, and participant-estimated topic knowledge as both a linear and quadratic term. Story and participant were included as random effects. Controlling for the number of sentences heard and remaining, curiosity ratings significantly predicted continuation rates (see Figure 2). A 1-point increase in curiosity ratings was associated with a 5-fold increase in the odds of continuation. There was a marginal effect of the number of sentences remaining on the likelihood of continuing to the end of the story, with participants being more likely to continue to the end of the story when there were fewer sentences remaining.

Table 2: Regression coefficients for continuation analysis

Term	Coef.	SE	Z	<i>p</i>
<i>Intercept</i>	0/21	0.50	0.43	> 0.1
<i># Sentences Heard</i>	-0.03	0.10	-0.27	> 0.1
<i># Sentences Remaining</i>	-0.18	0.10	-1.92	0.05 .
<i>Curiosity</i>	1.61	0.12	13.31	< 0.001 ***
<i>Knowledge Estimate</i>	0.01	0.02	0.70	> 0.1
<i>Knowledge Estimate (squared)</i>	-0.00	0.00	-1.11	> 0.1

*** *p* < 0.001

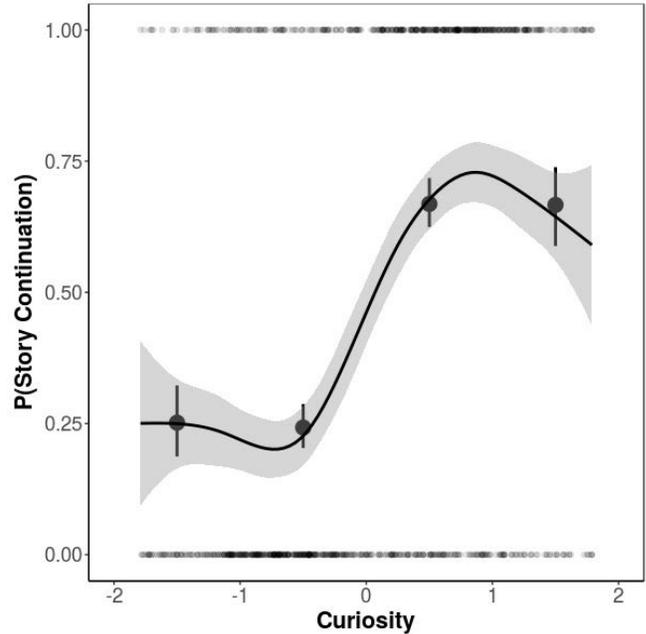


Figure 2: Average probability of story continuation binned across curiosity ratings. The line and confidence intervals are generated from a generalized additive model fit to the data. The likelihood of continuing to the end of a story was significantly greater for subjects who reported higher curiosity.

Sentences heard & sentences remaining predict

Knowledge Next, we investigated what factors influenced participant-generated topic knowledge estimates. We predicted knowledge estimates from the number of sentences heard and the number of sentences remaining influenced participants’ knowledge estimates, with story and participant included as random effects. Knowledge estimates were significantly predicted by both main effects and their interaction. Participants judged that they had more topic knowledge when they heard more sentences, $\beta = 2.99$, $SE = 1.08$, $t(879.5) = 2.77$, $p < 0.01$, and when there were fewer sentences remaining after the decision point, $\beta = -2.63$, $SE = 1.09$, $t(880.8) = -2.42$, $p = 0.02$. The interaction between the number of sentences heard and the number of sentences remaining was marginally significant, $\beta = 1.09$, $SE = 0.57$, $t(880.6) = 1.92$, $p = 0.055$. A median split analysis shows that sentences heard had a marginally larger contribution to a learner’s knowledge estimate when the remaining content was large ($\beta = 8.49$, $p < 0.001$, for 3-5 sentences remaining) compared to when the remaining content was small ($\beta = 4.07$, $p < 0.001$, for 1-2 sentences remaining). Thus, participant knowledge estimates were

sensitive to both the attended and remaining content in the stories, but the degree to which each cue was used varied as a function of the number of sentences heard and the number of sentences remaining.

Summary

We investigated the role of topic knowledge on curiosity and subsequent information seeking using a novel auditory news story task. By varying the number of sentences heard and the number of sentences remaining in a story, we manipulated participants' perception of their topic knowledge. This paradigm allows us to decontextualize gained information from the way it was acquired by the learner (e.g., through curiosity-driven information seeking, formal education, or otherwise). We found a curvilinear relationship between topic knowledge and curiosity, with lower curiosity for stories associated with near-no or near-all topic knowledge and higher curiosity for stories associated with intermediate levels of topic knowledge. People were more likely to continue to the end of stories when they reported higher curiosity for the rest of the story and when there were fewer sentences remaining (though this was a marginal effect in our data). Topic knowledge estimates themselves did not independently predict information-seeking behavior in our study. Taken together, we find a relationship between a learner's curiosity for news stories and their prior knowledge. The learner's curiosity, in turn, was predictive of their continuation to the end of the story.

Discussion & Conclusion

The results of our study suggest that curiosity is the mechanism by which prior knowledge influences information-seeking. Previous modeling work suggests that ideal learners should maximize information gain by attending to objects they possess some information about over others which they possess little-to-no information about (Pelz, Piantadosi & Kidd, 2015). Additionally, an ideal learner should disengage from information sources when potential information gain is minimal: that is, when they have near-complete knowledge about an object. These predictions are supported by our behavioral findings: learners are more curious about topics for which they possess intermediate information about (compared to near-zero or near-complete information), and they are more likely to continue attending to topics that they are more curious about. Our study provides the unique insight that curiosity is the mechanism by which a learner's topic knowledge influences information-seeking.

The results of our study are consistent with current theories of curiosity such as George Loewenstein's information-gap hypothesis (Loewenstein, 1994; Golman & Loewenstein, 2015) as well as Dubey and Griffith (2019)'s rational model of curiosity. While these two existing theories suggest that both a learner's current knowledge and the learner's estimate of potential information gain influence their curiosity and information-seeking behaviors, our work suggests that the learner's estimate of their own knowledge impacts their curiosity. Future work should test whether the same effect applies in more complex learning situations (e.g., a multiple-object environment).

One interesting observation from our study is that the degree to which acquired knowledge and remaining knowledge seem to influence our perception of topic knowledge relies on what information we've gained and what we perceive to be missing. When there was a larger amount of remaining information in our task (e.g., 3-5 sentences of the story left), topic knowledge judgments were more strongly informed by the information that the learner had heard (compared to what was remaining). Our results could be extended to suggest that when a learner has more limited topic knowledge, their perception of their knowledge may be more heavily anchored by what they know over what they do not know compared to someone who has more comprehensive knowledge of the topic. This shift in focus might contribute to why we observe overconfidence in less competent learners (e.g., Dunning & Kruger, 1999).

It is likely that the accuracy of a learner's perception of their topic knowledge in the real world is difficult to quantify, though we can reasonably presume it will vary across domains due to differences in the breadth and depth, of a learner's knowledge as well as the volatility of the particular domain (e.g., possible knowledge about prehistoric animals or historical events is likely more stable than knowledge about new gadgets or music albums). Our study utilizes a toy domain in which a learner's perception of their topic knowledge may be more intuitive or accessible than in other domains (for example, biology). Future research should consider how properties of knowledge domains might influence learners' assessments of knowledge and the relationship between topic knowledge and curiosity.

An open question is whether our results may extend to educational domains, such as science, technology, engineering, and mathematics (STEM). There is some evidence to suggest that topic knowledge is a better predictor of interest for popular culture information compared to STEM information. Ainley and colleagues (2002) found that topic knowledge predicted interest for popular culture and hobby texts (e.g., about body image, X-Files/Star Trek, or chameleons), but did not predict interest for science texts (e.g., about X-rays). Property-level

domain differences might explain why we find a relationship between prior knowledge and interest in some domains or tasks, but not in others. First, it is not clear *how* topic knowledge was acquired across these domains, but is likely that the acquisition process differed. While information about X-rays may be taught in school, body image, chameleons, and Star Trek/X-Files are less likely to be taught in school. Thus, information in popular culture topics are likely to be selected and acquired at the discretion of the learner. Additionally, the process by which knowledge was acquired likely influences the variability of topic knowledge collected within the sample. For example, if what is learned comes from a fixed curriculum, learners may possess similar amounts of knowledge to others. In contrast, if what is learned comes from voluntary investigation of the topic, learners may possess more variable amounts of knowledge. Finally, there may merely be a difference in difficulty of comprehending STEM texts over non-STEM, popular culture texts. Future studies should consider how differences in knowledge-acquisition, conceptual difficulty, and comprehension difficulty across STEM and non-STEM texts impact the relationship between topic knowledge on curiosity.

In our study, we observe a curvilinear relationship between topic knowledge and curiosity, such that curiosity is greatest when a learner estimates intermediate topic knowledge. Since we did not require participants to learn or recall anything from the task, our results cannot speak to the question of whether curiosity in this task could give rise to better learning of attended material. However, work from ourselves and others supports the prediction that curiosity gives rise to better learning outcomes (e.g., Alexander et al., 1994; Ainley et al., 2002; Kang et al., 2009; Gruber et al., 2014; Wade & Kidd, 2019). Furthermore, our results support the idea that curiosity-driven information-seeking may naturally give rise to “mountains” and “deserts” of knowledge across domains. Learners may be more willing to develop “mountains” of knowledge where they detect intermediate, incomplete topic knowledge. In contrast, learners may be less likely to acquire knowledge on topics where they perceive they have near-empty or near-complete knowledge.

While we did not manipulate the predictability of the news stories, an interesting question is how changes in text predictability might lead to re-evaluations of topic knowledge and curiosity. Previous work suggests that surprising events—those that violate one’s expectations—may increase curiosity and change the nature of subsequent information-seeking behaviors (e.g., Baillargeon, 1986; Stahl & Feigenson, 2015; 2017; Law et al., 2017). It remains to be seen whether surprising content produces an additional boost to curiosity above and beyond what would be predicted by the learner’s topic knowledge.

Acknowledgements

We thank Madeline Pelz for recording stimuli; Amanda Yung for programming feedback; Hannah Puttre, Sarah Field, and Sarina Zahid for stimuli development; Steve T. Piantadosi, Holly Palmeri, and Brian Bi for general feedback; and the Google Faculty Research Award program, the Jacobs Foundation, the John Templeton Foundation, Human Frontiers Science Program (HFSP), the Jacobs Foundation, University of California, Berkeley, and the University of Rochester for funding in support of this project. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1419118. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

- Ainley, M., Hidi, S., & Berndorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology*, *94*(3), 545.
- Alexander, P. A., Kulikowich, J. M., & Schulze, S. K. (1994). The influence of topic knowledge, domain knowledge, and interest on the comprehension of scientific exposition. *Learning and Individual Differences*, *6*(4), 379-397.
- Baillargeon, R. (1986). Representing the existence and the location of hidden objects: Object permanence in 6-and 8-month-old infants. *Cognition*, *23*(1), 21-41.
- Baldwin, R. S., Peleg-Buckner, A., & McClintock, A. H. (1985). Effects of topic interest and prior knowledge on reading. *Reading Research Quarterly*, *20*(4), 498-503.
- Bureau of Labor Statistics, (2019, June 19). *American Time Use Survey — 2018 Results* [Press release]. Retrieved from <https://www.bls.gov/news.release/pdf/atus.pdf>
- Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: how difficulties in recognizing one's own incompetence lead to inflated self-assessments. *Journal of personality and social psychology*, *77*(6), 1121-1135.
- Dubey, R., & Griffiths, T. L. (2019). Reconciling novelty and complexity through a rational analysis of curiosity. *Psychological Review*.
- Garner, R., & Gillingham, M. G. (1991). Topic knowledge, cognitive interest, and text recall: A microanalysis. *The Journal of Experimental Education*, *59*(4), 310-319.
- Golman, R., & Loewenstein, G. (2015). Curiosity, information gaps, and the utility of knowledge. *Information Gaps, and the Utility of Knowledge (April 16, 2015)*.

- Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of curiosity modulate hippocampus-dependent learning via the dopaminergic circuit. *Neuron*, *84*(2), 486-496.
- Gureckis, T. M., Martin, J., McDonnell, J., Rich, A. S., Markant, D., Coenen, A., ... & Chan, P. (2016). psiTurk: An open-source framework for conducting replicable behavioral experiments online. *Behavior research methods*, *48*(3), 829-842.
- Haith, M. M. (1980). *Rules that babies look by: The organization of newborn visual activity*. Lawrence Erlbaum Associates.
- Itti, L., & Baldi, P. (2009). Bayesian surprise attracts human attention. *Vision research*, *49*(10), 1295-1306.
- Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T. Y., & Camerer, C. F. (2009). The wick in the candle of learning epistemic curiosity activates reward circuitry and enhances memory. *Psychological Science*, *20*(8), 963-973.
- Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2012). The Goldilocks effect: Human infants allocate attention to visual sequences that are neither too simple nor too complex. *PloS one*, *7*(5).
- Kintsch, W. (1980). Learning from text, levels of comprehension, or: Why anyone would read a story anyway. *Poetics*, *9*, 87-98.
- Law, E., Cai, V., Liu, Q. F., Sasy, S., Goh, J., Blidaru, A., & Kulić, D. (2017, August). A Wizard-of-Oz study of curiosity in human-robot interaction. In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (pp. 607-614). IEEE.
- Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological bulletin*, *116*(1), 75-98.
- Long, S. A., Winograd, P. N., & Bridge, C. A. (1989). The effects of reader and text characteristics on imagery reported during and after reading. *Reading Research Quarterly*, *353-372*.
- Pelz, M., Piantadosi, S. T., & Kidd, C. (2015). The dynamics of idealized attention in complex learning environments. In *Development and Learning and Epigenetic Robotics (ICDL-EpiRob)*, 2015 Joint IEEE International Conference on (pp. 236-241). IEEE.
- Pluck, G., & Johnson, H. L. (2011). Stimulating curiosity to enhance learning. *GESJ: Education Sciences and Psychology*, *2*(19), 24-91.
- Reio, T. G. (2004). Prior knowledge, self-directed learning readiness, and curiosity: Antecedents to classroom learning performance. *International Journal of Self-directed learning*, *1*(1), 18-25.
- Stahl, A. E., & Feigenson, L. (2015). Observing the unexpected enhances infants' learning and exploration. *Science*, *348*(6230), 91-94.
- Stahl, A. E., & Feigenson, L. (2017). Expectancy violations promote learning in young children. *Cognition*, *163*, 1-14.
- Téglás, E., Vul, E., Girotto, V., Gonzalez, M., Tenenbaum, J. B., & Bonatti, L. L. (2011). Pure reasoning in 12-month-old infants as probabilistic inference. *Science*, *332*(6033), 1054-1059.
- Tobias, S. (1994). Interest, prior knowledge, and learning. *Review of Educational Research*, *64*(1), 37-54.
- Wade, S., & Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psychonomic bulletin & review*, *26*(4), 1377-1387.