Curious About What You Know? Curiosity and Prior Knowledge's Effects on Learning

By

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Abstract

Curiosity, the drive to learn what is unknown, is strongly associated with increases in learning. However, the mechanisms that drive this relationship are unclear, as most prior work has focused on natural variations of curiosity rather than experimentally manipulating it. Prior work has shown evidence that when curiosity is directly manipulated, an increase in learning is not present, which suggests a potential third variable may be driving the effect (Arnold et al., 2018). We aimed to determine if there is a causal relationship between curiosity and learning and what role, if any, prior knowledge may play in this relationship. I expected to find a causal relationship such that presenting the material in a way that enhanced curiosity would lead to an increase in learning, but only when participants had sufficient prior knowledge. That is, I expected prior knowledge to modify the relationship between curiosity and learning with a difference between high and low curiosity conditions found only when participants had a certain level of prior knowledge in the relevant domain. Participants first completed a prior knowledge test across two domains of information, NFL football and cooking. Next, they were presented with false "pseudofacts" in the form of trivia questions (high curiosity) or statements (low curiosity) to learn. Lastly, they were given a final test on the pseudofacts. Prior knowledge increased learning for items within the same domain, but not for the opposite domain. Curiosity increased learning in the cooking domain, but not the NFL domain. However, no interaction was detected.

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Curious About What You Know? Curiosity and Prior Knowledge's Effects on Learning

Epistemic curiosity has been described as a drive or desire to learn new information and that this drive from curiosity enhances learning (Lowenstein, 1994). While researchers have found a positive correlational relationship between curiosity and learning (Kang et al., 2009), it is still unclear whether curiosity is the actual cause of the increase in learning, or if there is a third factor driving the relationship. A potential third factor could be prior knowledge. Having high prior knowledge within the same area as to-be-learned information has been shown to both elicit higher levels of curiosity (Witherby & Carpenter, 2021) and increase learning (Wade & Kidd, 2019), making it a strong possible candidate to explain this relationship.

To talk about how curiosity might relate to learning, it is first necessary to talk about what curiosity is. A common description of curiosity was proposed by George Lowenstein (1994). He proposed the information-gap theory of curiosity, which states that when individuals find a gap in their knowledge, curiosity arises as a metaphysical drive, causing the individual to want to fill that gap. This drive will persist until that gap is filled. This drive to fill the information gap is a positive drive that individuals enjoy satisfying, unlike hunger, where an individual feels unpleasant until the drive is satisfied. Curiosity can be separated from another related concept, interest, because it acts as a drive to fulfill a need for knowledge. The two terms are frequently used interchangeably but define very different experiences. While curiosity is drive-like and is a desire to fill a gap in one's knowledge, interest is when an individual feels positively about (and is motivated to learn about) a specific topic (Fastrich et al., 2018). While curiosity and interest are both pleasurable experiences, interest occurs when an individual enjoys learning about a topic, not when they feel driven to fill a gap in knowledge. This distinction is important because they may have different impacts on learning.

This information gap theory was later supported by Kang et al. (2009), where researchers found that individuals were willing to spend scarce resources (such as their own time or a type of token provided to simulate currency in the study) to acquire answers to questions that made them curious. Curiosity acting as a drive that the individual needs to fulfill is visible through participants being willing to spend resources in order to satisfy their curiosity. The information-gap theory serves as a good explanation for why curiosity drives individuals to learn new information. However, it only provides an explanation for why individuals become curious and why they are driven to satisfy that curiosity, not how curiosity relates to learning.

To try and explain why learning seems to be improved when individuals are in a state of curiosity, three major hypotheses prevalent in the literature will be discussed here: curiosity increases learning because it causes certain systems and pathways in the brain that are conducive to learning to activate, curiosity causes individuals to use better study strategies that will lead to deeper encoding of information, and/or that it is not solely curiosity that is driving enhanced learning; rather, prior knowledge is what is enhancing learning and is also separately enhancing curiosity.

The first of these hypotheses is that curiosity actively puts the brain into a state of increased readiness for learning by enhancing encoding as well as consolidation of information into memory. This was suggested by Kang et al. (2009) from data gathered through fMRI scans of participants' brains while in or out of curiosity states. Their study showed increased activity of the caudate region and both lateral prefrontal cortices in participants who were currently in a curiosity state. The caudate region is a part of the reward anticipation pathway of the brain and has also been associated with memory and reward-based learning (Delgado et al., 2003). Kang and his colleagues (2009) also found activation in the left inferior frontal gyrus (IFG) when participants made incorrect guesses, and this activation was positively correlated to their self-reported curiosity. The left IFG is a region that is implicated in both encoding and consolidation. Therefore, increased activation of this area would imply increases in learning and memory. Since curiosity states trigger increased activation in both reward circuits (especially those related to reward-based learning) and areas associated with learning, they concluded that curiosity enhances learning by activating parts of the brain related to it, and therefore puts the brain into a state more conducive to learning.

Gruber and Ranganath (2019) expanded upon this idea. Using fMRI data, they found activation within the hippocampus, a region central to memory consolidation, during curiosity states, as well as activation in the prefrontal cortex. Activation of the prefrontal cortex, however, was present throughout the whole anticipatory period of waiting on stimuli (the period prior to any questions being shown), whereas caudate and hippocampal activation increased dramatically after presentation of trivia questions (when a salient information gap was present) and was directly related to participants' reported curiosity. They also found that as soon as the anticipated information (the information that fills the gap in knowledge that triggered the curiosity state) was presented, activation in this region decreased, showing that the effects of curiosity end the moment that curiosity is satisfied. It is possible that participants may have been somewhat curious prior to exposure to stimuli; however, dramatic increases in neural regions typically associated with curiosity after presentation of stimuli indicate that, even if participants were curious prior to exposure, activation in regions associated with curiosity dramatically increased during exposure. This helps support the hypothesis that the benefits of a curiosity state are tied to specific neural activation patterns, such as the activation of the dopaminergic circuit, as these are active when individuals state that they are curious, and the activation ceases as soon as the curiosity state ends.

Gruber and Ranganath (2019) also found that participants presented with information unrelated to the target information while in a curiosity state showed increased learning of that unrelated information, though it was learned to a lesser degree than the target information. This unrelated information was presented after the target information, but prior to participants receiving an answer to the target. This implies that just the curiosity state itself can enhance learning generally, and not just for target information, lending support to the idea that curiosity puts the brain into a biological state of increased readiness for learning. However, it does not explain why the target information that elicited the curiosity state is learned better than extraneous information. If curiosity was simply a biological state of enhanced readiness for learning, then the information that triggered that state should not be learned better than extraneous information. Therefore, something else must be at play that causes target information to be learned better. A potential explanation, and another popular theory for why curiosity boosts learning, is that curiosity may also alter attention and encoding strategies.

The use of better study and encoding strategies allows individuals to encode the information at a deeper, more thorough level (Storm et al., 2016). This idea that curiosity might cause individuals to use better encoding strategies was explored by Mullaney et al. (2014) in a study examining the effects of delayed feedback. In their study, participants were asked to answer trivia questions and provide curiosity ratings for each question. Then, they received feedback in the form of the correct response either immediately or four seconds after answering. Participants showed greater learning for items where feedback was provided after a delay, but only if they had rated the item as high curiosity. Low curiosity items showed no difference in learning across feedback times. Mullaney et al. (2014) theorized that this was because “active anticipatory processing” was occurring during the delay. Effectively, this means that because participants were motivated to learn the answer due to being curious, they were actively thinking about the question that evoked the curiosity state as well as engaging in processes to better understand and answer the question prior to seeing the answer. One such process could be that the individual thoroughly reflects on their original guess, as studies have shown that individuals who remember their original errors and reflect on feedback show better retention of the correct answer (Hattie & Timperley, 2007). Feedback effects are well-documented (Hattie & Timperley, 2007); however, individuals need to engage with the provided feedback to see benefits (Hattie & Timperley, 2007), implying a more thorough study process compared to someone who may not engage with feedback.

Further support for this idea can be found in how curiosity-enhanced learning relates to post-learning sleep. Post-learning sleep is a phenomenon in which sleeping directly after learning information increases retention of the learned information. One potential cause of this effect is that during sleep, memory consolidation is enhanced, leading to a stronger memory trace (Rasch & Born, 2018). Stare et al. (2018) found that when participants were highly curious about something, enhanced learning of high curiosity items was not further enhanced by post-learning sleep. Tying into the idea of curiosity triggering enhanced neurological states, if the process of consolidation is already dramatically enhanced due to enhanced hippocampal and IFG activation that occur during a curiosity state, post-learning sleep may not be able to enhance consolidation anymore. It is important to note here that while Stare et al. (2018) were describing processes affecting consolidation, Mullaney et al. (2014) were describing processes referring to encoding. While the two are different, they are both core components of learning, and, as such, support the idea that high curiosity items are learned better at least partly due to individuals employing processes and strategies that lead to better learning of those items.

While both of these two hypotheses are potential explanations for the relationship between curiosity and learning, a third, non-mutually exclusive possibility explaining the relationship is prior knowledge. Within this concept of prior knowledge, three possible explanations for the role that prior knowledge plays in the relationship between curiosity and learning will be examined: prior knowledge is what is truly driving the effect, not curiosity, prior knowledge is mediating the relationship between curiosity and learning, or that prior knowledge is a moderator in that relationship.

The first of these is that idea that prior knowledge is what is truly driving the effect of increased learning, not curiosity. Prior knowledge within a domain has previously been shown to be a strong predictor of learning, with multiple studies providing evidence for this relationship. For example, Boscolo and Mason (2003) measured students' prior knowledge on the greenhouse effect and divided them into high and low prior knowledge conditions based on their results. Two weeks later, those students read a passage on the greenhouse effect and were tested on the passage. They found that students in the high prior knowledge condition performed significantly better on the final test than the low prior knowledge condition, though the researchers did not account for the potential that those in the higher prior knowledge condition simply knew more information rather than learning it better. Further evidence of prior knowledge increasing learning was shown by Reder et al. (2016) in a study examining how easily English-speaking individuals could learn Chinese word pairs. They presented participants with novel pairings of characters for them to learn each week. Pairings that included familiar symbols were learned more quickly than those that included entirely new characters. Reder et al. (2016) also found that this effect of prior knowledge may be due to a decrease in the amount of working memory resources required to encode new information. Performance on working memory tasks increased when those tasks involved familiar stimuli that participants had prior knowledge of (Reder et al., 2016). Wade and Kidd (2019) also found evidence that prior knowledge is what is truly driving this effect. To examined if prior knowledge might modulate the effect of curiosity, Wade and Kidd (2019) conducted a study on the relationship between curiosity and learning using trivia questions that examined prior knowledge. While participants were not directly tested for prior knowledge, they were questioned on how close they thought their answers were to being correct during the learning phase of the study (their study consisted of a learning phase followed by a recall test). Participants who had higher perceived prior knowledge (that is, they thought their answers were closer to correct) also rated themselves as being more curious about the answer. However, this perceived prior knowledge had no effect on their actual learning. Wade and Kidd (2019) did find a significant correlation between actual prior knowledge (how close subjects' answers were to correct, rather than how close they perceived them to be) and learning. This study implies that while perceived prior knowledge may play a role in how curious an individual is, actual prior knowledge plays a stronger role in learning. In other words, they found that curiosity itself did not directly enhance learning; prior knowledge did. A final piece of evidence that prior knowledge may not always have an effect on curiosity, and, when prior knowledge and curiosity are decoupled in this way, curiosity may not be associated with an increase in learning was found in a study of survey data collected at the beginning of undergraduate classes measuring how curious students were about the topic of the class (Reio, 2004). This study found that self-reported curiosity from the students had no correlation with how much prior knowledge the students had nor how much they learned throughout the class. This supports the hypothesis that curiosity does not have an effect on learning, and that prior knowledge is driving the observed increase in learning. However, this study did not experimentally manipulate curiosity, and, as such, causal conclusions cannot be drawn. The researchers also operationalized curiosity differently than the present study does; however, this operational definition of curiosity may be more closely related to interest. Interest is described as “an urge to gravitate towards certain stimuli” (Shin & Kim, 2019), so this study may not have been measuring what the present study identifies as curiosity.

However, another explanation is possible. It is possible that prior knowledge mediates the relationship between curiosity and learning. Witherby and Carpenter (2021) found evidence that the increase in learning was tied to prior knowledge, and that it wasn’t the result of individuals simply being more intelligent or better learners. In order to rule out if it was simply an increased ability to learn that led to higher knowledge, their study examined if the effects of prior knowledge on learning were specific to the domain of information the knowledge was in. They used a prior knowledge check at the beginning of their study that examined participants’ prior knowledge across two different and distinct domains of knowledge. A domain of knowledge is defined as an area of knowledge or information that is unique and unrelated to other areas of knowledge/information. For example, the two domains used in Witherby and Carpenter’s (2021) study were cooking and NFL football, with the intention that knowing a large amount about cooking should be completely unrelated to how much one knows about football. Witherby and Carpenter (2021) found evidence supporting the idea that it wasn’t simply increased ability to learn that explained the relationship between prior knowledge and learning. They found evidence that curiosity mediates the relationship between prior knowledge and learning, and that this relationship was also domain specific. They recorded how curious participants were to know the answers to the new items and found that participants with more prior knowledge in cooking were more curious about cooking items, but not football items, and vice versa, implying that more prior knowledge within a domain increases curiosity for new information within that domain, as well as enhances learning of new information within that domain. Individuals who had more prior knowledge showed more curiosity, as well as more learning, supporting the idea that prior knowledge may be the driving force in the relationship between curiosity and learning. There was no significant relationship between cooking prior knowledge and learning of cooking items; however, participants' average cooking prior knowledge score was incredibly low, implying that they may have been too difficult in relation to the NFL football items.

Prior knowledge, however, cannot explain the findings of Brod and Breitwieser (2019). Using a within-subjects design, and directly manipulating curiosity, they found an effect of curiosity on learning. Participants were presented with questions and asked to either generate an example or generate a prediction before being presented with the correct answer, with the idea that, while both would ensure encoding of the information, generating a prediction should stimulate curiosity, as it should create a salient information gap within the participant, while providing an example would not stimulate curiosity. Afterwards, participants were presented with the same questions and asked to provide the correct answer. Participants who made predictions were significantly more curious than those who provided examples, and they showed increased learning of the stimuli. If prior knowledge was what was driving the relationship, then participants should have showed increased learning regardless of whether they were in the high or low curiosity conditions. However, since this was not the case, it is possible that prior knowledge is playing a slightly different role in the relationship between curiosity and learning. It is possible that rather than driving or mediating the relationship, prior knowledge is moderating the relationship between curiosity and learning, a possibility the present study seeks to explore.

All the aforementioned studies on the relationship between curiosity and learning provide good explanations of that relationship; however, all of them lack one thing. None of them experimentally manipulated curiosity, and as such, none can provide causal evidence for how the relationship between the two functions. Curiosity has been successfully manipulated in the past, so there is precedent for this kind of manipulation. One example of this was performed in a study by Arnold et al. (2018). In this study, participants were presented with “Droodles,” simple nonsense images that have no discernable meaning. These Droodles have labels that explain what is happening in the image. Participants were divided into an “informed” or an “uninformed” condition. In the informed condition, participants were informed as to whether or not the labels existed, whereas in the uninformed condition, participants were not told about the labels. Both groups were then shown the Droodles without the labels and asked to rate how curious they were about the Droodles. After a delay, participants were given a recognition test to see which Droodles the participants remembered. While those in the informed condition were significantly more curious about the Droodles, there were no significant differences in recognition between the two conditions, implying that curiosity did not increase participants' memory.

In contrast to this, Brod and Breitwieser (2019) also successfully manipulated curiosity with their previously discussed “generate/predict” design but did find an effect of curiosity on learning. However, while Brod and Breitwieser (2019) were able to experimentally manipulate curiosity and provide evidence that it increases learning, they did not explain why curiosity might increase learning. It may be because participants had prior knowledge of the materials in their study, while there was no prior knowledge in Arnold et al.'s (2018) study. This leads to the present study, which aims to manipulate curiosity in order to better understand the relationship between curiosity and prior knowledge in relation to improving learning. The goal of the present study is to evaluate the presence of a causal link between curiosity and learning and what role prior knowledge may play in the enhanced learning that has been found in states of heightened curiosity.

The present study had three hypotheses. First, I hypothesized that prior knowledge on a domain of information will increase learning of new items within that domain but will not increase learning of items from within a different domain. For example, prior knowledge of cooking should increase learning of new cooking facts but not new football facts. Second, I hypothesized that curiosity will increase learning. This is in line with prior work that has manipulated curiosity (Brod & Breitwieser., 2019). Lastly, I expected prior knowledge to moderate the effect of curiosity on learning, such that as prior knowledge increased, curiosity's effect on learning would increase. While many prior works have found a strong relationship between curiosity and learning, that relationship is not present when prior knowledge of the to-be-learned information is absent. As such, I expect that a certain level of prior knowledge is necessary for curiosity to increase learning more effectively.

Prior knowledge was measured through a pre-test consisting of trivia question items in two separate domains of knowledge, NFL football and cooking. A composite score was compiled for all items within each separate domain to create two scores of prior knowledge: one for football and one for cooking. Participants then learned a series of fake facts about football and cooking, with curiosity for these items manipulated between-subjects. High curiosity items were presented as questions in order to make participants generate a prediction, highlighting a gap in their knowledge, whereas low curiosity items were presented as statements, so the to-be-learned information was presented immediately, and therefore there was not a gap in their knowledge. Learning was measured as the proportion of fake items that participants got correct on a final recall test.

Methods

Participants

Participants included 223 Radford University undergraduate psychology students. However, 33 participants were excluded for using external sources on the final test, 10 were excluded for failing both instruction checks, and three were excluded for not engaging with the task. This led to a total of 177 participants. Participants' ages ranged from 18 to 30 (M = 19.45, SD = 2.53). Of the 177 participants, 104 identified as White, 49 identified as Black, 13 identified as Hispanic, four identified as Asian, three identified as another ethnicity, and four preferred not to respond. Forty-six of the participants were male, 127 were female, three identified as other, and one preferred not to respond. For a breakdown of how many years of college each participant had, 105 were freshmen, 25 were sophomores, 24 were juniors, and 23 were seniors. A post-hoc power analysis was conducted through GPower and found this number of participants was sufficient to find a medium sized effect; a regression model with three predictors using an alpha of 0.05 has a power of .99 to find a medium effect size (f^2 = 0.15). Recruitment was conducted via the SONA system and course credit was awarded for participation. A priori power analysis showed that 119 participants were necessary to find the desired effect. Data was collected through the entire school semester to ensure that the desired power and effect size could be achieved after potential exclusions, resulting in more participants than was initially required. Participants were excluded if they failed both instruction checks, failed three of the five attention checks, if they weren't fluent in English, or if they received help from outside sources on any of the items in the experiment.

Design

The current study used a between-subjects design with one between-subjects independent variable—curiosity—and one additional predictor variable—prior knowledge—measured continuously. Curiosity was manipulated by either initially withholding the answer (creating a gap in knowledge) and asking participants to try to generate the information (high curiosity) before giving correct-answer feedback or by presenting the trivia fact in the form of a sentence with no missing information (no gap in knowledge; low curiosity). Participants were randomly assigned to receive either all high curiosity or all low curiosity items. Prior knowledge was measured via the proportion correct on the prior knowledge multiple-choice items within each domain.

The experiment consisted of three parts: a prior knowledge test, a new learning phase, and a final recall test. The prior knowledge test provided a score for a participant's prior knowledge in each domain used in the study (cooking and NFL football). The learning phase consisted of participants learning fake football and cooking facts via either question-feedback (high curiosity) or statements (low curiosity). These two domains were selected because they have very little overlap with each other. Based on prior research (Witherby & Carpenter, 2021), we anticipated that a participant with high prior knowledge of football is no more likely than chance to have high prior knowledge in cooking and vice versa. After answering all items in the new learning phase, participants underwent the final recall test. The final recall test examined how well participants learned the items from the new learning phase. Learning was measured via the proportion of items that participants got correct for each domain in the final recall test.

Materials

The study was distributed via Qualtrics. Prior knowledge was measured via 5-alternative multiple-choice questions in the first phase of the study. There were 56 total questions in the prior knowledge phase (28 for each of the two domains of knowledge: cooking and NFL football). Correct answers were assigned the value of 1, whereas incorrect answers were assigned a 0. A total prior knowledge score for each knowledge domain was calculated by averaging a participant's scores across all items of that domain. Prior knowledge questions were adapted from Rawson and van Overschelde's (2008) materials, using knowledge domains of NFL football and cooking information, with facts updated for more recent information. Average scores for cooking prior knowledge were exceptionally low on prior studies, implying that some of the items may be too difficult. As such, six of the original cooking items were replaced with new items that are less difficult. Pilot data on these six items showed higher scores on average than the previous items, and similar scores to the other items within the cooking domain. An example prior knowledge item would appear as follows: "In what city do the Seahawks play?" (A: Denver B: San Diego C: Seattle D: Detroit E: I don't know).

Learning phase items were adapted from Witherby and Carpenter (2021). Additional items were also created for each domain in this phase. These items in the new learning phase were false "pseudofacts" to ensure that participants did not know the answers prior to testing, even in the case of high prior knowledge. Participants were asked to respond to 30 items in this phase (15 for each domain). They were presented as short-answer questions followed by correct answer feedback in the high curiosity condition and statements in the low curiosity condition. An example of the items in the learning phase would be: "Who is known as the father of French cuisine?" A: Alain Ducasse (Question) / "Alain Ducasse is known as the father of French cuisine" (Statement). Items were randomized with the domains intermixed. Participants had as long as they needed to complete each item.

Throughout the prior knowledge and new learning phases, participants saw a series of "attention check" items, which asked them what was said in the last item they saw. This was to ensure that participants were actually attending to the stimuli. There were three attention checks in the prior knowledge section, and two in the new learning section. They were presented randomly during each phase. If they happened to occur at the start of a phase, participants were instructed to state that it was the first thing they had seen.

The final recall test used the same items found in the new learning phase; however, all items were presented as short-answer questions with no feedback.

Procedure

Participants were welcomed to the study and given basic details about what the study is about. Participants were not told about the final recall test, however. After providing consent, participants began the test of prior knowledge, in which they were presented with the multiple-choice trivia questions. Items were presented one at a time, and their order was randomized with the domains intermixed. They were given as much time as needed to complete each item and were instructed to answer these items to the best of their ability. Their score on these questions served as a measure of their prior knowledge on both domains.

After completing the prior knowledge check, participants immediately began the new learning phase, where they were exposed to another series of items that were comprised of either statements or short-answer trivia questions. Participants were randomized into either the high curiosity condition or the low curiosity condition. In the high curiosity condition, participants were shown each short-answer question one at a time. They had as much time as they needed to give a response and were instructed to respond with “I don’t know” if they did not know the answer. After submitting their response, they rated how curious they were to see the answer using a 1-5 scale, with 1 indicating not curious at all and 5 indicating very curious. This curiosity rating served as a manipulation check. They were then shown the correct answer. When they were ready to move on, they clicked the “next” button to display the next item. In the low curiosity condition, participants were shown statements one at a time. Statements were used to avoid the participant generating a prediction, a known trigger for a curiosity state (Brod & Breitwieser, 2019). Each statement corresponded to one of the questions in the high curiosity condition and included identical information. They had as much time as needed to examine and complete each item. After selecting that they were done looking at each statement, they rated how curious they were about the previous statement on a 1-5 scale, with 1 indicating not curious at all and 5 indicating very curious. Much like in the high curiosity condition, this rating served as a manipulation check. After submitting their curiosity rating, they were presented with the next item.

After completing the new learning phase, participants were asked a series of demographic questions prior to undergoing the final recall test. This served dual purposes of gathering useful demographic information as well as providing spacing to ensure that participants’ working memory had cleared prior to the final test. Demographic questions included items such as participants’ age, gender, ethnicity, and prior education. After answering these questions, participants began the final recall test, where they were presented with the same 30 items from the new learning phase. The items were randomized, and all items were presented one at a time as short-answer questions for all participants. They had as much time as necessary to answer each item.

After completing the final test, participants were debriefed on the purpose of the study. They were informed that the items that they learned and were tested on during the new learning and final test phases of the experiment were all false in order to ensure they did not know them before the study began. They then saw a list of all the true answers to the pseudofacts on a single page and had as much time as necessary to go over them.

Lastly, they were asked if they had been aware that the items presented in the new learning phase and final recall test were false before being told. They were also asked if they used any external sources when responding to the items (including looking up answers, writing down answers during the learning phase, asking for help from others, etc.). At the end of the Qualtrics survey, participants were thanked for their participation.

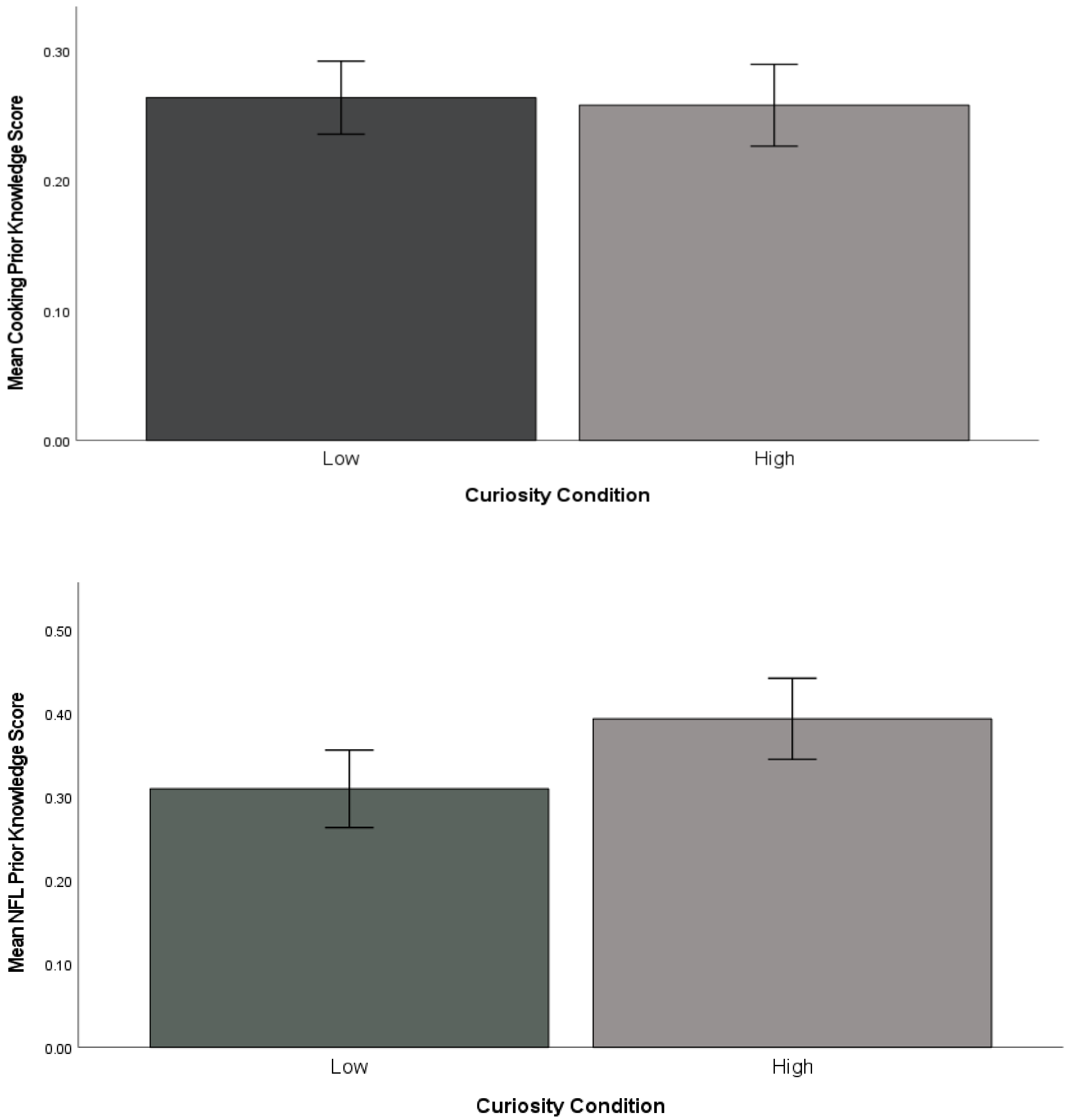
Results

Manipulation Checks

In order to ensure that participants in the high and low curiosity groups' prior knowledge for both NFL and cooking information were not significantly different from each other, t-tests were conducted to compare the two groups' prior knowledge across both domains. There were no significant differences between the high (M = 0.26, SD = 0.15) and low curiosity (M = 0.26, SD = 0.13) groups on prior knowledge of cooking, $t(175)$ = 0.28, p = .782, d = 0.14. Therefore, the high and low curiosity groups had similar levels of prior knowledge about cooking prior to the study. However, for the NFL domain, there was a significant difference between the high (M = 0.39, SD = 0.23) and low curiosity (M = 0.31, SD = 0.22) conditions, $t(175)$ = -2.48, p = .014, d = 0.22. Participants in the high curiosity condition had significantly higher prior knowledge of NFL football than those in the low curiosity condition, signaling a failure of random assignment (see Figure 1).

Figure 1

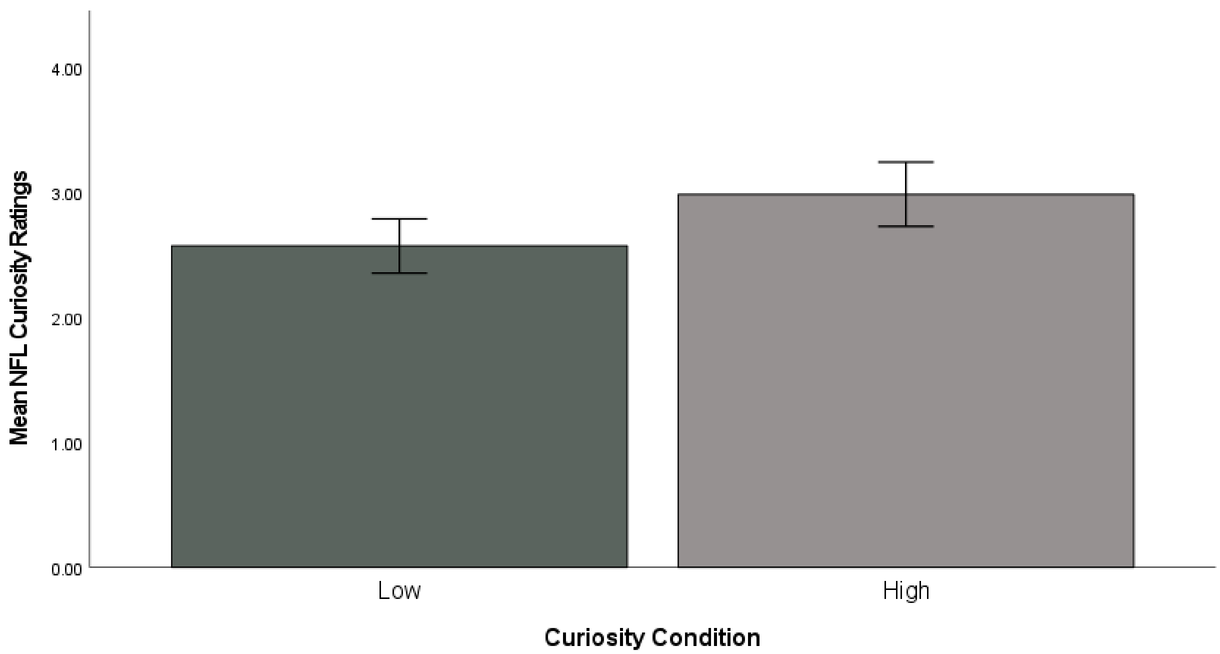
Mean Prior Knowledge Scores Across the High and Low Curiosity Conditions for Cooking (Top) and NFL (Bottom)

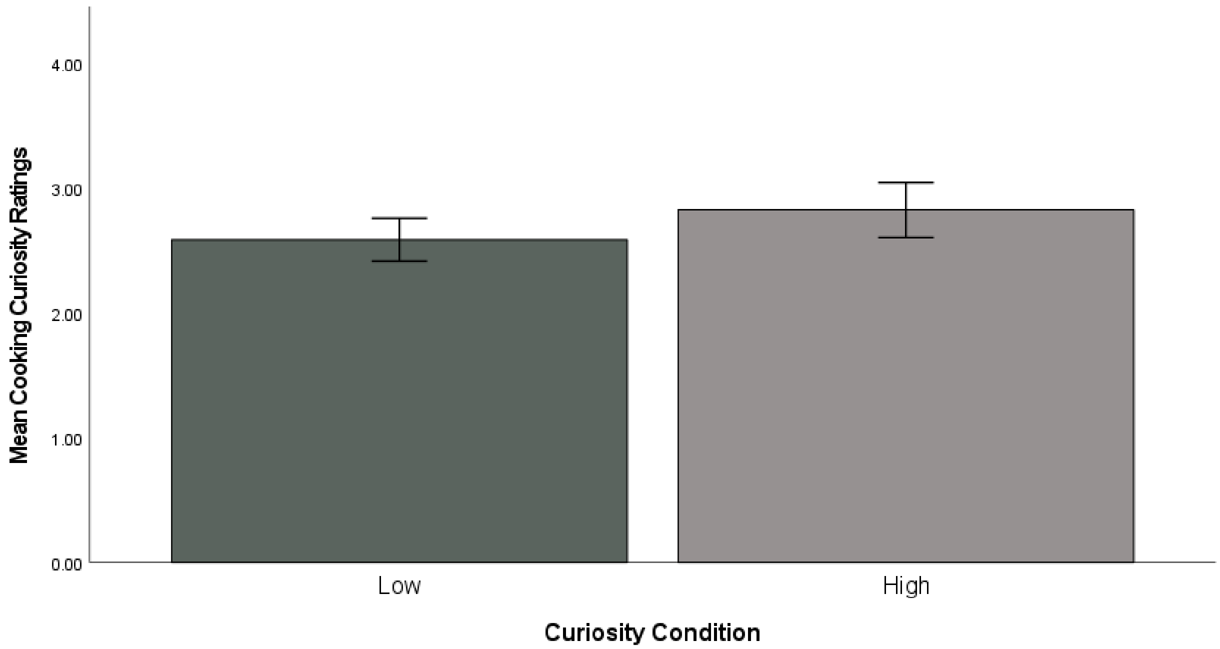


Next, a t-test was conducted for each domain of knowledge to make sure that the curiosity manipulation was successful and that participants in the high curiosity condition rated themselves as being more curious than those in the low curiosity condition. For the NFL condition, curiosity ratings in the high curiosity condition (M = 2.98, SD = 1.20) were significantly higher than those in the low curiosity (M = 2.57, SD = 1.05) condition, t(175) = -2.44, p = .016, d = 1.12, providing support that the manipulation was successful. In the cooking condition, however, differences for curiosity ratings between the high (M = 2.82, SD = 1.03) and low curiosity conditions (M = 2.58, SD = 0.82) were only marginally significant, t(175) = -0.24, p = .090, d = 0.93 (see Figure 2). This result suggests that the curiosity manipulation may not have been successful for cooking items.

Figure 2

Mean Self-Report Curiosity Ratings for the High and Low Curiosity Condition for the NFL (Top) and Cooking (Bottom) Domains

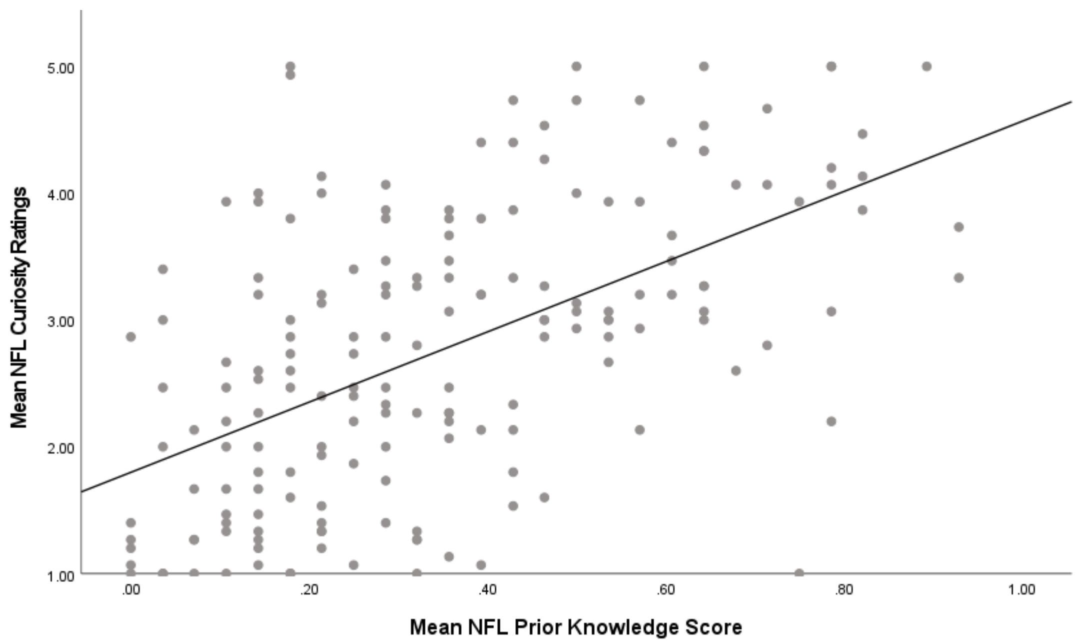


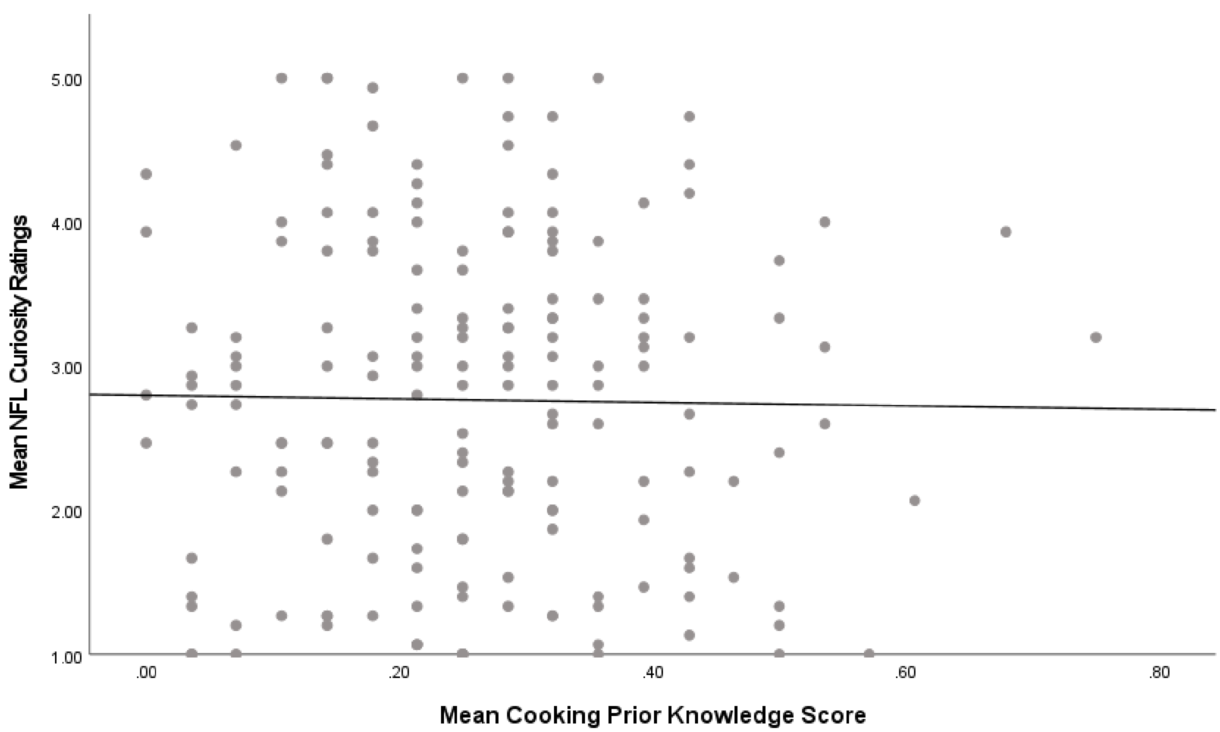


Lastly, correlations were run to ensure that curiosity ratings were correlated to prior knowledge within that domain, and uncorrelated with prior knowledge from the opposite domain. This was to make sure that curiosity was related to specifically prior knowledge of a domain and not a general increased need for cognition. NFL curiosity ratings were significantly related to prior knowledge of NFL information (r = .55, p < .001), and unrelated to cooking prior knowledge, r = -.02, p = .843 (see Figure 3).

Figure 3

Relationship Between NFL Curiosity Ratings and Prior Knowledge of NFL (Top) and Cooking (Bottom) Information

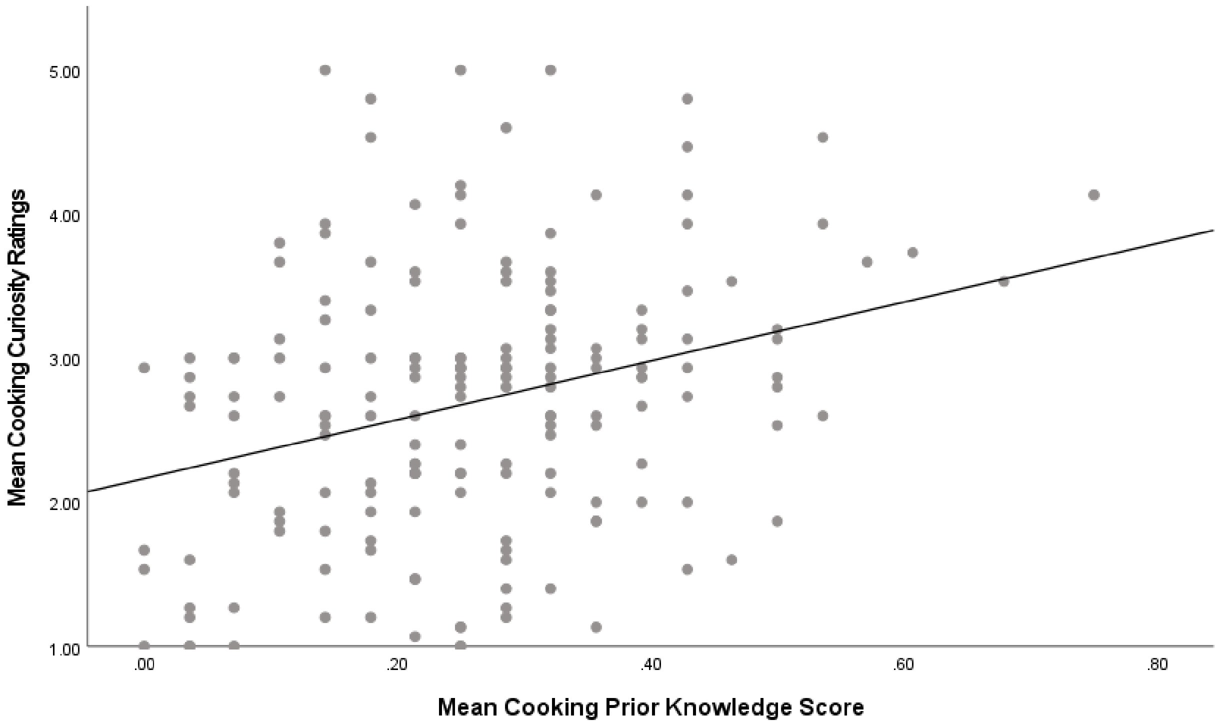


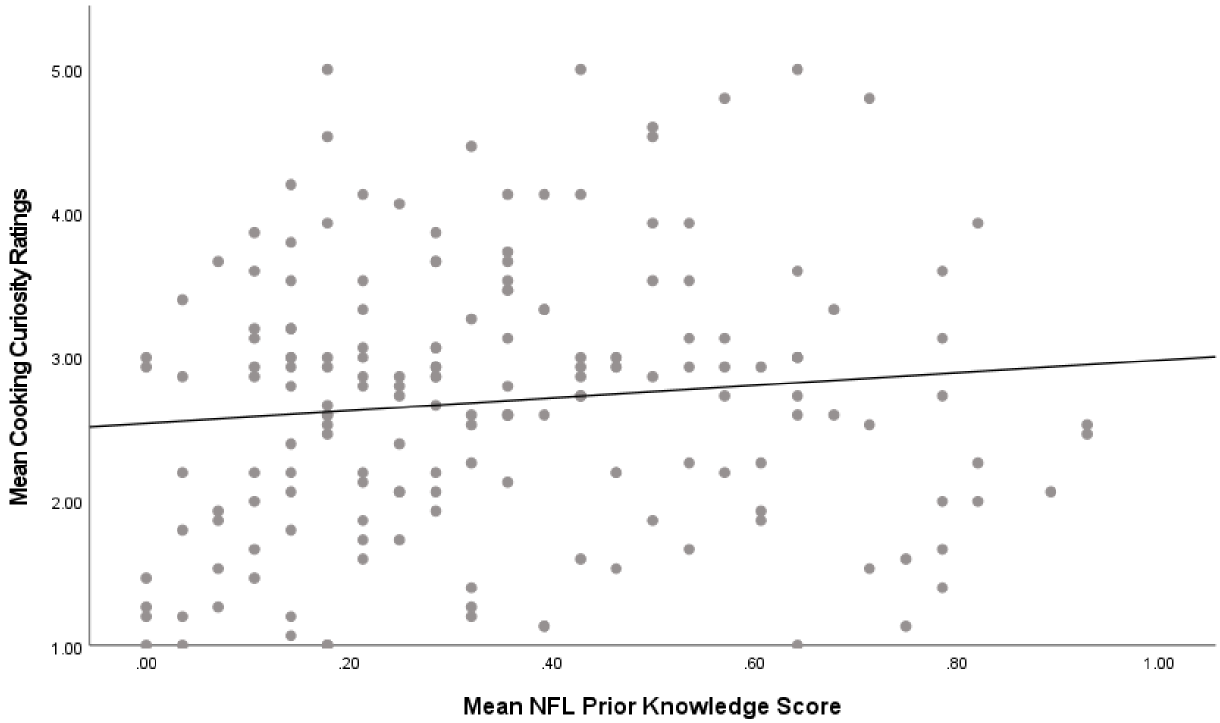


Cooking curiosity ratings were similarly significantly related to cooking prior knowledge (r = .31, p < .001) and unrelated to NFL prior knowledge, r = .11, p = .159 (see Figure 4).

Figure 4

Relationship Between Cooking Curiosity Ratings and Prior Knowledge of Cooking (Top) and NFL (Bottom) Information





Prior Knowledge Phase

Participants' prior knowledge across the two domains was measured during this first phase of the experiment. For the NFL domain, participants showed a wide range of variability on scores, with average scores on the NFL prior knowledge items ranging .00 to .93 (M = .35, SD = .23). Participants' performance on cooking prior knowledge items showed a slightly smaller range of scores, with average scores ranging between .00 and .75 (M = .26, SD = .14). While the range is slightly smaller than the NFL items, it is still larger than prior work (ranging from .00 to .46) (Witherby & Carpenter, 2021). This shows that the revision of cooking items did succeed in lowering the difficulty of the items. A bivariate correlation was also run to ensure that the two domains of prior knowledge were not correlated. This was to ensure that prior knowledge in one domain could not influence or predict prior knowledge in another domain. A weak, but significant correlation was found between the two prior knowledge domains, r = .17, p = .023. However, this is very likely due to the high power of the current study. Prior work using similar materials have found similar *r* values (.15), but these did not reach statistical significance (Witherby & Carpenter, 2021). This prior study had a sample size of 91 compared to the current study's 177.

Effects on Learning

The main question of the study was which factors are effective predictors of learning, which was operationally defined as recall of the pseudofacts on the final test. To examine which factors may have an effect, a series of four regression analyses were conducted to see whether prior knowledge in either cooking or NFL football, curiosity condition, or the interaction of the two were able to strongly predict a participant's final test performance. These regression analyses were conducted in pairs, with each pair examining if final test performance for one domain was significantly predicted by curiosity, prior knowledge in the same domain, or the interaction between both, then again using prior knowledge in the opposite domain as a predictor. All prior knowledge scores were centered around the mean. The curiosity conditions were dummy coded, with the low curiosity condition being coded with a 0 and the high curiosity condition being coded as 1.

The first pair examined what factors effectively predicted final test performance for NFL items. The first regression examined if NFL final test performance (M = 0.43, SD = 0.28) was significantly predicted by NFL prior knowledge, curiosity condition, or the resulting interaction. The overall model was able to significantly predict scores for learning, R^2= 0.42, F(3, 173) = 42.02, p < .001 (see Figure 5). A main effect of NFL prior knowledge was present, such that higher prior knowledge of NFL facts significantly predicted new learning of NFL items, β = 0.78, p < .001, replicating prior work (Witherby & Carpenter, 2021). The effect of curiosity condition was not significant, β = 0.05, p = .122. The interaction between NF L prior knowledge and curiosity condition did not significantly predict final test performance for NFL items, β = -0.32, p = .826 (see Table 1).

Figure 5

Predicted Performance in the NFL Domain with NFL Prior Knowledge and Curiosity Condition as Predictors

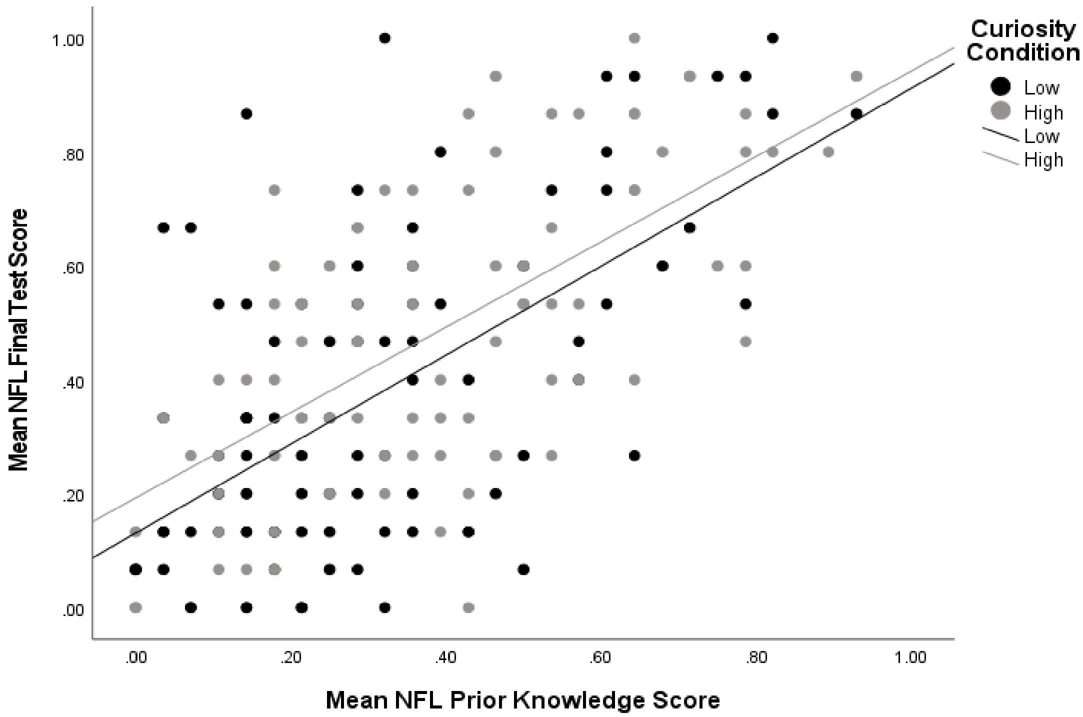


Table 1

Beta Weights, t-values, and p-values of the Regression Predicting NFL Final Test Performance from Curiosity Condition, NFL Prior Knowledge, and the Corresponding Interaction

Predictors	***β***	***t***	***p***
Curiosity Condition	.091	1.56	.122
NFL Prior Knowledge	.639	7.72	<.001**
NFL PK x Curiosity Condition	.101	-0.22	.826

*p is significant at the .05 level.
**p is significant at the .01 level.

The second regression predicted final test performance for NFL items using prior knowledge of cooking items, curiosity condition, and the interaction between the two. While the model still significantly predicted scores for final test performance, $R^2 = .058$, $F(3, 173) = 3.54$, $p = .016$, the only factor that significantly predicted performance was curiosity condition, $\beta = 0.12$, $p = .005$ (see Figure 6). This shows that the benefits or prior knowledge were, in fact, domain-specific, and the results were not just the participants working or studying harder (see Table 2).

Figure 6

Predicted Performance in the NFL Domain with Cooking Prior Knowledge and Curiosity Condition as Predictors

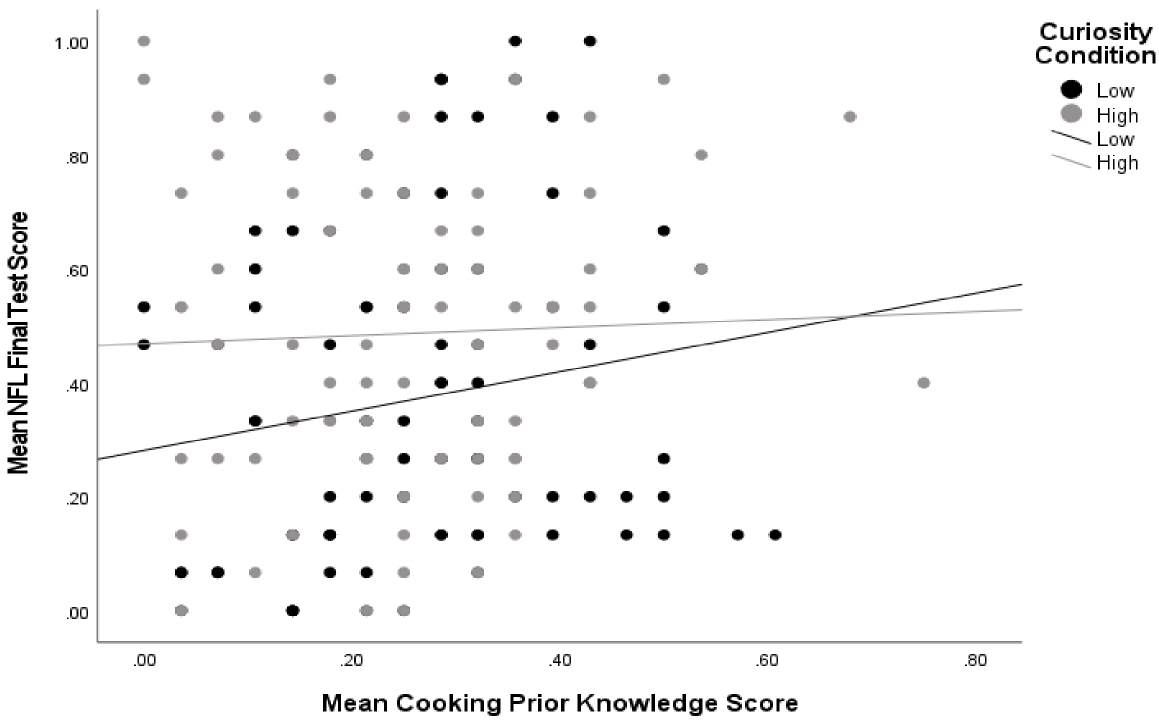


Table 2

Beta Weights, t-values, and p-values of the Regression Predicting NFL Final Test Performance from Curiosity Condition, Cooking Prior Knowledge, and the Corresponding Interaction

Predictors	***β***	***t***	***p***

Curiosity Condition	.209	2.83	.005**
Cooking Prior Knowledge	.174	1.62	.106
Cook PK x Curiosity Condition	-.101	-0.94	.349

**p* is significant at the .05 level.
***p* is significant at the .01 level.

The second pair of regressions examined what factors effectively predicted final test performance for cooking items. The first of these two regressions examined if cooking final test performance (M = 0.37, SD = 0.21) was predicted by cooking prior knowledge, curiosity condition, and/or the interaction between cooking prior knowledge and curiosity. The overall model was able to significantly predict final test performance, $R^2 = 0.17$, $F(3, 173) = 12.14$, $p < .001$ (see Figure 7). Main effects of both cooking prior knowledge, $\beta = 0.54$, $p < .001$, and curiosity condition, $\beta = 0.07$, $p = .012$, were significant, showing that both of those factors successfully predict learning of cooking final test items. However, the interaction between cooking prior knowledge and curiosity was not a significant predictor of cooking final test performance**,** $\beta = 0.04$, $p = .832$ (see Table 3). Again, prior knowledge being a significant predictor is in line with prior research (Witherby & Carpenter. 2021). Curiosity being a significant predictor of learning supports prior work that has found evidence of a causal relationship between curiosity and learning (Brod & Breitwieser, 2019). However, this finding must be interpreted cautiously because self-reported curiosity ratings were not significantly different between the high and low curiosity conditions in the cooking domain (more on this in the Discussion section).

Figure 7

Predicted Performance in the Cooking Domain with Cooking Prior Knowledge and Curiosity Condition as Predictors

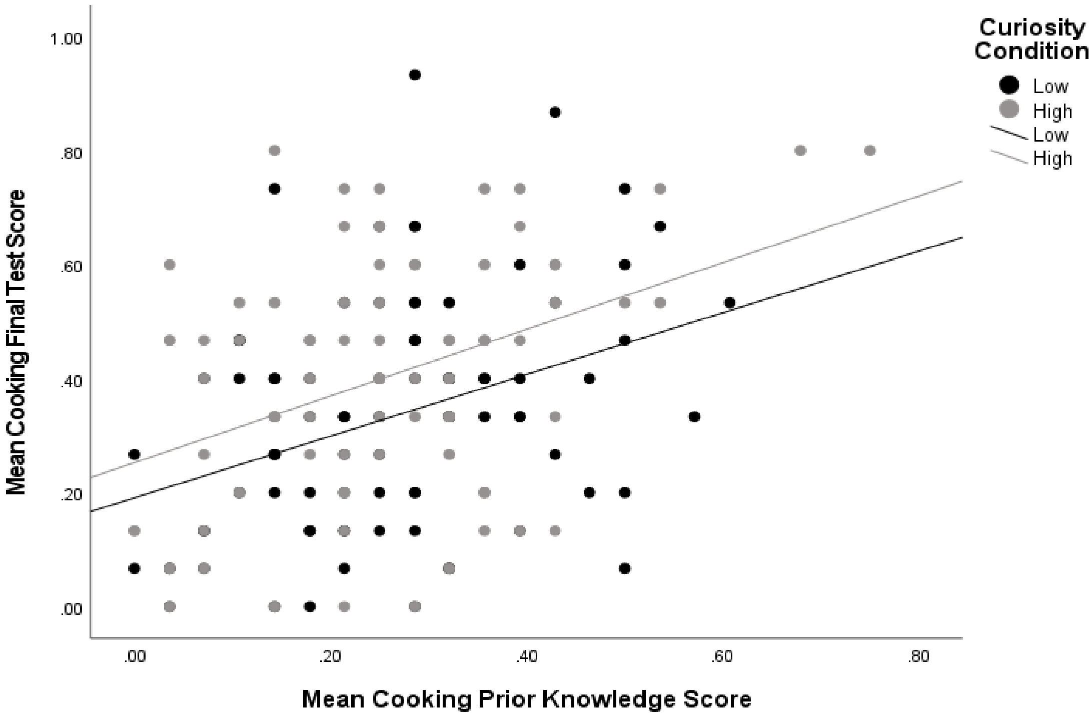


Table 3

Beta Weights, t-values, and p-values of the Regression Predicting Cooking Final Test Performance from Curiosity Condition, Cooking Prior Knowledge, and the Corresponding Interaction

Predictors	***β***	***t***	***p***
Curiosity Condition	.176	2.55	.012*
Cooking Prior Knowledge	.366	3.64	<.001**
Cook PK x Curiosity Condition	.021	0.212	.832

**p* is significant at the .05 level.
***p* is significant at the .01 level.

The final regression examined if final test performance for cooking was predicted by prior knowledge of NFL items, curiosity, or their interaction. The overall model's predictive power was not significant, $R^2 = .034$, $F(3, 173) = 2.04$, $p = .111$ (see Figure 8), again showing that the benefits of prior knowledge on learning are domain-specific and not indicative of the participant just learning better or trying harder (see Table 4).

Figure 8

Predicted Performance in the Cooking Domain with NFL Prior Knowledge and Curiosity Condition as Predictors

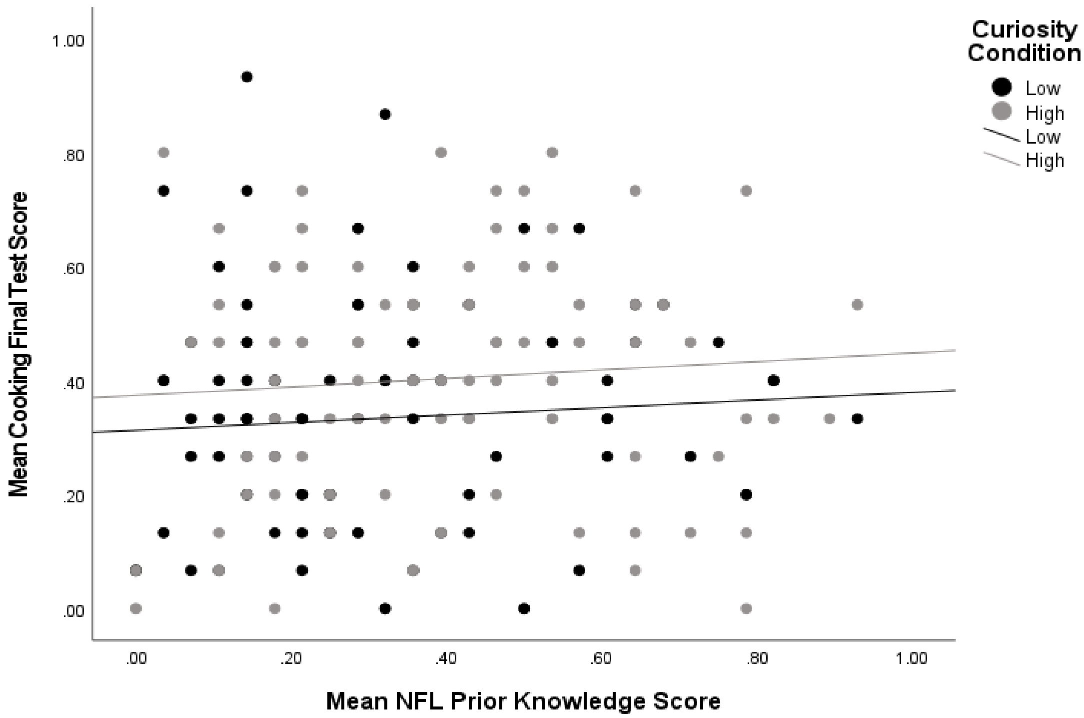


Table 4

Beta Weights, t-values, and p-values of the Regression Predicting Cooking Final Test Performance from Curiosity Condition, NFL Prior Knowledge, and the Corresponding Interaction

Predictors	***β***	***t***	***p***

Curiosity Condition	.154	2.01	.044*
NFL Prior Knowledge	..072	0.68	.499
NFL PK x Curiosity Condition	.006	0.06	.953

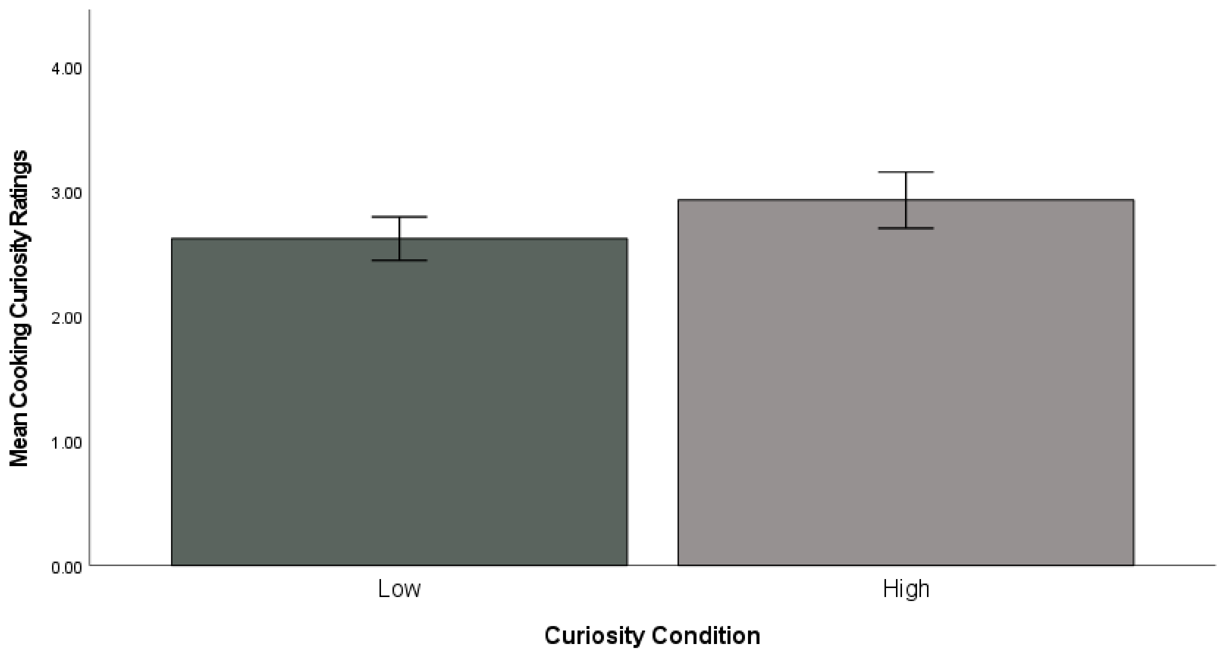
**p* is significant at the .05 level.
***p* is significant at the .01 level.

Post Hoc Analyses

Post hoc analyses were run to try to better understand why the curiosity manipulation failed for the cooking domain, when it had succeeded in the NFL domain and prior work (Brod & Breitwieser, 2019). One potential explanation is that the participants' perceived prior knowledge for cooking items was not high enough to trigger a curiosity state. Wade and Kidd (2019) found in their study that an individual's perceived prior knowledge in an area is a strong predictor of their curiosity within that area, and having just taken a prior knowledge test, our participants' actual prior knowledge of cooking items was likely made more salient, so their perception was more in line with reality. Therefore, if prior knowledge was incredibly low, they likely wouldn't be as curious. This is elaborated further in the Discussion section, but it prompted a comparison of curiosity ratings across the high and low curiosity conditions for the cooking domain when controlling for participants who answered none or one of the 28 cooking prior knowledge questions correctly. With these 13 participants (eight high curiosity; five low curiosity) removed, a t-test comparing curiosity ratings across the high (M = 2.92, SD = 1.00) and low curiosity (M = 2.61, SD = 0.81) groups showed that the curiosity manipulation was now significant, $t(162) = -2.17$, $p = 0.032$, $d = 0.91$, potentially showing that while our new cooking items helped get the domain off of floor (such as occurred in Witherby and Carpenter's 2021 study), it may still have been too difficult for the participants (see Figure 9). This could have led to lower perceived prior knowledge for the domain, and as such, lower curiosity. This is something that would require further examination in a follow-up study.

Figure 9

Mean Self-Report Curiosity Ratings for the High and Low Curiosity Condition for the Cooking Domain After Removing Participants with No-to-Low Prior Knowledge



Discussion

In order to understand if curiosity improves learning, our current study sought to examine if curiosity causes an increase in learning, and if it does, if prior knowledge modifies that relationship. We examined whether or not curiosity causally affected learning by directly manipulating it, as well as examining if prior knowledge affected learning. Lastly, we examined whether prior knowledge, another factor that has been shown to improve learning (Witherby & Carpenter, 2021), might moderate the effect between curiosity and learning. To examine this, we measured participants' prior knowledge across two domains of information, NFL football and cooking, then had them learn pseudofacts about both domains under conditions of high or low curiosity before having them take a final recall test on the items they just learned. Across both domains, prior knowledge increased learning. Possibly more interesting is that curiosity also increased learning within the cooking domain, providing support for the theory that curiosity does directly enhance learning (Brod & Breitwieser, 2019). No effect of prior knowledge within one domain predicted learning for the other domain, implying that it wasn't simply individuals being better learners or putting in more effort, and that the results were in fact domain specific. An interaction between curiosity and prior knowledge was not found in either domain, unfortunately not providing evidence of the expected moderation.

However, there were some issues in the data so some of these results should be interpreted with caution. For the domain of NFL football, participants in the high curiosity condition had significantly more NFL prior knowledge than participants in the low curiosity condition, even though they were randomly assigned to their respective conditions. This constitutes a failure of random assignment and could explain why we had no effect of curiosity condition in the NFL condition. With this failure of random assignment, prior knowledge and curiosity conditions were confounded. When prior knowledge of football was not included in the regression model, curiosity condition did predict learning.

In the cooking domain, there was no significant difference in curiosity ratings between the high and low curiosity conditions, implying that the curiosity manipulation did not significantly increase curiosity for those in the high curiosity condition. However, a significant effect of the curiosity manipulation was still detected in the cooking domain and was trending in the NFL domain, implying that some difference between the two conditions was still triggering an increase in learning. One possibility is that a difference in curiosity was impacting learning, as the differences between curiosity ratings between the two conditions were still marginally significant in the cooking domain, and, in the football domain, the curiosity condition significantly predicted learning when prior knowledge of football was not included in the model. A second, not mutually exclusive, possibility is that something other than curiosity was impacting learning; in the high curiosity condition participants were asked to generate an answer prior to being shown the pseudofact. This act of generating an answer, even if it was wrong, may have enhanced learning.

Generative learning is a phenomenon in which individuals learn better after making an incorrect prediction (an error) about a target answer (Huelser & Metcalfe, 2012). This increase in learning is only present when the cue (the question) is related to the target answer. However, in the case of the present study, this condition is met, as all pseudofacts had believable answers that were clearly related to the questions. As such, what we may be seeing driving this increase in learning in the high curiosity condition is the fact that the high curiosity condition asks questions and has the participants generate an incorrect answer (an error), triggering the benefits of generative learning.

However, curiosity and generative learning may not be mutually exclusive explanations; it is possible that curiosity may play a role in the effect of generative learning. One of the potential causes of generative learning is that generating an error to a question with a related answer may create more elaborative processing of the correct answer when it is eventually provided (Grimaldi & Karpicke, 2012). This deeper processing leads to stronger encoding and a more robust memory trace (Craik & Lockhart, 1972). Curiosity may cause the individual to engage in more thorough learning strategies and process information at a deeper, more elaborative level, promoting this stronger encoding (Mullaney et al., 2014). Recall that curiosity is triggered by the perceived presence of an information gap, which can be made salient by asking a question and having the individual generate a response to said question. This generation of a (likely incorrect) response makes the information salient, triggering the curiosity state. This process of asking a question, generating a response, and then providing a related answer that is used to elicit curiosity in trivia-question-based research is identical to the process of studying generative learning. It is possible that the more elaborative processing that is predicted to be the cause of generative learning might be induced by a curiosity state that was triggered by that salient information gap. However, further research is needed to examine the true nature of this relationship.

However, our curiosity manipulation producing only a marginally significant difference in curiosity in the cooking domain was still unexpected. This could potentially have been because the items in the cooking condition were still too difficult for participants. Even though items were adjusted from the original Rawson and van Overschelde (2008) items to lower difficulty, it may not have been enough. While mean scores (M = .26) and upper bounds for the range of the cooking prior knowledge items (.75) were higher than in prior work (M = .21, upper range = .46) (Witherby & Carpenter, 2021), this increase may not have been enough to reduce the difficulty as much as was intended. This difficulty might have resulted in a larger proportion of participants within the sample to have minimal-to-low perceived prior knowledge in the cooking domain. Prior work has shown that a lower perceived prior knowledge results in lower curiosity ratings, and as such by having a larger number of participants performing at or near floor in the cooking condition would also cause a noticeable decrease in curiosity ratings, as that lower prior knowledge is made much more salient (Wade & Kidd, 2018).

To examine if floor effects on cooking prior knowledge was causing our curiosity manipulation to fail within this domain, we performed post hoc analyses on the curiosity manipulation, removing those who scored lowest on the measure of cooking prior knowledge (e.g., participants who got 0 or 1 items correct) and re-running the comparison between the high and low curiosity conditions. These analyses did show a significant effect of our curiosity manipulation on participants' self-reported curiosity ratings, such that individuals in the high curiosity condition rated their curiosity to be significantly higher than those in the low curiosity condition, providing support for this explanation. In order to get more accurate measures of curiosity for the cooking domain, further work will need to be done on matching the difficulty of the prior knowledge questions to the average level of cooking prior knowledge within the population.

The results of the current study were promising, but unfortunately the complications with the data make it difficult to draw strong conclusions. With the failure of random assignment for the NFL domain, the effects of the predictors on learning are potentially confounded, and the lack of significant differences in curiosity ratings between the curiosity conditions in the cooking domain make it hard to reliably conclude that curiosity does cause an increase in learning. As such, future directions for this work should be two-fold. First, a replication study would be beneficial to clarifying the results of the NFL domain. A pure replication should ideally allow random assignment the chance to distribute participants normally, allowing for more valid results from the NFL domain. Second, further work needs to be done with the prior knowledge items in the cooking domain. The difficulty is still too high to get an effectively diverse range of curiosity ratings in the sample, at least when sampled from an undergraduate population. New items will need to be generated and pilot tested until the mean scores for cooking prior knowledge are high enough to avoid floor and capture a good range of scores. Then these new items should be included in the replication in order to help perceived prior knowledge be more normally distributed and therefore allow for a more diverse spread of curiosity ratings in the high curiosity condition.

The relationship between curiosity and learning is still unclear, and further understanding this relationship is valuable for helping individuals improve and enhance their learning. The current study sought to try and explain this by testing to see if prior knowledge is a moderator to the effects of curiosity on learning. While the targeted interaction was not present, the results present a promising explanation that curiosity may directly increase learning. Further exploration of this would expand our understanding of this effect and begin an important step to understanding how to use curiosity as a tool to improve learning in the classroom and beyond.

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