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When learning new information, students’ prior knowledge related to that information will often vary. Prior research has not systematically explored how prior knowledge relates to learning of new, previously unknown information. Accordingly, the goal of the present research was to explore this relationship. In three experiments, students first completed a prior knowledge test over two domains (football and cooking) and then learned new information from these domains by answering questions and receiving feedback. Students also made a judgment of learning for each. To ensure that the learning was new (i.e., previously unknown) for all students, the to-be-learned information was false. Last, students completed a final test over the same questions from the learning phase. Prior knowledge in each domain was positively related to new learning for items from that domain but not from the other domain. Thus, the relationship between prior knowledge and new learning was domain specific, which we refer to as the rich-get-richer effect. Prior knowledge was also positively related to the magnitude of judgments of learning. In Experiment 3, to explore a potential reason why prior knowledge is related to new learning, students rated their curiosity in learning each item prior to receiving feedback. Critically, students’ curiosity judgments mediated the relationship between prior knowledge and new learning. These outcomes suggest that for high-knowledge learners, curiosity may be related to attention-based mechanisms that increase the effectiveness of encoding during feedback.

Keywords: prior knowledge, learning, curiosity, judgments of learning

For nearly every learning context, students have some prior knowledge about the to-be-learned information. Although they may not have a comprehensive understanding of the topic, students undoubtedly have some surface-level ideas or beliefs about it. For instance, when taking a class on sensation and perception, most college students will already have some knowledge of the human senses. They may also have some rudimentary ideas about how sensations are transferred into perceptions (e.g., taste buds are important for the sensation of taste). In addition, some students will have more detailed prior knowledge of course topics, perhaps through previous courses they have taken or from information they have learned on their own.

Although prior knowledge is likely to vary in many learning situations, we currently understand very little about how prior knowledge might influence new learning. For example, if a student already has some understanding of gustatory perception, do they more readily acquire new knowledge over not-yet-learned information about auditory perception? In experimental studies on learning, prior knowledge is often viewed as something that should be minimized or controlled, so the ways in which prior knowledge might affect new learning or interact with other variables has been largely unexplored. Accordingly, in the present research, we explored the relationship between prior knowledge and students’ learning of new information as well as their perceptions of how prior knowledge might influence their learning.

The effects of prior knowledge have been explored in previous research but usually within the context of task designs that directly utilize or measure that knowledge rather than focus on the learning of new information. For example, research on expertise shows that experts perform better than novices on tasks related to their areas of expertise (Chase & Simon, 1973; Huet & Mariné, 2005; Kalakoski & Saariluoma, 2001; for a review, see Vicente & Wang, 1998). Specifically, prior knowledge facilitates performance on tasks that require experts to use that prior knowledge. For instance, when asked to recreate a chess board based on real game positions, chess experts outperform chess novices because they can rely on their stored knowledge of real game formations—information that chess novices may not have. Thus, performance on the recall task (e.g., recall of chess positions) utilized information that experts already had before beginning the experiment. By contrast, our focus in the present experiments was on how prior knowledge is related to learning of new information that was not previously known.

Few studies have explored the relationship between prior knowledge and new learning. Further, design features present in
these studies make it difficult to determine whether prior knowledge, or something else, contributed to the effects observed. As an example, researchers have explored students’ learning of scientific information from a text as a function of what students already know about that topic (e.g., Alexander et al., 1994a, 1994b; McNamara et al., 1996). To illustrate, Boscolo and Mason (2003) measured high school students’ prior knowledge of the greenhouse effect. To do so, students attempted to fill in a diagram of how the surface of the earth is warmed by the sun and took a true-false test assessing their knowledge of the greenhouse effect. Based on their performance on the prior knowledge tasks, students were classified as low- or high-knowledge learners. Two weeks after completing the prior knowledge tasks, students read a text about the greenhouse effect that they had never seen before. Text comprehension was assessed with a free-recall test (i.e., students recalled as much of the text as they could) and a short-answer test (i.e., students answered questions that were based on the text). Students who were classified as high-knowledge learners outperformed students who were classified as low-knowledge learners on both measures of text comprehension. Thus, students who knew more about the greenhouse effect to begin with learned the new text passage better than did students who knew little about the greenhouse effect at the outset.

In these studies, however, knowledge of the to-be-learned text passage was never pretested before students read it. That is, the information contained in the text that students were tested on was different from the information that was tested on the prior knowledge test. Thus, it is impossible to rule out the possibility that students already knew the information contained in the text passage before reading it. In other words, although the passage was new in the sense that students had not seen that exact passage before as part of their instruction, it is possible that the contents of the passage contained information that was already known by the high-knowledge learners. If so, comprehension of the text passage does not reflect new learning, but rather the recall of knowledge that students already had. This alone could explain why high-knowledge learners performed better on the comprehension test compared to low-knowledge learners.

One study ruled out this possibility by including a pretest over the to-be-learned information. In an introductory horticulture class, Carpenter et al. (2018) presented students with a list of questions about garden plants (e.g., “What causes blossom end rot on tomatoes?”) and presented feedback after students answered each question (e.g., “calcium deficiency”). After the list of questions with feedback was presented, students were given the same list of questions again as a posttest and were asked to provide the correct answers, this time without feedback. Students’ performance on the posttest was examined specifically for questions that they got wrong on the pretest. These questions, when answered correctly, demonstrated new learning because students did not know them on the pretest. Although students corrected many of their errors from the pretest to the posttest, the rate at which these errors were corrected was higher for students who got more of the pretest questions right to begin with. In other words, the more students knew about the material at the outset, the greater the likelihood of acquiring new knowledge that they did not already know.

Although Carpenter et al. (2018) included a pretest to verify that students did not already know the to-be-learned information, this study introduces a different issue for drawing conclusions about the effects of prior knowledge on new learning. Students who knew more to begin with had greater success acquiring knowledge of the information that they did not know previously. However, because all students learned a list of 53 horticulture facts, students who knew more to begin with also had fewer items left to learn. The positive relationship between prior knowledge and new learning could therefore be driven by the fact that it is easier to learn fewer items than more items.

Thus, clear conclusions about the relationship between prior knowledge and new learning cannot be drawn from existing research because it cannot be verified from these studies whether the learning was in fact new (Alexander et al., 1994a, 1994b; Boscolo & Mason, 2003; McNamara et al., 1996), and high-knowledge learners sometimes had less information to learn than did low-knowledge learners (Carpenter et al., 2018). Even if these issues were remedied and a positive relationship emerged between prior knowledge and new learning on a given topic, it can be hard to know whether prior knowledge is the primary contributor to this effect. A student who has learned a lot on a given topic may simply be a better learner, and would perform better at learning any information, compared to a student who has lower prior knowledge on that topic. The relationship between prior knowledge and new learning, in this case, would be driven by a third variable (e.g., general learning ability or use of effective learning strategies) such that prior knowledge itself does not contribute to new learning. To address this possibility, an ideal design would include information from two domains and measure the degree to which prior knowledge in one domain selectively predicts new learning in that same domain versus new learning in both domains.

To effectively explore the relationship between prior knowledge and new learning, what is needed is a paradigm with which (a) the to-be-learned information is guaranteed to be new to both low- and high-prior-knowledge learners, (b) the number of to-be-learned items is the same for low- and high-prior-knowledge learners, and (c) participants learn information from at least two domains so that the potential effects of prior knowledge can be measured both within and outside of the domain of prior knowledge. In the current research, we developed a paradigm that satisfies these requirements and can produce more definitive answers about the relationship between prior knowledge and new learning.

The current set of experiments was based on the same core design. Students first completed a pretest over the to-be-learned topics. Next, they completed a learning phase during which they learned new information (that was not pretested) relevant to those topics by answering questions and receiving feedback. Finally, students completed a posttest phase in which their memory for the correct answers for the questions from the learning phase was assessed. The pretest served to establish baseline prior knowledge on the topic, and having students answer questions during the learning phase (rather than simply presenting the information) allowed us to verify that they did not already know the information they were being asked to learn. These design features thus satisfy requirements (a) and (b) above.

To measure the domain specificity of learning (requirement c), we included two different knowledge domains over which students’ prior knowledge and new learning were assessed. Ideally, these two domains should be independent in that prior knowledge in one domain does not vary directly with prior knowledge in the other domain. Previous research by Rawson and Van Overschee
(2008) revealed two domains for which prior knowledge appeared to be independent—knowledge related to cooking and knowledge related to American football. Thus, in the current research, we focused on these two domains. We used Rawson and Van Overschelde’s tests of prior knowledge and created new materials for students to learn related to cooking and football. To ensure that the same proportion of items was new to both high- and low-knowledge learners and that students could not have known the material in advance, we created false items for all students to learn. Pilot testing revealed that these items were plausible and pilot participants did not identify them as false.

If prior knowledge facilitates new learning, then students with higher prior knowledge should more readily acquire new knowledge compared to students with lower prior knowledge. We refer to this as the rich-get-richer hypothesis. This learning should be domain specific, however, in that students who know a lot about one domain (i.e., cooking or football) should more readily acquire new knowledge in that same domain and not in the other domain. Alternatively, prior knowledge might positively predict new learning but in a domain-general way in that students with high prior knowledge in one domain more readily acquire new knowledge in both domains. Such a pattern would be consistent with the idea that a student who has acquired high knowledge on any topic is more likely to learn information in general, perhaps due to the tendency to use more effective learning strategies. Finally, it is quite possible that there is no reliable relationship between prior knowledge and new learning and that the positive correlations observed in previous studies were driven by the fact that high-knowledge learners knew the to-be-learned information all along (e.g., Alexander et al., 1994a, 1994b; Boscolo & Mason, 2003; McNamara et al., 1996) or had fewer items to learn than did the low-knowledge learners (Carpenter et al., 2018).

To shed further light on the relationship between prior knowledge and new learning, we included measures of metacognitive monitoring during the learning phase. After answering the question and receiving feedback of the correct answer, students were asked to make a judgment of learning (JOL) predicting how likely they were to remember the correct answer to that item on the final test. JOLs are commonly used to assess students’ awareness of their own learning (e.g., Dunlosky & Metcalfe, 2009; Rhodes, 2016), and they play a critical role in learning success as they directly inform decisions about how to effectively regulate subsequent study efforts (Ariel et al., 2009; Dunlosky & Ariel, 2011; Thiede, 1999; van Loon et al., 2013). Given that the potential effects of prior knowledge on new learning have not yet been systematically measured, it is unclear how prior knowledge relates to students’ monitoring processes when learning new information. The patterns associated with students’ JOLs help to inform the hypotheses above by revealing whether the relationship between prior knowledge and metacognitive monitoring is domain specific, domain general, or nonexistent.

**Experiment 1**

In Experiment 1, we evaluated the relationship between students’ prior knowledge in a domain and their learning of new information from that domain. Students completed two prior knowledge tests: one for football and one for cooking. Next, students learned new information about football and about cooking. After attempting to answer each question and receiving feedback, students made a JOL predicting the likelihood that they would remember the correct answer to that item on a later test. Finally, students completed a final test consisting of the same questions they had encountered during the learning phase.

To ensure that the new learning was truly new, the questions and answers that students learned during the learning phase included false information (i.e., answers that we made up), which students could not have known ahead of time. Although pilot participants did not identify any of these items as false, to increase the plausibility of the learning materials, we also included truthful items in Experiment 1. Although we took great care to ensure that the truthful items were obscure, it is still possible that students with high prior knowledge may come to the task already knowing some of these items. The nature of the learning phase (i.e., beginning with a test over each item) thus afforded the opportunity to check students’ knowledge of these items and ensure that they were unknown. To clearly evaluate the relationship between prior knowledge and new learning, we separately analyzed the data for false items versus truthful items.

**Method**

**Design and Participants**

A 2 (New Learning Domain: Football, Cooking) × 2 (Item Type: False, Truthful) within-participant design was used. Students completed a prior knowledge test for football and a prior knowledge test for cooking, and their scores on those tests were used to predict learning of new information related to football and cooking.

Target sample size was based on a power analysis (G*Power; Faul et al., 2007). Assuming a small to medium effect size in a regression model ($f^2 = .10$, power = .80, two tailed), the power analysis estimated that 81 participants would be sufficient to detect a relationship between prior knowledge and new learning. Ninety-two undergraduate students were recruited from introductory psychology courses at Iowa State University and participated in exchange for partial course credit. One student reported not taking the task seriously. As such, the data for this student were removed, and the final sample size for all analyses was 91 students. The reported experiments received approval from the Iowa State University Institutional Review Board.

**Materials**

The prior knowledge tests were adapted from Rawson and Van Overschelde (2008). The football prior knowledge test consisted of 28 multiple choice questions with four alternative responses and a fifth option to indicate that the student did not know the answer. All questions and answers were checked for up-to-date rules and records, and three questions were updated because of changes that occurred since 2008. For instance, one question asked, “What is the longest field goal on record?” In 2008, the correct answer was 63 yards, but that record was broken in 2013. Thus, we updated the answer to reflect the new record (64 yards). The cooking prior knowledge test originally consisted of 20 multiple choice questions with four alternative responses and a fifth option to indicate that the student did not know the answer. We created an additional eight questions to equate the length of both prior knowledge tests.
For the learning phase, we created 40 short-answer questions (see Appendix). Twenty questions were related to cooking and 20 were related to football. All questions were different from the questions on the prior knowledge tests. For each domain, 10 of the questions contained truthful information and 10 contained false information. Specifically, for the truthful questions, the answer contained factual information. By contrast, for the false questions, information in the question or the answer was made up.\(^1\)

**Procedure**

Students began the experiment by completing the prior knowledge questions over both football and cooking. Football and cooking prior knowledge questions were presented one at a time in an intermixed fashion, and question order was randomized anew for each student with the constraint that no more than three questions in a row could be from the same domain. To respond to each question, students clicked on the letter corresponding to the answer they chose. Students were given unlimited time to respond to each question. After completing all 56 prior knowledge questions, students were informed about the nature of the upcoming learning task. Students were given the following instructions:

In the next task, you are going to learn new facts about football and about cooking. To do so, you will be presented with a question and asked to type a response. It is possible that you will already know the answer to a few of these questions. However, for most questions, you will probably have to guess. **That is okay!** You will be presented with 40 short answer questions, one at a time. For each question, provide your best guess. After you’ve typed your answer, press **ENTER** to move on.

Question order was randomized anew for each student, with the constraint that no more than three questions in a row could be from the same domain. Students were given unlimited time to answer each question by typing it into the computer. After providing a response, students were given feedback as to the correct answer (for false questions, students were provided with the made-up answer). Feedback was self-paced, and students clicked a “continue” button when they were done studying the correct answer. Next, students made a self-paced JOL on a scale from 0 (**certainty** you **will be able to remember the answer**) to 100 (**certainty** you **will be able to remember the answer**) by typing it into the computer. The correct answer was not visible while students made JOLs.

After completing this procedure for all questions, students completed a self-paced final test. On the final test, students answered the same 40 questions from the learning phase. Questions were presented in a new random order for each student with the same constraint as during the learning phase. Students typed their response for each question and pressed enter. Feedback was not provided on the final test.

**Results**

**Scoring**

In all experiments, responses to the questions during the learning phase and final test phase were hand scored. Students received 1 point for a fully correct answer and 0 points if any part of the answer was missing or incorrect. Small spelling errors that did not change the meaning of the word (e.g., *gastreque* instead of *gastrique*) or changes in pluralization (e.g., *sauce* instead of *sauces*) were counted as correct.

**Prior Knowledge Performance**

Scores on the prior knowledge test revealed a range of prior knowledge for football (min. = .00, max. = .86; \(M = .34, SE = .02\)) and cooking (min. = .00, max. = .46; \(M = .21, SE = .01\)). Specifically, 66% of participants scored below 25% on the cooking prior knowledge test. Most important, football and cooking prior knowledge were unrelated, \(r = .15, p = .14\).

**New Learning Performance**

Average performance during the learning phase was low across all items (see Table 1). This verifies that the items we created were not widely known by students ahead of time. Given that the primary purpose of these questions was to verify that students did not already know the to-be-learned information and we had no a priori hypothesis concerning small differences between the item types, we report these data for descriptive purposes in all three experiments.\(^2\) Likewise, in Table 1, we also report the average final test performance across items, although we had no a priori hypotheses regarding performance differences between item types.

**Effects of Prior Knowledge on New Learning**

Our primary analysis concerned the effects of prior knowledge on new learning. To examine this, regression analyses were carried out with which prior knowledge scores for both football and cooking were used to predict final test performance over each of these knowledge domains. Because of the nested structure of the data (i.e., items were nested within participant), mixed-effects models with random participant effects were used for this analysis in all experiments. Mixed-effects models are necessary for analyzing nested data because they account for within-participant variance and nonindependence (cf. Middlebrooks & Castel, 2018; Middlebrooks et al., 2016; Murayama et al., 2014). Thus, football prior knowledge (mean centered) and cooking prior knowledge (mean centered) were entered simultaneously to predict final test performance using logistic mixed-effects models.

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1. Our goal was to teach students information that they could not have known in advance. Thus, for these to-be-learned items, we presented them with a question with a made-up “correct” answer. For some of these questions (e.g., “What is the length of the longest field goal ever attempted in an NFL game?”), there is a true, correct answer. These items are marked with a lowercase letter in the Appendix. Although we conducted extensive pilot testing to make sure these items were obscure and the correct answers were unlikely to be known, to be sure that knowledge (or guessing) of the correct answers did not influence outcomes, we examined the rate at which participants entered the correct answer on the initial test. This happened less than 7% of the time across items in all three experiments. In Experiment 1, students recalled the correct answer on 6.9% of false cooking trials and 1.3% of false football trials. In Experiment 2, students recalled the correct answer on 5.4% of cooking trials and 1.2% of football trials. In Experiment 3, students recalled the correct answer on 5.3% of cooking trials and 2.1% of football trials. The outcomes reported for all experiments were maintained when excluding these trials.

2. Given that the false items were made up, it is perhaps surprising that performance during the learning phase was not zero. However, as evident from inspecting the to-be-learned items (Appendix), it was possible to correctly guess the made-up answer for some of the items (e.g., some of the football items could be guessed by randomly picking an NFL team).
analyses (i.e., 0 = incorrect, 1 = correct) for new learning of both football and cooking items.

Football prior knowledge significantly predicted final test performance for false football items, $b = 2.79$ (SE = .49), $t = 5.73$, $p < .001$, 95% CI [1.83, 3.74], and truthful football items, $b = 2.64$ (SE = .44), $t = 6.03$, $p < .001$, [1.78, 3.50] (see Figure 1). By contrast, it did not predict final test performance for false or truthful cooking items, $t < 1$ (see Figure 2). Cooking prior knowledge significantly predicted final test performance for false cooking items, $b = 2.38$ (SE = .59), $t = 4.01$, $p < .001$, [1.22, 3.54], and truthful cooking items, $b = 2.65$ (SE = .70), $t = 3.81$, $p < .001$, [1.29, 4.01] (see Figure 2). Unexpectedly, cooking prior knowledge did not predict final test performance for truthful football items, $b = 1.89$ (SE = .73), $t = 2.60$, $p = .01$, [.46, 3.32], and it was marginally related to final test performance for false football items, $b = 1.57$ (SE = .81), $t = 1.94$, $p = .052$, [.01, 3.16] (see Figure 1). Even so, these effects were smaller relative to the domain-specific effects for both domains.

Judgments of Learning

Table 1 includes average JOLs for each item type. Consistent with the outcomes for final test performance, prior knowledge in each domain was positively related to JOLs for items from that domain. Specifically, outcomes from linear mixed-effects models revealed that football prior knowledge significantly predicted JOLs for false football items, $b = 52.26$ (SE = 9.01), $t = 5.80$, $p < .001$, 95% CI [34.60, 69.92], and truthful football items, $b = 48.59$ (SE = 9.00), $t = 5.40$, $p < .001$, [30.95, 66.23]. By contrast, football prior knowledge did not predict JOLs for false or truthful cooking items, $t < 1$. Cooking prior knowledge significantly predicted JOLs for false cooking items, $b = 38.69$ (SE = 14.72), $t = 2.63$, $p = .01$, [9.84, 67.53], and truthful cooking items, $b = 39.39$ (SE = 14.87), $t = 2.65$, $p = .01$, [10.25, 68.54], but it did not predict JOLs for false football items, $t < 1$, or truthful football items, $b = 17.65$ (SE = 15.71), $t = 1.12$, $p = .26$, [−13.14, 48.45].

To evaluate the relationship between JOLs and final test performance, logistic mixed-effects models were conducted with which JOLs for each item type (e.g., false football items) were used to predict final test performance for that same item type. JOLs were positively related to final test performance. That is, as JOLs increased, students were more likely to answer the question correctly on the final test. Specifically, JOLs positively predicted final test accuracy for false football items, $b = .02$ (SE = .003), $t = 2.38$, $p = .02$, [.01, 3.61]. By contrast, it did not predict final test performance for false or truthful cooking items, $t < 1$ (see Figure 2). Cooking prior knowledge significantly predicted final test performance for false cooking items, $b = 2.38$ (SE = .59), $t = 4.01$, $p < .001$, [1.22, 3.54], and truthful cooking items, $b = 2.65$ (SE = .70), $t = 3.81$, $p < .001$, [1.29, 4.01] (see Figure 2). Unexpectedly, cooking prior knowledge did not predict final test performance for truthful football items, $b = 1.89$ (SE = .73), $t = 2.60$, $p = .01$, [.46, 3.32], and it was marginally related to final test performance for false football items, $b = 1.57$ (SE = .81), $t = 1.94$, $p = .052$, [.01, 3.16] (see Figure 1). Even so, these effects were smaller relative to the domain-specific effects for both domains.

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Time Spent on Feedback

As with test performance, we had no a priori hypothesis regarding how time spent on feedback would differ based on item type. Thus, average time spent on feedback is reported in Table 1 for descriptive purposes.

Linear mixed-effects models revealed that prior knowledge was unrelated to time spent on feedback. Specifically, football prior knowledge did not predict time spent on feedback for any item type, ts < 1.01. Likewise, cooking prior knowledge did not predict time spent on feedback for false cooking items, b = 2.46 (SE = 1.67), t = 1.48, p = .14, 95% CI [−.80, 5.73], truthful cooking items, t < 1, or either type of football item, ts < 1.

Discussion

These outcomes are consistent with the rich-get-richer hypothesis and the relationship between prior knowledge and new learning was largely domain specific. Football prior knowledge was positively related to new learning of football information and unrelated to new learning of cooking information. In addition, cooking prior knowledge was positively related to new learning of cooking information. Surprisingly, cooking prior knowledge was marginally related to new learning of false football information and significantly related to new learning of truthful football information. Even so, these effects were smaller (i.e., b = 1.57, b = 1.89) compared to the effects of football prior knowledge (i.e., b = 2.79, b = 2.64), and the general pattern of results for both knowledge domains suggests that prior knowledge is more predictive of new learning in the same domain than in a different domain. Prior knowledge was unrelated to time spent on feedback. Thus, the positive relationship between prior knowledge and new learning does not arise because students simply increase the amount of time they spend studying items from their high-knowledge domain.

One explanation for the significant relationship between cooking prior knowledge and new learning of truthful football items is that students may have actually known the answers to some of these items, even if they were not able to retrieve them on the initial test (cf. knew-it-all-along effect; Metcalfe & Finn, 2011).

Figure 1
Predicted Performance on the Final Test for Truthful (Top) and False (Bottom) Football Items as a Function of Football and Cooking Prior Knowledge in Experiment 1

Note. This figure is for illustrative purposes and is based off the regression equations from a clustered linear regression analysis. The pattern of results was the same for the clustered and multilevel analyses.

Figure 2
Predicted Performance on the Final Test for Truthful (Top) and False (Bottom) Cooking Items as a Function of Football and Cooking Prior Knowledge in Experiment 1

Note. This figure is for illustrative purposes and is based off the regression equations from a clustered linear regression analysis. The pattern of results was the same for the clustered and multilevel analyses.
That is, they may have known the answer for some of the truthful questions, but they may have had trouble accessing that information during the learning phase. More generally speaking, it is possible that students could have had some partial or marginal knowledge of the truthful items. If this marginal knowledge pertained primarily to the domain for which students had higher prior knowledge, then the truthful items could have been more easily learned (or relearned) because these items had been known at one time (cf. Sitzman et al., 2015, 2020). Given these challenges for interpreting the relationship between prior knowledge and learning for truthful items and the fact that we only included the truthful items to increase the perceived authenticity of the false items, we removed truthful items from the study list in the following experiments.

**Experiment 2**

The goal of Experiment 2 was to replicate the outcomes from Experiment 1 under conditions in which potential marginal knowledge was unlikely to influence new learning. We included truthful items in Experiment 1 to increase the plausibility of the false items. Even so, it is challenging to draw conclusions about the relationship between prior knowledge and new learning with truthful items because we cannot rule out the possibility that students knew some of these items before completing the experiment. Given that no students in Experiment 1 raised concerns about the believability of the to-be-learned items, we did not feel that it was necessary to include truthful items in the remaining experiments. Thus, we removed the truthful items and included only the false items during the learning phase. Students completed the football and cooking prior knowledge tests, learned new false items about football and cooking and made a JOL for each, and then completed the final test.

**Method**

Based on the same sample size rationale from Experiment 1, 94 undergraduate students participated in exchange for partial course credit. The basic design, materials, and procedure were identical to Experiment 1, with the exception that students only learned the false items during the learning phase. Thus, students completed the same prior knowledge test from Experiment 1. Next, they completed the learning phase, during which they answered 20 short-answer questions (10 football and 10 cooking) that contained false information. After answering each question, students were presented with feedback and made a JOL as in Experiment 1. Students then completed a final test on the 20 short-answer questions. All timing and presentation order constraints were identical to Experiment 1.

**Results**

**Prior Knowledge Performance**

Scores on the prior knowledge test again revealed a range of prior knowledge for football items (min. = .00, max. = .89; $M = .40, SE = .02$). The range for cooking items was again restricted, with 81% of the scores falling between 0 and 25% (min. = .00, max. = .46; $M = .18, SE = .01$). As in Experiment 1, football and cooking prior knowledge scores were unrelated, $r = .04, p = .73$.

**New Learning Performance**

Average scores during the learning phase and final test phase across all items are provided in Table 1. As in Experiment 1, performance during the learning phase was quite low, reflecting the fact that students were not familiar with the to-be-learned materials ahead of time.

**Effects of Prior Knowledge on New Learning**

Consistent with the outcomes of Experiment 1, prior knowledge predicted learning for domain-relevant information (see Figure 3). Specifically, football prior knowledge significantly predicted final test performance for football items, $b = 2.57$ ($SE = .40$), $t = 6.36$, $p < .001$, 95% CI [1.78, 3.36], but not for cooking items, $t < 1$. Although cooking prior knowledge was positively related to final test performance for cooking items, this effect was not significant,
Judgments of Learning

Average JOLs for Experiment 2 are provided in Table 1. As in Experiment 1, prior knowledge was positively related to JOLs. Football prior knowledge significantly predicted JOLs for football items, $b = 44.51$ ($SE = 8.80$), $t = 5.06, p < .001$, 95% CI [27.27, 61.75], but not for cooking items, $b = -10.55$ ($SE = 6.96$), $t = 1.52, p = .13, [-24.20, 3.09]$. Cooking prior knowledge marginally predicted JOLs for cooking items, $b = 26.41$ ($SE = 14.17$), $t = 1.86, p = .06, [-1.36, 54.18]$, but not for football items, $t < 1$. JOLs positively predicted final test accuracy for football items, $b = .02$ ($SE = .003$), $t = 6.71, p < .001$, [.01, .02], and cooking items, $b = .04$ ($SE = .004$), $t = 9.72, p < .001$, [.03, .05].

Time Spent on Feedback

As in Experiment 1, time spent on feedback was unrelated to prior knowledge (for descriptive information, see Table 1). Football prior knowledge did not predict time spent on feedback for football or cooking items, $b = -0.90$ ($SE = .74$), $t = 1.22, p = .22, 95\%$ CI $[-2.35, .55]$, and $t < 1$, respectively. Likewise, cooking prior knowledge did not predict time spent on feedback for football or cooking items, $b = -1.87$ ($SE = 1.50$), $t = 1.24, p = .21, [-4.81, 1.08]$, and $t < 1$, respectively.

Discussion

Experiment 2 replicated the same general outcomes from Experiment 1, using only false items that minimized the potential influence of marginal knowledge on new learning. Under these conditions, the relationship between prior knowledge and new learning was domain specific. Although the effect for cooking did not reach statistical significance, it is quite possible that this effect was obscured by a restricted range of scores in cooking prior knowledge. Mean performance on the cooking prior knowledge test was only 18%, and 81% of the scores were clustered between 0 and 25%, indicating that prior knowledge of cooking was generally very low and did not represent the full range of prior knowledge levels. Given that the pattern of results is highly consistent with Experiment 1 for false items, we view these outcomes as consistent with the rich-get-richer hypothesis.

Experiment 3

The outcomes of Experiments 1 and 2 are consistent with the rich-get-richer hypothesis. That is, prior knowledge in each domain was positively related to new learning of items from that domain. These outcomes held after controlling for the confounds present in previous studies, suggesting that prior knowledge is a key predictor for new learning of domain-relevant information. Given the novelty of this finding, in Experiment 3, we set out to provide additional data on the consistency of these outcomes and explore a potential mechanism that may mediate this relationship. Based on the results of Experiments 1 and 2, it is clear that students with high prior knowledge on a given topic are not simply better learners than are students with low prior knowledge. Instead, the relationship was domain specific. Such results suggest that students treat domain-relevant information differently from domain-irrelevant information. In Experiments 1 and 2, prior knowledge was not related to the amount of time that students spent studying the answers to the questions. Thus, the relationship between prior knowledge and new learning does not arise due to differences in study time. An alternative possibility is that students process information from their high-knowledge domain differently relative to information from their low-knowledge domain because they are more motivated to learn information from that domain, perhaps due to increased interest or curiosity.

Interest and curiosity are highly related constructs that have often been used interchangeably in prior research (for a review, see Grossnickle, 2016). One way that researchers have distinguished between these constructs is by operationalizing curiosity as the desire to know something that is currently unknown. By contrast, a key feature of interest is the presence of existing knowledge about the topic of interest and positive feelings toward that topic. Given that the paradigm used in the present experiments involves teaching students false information that they could not have already known, students’ curiosity may be particularly important. Moreover, the paradigm used in Experiments 1 and 2 is ideally suited for measuring students’ curiosity at the item level (i.e., students’ desire to know the answer to each question prior to receiving feedback). Accordingly, in Experiment 3, we evaluated whether curiosity would mediate the relationship between prior knowledge and new learning.

We hypothesized that students would have a higher degree of curiosity in learning domain-relevant information and that this curiosity may predict new learning. Although curiosity is not an explanatory construct in itself, it correlates positively and reliably with learning outcomes (e.g., Kang et al., 2009; Maw & Maw, 1961; Mullaney et al., 2014) and could reflect attention-based processing that directly promotes learning (e.g., Kang et al., 2009). Prior research has not explored the relationship between prior knowledge and curiosity, however, and whether curiosity selectively predicts new learning of domain-relevant information.

To evaluate these issues, in Experiment 3, students rated their curiosity in knowing the answer to each question after they attempted to answer it during the learning phase. Next, they received feedback, made a JOL, and completed the final test as in Experiment 2. We performed the same analyses as in Experiments 1 and 2 to explore the relationship between prior knowledge and new learning as well as a new analysis to explore whether this relationship is mediated by curiosity.

Method

Based on the same sample size rationale from Experiment 1, 94 undergraduate students participated in exchange for partial course credit. The materials were identical to Experiment 2, and the procedure for the prior knowledge test was identical to Experiments 1 and 2. The procedure for the learning phase was nearly identical to

\[ b = .65 \ (SE = .59), t = 1.11, p = .27, [-.50, 1.80]. \]
Experiment 2, with the exception that students made a curiosity judgment before receiving feedback. Specifically, after typing their answer, students were asked, “How curious are you to know the answer to this question?” while the question was still visible at the top of the screen. Students made their rating on a scale from 1 (not curious at all) to 6 (very curious). The curiosity judgment was self-paced, and students made their judgment by typing it into the computer. After making their curiosity judgment, students received feedback and made a JOL as in the previous experiments. The procedure for the final test was identical to Experiment 2.

Results

Prior Knowledge Performance

Scores on the prior knowledge test revealed a range of prior knowledge for football items (min. = .00, max. = .86; M = .41, SE = .02). As in Experiments 1 and 2, the range of cooking prior knowledge was restricted, with 69% of the scores falling between 0 and 25% (min. = .00, max. = .64; M = .22, SE = .01). As in Experiments 1 and 2, football and cooking prior knowledge scores were unrelated, r = −.08, p = .47.

New Learning Performance

As in Experiments 1 and 2, performance during the learning phase was quite low. Thus, students were not familiar with the to-be-learned materials ahead of time (see Table 1).

Effects of Prior Knowledge on New Learning

Consistent with Experiments 1 and 2, prior knowledge was positively related to new learning for domain-relevant information (see Figure 4). Football prior knowledge significantly predicted final test performance for football items, b = 1.84 (SE = .42), t = 4.39, p < .001, 95% CI [1.02, 2.66], but not for cooking items, t < 1. Cooking prior knowledge significantly predicted final test performance for cooking items, b = 1.19 (SE = .54), t = 2.20, p = .028, [1.13, 2.25], but not for football items, b = −1.12 (SE = .73), t = 1.52, p = .13, [−2.55, .32].

Judgments of Learning

One student entered ranges for JOLs (e.g., 20–25%). As such, data from this student were excluded from JOL analyses. Average JOLs for the remaining students are provided in Table 1. Prior knowledge was positively related to JOLs for domain-relevant information. Football prior knowledge significantly predicted JOLs for football items, b = 49.25 (SE = 8.43), t = 5.85, p < .001, 95% CI [32.74, 65.76], but not cooking items, t < 1. Likewise, cooking prior knowledge significantly predicted JOLs for cooking items, b = 48.57 (SE = 14.68), t = 3.31, p = .001, [19.80, 77.33], but not for football items, t < 1. JOLs positively predicted final test accuracy for football items, b = .02 (SE = .003), t = 6.20, p < .001, [0.01, .02], and cooking items, b = .03 (SE = .003), t = 10.33, p < .001, [0.02, .03].

Time Spent on Feedback

Average time spent on feedback is provided in Table 1. Football prior knowledge was unrelated to time spent on feedback for football items, t < 1, and cooking items, b = −.57 (SE = .40), t = 1.41, p = .16, 95% CI [−1.36, .22]. Similarly, cooking prior knowledge was unrelated to time spent on feedback for cooking items, t < 1, and football items, b = −1.18 (SE = .90), t = 1.31, p = .19, [−2.96, .59].

Curiosity Judgments

Students used the full range of the 1–6 scale for football items (M = 3.15, SE = .13) and cooking items (M = 2.64, SE = .12), although the range was more restricted for cooking (with 57% of ratings being a 1 or 2) than for football (with 41% of ratings being a 1 or 2). A linear mixed-effects model revealed that football prior knowledge significantly predicted curiosity judgments for football items, b = 2.68 (SE = .51), t = 5.28, p < .001, 95% CI [1.69, 3.68], but not for cooking items, b = −.66 (SE = .52), t = −1.26, p = .21, [−1.68, .36]. Although cooking prior knowledge was positively related to curiosity judgments for cooking items, this effect was only marginally significant, b = 1.62 (SE = .94), t = 1.72, p = .09, [−2.3, 3.46]. In addition, cooking prior knowledge marginally predicted curiosity judgments for football items, but in the negative direction, b = −1.85 (SE = .92), t = 2.01, p = .05, [−3.65, −.04]. Thus, the relationship between prior knowledge and curiosity was domain specific in that prior knowledge in each domain positively predicted curiosity judgments in that same domain but not in the other domain.

We also evaluated whether curiosity judgments were related to final test performance with a logistic mixed-effects model. Curiosity ratings for football items significantly predicted final test performance for football items, b = .04 (SE = .01), t = 3.81, p < .001, 95% CI [.02, .06]. However, curiosity ratings for cooking items did not predict final test performance for cooking items, t < 1.

Mediation Analysis

Based on current recommendations, we used multilevel structural equation modeling to explore whether students’ curiosity judgments mediated the relationship between prior knowledge and final test performance (e.g., Preacher et al., 2011, 2010). Moreover, because final test performance was dichotomous (0 = incorrect, 1 = correct), we used the Bayesian estimator with default (noninformative) priors (cf. Cho et al., 2015). Given that the relationships between prior knowledge and curiosity judgments (i.e., path a) and between curiosity judgments and final test performance (i.e., path b) were not significant for cooking items (likely due to the restricted range in both prior knowledge and curiosity judgments), we did not conduct a mediation analysis for the cooking domain.

For football items, a significant indirect effect indicated that curiosity judgments significantly mediated the relationship between prior knowledge and final test performance (see Figure 5), b = .41 (SD = .23), p = .04, 95% credibility interval [.01, .89]. While controlling for all effects in the mediation model, the relationship between football prior knowledge and curiosity judg-

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The outcomes for final test performance maintained when excluding items that students correctly guessed on the initial test. Specifically, football prior knowledge significantly predicted final test performance for football items, b = 1.77 (SE = .42), t = 4.24, p < .001, 95% CI [.95, 2.59], but not cooking items, t < 1. Cooking prior knowledge marginally predicted final test performance for cooking items, b = 1.06 (SE = .55), t = 1.93, p = .053, [−.01, 2.14], but not for football items, b = −1.12 (SE = .73), t = 1.53, p = .13, [−2.55, .32].
ments for football items was significant, $b = 2.76$ ($SD = .53$), $p < .001$, [1.73, 3.84], as was the relationship between football prior knowledge and final test performance for football items, $b = 1.09$ ($SD = .32$), $p < .001$, [.47, 1.72]. The relationship between curiosity judgments for football items and final test performance was also significant, $b = .15$ ($SD = .07$), $p = .04$, [0.01, .30].

**Discussion**

As in the previous experiments, Experiment 3 showed that the effects of prior knowledge on new learning were domain specific, consistent with the rich-get-richer hypothesis. New outcomes from Experiment 3 further demonstrated that prior knowledge positively predicted curiosity to learn new items, and this relationship was also domain specific. The mediation analysis for football items showed that the positive relationship between prior knowledge and new learning was significantly mediated by students’ curiosity. We were unable to conduct this analysis for the cooking domain because the $a$ path (i.e., cooking prior knowledge on cooking curiosity judgments) and the $b$ path (i.e., cooking curiosity judgments on recall of cooking items) were not significant; thus, there could not be significant mediation. Even so, the football outcomes shed important light on the potential mechanisms that may underlie the rich-get-richer effect by demonstrating that students with high prior knowledge in a given domain tend to be more curious to learn new material in that domain. This curiosity, over and above prior knowledge, appears to relate to the success of that new learning.

**General Discussion**

In the present experiments, we demonstrated that prior knowledge positively predicted new learning of domain-relevant information, which is consistent with the rich-get-richer hypothesis. Critically, the paradigm used in the present experiments allowed us to rule out three alternative explanations for the positive relationship between prior knowledge and learning in prior work. Specifically, this relationship was not driven by high-prior-knowledge students already knowing some of the to-be-learned items (e.g., Alexander et al., 1994a, 1994b; Boscolo & Mason, 2003; McNamara et al., 1996), by a confound in the number of to-be-learned items between low- and high-prior-knowledge students (Carpenter et al., 2018), or by a general tendency of high-prior-knowledge students to simply be better learners compared to low-prior-knowledge students. Instead, prior knowledge appears to play a key role in the selective acquisition of new, domain-relevant information.

The outcomes for the football domain were consistent across experiments, whereas the outcomes for the cooking domain were less consistent. In all experiments, students demonstrated relatively low cooking prior knowledge, which is consistent with the findings of Rawson and Van Overschelde (2008). Even so, in Experiments 1 and 3, cooking prior knowledge significantly predicted new learning of cooking information but not football information (except for truthful football items in Experiment 1). In Experiment 2, cooking prior knowledge did not predict learning of cooking or football items. Although the effects were in the expected direction, this outcome from Experiment 2 was likely due to a restricted range of scores in cooking prior knowledge. That is, cooking prior knowledge in this sample of students was generally very low and concentrated within a narrow range of scores, with...
81% of scores falling between 0 and 25%. This likely limited the predictive effect of prior knowledge on new learning. Although the range of cooking prior knowledge was restricted in all experiments, it was somewhat less restricted in Experiments 1 and 3, which likely contributed to the ability to detect significant effects of cooking prior knowledge on new learning of cooking information in those experiments.

**Theoretical Explanations of the Rich-Get-Richer Effect**

Theoretical mechanisms contributing to the rich-get-richer effect appear to operate specifically to enhance learning for new information that is relevant to prior knowledge. Given that prior knowledge was not related to time spent on feedback in any experiment, this relationship was not a result of the time students spent studying information from their high-knowledge domain. By contrast, outcomes from Experiment 3 revealed that prior knowledge in each domain predicted greater curiosity to learn new information in that domain, and this curiosity in turn (for football items) predicted better learning. Thus, the relationship between prior knowledge and new learning is likely driven by a qualitative, and not quantitative, way in which students process the to-be-learned information. This is generally consistent with prior research showing that students learn information better when they find it more interesting (e.g., Asher et al., 1978; Baldwin et al., 1985; Bernstein, 1955; Boscolo & Mason, 2003) or are more curious about it (e.g., Kang et al., 2009; Maw & Maw, 1961; Mullaney et al., 2014). Such findings could reflect enhanced processing of these items in the form of greater attention or effort invested to learn them. For instance, Kang et al. (2009) found that questions that evoked curiosity activated areas of the brain associated with anticipation of a reward, suggesting that students find it rewarding to learn information that they are curious about. In addition, curiosity increased pupil dilation, which is an indication of increased attention and cognitive effort. Given that curiosity mediated the relationship between prior knowledge and new learning, we believe that processing differences that likely arose when students learned information that they were curious about (e.g., heightened attention or cognitive effort) may have played a key role in this relationship.

Theoretical perspectives often view curiosity as a motivation to gain new information to fill knowledge gaps (for a review, see Grossnickle, 2016). Information gap theory proposes that curiosity increases with prior knowledge because the more one knows about a topic, the less there is for them to learn; therefore, it will be easier to close knowledge gaps (Loewenstein, 1994). This may explain why students are willing to invest limited resources in learning information that they are highly curious about (e.g., Kang et al., 2009). A related perspective, the region of proximal learning, proposes that under some circumstances, students will prioritize learning information that is just beyond their current state of learning (e.g., Metcalfe, 2002; Metcalfe & Kornell, 2003). Thus, students may prioritize learning information from domains for which they have high prior knowledge because they might feel that information is likely to be easier to learn compared to information from domains for which they have low prior knowledge.

These outcomes are also relevant for theories of text comprehension. For instance, from Kintsch’s (1988) construction-integration theory, successful text comprehension requires students to integrate new information from the text with their existing knowledge. Specifically, in the construction phase, information from the text is added to the student’s existing knowledge network. In the integration phase, the relationships between new information and existing knowledge are strengthened through spreading activation. Thus, prior knowledge provides a foundation on which new knowledge is integrated and remembered. Related to the present research, students with high prior knowledge (relative to low prior knowledge) in a domain are likely to have a larger knowledge base upon which new information can be added and integrated. As a result, high-prior-knowledge students should be more successful in acquiring and retaining information related to the domain of prior knowledge.

One challenge for future research will be to sort out the causal chain that connects prior knowledge and new learning. Given that prior knowledge is an individual difference variable, it is challenging to randomly assign students to high- and low-prior-knowledge groups. Indeed, a limitation of the present study is that students came into the task with preexisting levels of prior knowledge. Thus, we are unable to make causal conclusions about the impact of prior knowledge on learning because other variables that covary with prior knowledge may drive the effect. In particular, prior knowledge often covaries with interest. Interest is positively related to text comprehension (e.g., Asher et al., 1978; Baldwin et al., 1985; Bernstein, 1955; Renninger, 1992) and learning of facts (e.g., Fastrich et al., 2018; McGillivray et al., 2015; Shanks & Serra, 2014). Thus, prior knowledge and interest, which often covary, could both be related to learning.

However, there is a chicken-egg problem in determining directionality. It is possible that prior knowledge about a topic leads to increased interest in that topic. Alternatively, interest in a topic may lead students to seek out information about that topic, increasing their knowledge. Beyond sorting out this directionality issue, researchers have explored the relative contributions of domain interest and prior knowledge to learning, though it should be noted that these studies included some of the limitations discussed in the introduction for making conclusions about the impact of prior knowledge on new learning. These studies have primarily focused on reading comprehension and involved students completing a prior knowledge test for some domain, rating their interest in the text (at the passage or paragraph level), and measuring their performance on measures of text comprehension. Prior knowledge and interest often both contribute to text comprehension (e.g., Baldwin et al., 1985; Boscolo & Mason, 2003; Schiefele, 1996; Schiefele & Krapp, 1996). Even so, the strength of these relationships has varied, with some evidence that prior knowledge has a strong effect and interest has a weaker (or nonexistent) effect (e.g., Alexander et al., 1994b; Hare & Devine, 1983; Shapiro, 2004; Surber & Schroeder, 2007) and some evidence that prior knowledge and interest both have weak effects (Oasako & Anders, 1983).

Upon reviewing this literature, Tobias (1994) concluded that prior knowledge and interest both have independent effects on learning, but prior knowledge appears to be a stronger predictor.

These outcomes suggest that prior knowledge and domain-level interest could provide unique contributions to learning. Even so, it is possible that the contributions of these constructs will vary with the demands of the learning task. For more mundane tasks that are unlikely to be interesting, prior knowledge may play a predominant role. For example, Castel (2005) had older and younger adults
complete an associative learning task in which they studied a list of grocery items and corresponding prices. For half of the items, the price was realistic (i.e., close to market value), and for the other half, the price was unrealistic. For recall of unrealistic prices, age-related deficits were observed such that older adults performed worse than did younger adults. By contrast, for realistic prices, this age-related deficit was attenuated. Thus, older adults were able to rely on their existing knowledge of market prices to perform as well as younger adults. These outcomes suggest that prior knowledge alone may be sufficient for enhancing learning. Even so, important directions for future research will be to (a) use a paradigm like the one in the present experiments to explore the relative contributions of prior knowledge and interest (both at the domain and item level) to new learning; (b) investigate the causal chain that links prior knowledge, interest, and learning; and (c) explore conditions in which prior knowledge or interest will be a larger contributor to learning.

Item-level interest could also be an important predictor of the rich-get-richer effect. McGillivray et al. (2015) had participants learn trivia facts. To do so, they attempted to answer a trivia question and then rated their curiosity in knowing the answer (like in the current Experiment 3). Next, they were given feedback as to the correct answer and rated their interest in the question and answer. Although ratings of curiosity and interest were highly correlated, when both were entered into a model to predict final test performance, interest was the only significant predictor. Using a similar design, Fastrich et al. (2018) found that interest mediated the relationship between curiosity and final test performance. Thus, although many researchers use curiosity and interest interchangeably (for reviews, see Grossnickle, 2016; Schmidt & Rotgans, 2020), these constructs can be separable, and item-level interest may be more predictive of learning relative to curiosity. Thus, additional work is needed to explore whether item-level interest contributes to new learning and whether it mediates the relationship between prior knowledge and new learning.

The Relationship Between Prior Knowledge and Metacognition

The current results shed light on potential metacognitive mechanisms that might contribute to the rich-get-richer effect. In all experiments, prior knowledge in each domain was positively related to JOLs for items from that domain and unrelated to JOLs for items from the other domain. Thus, students appear to use their prior knowledge as a cue when monitoring their learning (cf. Löffler et al., 2016; Shanks & Serra, 2014; Toth et al., 2011). This outcome is informative because most of the research on JOLs has focused on the characteristics of the to-be-learned items or the conditions of learning (i.e., intrinsic or extrinsic cues; Koriat, 1997). By contrast, limited research has explored how characteristics of the learner influence JOLs (e.g., Tauber et al., 2019). The present research adds to this neglected but important area of research by showing that students do appear to make judgments of their own learning that are consistent with their prior knowledge.

An important question for future research is whether students can effectively monitor and regulate their own learning as a function of prior knowledge. When learning new information from domains of low versus high prior knowledge, can students effectively distinguish between items that are well learned and those that are not and regulate study decisions accordingly? When choosing items to study, students often select items that they have given low JOLs compared to items that they have given high JOLs (e.g., Ariel et al., 2009; Thiede, 1999). Shanks and Serra (2014) found that participants gave higher JOLs to items from domains for which their self-reported prior knowledge was high relative to domains for which their self-reported prior knowledge was low. Critically, when study time was unlimited, participants chose to restudy items from the domains for which they reported having low knowledge. Even so, students’ agendas, or plans for learning, can be influenced by multiple factors (e.g., Ariel et al., 2009; Dunlosky & Ariel, 2011). In some instances, students will invest more time and resources in learning information that evokes high interest or curiosity (e.g., Kang et al., 2009) or that is just beyond their current state of learning (e.g., Metcalfe, 2002; Metcalfe & Kornell, 2003). The latter is especially likely when study time is limited (cf. Shanks & Serra, 2014). As such, under some circumstances, students may choose to prioritize learning new information from domains for which they have high prior knowledge. Exploring the relationship between prior knowledge and students’ study decisions when students learn new information will shed important light on whether enhanced metacognitive processing might contribute to the relationship between prior knowledge and new learning.

Relatedly, a recent emphasis in metamemory research is to investigate the potential direct impact that making JOLs can have on learning. Under some conditions, simply making JOLs (relative to not making them) enhances learning (e.g., Myers et al., 2020; Soderstrom et al., 2015; Witherby & Tauber, 2017). In a review of the preliminary work on the reactive effects of JOLs, Double et al. (2018) suggested that JOLs enhance learning when the to-be-learned items are related (e.g., loaf-bread) but not when they are unrelated (e.g., table-dog). Related to the present experiments, when students learned information related to the domain for which they had high prior knowledge, the act of making JOLs for that information may have increased the likelihood that it was remembered on the final test. That is, JOL reactivity may have contributed to the rich-get-richer effect. To date, only one study has investigated how JOLs influence learning of educationally relevant information (Ariel et al., 2020). Thus, more research is needed to explore how JOLs influence learning for educational material, and it will be important to explore how prior knowledge influences these effects.

In addition to JOLs, a fruitful avenue for research will be to explore how prior knowledge is related to students’ confidence. For instance, the hypercorrection effect refers to the finding that people are more likely to correct high-confidence relative to low-confidence errors (e.g., Butterfield & Metcalfe, 2001, 2006; Fazio & Marsh, 2009). Some evidence suggests that prior knowledge plays a critical role in this effect (e.g., Carpenter et al., 2018; Sitzman et al., 2015, 2020). Even so, the relationship between domain knowledge and hypercorrection is unclear. Carpenter et al. (2018) found that students with high prior knowledge of horticulture demonstrated a greater hypercorrection effect compared to students with low prior knowledge. However, high-prior-knowledge students made fewer initial errors and thus had fewer errors to correct relative to low-prior-knowledge students. An important direction for future research will be to investigate the relationship between prior domain knowledge and error correction.
when the number of to-be-corrected items is held constant for low- and high-prior-knowledge students. In addition, research investigating the role of curiosity in this relationship would be informative. If a student thinks they know the answer to a question, they may express low curiosity in seeing the answer even if their answer is incorrect. Upon receiving feedback, the student may feel surprised, which could increase the likelihood that they would show a hypercorrection effect (cf. Fazio & Marsh, 2009).

Finally, although the present work focused on the positive relationship between prior knowledge and learning, it is worth noting that prior knowledge is not always related to learning (e.g., DeMarie-Dreblow, 1991) and in some cases can lead to memory errors. For instance, when students have high prior knowledge, activating inaccurate knowledge during learning can result in that inaccurate knowledge carrying over to a final test (van Loon et al., 2013). Likewise, Castel et al. (2007) found that prior knowledge was related to increased rates of false memories in an episodic memory task. Critically, these studies focused on memory errors for information that was already known by participants. It is unclear whether prior knowledge might also contribute to memory errors when participants learn new information. Thus, it will be important for researchers to explore if, and why, prior knowledge can have negative effects on new learning. Given that prior knowledge is positively related to JOLs, one possibility is that memory errors may be driven by overconfidence in one’s ability to learn information from a high-knowledge domain.

**Conclusions**

In sum, the present research demonstrated that prior knowledge was positively related to new learning of domain-relevant information, and curiosity to learn the information appears to mediate this relationship. This relationship was established with a novel paradigm that controlled for alternative explanations present in prior work. Such a paradigm will be important to adopt in follow-up research aimed at addressing several important questions about when, and why, prior knowledge will predict new learning. Although prior knowledge is typically viewed as a variable to be controlled or eliminated in many research designs, the present results suggest that prior knowledge can have important predictive effects on new learning that should be measured and modeled in order to better understand the factors contributing to successful learning.

**References**


Grossnickle, E. M. (2016). Disentangling curiosity: Dimensionality, definitions, and distinctions from interest in educational contexts. *Educa-

(Appendix follows)
## Football and Cooking Questions

### Football questions

<table>
<thead>
<tr>
<th>Question</th>
<th>Answer</th>
<th>Truthfulness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Which NFL team has only made 6 playoff appearances, which is the fewest in the league?</td>
<td>Carolina Panthers</td>
<td>False</td>
</tr>
<tr>
<td>The Lamar Hunt trophy was named after the former owner of which NFL team?</td>
<td>New York Jets</td>
<td>False*</td>
</tr>
<tr>
<td>Which NFL team scored 37 points in the 4th quarter (which is an NFL record)?</td>
<td>Minnesota Vikings</td>
<td>False</td>
</tr>
<tr>
<td>Who holds the record for the most sacks in NFL history?</td>
<td>Michael Strahan</td>
<td>False*</td>
</tr>
<tr>
<td>What was the original name of the Tampa Bay Buccaneers’ mascot?</td>
<td>Pirate Pete</td>
<td>False</td>
</tr>
<tr>
<td>How much does the Super Bowl trophy cost?</td>
<td>65,000</td>
<td>False*</td>
</tr>
<tr>
<td>What is the length of the longest field goal ever attempted in an NFL game?</td>
<td>72 yards</td>
<td>False*</td>
</tr>
<tr>
<td>What is the most points scored, combined between both teams, in a single NFL game?</td>
<td>105</td>
<td>False*</td>
</tr>
<tr>
<td>Which NFL team holds the record for the most tie games in one season?</td>
<td>Jacksonville Jaguars</td>
<td>False*</td>
</tr>
<tr>
<td>Which team is the oldest in the NFL?</td>
<td>New York Giants</td>
<td>False*</td>
</tr>
<tr>
<td>How many playoff appearances have the Dallas Cowboys had (which is the most of all teams in the NFL)?</td>
<td>33</td>
<td>Truthful</td>
</tr>
<tr>
<td>How long after Vince Lombardi passed away did it take for the NFL to change the name of the Super Bowl trophy to the Lombardi trophy?</td>
<td>1 week</td>
<td>Truthful</td>
</tr>
<tr>
<td>Who holds the record for the most consecutive quarterback starts in the NFL?</td>
<td>Brett Favre</td>
<td>Truthful</td>
</tr>
<tr>
<td>Which NFL team was John Elway drafted by before being traded to the Broncos?</td>
<td>Colts</td>
<td>Truthful</td>
</tr>
<tr>
<td>What is the name of the Baltimore Ravens’ mascot?</td>
<td>Poe</td>
<td>Truthful</td>
</tr>
<tr>
<td>Which is the only NFL team to have lost 4 Super Bowls in a row?</td>
<td>Buffalo Bills</td>
<td>Truthful</td>
</tr>
<tr>
<td>How many years did it take the New Orleans Saints to win their first playoff game?</td>
<td>32</td>
<td>Truthful</td>
</tr>
<tr>
<td>Which NFL team holds the record for the most points scored in a Super Bowl?</td>
<td>San Francisco 49ers</td>
<td>Truthful</td>
</tr>
<tr>
<td>What is the name of the only female NFL official?</td>
<td>Sarah Thomas</td>
<td>Truthful</td>
</tr>
<tr>
<td>The actor Terry Crews played 5 years in the NFL with which team?</td>
<td>Los Angeles Rams</td>
<td>Truthful</td>
</tr>
</tbody>
</table>

### Cooking questions

<table>
<thead>
<tr>
<th>Question</th>
<th>Answer</th>
<th>Truthfulness</th>
</tr>
</thead>
<tbody>
<tr>
<td>In a kitchen, a claster is a type of what?</td>
<td>Knife</td>
<td>False</td>
</tr>
<tr>
<td>Who wrote <em>Essentials of Classic Italian Cooking</em>, the first cookbook ever written?</td>
<td>Fernand Point</td>
<td>False*</td>
</tr>
<tr>
<td>Who is known as the father of French cuisine?</td>
<td>Alain Ducasse</td>
<td>False*</td>
</tr>
<tr>
<td>How many hot dogs did the winner of the 2010 Nathan’s Hot Dog Eating contest eat in 10 minutes?</td>
<td>73</td>
<td>False*</td>
</tr>
<tr>
<td>What is the name of the cooking technique in which you quickly sear meat before putting it in the oven?</td>
<td>Confit</td>
<td>False*</td>
</tr>
<tr>
<td>When cooking, a _______ is a reduction of wine and flour.</td>
<td>Gastrique</td>
<td>False</td>
</tr>
<tr>
<td>In a professional kitchen, the Boucher is the chef in charge of making what?</td>
<td>Sauces</td>
<td>False*</td>
</tr>
<tr>
<td>How many Michelin stars does Wolfgang Puck have?</td>
<td>10</td>
<td>False*</td>
</tr>
<tr>
<td>Where did Emeril Lagasse receive most of his culinary training?</td>
<td>France</td>
<td>False*</td>
</tr>
<tr>
<td>What is the national dish of Turkey?</td>
<td>Goulash</td>
<td>False*</td>
</tr>
<tr>
<td>In a kitchen, a chinois is a type of what?</td>
<td>Strainer</td>
<td>Truthful</td>
</tr>
<tr>
<td>In what year was the popsicle invented?</td>
<td>1905</td>
<td>Truthful</td>
</tr>
<tr>
<td>What is the name of the oldest restaurant in the United States?</td>
<td>Union Oyster House</td>
<td>Truthful</td>
</tr>
<tr>
<td>Which herb has been used as a symbol for bravery?</td>
<td>Thyme</td>
<td>Truthful</td>
</tr>
<tr>
<td>From where did nutmeg originate?</td>
<td>Indonesia</td>
<td>Truthful</td>
</tr>
<tr>
<td>What is the main protein in the French dish Coq au Vin?</td>
<td>Chicken</td>
<td>Truthful</td>
</tr>
<tr>
<td>In cooking, what is the name of the reaction between sugars and proteins that occurs at high temperatures and is responsible for the browning of meat?</td>
<td>Maillard reaction</td>
<td>Truthful</td>
</tr>
<tr>
<td>When cooking, what is the name for a fruit or vegetable puree used as a sauce?</td>
<td>Coulis</td>
<td>Truthful</td>
</tr>
<tr>
<td>What kind of food is Tilsit?</td>
<td>Cheese</td>
<td>Truthful</td>
</tr>
<tr>
<td>When cooking, what is the slicing technique in which leafy vegetables are cut into long strips?</td>
<td>Chiffonade</td>
<td>Truthful</td>
</tr>
</tbody>
</table>

*False items that have a true, correct answer.