Cognition 155 (2016) 67–76

Contents lists available at ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/COGNIT

Original Articles

The seductive allure is a reductive allure: People prefer scientific explanations that contain logically irrelevant reductive information

Emily J. Hopkins *, Deena Skolnick Weisberg, Jordan C.V. Taylor

University of Pennsylvania, United States

ARTICLE INFO

Article history:
Received 18 March 2016
Revised 10 June 2016
Accepted 18 June 2016
Available online 28 June 2016

Keywords:
Explanations
Seductive allure
Decision making

ABSTRACT

Previous work has found that people feel significantly more satisfied with explanations of psychological phenomena when those explanations contain neuroscience information—even when this information is entirely irrelevant to the logic of the explanations. This *seductive allure effect* was first demonstrated by Weisberg, Keil, Goodstein, Rawson, and Gray (2008), and has since been replicated several times (Fernandez-Duque, Evans, Christian, & Hodges, 2015; Minahan & Siedlecki, 2016; Rhodes, Rodriguez, & Shah, 2014; Weisberg, Taylor, & Hopkins, 2015). However, these studies only examined psychological phenomena. The current study thus investigated the generality of this effect and found that it occurs across several scientific disciplines whenever the explanations include reductive information: reference to smaller components or more fundamental processes. These data suggest that people have a general preference for reductive information, even when it is irrelevant to the logic of an explanation.

1. Introduction

What is the relationship between the form of an explanation and its content? In ideal circumstances, the quality of an explanation should be determined by its success at generating understanding of the target phenomenon. Form should matter less, if at all. However, there are many cases where the form of an explanation erroneously influences people's judgment of its quality, leading people to feel that they have gained a sense of understanding from statements or situations that aren't actually explanatory (see Trout, 2002). For example, people judge longer explanations as better (Kikas, 2003; Langer, Blank, & Chanowitz, 1978). Similarly, both adults (Lombrozo & Carey, 2006) and children (Kelemen, 1999) preferentially endorse teleological explanations that refer to goals or end-states, even when mechanistic explanations would be more appropriate.

One particularly interesting instance of this kind of error is the *seductive allure effect* in psychology: People judge explanations of psychology findings as better when those explanations contain logically irrelevant neuroscience information (Weisberg, Keil, Goodstein, Rawson, & Gray, 2008). That is, people feel that they understand a psychological phenomenon better when it is described using the language of neuroscience, although this language should make no difference. Although this finding has been replicated several times, demonstrating its robustness (Fernandez-Duque, Evans, Christian, & Hodges, 2015; Minahan & Siedlecki, 2016; Rhodes, Rodriguez, & Shah, 2014; Weisberg, Taylor, & Hopkins, 2015), it is still unclear why this effect happens. One possibility is that it is specific to psychology and neuroscience; something about neuroscientific language in particular plays a role in improving explanations of psychological phenomena. However, recent work has not yet identified the mechanism by which neuroscience content may have this effect. Although early evidence suggested that neuroscience images influence people's judgments (McCabe & Castel, 2008), these results have failed to replicate (Gruber & Dickerson, 2012; Hook & Farah, 2013; Michael, Newman, Vuorre, Cumming, & Garry, 2013; see Farah & Hook, 2013 for a review). Additionally, neuroscience jargon (e.g., "fMRI imaging") has no effect over and above references to the brain in plain language (e.g., "brain scans": Weisberg et al., 2015, Study 3).

Therefore, neither appealing imagery nor scientific-sounding jargon is responsible for making neuroscience information seductive. Although it is still possible that some other property unique to the pairing of psychology and neuroscience is responsible for the seductive allure effect, an alternative explanation is that this effect is representative of a more general bias in judging explanations.

The current work investigates one potential candidate for this general bias: a preference for reductive explanations. Reductive

* Corresponding author at: University of Pennsylvania, 425 South University Avenue, Room 301, Philadelphia, PA 19104, United States.

E-mail address: hopkinse@upenn.edu (E.J. Hopkins).

http://dx.doi.org/10.1016/j.cognition.2016.06.011
0010-0277/

explanations are those that refer to more fundamental processes that underlie the target phenomenon or that describe components that constitute the target phenomenon (see Craver, 2007; van Riel & Van Gulick, 2016). People may judge explanations of psychological phenomena that contain irrelevant neuroscience information as better because they believe that this is the proper form of a scientific explanation or because explanations that include more fundamental information seem more informative (Kim & Keil, 2003). On this theory, because lay theories in Western culture posit that the brain underlies psychological states, explanations of psychological phenomena that contain references to the brain are judged as better. But this effect should not be limited to psychology; if explanations with reductive forms are preferred, then the seductive allure effect should occur whenever an explanation includes reductive information.

Reductive explanations can be fruitful in some circumstances (e.g., explaining why a car broke down by referring to its component parts). But past experience with effective reductive explanations may lead participants to overly value explanations that merely appear to reduce a phenomenon to a more fundamental level. This is consistent with past work showing that people prefer longer explanations or teleological explanations (Kikas, 2003; Langer et al., 1978; Lombrozo & Carey, 2006): There are circumstances in which such explanations are appropriate, suggesting that people's undue preference for them in experimental settings represents the over-application of a heuristic for judging explanations rather than a complete error. Similarly, a preference for reduction is not always wrong, but can lead to errors in judgment when explanations have only the appearance of reduction without the content.

The philosophical literature does not provide a single, agreed-upon definition for reductionism. Indeed, much of the debate in the field centers around when reductive explanations are appropriate (Fodor, 1975; Nagel, 1961). Because our goal is to investigate the psychological effects of explanations that have a reductionist form, remaining neutral about whether such explanations are in fact better, for the present purposes we restrict our investigation to explanations that contain irrelevant information from a lower level in a reductive hierarchy of sciences (Fig. 1). We hypothesize that the seductive allure effect should be seen broadly across the sciences, leading to preferences of explanations for biological phenomena that contain some information from chemistry, for example.

To test this hypothesis, we presented subjects with descriptions of phenomena across a range of sciences in a plausible reductive hierarchy: social science, psychology, neuroscience, biology, chemistry, and physics (Fig. 1). This particular ordering of the hierarchy makes intuitive sense: Society-level processes reduce to individual human behavior which reduces to neural activity which reduces to the activity of individual cells, etc. It is also consistent with research on the relations between academic disciplines. This research typically uses a variety of bibliographic measures, such as overlap in references, clustering of journals, and prerequisites in college course catalogues, to generate maps of the scientific landscape (e.g., Fanelli & Glänzel, 2013). A recent meta-analysis of 20 such maps generated an ordering very similar to the one used here; although it included a larger number of disciplines, the ordering of our six target fields was the same as depicted in Fig. 1 (Klavans & Boyack, 2009). To further confirm that this hierarchy was intuitive to the participants in the current study, we included a measure of attitudes towards these difference sciences.

For the main task of the current study, participants read a brief description of phenomena drawn from each of these sciences. Following each description, they were presented with one of four possible explanations, according to a Quality (good/bad) × Explanation Level (horizontal/reductive) design. They were asked to rate the quality of this explanation and to provide a justification for this rating for a subset of the items. Horizontal explanations referred only to the science from which the phenomenon itself was drawn (e.g., using biological language to explain a biological phenomenon). Reductive explanations included information from the next lower level in the hierarchy (e.g., using chemical language to explain a biological phenomenon). Crucially, the reductive information we provided did not alter the logic that was central to each explanation. Thus, the items in our reductive condition are not accurately representative of true reductive explanations, since true reduction would likely entail a change not just in vocabulary, but also in logical structure as more fundamental mechanisms and principles are invoked. Our items are designed merely to appear reductive. As with the general preference for greater length or references to teleology in explanations described above, a preference for reductive explanations is not in itself an error. However, our stimuli were carefully constructed so that the reductive information would not provide any explanatory power, allowing us to separate out a potential preference for explanations with a reductive form even in the absence of any helpful reductive content.

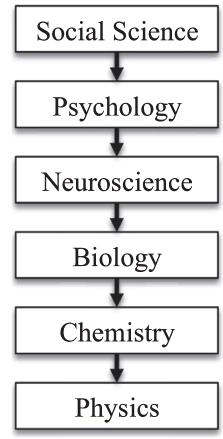

Fig. 1. Hierarchy of sciences used in current study.

Using the form of a reductive explanation without its accompanying content allows us to test for a reductive bias while maintaining logical consistency of explanations across both horizontal and reductive conditions. This design duplicates the design of previous experiments that demonstrate the seductive allure of neuroscience, yet applies to the numerous stepwise pairings of disciplines implied by the aforementioned hierarchy. If participants show a general preference for the appearance of reduction, they should judge reductive explanations as better than horizontal explanations for all sciences, even though the explanatory content of both is the same. If the seductive allure effect is unique to the pairing of psychology and neuroscience, however, we should observe this preference only for psychology and not for the other sciences.

In addition to collecting participants' ratings of our explanations, we assessed a variety of individual difference measures to determine what might influence these ratings. As noted above, we asked participants to rate the prestige of the sciences that we included (design based on Fernandez-Duque et al., 2015). We additionally measured participants' logical reasoning abilities and their degree of cognitive reflection (Toplak, West, & Stanovich, 2014), which might impact their abilities to accurately rate explanations in general, as well as their overall science literacy (National Science Board, 2014), which might impact their abilities to think about explanations within the sciences.

2. Method

2.1. Participants

Participants were recruited from two populations: workers on Amazon's Mechanical Turk ($n = 167$) and undergraduate students enrolled in psychology classes ($n = 152$). MTurk workers were paid $0.50 for their participation, and undergraduate students received course credit. Some participants (20 MTurk workers and 40 undergraduates) were excluded from the sample for failing attention check questions (described in Section 2.4). The final sample used for all analyses thus consisted of 147 MTurk workers and 112 undergraduates. MTurk workers (80 women, 55 men, 12 did not report gender) were 39.8 years of age on average (range: 19–71), and undergraduates (64 women, 44 men, 4 did not report gender) were 19.8 years of age on average (range: 18–23). Most of the MTurk workers (89.8%) had completed at least some college; 46.3% reported having an associate's or bachelor's degree, and 15.0% reported having a master's degree or higher. Among the undergraduates, 36.0% were freshmen, 28.8% were sophomores, 20.7% were juniors, and 13.5% were seniors; 1 participant did not report his or her year.

2.2. Design

All participants completed an online survey hosted by Qualtrics. The survey had six components: Rating Explanations, Science Literacy, Reflective Thinking, Logical Syllogisms, Perceptions of Science, and Demographic Information. All participants completed the Rating Explanations component first and the Demographic Information last. The other four components were presented in a random order after the Rating Explanations component.

The Rating Explanations task used a 2 (Explanation Level: horizontal, reductive) × 2 (Quality: good, bad) × 6 (Science: physics, biology, chemistry, neuroscience, psychology, social science) design. To be consistent with previous studies of this effect (Weisberg et al., 2008, 2015), explanation level was between-subjects: Participants were randomly assigned to either the horizontal (74 MTurk workers, 54 undergraduates) or reductive (73 MTurk workers, 58 undergraduates) condition. Quality and science were within-subjects: All participants rated two explanations from each science, one good and one bad.

2.3. Materials

The Rating Explanations task used 24 different phenomena (four per science). All phenomena and their corresponding explanations are available in the online supplemental materials and via the Open Science Framework (see Table 1 for an example). The phenomena described concepts, principles, or research findings from each of the six sciences. To select the 24 phenomena, we began with a set of 46 (between 5 and 10 per science) and presented them to participants from MTurk ($N = 58$) and the psychology participant pool ($N = 72$). We presented a subset of 23 phenomena to each participant, chosen so that each participant received half of the pilot phenomena from each discipline. Participants read only the phenomena without any accompanying explanations. We asked (a) how interested participants were in the phenomenon (3-point scale: not interested, somewhat interested, very interested), (b) whether they already knew an explanation for the phenomenon, and (c) in which discipline the phenomenon belonged (anthropology, chemistry, physics, sociology, economics, neuroscience, psychology, political science, biology, or other). For a subset of 3 of the items where participants indicated that they already knew the explanation, we asked participants to provide the explanation in order to verify their initial ratings. To select which phenomena from this pilot set would be used in the study, we chose the 4 from each discipline that had the best combination of high interest scores, low rates of participants claiming that they already knew the explanation, poor explanations for those participants who provided them, and accurate categorizations by discipline. All of the phenomena we chose received a majority of "somewhat interested" or "very interested" scores and were categorized into their correct field by a majority of participants. Participants said that they already knew the explanation for these phenomena only 26% of the time on average. The complete set of pilot data is provided in the online supplemental materials.

For each phenomenon, we constructed four corresponding explanations: horizontal-good, horizontal-bad, reductive-good, and reductive-bad. All of the explanations were verified by experts in the respective fields. This was done by consulting with these experts, both in person and over email, throughout the process of developing the stimuli. In our conversations with the experts from each field, we explained the goals of the experiment, and the authors and the expert edited the explanations together to ensure that they met these goals. More details are provided below as we describe each explanation category.

Table 1
Sample phenomenon and explanations from biology.

Male anole lizards bob their heads up and down rhythmically as part of a mating ritual to attract females. They typically increase their rate of head-bobbing when they see a female lizard of their species. However, their rate of head-bobbing also increases when they see another male lizard of the same species, even if no female lizards are present.
Why do male lizards bob their heads when other males are nearby?

	Good	Bad
Horizontal	This happens because the male lizards are extremely territorial, and head-bobbing is a distinctive behavior typical of this particular species of lizard. During mating season when they are in competition with each other for females, males use various dominance displays to defend their territory. They perceive other males as a threat and engage in increased head-bobbing, which is a sign of aggression	This happens because the male lizards are seeking mates, and head-bobbing is a distinctive behavior typical of this species of lizard. During mating season when they are trying to attract females, males use a variety of behaviors that are characteristic of anole lizards. They perceive the presence of other males and engage in increased head-bobbing, which is commonly seen during mating season
Reductive	This happens because the male lizards are extremely territorial. During mating season when they are in competition with each other for females, males use various dominance displays to defend their territory. They perceive other males as a threat and engage in increased head-bobbing, which is a sign of aggression. **Aggressive behavior is known to be associated with elevated levels of testosterone and other aggression-enabling hormones**	This happens because the male lizards are seeking mates. During mating season when they are trying to attract females, males use a variety of behaviors that are characteristic of lizards. They perceive the presence of other males and engage in increased head-bobbing, which is commonly seen during mating season. **Aggressive behavior is known to be associated with elevated levels of testosterone and other aggression-enabling hormones**

The horizontal-good versions of the explanations were the ones that researchers or textbooks provided for the phenomena, and our expert consultants verified that these explanations were clear and accurate (Table 1). The bad explanations were constructed by removing the key explanatory information from the good explanations and replacing it with either circular restatements of the phenomenon or with non-explanatory information. For the example in Table 1, the information about male lizards being in competition with each other for mates was replaced with a restatement of the information from the phenomenon about males trying to attract females. In another example, information about why microwaves can cook a potato faster than traditional ovens was replaced with irrelevant information about how gas ovens use fuel and microwaves use electricity. As in these examples, all of the bad explanations made statements that were true; at no point did we provide participants with false information. This was done so that participants could not merely use the accuracy or inaccuracy of the information provided by the explanation in making their judgments. Crucially, however, the bad explanations provided no mechanistic information that could explain the phenomenon. We worked closely with our expert consultants to ensure that the bad explanations were indeed non-explanatory. After the creation of the full stimulus set, we coded each item for whether the bad explanations used circularity or irrelevant information to determine whether this influenced participants' judgments.

Both horizontal-good and horizontal-bad explanations used only terminology and concepts from the same discipline as the phenomenon. That is, biological phenomena were described only in biological terms, chemical phenomena were described in chemical terms, etc. Explanations in the reductive condition additionally used terminology from the discipline below that of the phenomena in our reductive hierarchy: biological explanations were supplemented with chemistry information, chemistry explanations were supplemented with physics information, etc. For phenomena from the domain of physics, the reductive explanations referred to smaller particles and/or more fundamental forces (e.g., reducing "friction" to "vibration of molecules"). We did not rewrite the entirety of the horizontal explanations in the terms of the reductive discipline, but rather included terminology and concepts from that discipline where possible within the explanation's existing structure. This allowed us to match our stimuli closely across conditions and to maintain the same explanatory information in both conditions.

The bold text in Table 1 is the added reductive information (bold text is used here for emphasis, but was not used in the stimuli presented to participants). In this case, it was presented as an additional piece of information at the end of the explanation. In other cases, the reductive explanations translated some of the information into different but equivalent terms from the reductive field. In the microwave example mentioned above, the good-reductive explanation replaced "create friction in the water inside the potato" with "cause the water molecules inside the potato to vibrate." We coded how the reductive information was incorporated into the explanations to determine if this affected participants' ratings.

We worked with our expert consultants to ensure that all of the information provided by the reductive explanations was both true and irrelevant to the logic of the explanation: Saying that microwaves create friction inside the potato is equivalent to saying that microwaves cause vibration in water molecules inside the potato. Thus, the reductive information never added any additional explanatory information. In this way, our reductive explanations allowed us to test whether participants were genuinely paying attention to the logic of the explanation (which was equivalent between the horizontal and reductive versions of each explanation) or whether their ratings of explanation quality would be swayed by the inclusion of true, but logically irrelevant, information from a more fundamental discipline.

For each phenomenon, the four versions of the explanation were matched as closely as possible outside of the manipulations for quality and explanation level. The added reductive text was identical for good and bad versions of the explanation. Length of explanation was carefully matched; within a phenomenon, the four versions of the explanation never differed in length by more than 4 words. Additionally, there were no significant differences in average word count among the six sciences.

The 24 phenomena were divided into two pre-determined sets of 12 (two per science), and participants were randomly assigned to receive one of the two sets. Each set was further subdivided into two blocks of six phenomena (one per science); the order in which these two blocks were presented was randomly determined for each participant. Within each block, the six phenomena were presented in a random order. Each participant saw one good and one bad explanation from each science; two combinations of good and bad explanations were pseudorandomly determined ahead of time and participants were randomly assigned to one of the two different permutations. Further, participants were randomly assigned to either the horizontal or reductive condition, and all 12 explanations that they rated came from their assigned explanation level. This counterbalancing method led to 16 different randomly-assigned presentation orders in a 2 (Item Set: A or B) $\times$ 2 (Block Order) $\times$ 2 (Good/Bad combination) $\times$ 2 (Explanation Level: horizontal, reductive) design.

2.4. Procedure

2.4.1. Rating explanations

All participants completed the Rating Explanations task first. For this task, participants used a sliding scale ranging from 3 to -3 to indicate their responses. They were first given instructions on how to use the slider; this also served as a check that participants were reading instructions. They were told to use the slider to select 0 on the first page in order to proceed with the survey. If they selected anything other than 0, they were directed to another page asking them again to select 0. Participants who did not select the correct response on this second page (three MTurk workers and nine undergraduates) were excluded from analyses.

After these general instructions on using the slider, participants were given instructions for the explanations task (modified from Fernandez-Duque et al., 2015):

> You will now be presented with descriptions of various scientific findings. All the findings come from solid, replicable research; they are the kind of material you would encounter in a textbook. You will also read an explanation of each finding. Unlike the findings themselves, the explanations of the findings range in quality. Some explanations are better than others: They are more logically sound.
>
> Your job is to judge the quality of such explanations, which could range from very poor (-3) to very good (+3).

On each trial, participants were presented with a description of a scientific phenomenon, which was displayed for 10 s before participants could advance to the next screen. On the next screen, an explanation was displayed below the phenomenon, and participants were instructed to rate the quality of the explanation. Participants rated 12 explanations, with an attention check trial administered after the first six (Oppenheimer, Meyvis, & Davidenko, 2009). This trial was similar in format to the others. First, a description of a phenomenon was presented for 10 s. When participants advanced to the next screen, instead of seeing an explanation, they saw text instructing them to select 3 on the scale. Participants who did not select 3 (17 MTurk workers and 31 undergraduates) were excluded from analyses.

After completing all 12 trials, participants were asked to give further justification of their responses for two of the phenomena they had viewed. The survey software randomly selected one phenomenon for which the participant had given a positive rating and one for which they had given a negative rating. These two were presented to participants in a random order. Participants were shown the phenomenon and explanation again and reminded of whether their rating had been positive or negative. They were then asked to explain why they gave that rating and to describe what additional information would have improved the explanation. These open-ended questions were followed by two multiple choice questions.[1] First, participants were asked how reading the explanation changed their understanding of the phenomenon, with five response options: "I understand it much better than I did before", "I understand it a little better than I did before", "My understanding has not changed", "I understand it a little less than I did before", "I understand it a lot less than I did before". The last question asked whether participants would like to change their rating after having thought more about the explanation; they could respond that they would make their rating higher, make it lower, or keep it unchanged.

After the explanations task, participants completed four additional measures, presented in random order: Science Literacy, Reflective Thinking, Logical Syllogisms, and Perceptions of Science. The complete set of questions for each of these measures are included in the online supplemental materials and via the Open Science Framework.

2.4.2. Science literacy

To assess participants' general understanding of science, we used a set of science indicator questions from the National Science Foundation (National Science Board, 2014). Questions assessed participants' basic understanding of probability and experimental design, as well as factual knowledge from a variety of scientific disciplines. Participants were given one score for this measure that represented the total number of questions they answered correctly (out of 15).

2.4.3. Reflective thinking

Reflective thinking was measured using an updated version of the Cognitive Reflection Test (Toplak et al., 2014). This measure consists of four mathematical word problems. For each, there is an intuitive, but incorrect, answer that follows from a quick reading of the question. Computing the correct answer requires participants to think more carefully about the problem. Participants' scores on this measure represented the number of questions they answered correctly (out of 4).

2.4.4. Logical syllogisms

To assess logical reasoning, participants were asked to solve four logical syllogisms presented in multiple choice format. Each consisted of two premises (e.g., "Some mechanics are baseball fans. No baseball fans enjoy board games"). Participants were then given three possible conclusions and a "None of the above" option and asked to indicate which conclusion must be true given the premises. In pilot testing ($N = 35$), participants averaged 2.3 out of 4 correct on these items ($SD = 1.0$; Range = 0–4). Participants' scores on this measure represented the number of questions they answered correctly (out of 4).

[1] Analysis of these questions is included in the online supplemental materials.

2.4.5. Perceptions of science

This measure was adapted from Fernandez-Duque et al. (2015) to assess participants' views of 10 scientific disciplines: anthropology, chemistry, physics, sociology, economics, neuroscience, psychology, political science, and biology. Participants rated each science on a 10-point scale in response to three different questions (presented in a random order). The questions asked about the perceived scientific rigor of each discipline, the extent of the knowledge gap between a novice and an expert in each discipline, and the societal prestige of each discipline. For each discipline, the ratings on the three items were summed to create a single score (out of 30).

2.4.6. Demographics

At the end of the survey, participants answered a series of demographic questions, including gender, age, and year in school (for undergraduates) or highest degree completed (for MTurk workers). Participants from both samples were asked to pick the category that most closely matched the field of their highest degree (physical sciences, social sciences, engineering, humanities, health, and business) and to give the exact field. They were also asked whether they had taken any college- or graduate-level courses in anthropology, chemistry, physics, sociology, economics, neuroscience, psychology, political science, biology, or philosophy.

3. Results

Data from the explanations task were analyzed with a mixed-effects linear regression model (using the lme4 package in R) predicting the rating given on each trial from the sample (MTurk, undergraduates), the quality of the explanation (good, bad), the explanation level (horizontal, reductive), and the science from which the phenomenon was drawn (physics, chemistry, biology, neuroscience, psychology, and social science). Sample and explanation level were between-participants variables and quality and science were within-participants. All possible interactions between variables were tested. The four-way interaction and most of the three-way interactions did not significantly improve model fit, as assessed by likelihood ratio testing, and these were dropped; this did not change the significance of any other predictors in the model.

Different random-effects structures were tested, and the best-fitting model included random intercepts by participant and item as well as a random effect of item on the slope for the quality variable. The final regression model can be seen in Table 2. Significance levels were calculated by generating bootstrapped confidence intervals for the regression coefficients at 90%, 95%, and 99%.[2] The science variable was deviation coded such that the coefficient for each science represents the difference between the effect of that science and the grand mean of sample; physics was the reference level included in the model intercept. In all tables and graphs, the science listed refers to the discipline from which the phenomenon was drawn (e.g., the bars for Biology in Fig. 2 show participants' responses to explanations for biological phenomena, which either did or did not include information from chemistry).

3.1. Explanation level

The primary research questions were whether participants would prefer reductive explanations and whether this would differ by the science of the phenomenon. The regression revealed a

[2] Significance levels obtained using this method were the same as those found using the lmerTest package in R, which uses Satterthwaite's approximation to determine degrees of freedom.

Table 2
Mixed-effects regression predicting ratings of explanations.

Predictor	Estimate	[95% CI]	*t* value
Intercept	1.13	[0.96, 1.29]	13.32**
Sample	−0.25	[−0.44, −0.07]	−2.66**
Quality	1.27	[1.07, 1.47]	12.20**
Explanation Level	0.21	[0.02, 0.42]	2.23*
Science			
Chemistry	0.08	[−0.24, 0.42]	0.49
Biology	0.05	[−0.27, 0.42]	0.33
Neuroscience	0.28	[−0.07, 0.63]	1.67
Psychology	−0.27	[−0.60, 0.08]	−1.59
Social Science	−0.14	[−0.45, 0.15]	−0.86
Sample × Quality	0.54	[0.30, 0.76]	4.92**
Sample × Explanation Level	−0.13	[−0.52, 0.27]	−0.67
Sample × Science			
Chemistry	0.05	[−0.17, 0.29]	0.43
Biology	−0.14	[−0.37, 0.11]	−1.13
Neuroscience	0.20	[−0.05, 0.42]	1.66+
Psychology	0.12	[−0.10, 0.35]	0.98
Social Science	−0.12	[−0.36, 0.13]	−1.00
Quality × Explanation Level	−0.14	[−0.37, 0.10]	−1.33
Quality × Science			
Chemistry	−0.19	[−0.62, 0.20]	−0.83
Biology	0.00	[−0.49, 0.43]	0.00
Neuroscience	−0.30	[−0.75, 0.14]	−1.31
Psychology	0.44	[0.00, 0.87]	1.90+
Social Science	−0.02	[−0.42, 0.38]	−0.09
Explanation Level × Science			
Chemistry	0.04	[−0.19, 0.27]	0.32
Biology	0.03	[−0.20, 0.27]	0.21
Neuroscience	0.08	[−0.16, 0.33]	0.69
Psychology	0.22	[−0.02, 0.44]	1.79+
Social Science	−0.39	[−0.65, −0.15]	−3.19**
Sample × Quality × Explanation Level	0.49	[0.01, 0.94]	2.23*

* $p < 0.05$.
** $p < 0.01$.
\+ $p < 0.10$.

significant main effect of explanation level (Fig. 2): Reductive explanations ($M = 1.26$, $SD = 1.71$) were rated significantly higher than horizontal explanations ($M = 1.04$, $SD = 1.88$). There were also significant Explanation Level × Science interactions, indicating that the magnitude of this overall effect differed by science. Specifically, the effect of explanation level was marginally larger for psychology compared to the rest of the sample. Additionally, the explanation level coefficient for social science was significantly smaller than the rest of the sample.

To further investigate this interaction, we conducted separate regression analyses for each science predicting rating from explanation level. Because this analysis still included multiple ratings per participant and different items representing each science, random intercepts for subject and item were included. The results can be seen in Table 3. The effect of explanation level was statistically significant for psychology and neuroscience and marginally significant for physics, chemistry, and biology. In all of these sciences, in line with our hypothesis, reductive explanations were rated higher than horizontal ones. Within social science, reductive explanations were given lower ratings than horizontal explanations, but the difference was not statistically significant. The statistically significant difference between social science and the rest of the sample observed in the main regression reflects this lack of a condition effect in social science compared to the other sciences.

3.2. Quality and sample

We were also interested in participants' general ability to tell good from bad explanations and in any differences between undergraduate students and MTurk workers. The regression analysis (Table 1) revealed significant main effects of quality and sample. Good explanations ($M = 1.76$, $SD = 1.43$) were rated significantly higher than bad explanations ($M = 0.53$, $SD = 1.93$). Undergraduate students ($M = 1.01$, $SD = 1.85$) gave significantly lower ratings on average than MTurk workers ($M = 1.26$, $SD = 1.76$). However, both of these effects are qualified by significant Sample × Quality and Sample × Quality × Explanation Level interactions. These interactions indicate that the difference between good and bad explanations was larger for undergraduate students than for MTurk workers, and that the Quality × Explanation Level interaction was larger for MTurk workers than for undergraduate students (Fig. 3).

To further explore these interactions, we conducted separate regressions for each sample predicting rating from quality and explanation level (including the same random effects structure as the primary regression model). Among MTurk workers, there were significant main effects of quality ($\beta = 1.00$, 95% CI[0.82, 1.21]) and explanation level ($\beta = 0.28$, 95% CI[0.01, 0.54]) and a significant interaction between the two ($\beta = -0.39$, 95% CI[−0.68, −0.10]). Among undergraduate students, there was a significant main effect

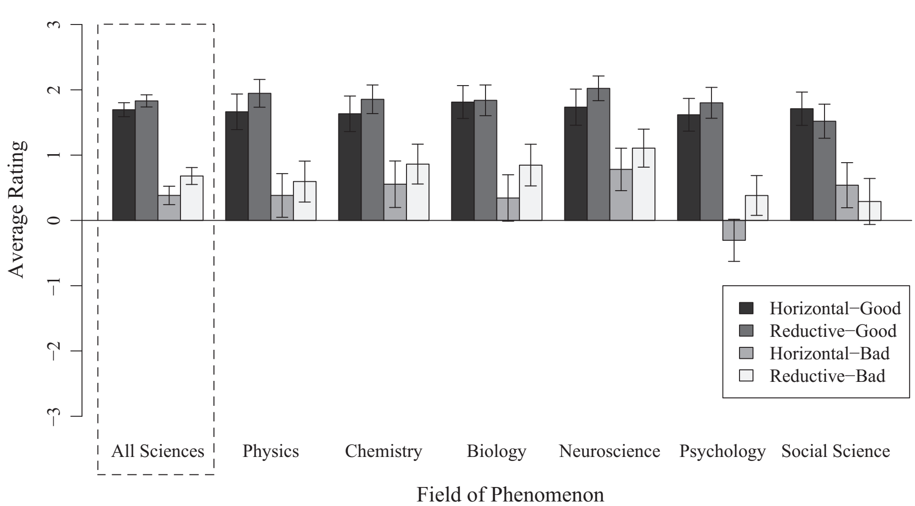

Fig. 2. Average ratings of explanations by science, explanation level, and quality. Error bars represent 95% confidence intervals.

Table 3
Effect of explanation level by science.

Science	Horizontal: mean (SD)	Reductive: mean (SD)	Regression coefficient [95% CI]
Physics	1.02 (1.87)	1.27 (1.70)	0.25 [−0.08, 0.54][+]
Chemistry	1.09 (1.90)	1.36 (1.63)	0.26 [−0.05, 0.54][+]
Biology	1.08 (1.92)	1.34 (1.71)	0.25 [−0.03, 0.60][+]
Neuroscience	1.26 (1.81)	1.56 (1.50)	0.31 [0.02, 0.56][*]
Psychology	0.66 (1.92)	1.09 (1.74)	0.43 [0.09, 0.74][*]
Social Science	1.13 (1.84)	0.90 (1.91)	−0.17 [−0.49, 0.09]

[*] $p < 0.05$.
[+] $p < 0.10$.

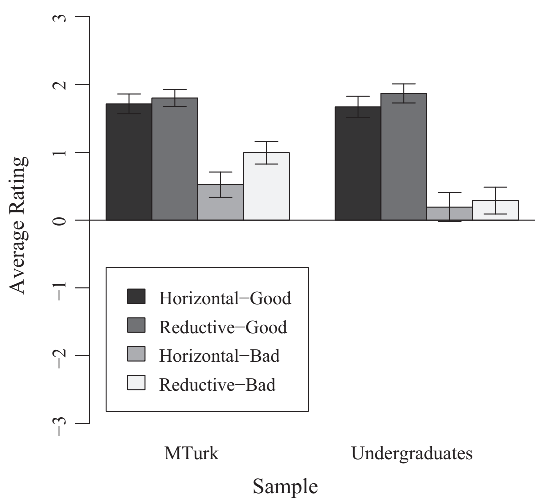

Fig. 3. Sample × Quality × Explanation Level interaction.

of quality (β = 1.54, 95% CI[1.27, 1.82]), but the main effect of explanation level (β = 0.15, 95% CI[−0.15, 0.42]) and the interaction (β = 0.09, 95% CI[−0.21, 0.42]) were not significant. Thus, although both groups rated reductive explanations higher on average than horizontal explanations, this difference was only statistically significant among the MTurk workers. Furthermore, MTurk workers were more affected by reductive information in their rating of bad explanations than good explanations; no such interaction was observed for undergraduates.

3.3. Interim summary

First, it is clear that participants are able to tell good from bad explanations, although undergraduate students were more critical of bad explanations than MTurk workers. More importantly, these data provide evidence that the seductive allure effect is not specific to the pairing of psychology and neuroscience. In five of the six scientific disciplines tested, participants gave marginally or significantly higher ratings to explanations that included reductive information, although the effect was strongest for psychology explanations with added neuroscience. The opposite effect was observed for social science phenomena; participants gave lower ratings to the reductive explanations that included information from psychology.

3.4. Justifications

After participants rated their 12 phenomena and explanations, they were asked to explain briefly why they gave the rating that they did for two of those items: one that they had rated positively and one that they had rated negatively. For participants in the reductive condition, two independent raters coded whether the justifications included specific reference to the reductive information from the explanation (Cohen's kappa = 0.89). Of the 231 justifications given by participants in the reductive condition, 20.8% contained a reference to the reductive information (e.g., "It relates the phenomenon to specific cognitive structures, like the frontal lobe"; "It does not explain how the error in the P53 gene occurs") According to a mixed-effects logistic regression predicting whether a justification included reference to the reductive information, undergraduate students mentioned reduction significantly more (27% of justifications) than MTurk workers (15% of justifications; odds ratio = 2.12, 95% CI[1.05, 4.29]). This is consistent with earlier work on the seductive allure effect in which undergraduate students were more likely to refer to the brain when justifying their ratings of psychology explanations (Weisberg et al., 2015).

3.5. Additional measures

We next investigated whether ratings of explanations were affected by measures of general understanding of science and logic. To do this, difference scores were computed for each subject by subtracting their average rating of the bad explanations from their average rating of the good explanations. Each participant thus had a single score reflecting their ability to discriminate good from bad explanations. Correlations between these difference scores and scores on the logic, reflective thinking, and science literacy measures are presented in Table 4. Difference scores were significantly positively correlated with scores on logical reasoning, reflective thinking, and science literacy: For each of these measures, participants who scored higher were better able to tell good from bad explanations.

Participants also provided information about courses taken in different scientific fields (physics, chemistry, biology, neuroscience, psychology, and sociology). The total number of sciences (out of 6) in which a participant had taken courses was a significant predictor of overall difference scores in a linear regression: $F(1,214) = 6.27$, $p < 0.05$, $R^2 = 0.02$. That is, participants who had studied a larger number of sciences at a college level or higher were better at discriminating good from bad explanations in this task. We also predicted that participants who had completed coursework in philosophy might be better at detecting bad explanations because philosophy courses often include explicit instruction in logic and analyzing explanations. Students who had taken philosophy courses did perform significantly better on logical syllogisms than those who had not, $t(214) = 2.56$, $p < 0.05$, $d = 0.35$. However, philosophy coursework was not a significant predictor of difference scores on the explanations task in a linear regression: $F(1,214) = 0.14$, $p = 0.71$.

3.6. Perceptions of science

As described in Section 2, participants rated each science on a 10-point scale for three different questions; the three ratings were summed to give a single score out of 30 for each science. The summed scores for sociology, economics, and political science were highly correlated (alpha = 0.79 for undergraduates and 0.82 for MTurk workers), and the three were averaged to create a "social science" score. By and large, these ratings mirror our reductive scale of the sciences, with the more fundamental sciences being rated as more rigorous, difficult, and prestigious. The exception to this is neuroscience, which was rated higher than the three more "fundamental" sciences. Paired t-tests were conducted on all adjacent pairs of fields (e.g., physics vs. chemistry, chemistry vs. biology, etc.); all comparisons were statistically significant

Table 4
Correlations between difference scores and other variables.

	Reflective thinking	Science literacy	Difference scores
Logic	0.27*	0.13	0.18*
Reflective thinking		0.33*	0.27*
Science literacy			0.26*

* $p < 0.008$ (Alpha corrected for multiple comparisons).

($p < 0.001$). Means and effect sizes (Cohen's d for within-subjects tests) are shown in Fig. 4.

3.7. Item by item analyses

The analyses discussed thus far revealed some interesting differences between sciences. However, it is possible that these differences could be explained in terms of differences among the individual stimulus items, rather than to more general differences between the sciences. Although we made every effort to match stimuli as closely as possible, there were still item-by-item differences in how bad explanations differed from good ones and how reductive explanations differed from horizontal ones. To assess this, we coded all of the stimuli on two dimensions of interest: whether the bad explanations were circular and whether reductive information was embedded in the central part of the explanation. The 24 phenomena were coded independently by each of the three authors; disagreements were resolved through discussion.

The first dimension regarded the difference between good and bad explanations within a stimulus item. The bad versions of each explanation were coded as either circular or non-circular. Circular explanations involved merely restating the information presented in the phenomenon without providing any additional information; non-circular items included information not present in the phenomenon, but this information was not sufficient to explain the phenomenon. We hypothesized that circular explanations would be rated lower because the circularity would make it easier for participants to see that the bad explanation did not provide an answer to the phenomenon in question.

The second dimension regarded the difference between horizontal and reductive explanations. Specifically, we coded whether the reductive information was presented as central or peripheral to the explanation. For example, in Psychology Item 2 about the other-race effect (see online supplemental materials), the reductive information (substituting "fusiform face area" for "perceptual system") is present within a sentence explaining that experience with people of other races tunes the brain to better recognize differences between faces. In contrast, in Psychology Item 4 about arithmetic abilities in infancy, the labeling of the math area of the brain as the parietal lobe is in its own sentence, separate from the explanation about how infants' expectations affect their looking time. We hypothesized that reductive information would be more persuasive if it was embedded within the crux of an explanation because it would seem to contribute more to the explanation. On the other hand, when the reductive information was added outside of the primary explanation, it could have boosted an explanation's perceived quality by appearing to provide additional information.

Table 5 displays the number of items per science that were coded as displaying each property. Because the sciences differ in the extent to which each property was present, it is possible that previously observed differences by science could be explained by differences in these stimulus properties. Therefore, we examined whether each property significantly predicted ratings of explanations and whether controlling for that property in our primary regression analyses affected the results.

As hypothesized, in a regression predicting explanation rating from quality, explanation level, and circularity (including random intercepts for participants), there was a significant Quality × Circularity interaction ($\beta = -0.26$, 95% CI[-0.49, -0.04]): The difference between good and bad explanations was larger when the bad explanation was circular ($M_{good} = 1.68$, $M_{bad} = 0.32$) than when it was not ($M_{good} = 1.84$, $M_{bad} = 0.72$). There were no significant interactions involving circularity and explanation level. In other words, participants gave lower ratings to bad explanations that were circular than bad explanations that contained irrelevant information, regardless of explanation level. However, controlling for circularity

Table 5
Coding of explanation properties.

Item	Circularity of bad explanations	Centrality of reductive explanations
Physics	1	4
Chemistry	1	2
Biology	2	0
Neuroscience	0	3
Psychology	4	2
Social Science	2	4
Total (out of 24)	10	15

Note: Cell values represent the number of items per science (out of 4) that were coded as displaying each property. More information about this coding is available in the online supplemental materials.

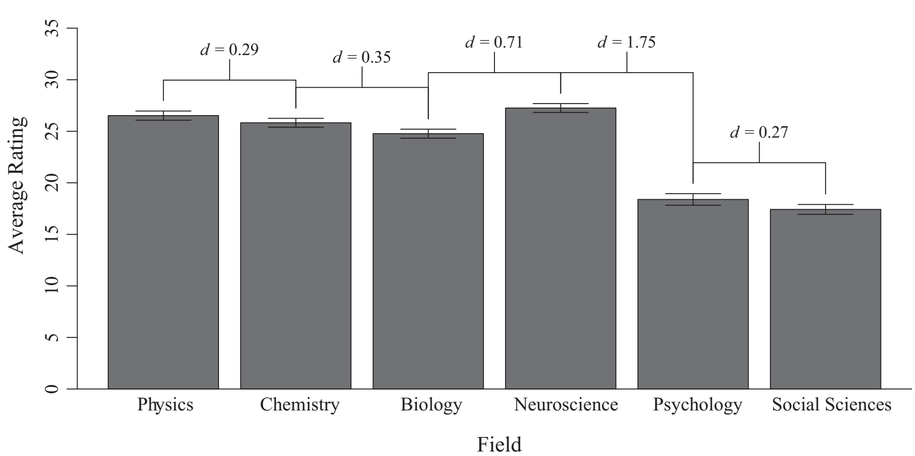

Fig. 4. Average rating on perception scale for each scientific field. Error bars represent 95% confidence intervals.

in the primary regression analysis reported earlier did not affect the magnitude or significance of any other predictors.

In a regression predicting explanation rating from explanation level, quality, and centrality, there was a marginally significant Explanation Level × Quality × Centrality interaction ($\beta = 0.44$, 95% CI[0.00, 0.94]): Among bad explanations only, the difference between the reductive and horizontal conditions was larger when the reductive explanation was *not* presented centrally ($M_{reductive} = 0.80$, $M_{horizontal} = 0.23$) than when it was ($M_{reductive} = 0.61$, $M_{horizontal} = 0.48$). Centrality had a much smaller effect on the difference between the reductive and horizontal conditions for good explanations: central ($M_{reductive} = 1.86$, $M_{horizontal} = 1.68$), non-central ($M_{reductive} = 1.78$, $M_{horizontal} = 1.72$). Reductive content may have increased the perceived quality of bad explanations when it was peripheral to the explanation because it appeared to add additional verifiable information. However, as with circularity, controlling for centrality in the primary regression analysis reported earlier did not affect the magnitude or significance of any other predictors.

4. Discussion

The main goal of the current study was to investigate the generality of the seductive allure effect. Prior research has demonstrated that adding irrelevant neuroscience information to explanations of psychological phenomena makes these explanations seem better to naïve participants. We hypothesized that this effect is due to a general preference for reductive explanations, which means that it should manifest across different scientific domains. Our data support this hypothesis: Participants judged explanations containing irrelevant reductive information as better across a range of sciences. The seductive allure effect is thus not unique to the pairing of psychology and neuroscience.

Although this effect of explanation level was seen across sciences, it was strongest for the psychology/neuroscience pairing. In this case, the impact of reduction may be heightened by a relatively positive view of neuroscience combined with a relatively negative view of psychology. Participants gave neuroscience the highest ratings of any science on the Perceptions of Science scale. This suggests that neuroscience information may exert some unique allure, even if this does not fully explain its appeal in explanations of psychological phenomena. This appeal may be further strengthened by a disinclination for psychology explanations, in line with previous work finding generally poor public opinions about psychology as a science (Keil, Lockhart, & Schlegel, 2010; Lilienfeld, 2012). In support of these findings, the effect of reductive information for the social science/psychology pairing was in the opposite direction from the rest of the sciences; participants gave lower ratings to explanations that included reductive information, which in this case was person-level psychology information.

Future work should investigate this particular effect, as well as why reduction is so appealing as an explanatory form in the sciences. One possibility, as discussed in the Introduction, is that people have past experience with situations where reductive information was in fact helpful in understanding or explaining a phenomenon. The results of the present study may thus represent an over-generalization of this preference to cases with only the appearance of reduction.

An alternative explanation is that participants do not prefer reduction per se, but rather any explanation that integrates information from multiple fields of science. One piece of evidence that goes against this possibility comes from Fernandez-Duque et al. (2015), who found that superfluous neuroscience information had a larger effect on participants' ratings of psychological phenomena than superfluous information from hard sciences, suggesting that simply adding any additional information from an outside field is not sufficient to explain the effect. However, it is possible that people prefer integrative explanations, but that the added information must come from relevant fields. Hard sciences such as genetics and quantum mechanics may be too far removed from psychology to be seen useful in explanations of psychological phenomena.

This opens up an interesting set of questions concerning the proper level for reduction: Are explanations seen as more appealing when they contain information only from the immediately adjacent science (e.g., chemistry for biology), or would further reduction make explanations seem even better (e.g., physics for biology)? An ongoing study in our lab aims to tease out these possibilities. Participants were asked to select which methods would be useful for investigating the same phenomena used in this study, and they could select from among six methods that were typical of our target scientific fields. Preliminary results show that participants almost always selected methods from the field of the phenomenon (58% of the time) or the immediately reductive field (33%) as the most informative for understanding the phenomenon, suggesting that they believe that information from nearby fields is more explanatory than either further reduction or integration of information from higher levels of the reductive hierarchy.

In addition to a preference for reductive information, several other factors influenced participants' ratings of explanations in the current study. First, participants were reliably able to discriminate good from bad explanations across all sciences, demonstrating an intact ability to sense explanation quality. They gave lower ratings to bad explanations that were circular than bad explanations that simply provided irrelevant information. The type of circularity used here may be a particularly salient indicator of poor explanation quality (Rips, 2002); even young children prefer non-circular explanations (Baum, Danovitch, & Keil, 2008; Corriveau & Kurkul, 2014; Mercier, Bernard, & Clément, 2014).

Second, individual differences between participants on some of our auxiliary measures were related to differences in explanation ratings. Reflective thinking, as measured by the CRT, led to more accurate discrimination between good and bad items. Furthermore, participants with better logical reasoning were more accurate in rating explanations, suggesting that domain-general training in logic may minimize the allure of reductive information. In a current study, we are testing whether philosophy experts, who receive specific training in logic, are less susceptible to the reductive allure effect.

Finally, greater general science knowledge led to more accurate ratings. Participants who scored higher on our measure of scientific literacy or who had taken courses in a wider variety of sciences were better able to tell good from bad explanations. This is consistent with previous research that found that neuroscience experts were not seduced by irrelevant neuroscience (Weisberg et al., 2008, Study 3). These results suggest that further training in science may help people to better understand what makes something a good explanation, possibly mitigating the reductive allure effect. Ongoing work in our lab tests this hypothesis by recruiting experts in all six of our target sciences to determine the role of expertise in more detail: Does training in a particular science protect against the reductive allure effect for that science, or in general? Answering this question can provide further insight into the nature of the effect itself and into how to improve people's judgments of scientific explanations.

Acknowledgements

This research was funded by the John Templeton Foundation through the *Varieties of Understanding* project. We'd like to thank

Don Berry, Martha Farah, Simon Garcia, Cindy Keeler, Phil Nelson, Sam Reznik, and Paul Sneigowski for their assistance with stimulus creation.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2016.06.011.

References

Baum, L. A., Danovitch, J. H., & Keil, F. C. (2008). Children's sensitivity to circular explanations. *Journal of Experimental Child Psychology, 100*(2), 146–155. http://dx.doi.org/10.1016/j.jecp.2007.10.007.

Corriveau, K. H., & Kurkul, K. E. (2014). "Why does rain fall?": Children prefer to learn from an informant who uses noncircular explanations. *Child Development, 85*(5), 1827–1835. http://dx.doi.org/10.1111/cdev.12240.

Craver, C. F. (2007). *Explaining the brain: Mechanisms and the mosaic unity of neuroscience*. Oxford: Clarendon Press.

Fanelli, D., & Glänzel, W. (2013). Bibliometric evidence for a hierarchy of the sciences. *PLoS One, 8*(6). http://dx.doi.org/10.1371/journal.pone.0066938.

Farah, M. J., & Hook, C. J. (2013). The seductive allure of "seductive allure". *Perspectives on Psychological Science, 8*(1), 88–90. http://dx.doi.org/10.1177/1745691612469035.

Fernandez-Duque, D., Evans, J., Christian, C., & Hodges, S. D. (2015). Superfluous neuroscience information makes explanations of psychological phenomena more appealing. *Journal of Cognitive Neuroscience, 27*(5), 926–944. http://dx.doi.org/10.1162/jocn_a_00750.

Fodor, J. A. (1975). *The language of thought*. Cambridge, MA: Harvard University Press.

Gruber, D., & Dickerson, J. A. (2012). Persuasive images in popular science: Testing judgments of scientific reasoning and credibility. *Public Understanding of Science, 21*(8), 938–948. http://dx.doi.org/10.1177/0963662512454072.

Hook, C. J., & Farah, M. J. (2013). Look again: Effects of brain images and mind-brain dualism on lay evaluations of research. *Journal of Cognitive Neuroscience, 25*, 1397–1405. http://dx.doi.org/10.1162/jocn_a_00407.

Keil, F. C., Lockhart, K. L., & Schlegel, E. (2010). A bump on a bump? Emerging intuitions concerning the relative difficulty of the sciences. *Journal of Experimental Psychology: General, 139*(1), 1–15. http://dx.doi.org/10.1037/a0018319.

Kelemen, D. (1999). Why are rocks pointy? Children's preference for teleological explanations of the natural world. *Developmental Psychology, 35*(6), 1440–1452. http://dx.doi.org/10.1037/0012-1649.35.6.1440.

Kikas, E. (2003). University students' conceptions of different physical phenomena. *Journal of Adult Development, 10*(3), 139–150. http://dx.doi.org/10.1023/A:1023410212892.

Kim, N. S., & Keil, F. C. (2003). From symptoms to causes: Diversity effects in diagnostic reasoning. *Memory & Cognition, 31*(1), 155–165. http://dx.doi.org/10.3758/BF03196090.

Klavans, R., & Boyack, K. W. (2009). Toward a consensus map of science. *Journal of the American Society for Information Science and Technology, 60*(3), 455–476. http://dx.doi.org/10.1002/asi.

Langer, E. J., Blank, A., & Chanowitz, B. (1978). The mindlessness of ostensibly thoughtful action: The role of "placebic" information in interpersonal interaction. *Journal of Personality and Social Psychology, 36*(6), 635–642. http://dx.doi.org/10.1037/0022-3514.36.6.635.

Lilienfeld, S. O. (2012). Public skepticism of psychology: Why many people perceive the study of human behavior as unscientific. *American Psychologist, 67*(2), 111–129. http://dx.doi.org/10.1037/a0023963.

Lombrozo, T., & Carey, S. (2006). Functional explanation and the function of explanation. *Cognition, 99*, 167–204. http://dx.doi.org/10.1016/j.cognition.2004.12.009.

McCabe, D. P., & Castel, A. D. (2008). Seeing is believing: The effect of brain images on judgments of scientific reasoning. *Cognition, 107*(1), 343–352. http://dx.doi.org/10.1016/j.cognition.2007.07.017.

Mercier, H., Bernard, S., & Clément, F. (2014). Early sensitivity to arguments: How preschoolers weight circular arguments. *Journal of Experimental Child Psychology, 125*(1), 102–109. http://dx.doi.org/10.1016/j.jecp.2013.11.011.

Michael, R. B., Newman, E. J., Vuorre, M., Cumming, G., & Garry, M. (2013). On the (non)persuasive power of a brain image. *Psychonomic Bulletin & Review, 20*(4), 720–725. http://dx.doi.org/10.3758/s13423-013-0391-6.

Minahan, J., & Siedlecki, K. L. (2016). Individual differences in Need for Cognition influence the evaluation of circular scientific explanations. *Personality and Individual Differences, 99*, 113–117. http://dx.doi.org/10.1016/j.paid.2016.04.074.

Nagel, E. (1961). *The structure of science: Problems in the logic of explanation*. New York: Harcourt, Brace & World Inc.

National Science Board (2014). *Science and engineering indicators*. Arlington, VA: National Science Foundation.

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology, 45*(4), 867–872. http://dx.doi.org/10.1016/j.jesp.2009.03.009.

Rhodes, R. E., Rodriguez, F., & Shah, P. (2014). Explaining the alluring influence of neuroscience information on scientific reasoning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 40*(5), 1432–1440. http://dx.doi.org/10.1037/a0036844.

Rips, L. (2002). Circular reasoning. *Cognitive Science, 26*(6), 767–795. http://dx.doi.org/10.1016/S0364-0213(02)00085-X.

Toplak, M. E., West, R. F., & Stanovich, K. E. (2014). Assessing miserly information processing: An expansion of the Cognitive Reflection Test. *Thinking & Reasoning, 20*(2), 147–168. http://dx.doi.org/10.1080/13546783.2013.844729.

Trout, J. D. (2002). Scientific explanation and the sense of understanding. *Philosophy of Science, 69*, 212–233. http://dx.doi.org/10.1086/341050.

van Riel, R., & Van Gulick, R. (2016). Scientific reduction. In E. N. Zalta (Ed.), *The Stanford encyclopedia of philosophy*. (Spring 2016). Retrieved from<http://plato.stanford.edu/archives/spr2016/entries/scientific-reduction>.

Weisberg, D. S., Keil, F. C., Goodstein, J., Rawson, E., & Gray, J. R. (2008). The seductive allure of neuroscience explanations. *Journal of Cognitive Neuroscience, 20*(3), 470–477. http://dx.doi.org/10.1162/jocn.2008.20040.

Weisberg, D. S., Taylor, J. C. V., & Hopkins, E. J. (2015). Deconstructing the seductive allure of neuroscience explanations. *Judgment and Decision Making, 10*(5), 429–441. http://dx.doi.org/10.1162/jocn.2008.20040.