Inferred Evidence in Latent Scope Explanations

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Abstract

Explanations frequently lead to predictions that we do not have the time or resources to fully assess or test, yet we must often decide between potential explanations with incomplete evidence. Previous research has documented a *latent scope bias*, wherein explanations consistent with fewer predictions of unknown truth are preferred to those consistent with more such predictions. In the present studies, we evaluate an account of this bias in terms of *inferred evidence*: That people attempt to infer what would be observed if those predictions were tested, and then reason on the basis of this inferred evidence. We test several predictions of this account, including whether and how explanatory preferences depend on the *reason* why the truth of the effect is unknown (Experiment 1) and on the base rates of the known and unknown effects (Experiment 2), and what evidence people see as relevant to deciding between explanations (Experiment 3). These results help to reveal the cognitive processes underlying latent scope biases and highlight boundary conditions on these effects.

Keywords: Explanation; causal reasoning; uncertainty; inferred evidence; latent scope.

Introduction

We often must make inferences in the face of incomplete evidence. For example, two trial attorneys may present two competing theories of a case to the jury (see Figure 1). If Colonel Mustard did it (call this hypothesis C_1), then there would be broken glass in the billiard room (call this evidence E_1); if Professor Plum did it (C_2), then there would be broken glass in the billiard room (E_1) and a dent in the candlestick (E_2). If we know that E_1 is true but do not know whether E_2 is true, then what can we say about the relative likelihood that Mustard or Plum is the culprit?

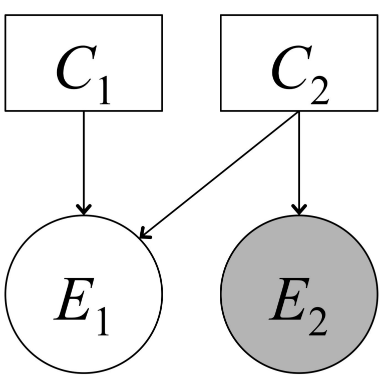

Figure 1: Causal structure used in all experiments. The white circle indicates an observed prediction and the gray circle indicates a latent (unknown) prediction.

Normative probability theory tells us that we have no evidence either way. The posterior odds in favor of C_1 over C_2 simply are the ratio of the prior probability of each hypothesis, $P(C_1)/P(C_2)$, if we assume that the likelihoods are equal (i.e., $P(E_1|C_1) = P(E_1|C_2)$; for the deterministic causal networks used in this paper, both likelihoods are equal to 1). That is, if we had no reason to think Mustard or Plum was the more likely culprit before gathering evidence, then we still have no reason after learning that E_1 occurred but not knowing about E_2.

Nonetheless, Khemlani, Sussman, and Oppenheimer (2011) have documented a striking effect: People prefer explanations with narrower *latent scope*, that is, explanations consistent with fewer potential observations not known to be true or false. In the above example, E_1 is observed, and is predicted by both C_1 and C_2, so E_1 is part of the *manifest scope* of both explanations. However, we do not know whether E_2 is true, so E_2 is part of the *latent scope* of C_2 (see Figure 1). Using a variety of stimulus materials and tasks, Khemlani et al. (2011; see also Sussman, Khemlani, & Oppenheimer, 2014) showed that people consistently prefer narrow latent scope explanations in diagnostic reasoning and in categorization. In our example, people would infer that Colonel Mustard is the more likely culprit because this explanation can account for all of the evidence (the broken glass) but makes no additional commitments about unknown evidence (the dented candlestick). The Colonel Mustard explanation has the narrower latent scope because it makes no additional predictions, whereas the Professor Plum explanation has the broader latent scope because it makes an additional (unverified) prediction.

One possible explanation of this effect is that people prefer explanations that are *representative* of the available evidence (Kahneman & Tversky, 1972; Sussman et al., 2014). According to this account, people reason only on the basis of the observed evidence, which is more similar to the prediction of the narrow latent scope explanation. People might reason that E_1 is the evidence that would be most consistent with hypothesis C_1, but $\{E_1,E_2\}$ would be the evidence most consistent with C_2. Since the observed evidence is most similar or most representative of the evidence that would be generated by C_1, participants infer that C_1 is the more likely explanation. That is, people may discount the relevance of evidence that is unavailable.

Another possibility, however, is that people do see the unavailable evidence as relevant—so relevant, in fact, that they attempt to infer what they would have observed had observation been possible. On the basis of this *inferred evidence*, they may then reason about the relative plausibility of the explanations given their inferences about the unknown effects—that is, inferences about E_2. Inferred evidence can be distinguished from evidence that is gathered from the world: Sometimes we can infer whether an effect is likely to have occurred from base rates or other plausibility metrics even when this inferred knowledge is irrelevant for distinguishing the hypotheses.

Let's consider how this would work in the case of Mustard or Plum. We know that there was broken glass in the billiard room (E_1), which does not help us to decide between Mustard or Plum because this is equally consistent with either explanation. We also know that it would be useful to know whether there was a dent in the candlestick (E_2); if this were observed, then the evidence would favor Plum's guilt, and if it were not observed, then the evidence would favor Mustard's guilt. If we stopped here, we would come to the (correct) conclusion that Mustard and Plum are equally likely culprits. However, according to the inferred evidence account, we do not settle for ignorance, but instead attempt to infer whether E_2 happened: Since candlesticks do not usually have dents (i.e., this effect has a low base rate), one might conjecture that if we found the candlestick, we would be unlikely to see a dent. If we assume that E_2 is false, then we would infer that Mustard is probably guilty—the narrow latent scope explanation (C_1).

This logic, however, is flawed: Only the ratio of the base rates $P(C_1)/P(C_2)$ affects the posterior odds, and $P(E_2)$ has no influence once $P(C_1)/P(C_2)$ is set. Intuitively, this is because two opposing forces balance each other: As $P(E_2)$ becomes increasingly high, it becomes more and more likely that E_2 would be observed, but E_2 also becomes less and less diagnostic evidence for the broad latent scope explanation. For example, if $P(E_2) = 1$, then observing E_2 would be completely non-diagnostic because it would be observed regardless of whether C_1 or C_2 were the correct explanation. In contrast to this normative fact, the inferred evidence account predicts an effect of $P(E_2)$.

Here, we test two different sorts of evidence that people might use for inferring the whether the unknown effect occurred. First, we test whether the *reason* why E_2's value is unknown affects the size of the latent scope bias (Experiment 1). We anticipated that when a reason for our ignorance about E_2 made it relatively easy to imagine observing E_2, then participants would infer that E_2 was more likely, and would therefore be more favorable to the broad latent scope explanation (which predicts E_2). Second, we test whether the base rates of E_1 and E_2 affect the size and direction of the latent scope bias (Experiment 2). In most cases investigated in the literature, E_2 has been a relatively unusual event (such as an abnormal test result or a magical misfortune), and our account is consistent with a narrow latent scope bias in such cases where E_2 is relatively rare. But when E_2 is very common, people might infer that E_2 would be likely to be observed. This could lead to a reversal of the latent scope bias, such that *broad* latent scope explanations are preferred. Finally, we examine beliefs about the relevance of the base rates of C_1, C_2, E_1, and E_2 for determining the best explanation (Experiment 3). We anticipated that $P(E_2)$ would be seen as more relevant than $P(E_1)$ because the base rate of E_2 but not of E_1 would be seen as relevant for inferring evidence. We also predicted that $P(C_2)$ would be seen as more relevant than $P(C_1)$, because C_2 causes E_2 and high base rates of C_2 would therefore be accompanied by high base rates of E_2.

Experiment 1

Other things being equal, possibilities that are more easily imagined are judged more likely to be true (Koehler, 1991). Thus, we expected that we could manipulate the *epistemic distance* to the unknown effect (E_2) by giving different reasons for our ignorance about E_2, and observe downstream consequences for explanatory preferences. According to the inferred evidence account, we would expect a stronger preference for the narrow latent scope cause (C_1) when it is difficult to imagine observing E_2 (i.e., E_2 is more *epistemically distant*) because people would infer that E_2 is unlikely. But when the reason for not knowing about E_2 makes it relatively easy to imagine later finding out that E_2 is true, then we would expect a weaker preference for the narrow latent scope explanation (C_1) because E_2 would be thought more likely to have occurred. This inference that E_2 is relatively likely should push people more toward choosing the explanation (C_2) that would be consistent with observing E_2.

For example, suppose a doctor knew that a patient had symptom E_1 but did not know about symptom E_2, and had to decide between two potential diagnoses: C_1, which causes only E_1, or C_2, which causes both E_1 and E_2 (see Figure 1). A more epistemically proximal reason for the doctor's ignorance about E_2 would be the lab technician's illegible handwriting, making the doctor unable to tell whether a blood test was positive or negative. Because it is easy to imagine later learning that E_2 occurred, this would lead to a more modest narrow latent scope preference (i.e., for C_1). In contrast, a more epistemically distant reason would be that no blood test exists for detecting whether E_2 is true. In that case, it would be more difficult to imagine later observing E_2, leading to a stronger narrow latent scope bias.

Method

Participants We recruited 100 participants from Amazon Mechanical Turk; 19 were excluded from data analysis because they failed more than 30% of a set of check questions.

Procedure Participants completed seven items in each of two scenarios (magical and medical diagnosis). For example, in the medical scenario, participants diagnosed seven patients, each with a different name, set of symptoms (fictitious names for E_1 and E_2), and diagnosis options (fictitious names for C_1 and C_2). Five of the items consisted of an "excerpt from a medical reference book," stating that one disease (C_1) always caused one biochemical to have abnormal levels (E_1), while a second disease (C_2) always caused two biochemicals to have abnormal levels (E_1 and E_2) but that nothing else was known to lead to those abnormal biochemical levels. Participants then read a "note from the lab," confirming result E_1 but giving various reasons why the value of E_2 was unknown. These reasons were (in order of hypothesized epistemic distance): (1) the lab technician's handwriting was illegible; (2) the results were misplaced; (3) the test could not be conducted due to equipment failure; (4) a blood test for that biochemical has not been developed; or (5) that biochemical is too small to be detected in principle. Parallel reasons were given for the magic scenario (i.e., illegible handwriting; misplaced results; wand failure; a detector spell for that trace has not been developed; no spell could ever detect that trace due to special magical properties). Two additional problems were used as check questions, where both E_1 and E_2 were either observed or disconfirmed. Additional check questions were included at the end of every experiment.

For each scenario, a Latin square was used to assign the seven different patients to the seven different problem structures, consisting of the five latent scope problems varying the reason for ignorance, and the two check questions. For each item, participants were asked which explanation they found most satisfying on a scale from 0 ("Definitely [C_1]") to 10 ("Definitely [C_2]"). The order in which participants completed the medical and magic scenarios was counterbalanced, and the order of the seven items was randomized within each scenario.

Results and Discussion

In reporting the results of Experiments 1 and 2, scores were centered so that 0 indicates no preference (the scale midpoint), and oriented so that positive scores (between 0 and 5) indicate a broad latent scope preference and negative scores (between 0 and −5) indicate a narrow latent scope preference. In this experiment, there was no main effect or interaction with scenario (Fs < 1, ps > .80), so we collapsed across this variable.

As shown in Figure 1, participants preferred the narrow latent scope explanations for each reason (ts > 2.4, ps < .02). However, the size of the latent scope effect differed depending on the reason, $F(4,324) = 5.03$, $p = .001$, $\eta_p^2 = .06$. To probe this main effect, we divided the reasons into two groups: those for which it would eventually be *possible* to observe the unknown effect (i.e., illegible handwriting, misplaced results, and equipment failure), and those for which it would be *impossible* to observe the unknown effect (i.e., no diagnostic test and unobservable in principle). Explanatory preference did not significantly

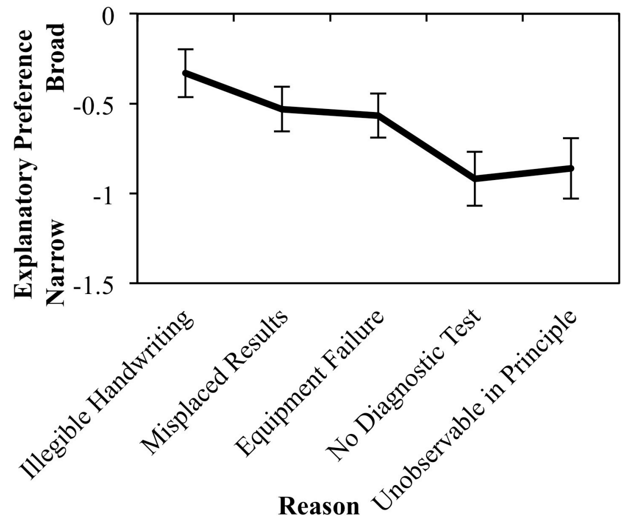

Figure 2: Results of Experiment 1.

differ among the *possible* reasons, ts < 1.8, ps > .075, nor between the two *impossible* reasons, $t(81) = 0.38$, $p = .71$. However, the narrow latent scope bias was significantly smaller for the *possible* reasons ($M = -0.42$, $SD = 0.85$) than for the *impossible* reasons ($M = -0.89$, $SD = 1.27$), $t(81) = 3.75$, $p < .001$, $d = 0.41$.

This sensitivity to epistemic distance is consistent with the inferred evidence account—the idea that people prefer narrow latent scope explanations because they attempt to 'fill in' whether the latent effect (E_2) occurred. When E_2 is unobserved *and unobservable*, it is more difficult to imagine that E_2 is true (see Koehler, 1991), causing an aversion to the broad latent scope explanation (C_2) that predicts E_2. In contrast, when E_2 is unobserved but potentially observable, it is easier to imagine observing E_2 in the future, shifting people relatively more toward the broad latent scope explanation (C_1) that predicts E_2.

However, this result alone may be interpretable in other ways. For example, perhaps participants find diseases with unobservable symptoms to be implausible, making those explanations less satisfying. Similarly, participants might infer that a diagnostic test does not exist for a symptom because the symptom itself does not exist. Although these accounts would be more strained for the more fantastical magic items, which patterned similarly to the medical items, we nonetheless sought converging evidence using a different manipulation in Experiment 2.

Experiments 2A and 2B

A more direct test of the inferred evidence account would be to vary the base rates of the observed and unknown effects—P(E_1) and P(E_2), respectively. For small values of P(E_2), people would infer that E_2 probably did not occur, and therefore would choose the narrow latent scope explanation. This would be consistent with previous demonstrations of latent scope biases (Khemlani et al., 2011, as well as Experiment 1 here) that used stimuli involving effects with low base rates and few plausible alternative causes (such as magical changes and biochemical abnormalities). However, as $P(E_2)$ increases, people would be increasingly likely to infer that E_2 occurred and therefore to choose the broad latent scope explanation; indeed, when $P(E_2) > 50\%$, they would have a *broad* latent scope preference because they would infer that E_2 probably did occur. On the other hand, manipulating $P(E_1)$ would have relatively little effect, because E_1 has already been observed, and therefore the base rate is not needed to infer whether E_1 occurred.

In addition, we specified that $P(C_1) = P(C_2)$, because the posterior odds favoring C_1 over C_2 equal $P(C_1)/P(C_2)$ for deterministic causes. As explained in the introduction, a dependence of explanatory preference on $P(E_1)$ or $P(E_2)$ would be non-normative, and uniquely predicted by the inferred evidence account.

Method

Participants We recruited 50 participants from Amazon Mechanical Turk for Experiment 2A, and another 50 participants for Experiment 2B; 17 participants from Experiment 2A and 14 participants from Experiment 2B were excluded because they failed more than 30% of the check questions. One additional participant from Experiment 2B was excluded due to missing data.

Procedure Participants completed four problems (diagnosing a robot's hardware problem, a spaceship's malfunction, a patient's disease, and a tree's condition), in a random order. For each item, two possible explanations were given: C_1, which always leads to E_1, and C_2, which always leads to E_1 and E_2. For example:

Generator shock always causes reverbitial sonic.
Pulsator damage always causes reverbitial sonic and thermal tear.

The order in which the two causes were listed was randomized for each problem. Participants were told that the base rates of C_1 and C_2 were equal, but the base rates of E_2 (in Experiment 2A) and of E_1 (in Experiment 2B) were varied across problems at 5%, 35%, 65%, and 95% using a Latin square. These probabilities were presented in frequency format (e.g., "A study of 200 spaceships found that 70 of them had thermal tear"), and the denominator of the frequency ratio (e.g., 200 in the previous example) was varied across problems in order to make the manipulation less transparent. In contrast to Experiment 1, where participants were told that no other causes led to E_1 and E_2, this instruction was omitted for Experiment 2 so that participants could infer alternative causes to explain the base rates of E_1 and E_2.

Then, participants were told that E_1 was observed but that we did not know whether E_2 had occurred (e.g., "Spaceship #53 was found to have [E_1]. We do not know whether or not it has [E_2]."). Participants rated how satisfying explanations C_1 and C_2 would be on the same scale used in Experiment 1, except that the left/right order of C_1 and C_2 on the scale was counterbalanced to match the order in which C_1 and C_2 were listed in the problem.

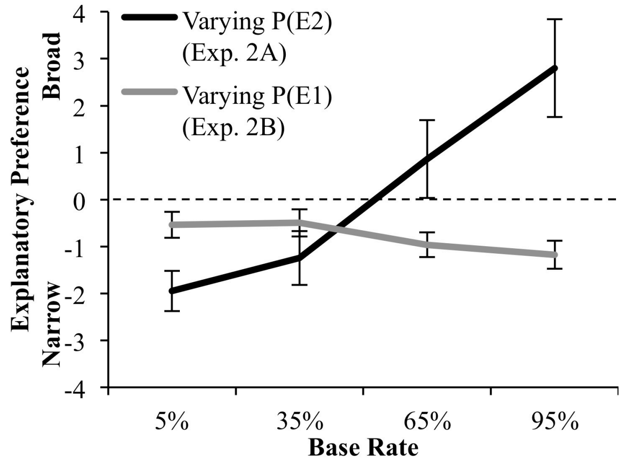

Figure 3: Results of Experiment 2.

Results and Discussion

As shown in Figure 2, manipulating the base rate of E_2 in Experiment 2A had a large effect on explanatory preferences, $F(3,96) = 44.36$, $p < .001$, $\eta_p^2 = .58$, with a strong preference for the narrow latent scope explanation (C_1) when the base rate of E_2 was 5% ($M = -1.95$, $SD = 2.01$), a weaker preference when the base rate was 35% ($M = -1.25$, $SD = 1.87$), a weak preference for the *broad* latent scope explanation (C_2) when the base rate of E_2 was 65% ($M = 0.86$, $SD = 2.07$), and a strong preference for the broad latent scope explanation when the base rate was 95% ($M = 2.80$, $SD = 1.96$). These means all differed from the scale midpoint, ts > 2.3, ps < .03. Thus, the base rate of E_2 not only modulates the size of the latent scope bias, but *reverses* it when the base rate of E_2 is very high.

In contrast, manipulating the base rate of E_1 in Experiment 2B had little effect, $F(3,99) = 2.44$, $p = .069$, $\eta_p^2 = .07$, and preferences in every condition were in the direction of a narrow latent scope preference (see Figure 2). This is consistent with the inferred evidence account, since E_1 was already observed and its base rate cannot be used to infer additional evidence. However, this null effect does show that scaling biases or demand effects are unlikely to account for the results of Experiment 2A, because the manipulation was identical in each experiment, differing only in whether C_1 or C_2 was varied.

Experiment 3

Finally, we tested information-seeking preferences to look for converging evidence. According to the inferred evidence account, when faced with a latent scope explanation, people try to infer whether or not E_2 occurred in the case at hand. Because $P(E_2)$ can be used in making this inference, people should find $P(E_2)$ more relevant than $P(E_1)$. To test this possibility, participants were told about structurally similar situations to Experiments 1 and 2 (see Figure 1), where they knew about one effect (E_1) but not another (E_2), and were deciding between a narrow latent scope explanation (C_1, which would only account for the observed E_1) and a broad latent scope explanation (C_2, which would account for both the observed E_1 and the unknown E_2). Participants were asked to rank the base rates of each cause and effect in terms of "how useful" they would be for determining the best explanation—that is, to rank the relevance of P(E_1), P(E_2), P(C_1), and P(C_2).

We anticipated that P(E_2) would be seen as more relevant for determining the best explanation compared to P(E_1), since this information may be seen as relevant to determining whether E_2 occurred in the case at hand. In addition, we anticipated that P(C_2) would be seen as more diagnostic than P(C_1). This is because P(C_2) is informative about the base rates of both E_2 and of E_1, whereas C_1 is informative about the base rate only of E_1. That is, if C_2 is very prevalent, then both E_1 and E_2 must also be very prevalent because C_2 causes both effects. But if C_1 is very prevalent, this implies only that E_1 must be very prevalent but is not informative about the prevalence of E_2. Since we anticipate that P(E_2) will be seen as more relevant than P(E_1), we would anticipate that likewise P(C_2) will be seen as more relevant than P(C_1). Both of these predictions stand in contrast to normative responding, since it is the ratio [P(C_1)/P(C_2)] that is equal to the posterior odds favoring C_1 over C_2.

Method

Participants We recruited 200 participants from Amazon Mechanical Turk; 18 were excluded from analysis because they failed more than 30% of the check questions, and 24 were excluded due to missing data.

Procedure Participants completed four problems in a random order, similar to those used in Experiment 2, but modified to elicit rankings of how useful each base rate would be for deciding between the explanations.

For example, for the robot item, participants read the same causal information as in Experiments 2 (with the causes listed in a random order), and were told that "Spaceship #53 was found to have [E_1]. We do not know whether or not it has [E_2]" and that "A study of 200 other spaceships was recently conducted, in which researchers collected measurements of several properties." They then ranked each base rate in terms of how useful it "would be for determining what malfunction Spaceship #53 has, where '1' is the most useful and '4' is the least useful." The base rates were listed in a random order and worded in the format, "How many out of the 200 spaceships had [*X*]," where [*X*] was replaced with C_1, C_2, E_1, or E_2.

Results and Discussion

The proportion of times that participants ranked C_1, C_2, E_1, and E_2 in each position are shown in Table 1. In absolute terms, the base rate of E_2 was ranked first more frequently (32%) than any other base rate, and the base rate of E_1 was ranked last more frequently (38%) than any other base rate. Thus, our prediction that P(E_2) would be seen as more relevant than P(E_1) has qualitative support.

Table 1: Results of Experiment 3.

	P(C_1)	**P(C_2)**	**P(E_1)**	**P(E_2)**
First ranked	15%	29%	25%	32%
Second ranked	29%	27%	19%	24%
Third ranked	33%	28%	19%	21%
Fourth ranked	23%	16%	38%	23%

Note: Entries indicate the total proportion of times each base rate was ranked in each position across the four problems completed by each participant.

In addition, P(C_2) was ranked first much more frequently than P(C_1) (29% vs. 15%) and was ranked last less frequently (16% vs. 23%). Again, this is qualitatively consistent with our prediction that P(C_2) would be seen as more relevant than P(C_1).

Statistical analyses confirmed these patterns. We calculated the mean rank of C_1, C_2, E_1, and E_2 across all four items for each participant, with '1' representing the first ranked choice and '4' representing the last ranked choice for each item. The mean rank for E_2 (M = 2.36, SD = 0.91) was higher than for E_1 (M = 2.69, SD = 0.99), $t(157) = 2.55$, $p = .012$, $d = 0.20$ and the mean rank for C_2 (M = 2.32, SD = 0.81) was higher than for C_1 (M = 2.63, SD = 0.70), $t(157) = 3.43$, $p < .001$, $d = 0.27$.

Taken together, these results underscore Experiment 2, where the base rates relevant to inferences about the unknown effect (i.e., E_2) were used more strongly than base rates that were not (E_1). In Experiment 3, these base rates were also sought out more readily when determining the best explanation. This shows that people actively seek the information needed to infer the data thought to be necessary for inferring evidence when reasoning about latent scope explanations. In addition, Experiment 3 confirmed an additional, novel prediction of the inferred evidence account—that the base rate of the broad latent scope cause (C_2) would be seen as more relevant than the base rate of the narrow latent scope cause (C_1). We made this prediction because C_2 (but not C_1) causes E_2, meaning that C_2's base rate is relevant to estimating P(E_2) but C_1's base rate is not. This overall response pattern—ranking P(C_1) and P(C_2) differentially and P(E_2) highest most often—stands in stark contrast to normative responding, since only the ratio of P(C_1) to P(C_2) is relevant to assessing the probability of each explanation.

General Discussion

Under a wide variety of circumstances, people prefer explanations that do not make predictions of unknown truth—that is, they prefer explanations with *narrow latent scope* (Khemlani et al., 2011; Sussman et al., 2014). Here, we tested four predictions of the *inferred evidence account*—that this bias results because people try to infer whether or not the latent effects occurred. First, the size of the latent scope bias depended on *epistemic distance*: When it was relatively difficult to imagine the effect being observed, people had a greater preference for narrow latent scope explanations (Experiment 1). Second, manipulating the base rate of the unknown effect led to large differences in explanatory preferences, with a strong narrow latent scope preference when the unknown effect had a low base rate and a strong *broad* latent scope preference when the unknown effect had a high base rate (Experiment 2A); in contrast, manipulating the base rate of the observed effect had little effect (Experiment 2B). Finally, in deciding what information to use, people found the base rate of the latent effect more relevant than the base rate of the observed effect, and the base rate of the broad latent scope cause more relevant than the base rate of the narrow latent scope cause (Experiment 3).

These results are all predicted by the inferred evidence account, but are difficult to account for on other accounts of the latent scope bias, such as representativeness (Kahneman & Tversky, 1972; Sussman et al., 2014). If people prefer narrow latent scope explanations simply because the predictions of narrow latent scope explanations are more similar to the *actually* observed evidence, then the manipulations we used in Experiments 1 and 2 should have had little effect. The reason for our ignorance seems irrelevant to judgments of the similarity of the observed evidence to the scope of each explanation, yet people robustly used these reasons in Experiment 1. Most strikingly, in Experiment 2, we found a preference for the explanation with the more *dissimilar* scope (the broader latent scope) when the base rate of the unknown effect was high. Our inferred evidence account predicted this result, but it is otherwise difficult to explain.

These results add to the growing literature on explanatory preferences (Lombrozo, 2007; Read & Marcus-Newhall, 1993). We often form our beliefs by engaging in *inference to the best explanation* (Lipton, 2004)—generating multiple candidate explanations, evaluating these candidates, and adopting the best of these competing explanations as a belief. We have shown here that latent scope explanations lead to a process in which additional evidence is *inferred* rather than *gathered*, which can lead either to a narrow or a broad latent scope bias depending on the epistemic distance, base rates, and perhaps other features,affecting how readily the additional evidence is inferred. Since relatively little is known about explanatory preferences under uncertainty, future research might look for further applications of inferred evidence.

Indeed, this strategy may be used more widely than explanatory reasoning. For example, inferred evidence may be used in category-based reasoning: Sussman et al. (2014) showed latent scope effects in categorization, which could be modulated by the manipulations we used here. Evidence for a related strategy can be found in studies of feature inferences from uncertain categorizations (e.g., Murphy & Ross, 1994). When asked to infer the value of a feature for an individual belonging to an unknown category, people attempt to infer the category membership of the individual, and respond according to the properties of the most likely category rather than integrating the properties in a weighted fashion across all possible category assignments. Our participants' strategy was in some ways reverse of this: Whereas Murphy and Ross's (1994) participants gave the most likely feature based on the inferred category membership, our participants gave the most likely cause (category membership) based on the inferred value of the unknown effect (feature).

Conclusion

Both in science and in everyday life, we must weigh explanations consistent with untested predictions, and we often cannot verify more than a small subset of these predictions. In this sense, *most* explanations are latent scope explanations. Here, we showed that rather than going out into the world to look for these signature predictions of competing explanations, people sometimes attempt to infer what they would observe if they did look. Although it may often be possible to make educated guesses from background knowledge, the present results show that people will also use irrelevant information in the service of inferring evidence: We do not settle for ignorance when apparent truth is within reach.

Acknowledgments

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