

Causal Attribution as a Search for Underlying Mechanisms: An Explanation of the Conjunction Fallacy and the Discounting Principle

WOO-KYOUNG AHN

University of Michigan

AND

JEREMY BAIENSON

Northwestern University

We propose that causal attribution involves searching for underlying mechanism information (i.e., the processes underlying the relationship between the cause and the effect). This processing account can explain both the conjunction effect (i.e., conjunctive explanations being rated more probable than their components) and the discounting effect (i.e., the effect of one cause being discounted when another cause is already known to be true). When two explanations cohere with respect to a single mechanism, they would be judged to be more likely than a single explanation which partly supports that mechanism. When the two explanations imply two separate mechanisms, one would be discounted. In Experiment 1, both effects occurred with mechanism-based explanations but not with covariation-based explanations in which the cause-effect relationship was phrased in terms of statistical covariations without referring to mechanisms. In Experiments 2 and 3, the amount of the discounting and conjunction effects varied depending on the relationships between specific mechanisms in the two given explanations. We discuss why the current results pose difficulties for previous attribution models. © 1996 Academic Press, Inc.

Judging causality when there are many possible explanations is a very common, yet poorly understood cognitive process. Our focus is on the processes involved in reasoning with multiple causes, especially on what is

We thank Brian Gordon, Keith Holyoak, Charles Kalish, Frances Kuo, Lance Rips, Brian Ross, Edward Smith, Paul Thagard, and two anonymous reviewers for their helpful comments on earlier drafts of the paper; Douglas Medin, Susan Gelman, and Charles Kalish for their help on developing materials used for Experiment 1; Marvin Chun for his help on developing materials used for Experiment 3; Judy Florian and Mary Lassaline for their helpful discussion of the results; and Brian Gordon, Kristin Sweitzer, and Brett Simons for collecting data. Experiment 1 was presented at the Sixteenth Annual Meeting of the Cognitive Science Society. Address correspondence and reprint requests to Woo-kyoung Ahn, Department of Psychology, Yale University, P.O. Box 208205, New Haven, CT 06520-8205.

known as the conjunction fallacy and the discounting principle. In their description of the conjunction fallacy, Leddo, Abelson, and Gross (1984) showed that people commit the fallacy of rating the probability of conjunctive explanations as more likely than the probabilities of their constituents. In contrast, according to the discounting principle proposed by Kelley (1972), people tend to discount the effect of one cause when another cause is already known to be true. How can both effects occur? Can a single cognitive process explain both phenomena? More generally speaking, given their knowledge of the world, how do people reason with multiple causes? When do people discount an alternative cause and when do they incorporate it into their existing hypothesis? The following sections will provide background for these phenomena and will discuss how the current prevailing attribution theories attempt to explain them.

THE CONJUNCTION EFFECT AND DISCOUNTING PRINCIPLE

The Conjunction Effect

Tversky and Kahneman (1983) demonstrated that when lay persons were asked to judge the probability of an event's occurrence, their judgments violated the normative rules of probabilities. In particular, the probability of an event was judged to be less likely than the probability of the event along with some other event. Leddo et al. (1984) found a similar phenomenon in causal attribution: People rated the probability of single explanations as less likely than the probabilities of conjunctive explanations. For example, subjects received a story about John's decision to attend Dartmouth. They were asked to rate the likelihood of various candidate explanations including single explanations (e.g., "John wanted to attend a prestigious college," "Dartmouth offered a good course of study for John's major") and conjunctive explanations (e.g., "John wanted to attend a prestigious college and Dartmouth offered a good course of study for John's major"). Normatively speaking, the probability that two assertions are both true can never exceed the probability that either one alone is true. However, subjects' ratings indicated that two typical reasons were judged as more likely than one typical reason.

Discounting Principle

While the research concerning the conjunction effect showed that subjects preferred multiple explanations, Kelley (1972) proposed that there is a tendency to discount all other causes when there is support that a given cause is already known to be responsible for a given event. Suppose Mary took John's radio and John did not know why she took it. Possibly, she could have taken it because her radio was broken and/or because she was mad at John. When John finds out that it was because her radio was broken, he would, according to the discounting principle, discount the possibility that it was because Mary was mad at him. Although this principle is intuitively appealing and has become widely accepted as a non-controversial principle

in social psychology, there have been very few direct tests of the principle (Hansen & Hall, 1985; but see Morris & Smith, in preparation). Recently, some researchers (e.g., Braun & Wicklund, 1989; McClure, Lalljee, & Jaspars, 1991) have found various conditions in which the discounting principle fails, but few processing accounts of the phenomenon have been offered.

Relationship between Conjunctive Effect and Discounting Principle

In their explanations of these two effects, most researchers have treated them as mutually exclusive or even paradoxical (e.g., Einhorn & Hogarth, 1986; Leddo et al., 1984; Zuckerman, Eghrari, & Lambrecht, 1986). The two effects have been considered paradoxical because the discounting principle implies that when two causes for an effect are available, one cause will be singly preferred, whereas the conjunction effect implies that explanations with two causes are better than explanations with one. Einhorn and Hogarth (1986), for example, stated that discounting involves a process of updating one's beliefs on the basis of negative, alternative explanations, while conjunction fallacies occur when the sufficiency of an explanation can be increased by adding more reasons. Because one reason cannot be perceived as both an alternative and an additive reason, their discussion implies that the two phenomena cannot happen simultaneously. We do not necessarily believe that the two phenomena are exclusive to each other for the following reasons.

Differences in tasks. It is important to note that conjunction and discounting tasks require the subjects to perform very different judgments. The conjunction task presents an effect and then asks the subjects whether the candidate cause(s) presented could have been the true cause of the effect. The discounting task asks the subjects to judge the importance of a candidate cause, given that there exists another cause which is at least partially responsible for the effect. Thus, the conjunctive judgment is carried out in a state of relative ignorance, whereas in the discounting task, the subjects already have a plausible cause-and-effect relationship at their disposal. Considering this task difference, the two effects seem neither paradoxical nor exclusive.

Normative issues. The conjunction and discounting effects might also look contradictory in terms of normative issues. Whereas preferring a conjunctive explanation over a single explanation with respect to likelihood is nonnormative, the discounting principle can be explained by a normative model of causal attribution such as Cheng and Novick's probabilistic contrast model (1991), as will be discussed later.

But some people have also discussed reasons why conjunction fallacies are not necessarily nonnormative or irrational. For example, Gigerenzer (1991) has stated that even within probability theories there is no consensus on what probabilities mean. According to him, the subjects in conjunction tasks could have interpreted probability judgment tasks as confidence rating tasks, in which case the conjunction "fallacy" is not necessarily nonnormative.

The other alternative interpretation of the conjunction fallacy is that subjects

could have misinterpreted the instructions as judging probabilities of an event given possible causes. The latter interpretation (i.e., $P(E|A) < P(E|A\&B)$) does not necessarily lead to violations of probability theories, even when conjunctive reasons are judged to be greater than single reasons. Zuckerman and his colleagues considered the possibility of instructional misinterpretation as an explanation for the conjunction fallacy (Zuckerman, Eghrari, & Lambrecht, 1986). They suggested that people assess the probability of an event in one of two ways: by "assessing the probability that certain inferences can be drawn from the event (inference set) or by assessing the probability that some explanation can cause the event (explanation set) (p. 748)." In their experiments, Zuckerman et al. (1986) found that, compared to the inference set, the explanation set led to more conjunction effects, suggesting instructional misinterpretation as a possible reason for the conjunction fallacy. Therefore, the conjunction and the discounting effects do not seem paradoxical with respect to a normative criterion.

Although the conjunction fallacy has been traditionally investigated from the perspective of rationality, the current study does not primarily concern itself with whether or not people behave irrationally. Instead, we focus on conditions under which one reason is preferred over two and vice versa. The previous arguments seem to show that the conjunction fallacy is not necessarily irrational. Therefore, the discounting effect and the conjunction fallacy might not be normatively conflicting processes. To explicate this point, we will call the conjunction fallacy the conjunction effect henceforth.

Simultaneous occurrence of the effects. Although the two effects might not be exclusive to each other, as has been discussed so far, few people have actually attempted to explain both phenomena within a single framework. It is possible that the two effects might result from two different processes or strategies, depending on the tasks or the experimental instructions. Another possibility is that the conjunction effect occurs with only certain types of materials whereas the discounting effect occurs with other types of materials. By using the same materials for the two tasks but with different tasks, Morris and Smith (in preparation) found that the two effects could simultaneously occur. In this paper we argue that the two phenomena are based on a single process and they can both occur with the same stimulus materials under certain situations. Before presenting our own view, the following section briefly reviews previous causal attribution theories in order to clarify our approach to this issue.

VARIOUS APPROACHES TO CAUSAL ATTRIBUTION

Covariation Approach

Traditionally, the principle of covariation has been accepted as the fundamental, normative principle underlying causal attribution. This principle, based on Mill's method of difference, states that "the effect is attributed to that condition which is present when the effect is present and which is absent

when the effect is absent” (Kelley, 1967, p. 194). Suppose one wants to find out why Kim had a traffic accident last night. The covariation approach will start out with possible candidate factors responsible for the accident, such as “Kim” and “last night.” One would examine the covariation between these factors and the event. For instance, if other people did not have accidents at that time and Kim tends to have car accidents on other occasions, the event is attributed to something special about Kim rather than last night.

While this framework has been dominant in attribution theory (e.g., Cheng & Novick, 1990, 1991, 1992; Hewstone & Jaspars, 1987; Kelley, 1967, 1973), it has also been criticized as having “distorted our ways of thinking about how attributions are made” (Leddo et al., 1984, p. 933). For example, covariation models have been criticized because they do not answer questions concerning *how* a factor causes an event (Ahn, Kalish, Medin, & Gelman, 1995). Rather, they simply assign a particular factor (or combination of factors) as the cause of the event (Hewstone, 1989). There is also a great deal of ambiguity in the covariation literature concerning at what level of detail a factor indicated as a cause is to be postulated (e.g., Kim, her brain, or a given pattern of evoked potentials as the cause of the event). In addition, covariation models allow for spurious correlations to be assigned as the cause of events.

A criticism was also made concerning methodology used in previous experiments supporting these models. Covariation models successfully predicted subjects’ causal attribution given a forced-choice task with only covariational explanations as the choice options (Cheng & Novick, 1990; McArthur, 1972). However, this result does not necessarily mean that people would spontaneously seek out covariation information in more open-ended tasks (Ahn et al., 1995; Lalljee, Lamb, Furnham, & Jaspars, 1984). In addition, the covariation approach does not specify factors which are sufficient for determining causality because correlation does not necessarily imply causation (e.g., Hewstone, 1989; Hilton, 1988).

Mechanism Approach

Recently, Ahn et al. (1995) proposed an alternative approach to causal attribution: When seeking the cause of an event, people primarily attempt to discover the *processes* or *mechanisms* underlying the relationship between the cause and the effect. Suppose Kim had a traffic accident last night. In explaining this event, the mechanism approach argues that people would not be satisfied with explanations described using relationships between information at the same general level used for the target events (e.g., something special about Kim, the accident, or the last night). Instead, causal explanations would go beyond this level in such a way that they involve a new set of theoretical entities, theories, or processes which were not present in the event description. We refer to these theoretical entities as “mechanisms.” Roughly speaking, mechanism information specifies the way in which something works or is constructed. The mechanism approach argues that the primary process

in answering “why” questions is to specify “how” the event occurred rather than “what” is correlated with the event. In finding out how something occurred, people rely on their previous background knowledge about various causal mechanisms. Therefore, the mechanism approach contrasts with the more traditional covariation approach in two aspects: by involving different types of information-seeking (asking “how” questions as opposed to “what” questions) and by requiring the use of background information. Each will be discussed in detail.

Causal reasoning processes. According to the mechanism approach, the causal attribution process is equivalent to using mechanism information to create a coherent story of how things come about. That is, causal reasoning is like reasoning with mental models in qualitative reasoning (Gentner & Stevens, 1983). It has been shown that when reasoning about physical systems, people create a model of the situation, which includes the essential components and their causal relations in the systems (Forbus & Gentner, 1986). By mentally manipulating the model, they simulate the real-world conditions and determine the likelihood that the model is an accurate description of the actual situation. For example, our concepts of the behavior of liquids would allow us to predict what would happen if we spill coffee on a roof. Although most of us have never done it before, we know that it will flow over the edge, drop to the floor, and then soak through ground. In making this prediction, we imagine liquids moving through time from one state to another. We argue that causal reasoning proceeds in this manner. We first select a causal candidate and then build up a story where one state leads to another, starting from the causal candidate and ending in the stage where the final event occurs. The more likely it is that the causal candidate would result in the effect, that is, the more plausible the constructed story is, the more likely we would believe the candidate is the actual cause of the effect.¹

A very similar notion can be found in a mental simulation heuristic proposed by Kahneman and his colleagues (Kahneman & Miller, 1986; Kahneman & Tversky, 1982). Kahneman and Tversky (1982) have argued that “the ease with which the simulation of a system reaches a particular state is eventually used to judge the propensity of the (real) system to produce that state (p. 201–202).” Among possible mental simulations, Wells and Gavanski (1989) focused on counterfactual simulations where the availability of alterna-

¹ Johnson-Laird (1983) also had a similar approach in deductive reasoning: People create a mental model using tokens for each premise in deductive syllogism in judging validity of the conclusion. The difficulty in syllogistic reasoning is related to the number and difficulty of mental models one has to create for each syllogism. Johnson-Laird’s notion of mental models, however, seems more appropriate for *static* representation of situations, such as in judgment of deductive validity or in understanding cognitive maps of spatial relationships (e.g., Franklin & Tversky, 1990). Therefore, this notion of mental models seems less relevant to our notion of story construction or construction of mental models in causal reasoning which involves temporal, dynamic sequences.

tives played a central role in judging causality. For example, subjects were asked to judge why a woman died after eating a meal ordered by her boss. If the subjects discovered that the boss considered ordering another meal without an ingredient to which the woman was allergic, people were more likely to attribute the woman's death to the boss's decision. Wells and Gavan-ski (1989) concluded that the ability to mentally simulate counterfactual scenarios played a central role in judging causality.

The mechanism approach is a hypothesis that is being elaborated through a series of studies including the current one. At this point, we are not committed to any fixed representational format of stories that are constructed by explainers. Our use of a "story" is different from traditional notions of a story grammar with fixed slots, such as theme, settings, resolution, etc. (e.g., Mandler & Johnson, 1977; Rumelhart, 1975; Thorndyke, 1977). Specifying the structure of stories seems more controversial than was initially proposed (Robinson & Hawpe, 1986). As Stein and Policastro (1984) concluded, no single structural definition can cover the wide range of compositions accepted as stories.

The sense of a "story" we use in our approach is close to the one used in Pennington and Hastie's studies on jury decision-making. Although not explicitly referring to the role of mechanism information, a number of studies by Pennington and Hastie (1986, 1988, 1992) showed the importance of story construction in decision-making. They found that in jurors' decision processes, the trial evidence was represented in a story form and that particular explanatory summaries of the story affected their judgments of the proper verdict for the case. For example, if evidence was presented in such an order as to allow jurors to construct a coherent story of how a suspect would have committed the crime, jurors were more likely to believe that the suspect was guilty. These results suggest that people have a strong tendency to construct a coherent story given evidence or multiple explanations and the content of the constructed story affects the causal attribution processes.

Use of background knowledge. The mechanism approach also contrasts with the traditional covariation approach in that the former requires heavy reliance on existing background knowledge. In identifying causes, people have to make inferences using background knowledge because the actual processes of how causal power transfers are not observable (see Hume, 1978/1739). There seem to be at least three ways of utilizing existing mechanism information: (a) instantiating familiar prepackaged mechanism information, (b) combining pieces of mechanism information, and/or (c) relying on an expectation that there exists a mechanism presumably known by an expert. Each will be further discussed below.

First, the explainer might already have pre-stored schemas of mechanisms and he/she simply applies or instantiates this background knowledge in order to explain a common or familiar event. This process is very similar to a knowledge-structure approach (Lalljee & Abelson, 1983; Read, 1987) in which general knowledge structures (e.g., scripts, plans, goals, and themes' proposed by Schank & Abelson, 1977) are used to construct causal scenarios.

Second, unlike the knowledge-structure view, we would like to further propose that the complete sequence of mechanisms does not have to be always known prior to the explanation. It is unlikely that people have stored explanations for every possible event. They can be flexibly constructed to apply to novel situations, similar to mental models in deductive reasoning (Johnson-Laird, 1983) or situational models in text comprehension (Kintsch & van Dijk, 1978). Suppose one finds that people wearing red socks tend to have more traffic accidents than other people do. It is unlikely that one has existing schemas about why and how these two factors are associated. Storing every conceivable causal combination would be an inefficient and computationally impossible processes. But by using several pieces of background knowledge or analogies, one might construct a plausible story on the spot based on a hypothetical set of mechanisms, such as people wearing red socks tend to be hot-tempered or deviant, and therefore have more traffic accidents.

Finally, the detailed mechanism information may not need to be explicitly specified as long as there exists a "mechanism place-holder," an expectation that there is some more fundamental level underlying the relationship between cause and effect (Ahn et al., 1995). Several researchers (Gelman & Wellman, 1991; Medin & Ortony, 1989) have made a similar proposal regarding conceptual representation. This notion, called psychological essentialism, asserts that people categorize objects and events in the world as if all the members of a category have an underlying essence. This function provides a conceptual unity despite the variation among the individual members of the class. According to this view, people act as if all members of the same category have a common essence, even when this unifying essence is unknown.

In brief, we believe that the major differences between the mechanism approach and the covariation approach lie in the types of information necessary for causal attributions (i.e., information about underlying processes vs covariation information) and the amount of background information necessary for causal reasoning.

Relationship between the Mechanism Approach and the Covariation Approach

Still, the two approaches can be viewed as compatible (Cheng, 1993) or, even more extremely, the same. In this section, we present several ways of trivializing the differences between the two approaches. Then, we clarify the differences and discuss why the current study on the conjunction and the discounting effects is one way of illuminating the crucial differences.

Is mechanism information qualitatively different from covariation information? One might even argue that, after all, a mechanism is a collection of more detailed covariation information. For example, a mechanism-based explanation, "Kim had a traffic accident because she was drunk," might seem as if it were based on mechanism information, which, in fact, is covariation information on how drunkenness covaries with traffic accidents. Therefore, according to this interpretation, causal reasoning based on mechanism infor-

mation might eventually be reduced to causal reasoning based on complex covariation information. In that sense, the mechanism approach can be seen as essentially the same as the covariation approach. It is important, however, to note that the mechanism approach concerns psychological aspects of causal reasoning rather than a metaphysical account of normative causality. The more psychologically appropriate question is, do people *think* of mechanism information as simply a collection of complex covariation information or is there a qualitative difference between the *perceived* mechanism information and a logically equivalent set of complex covariation information?

This question is extremely difficult to answer because mechanism information is perfectly confounded with covariation information. That is, whenever there exists a mechanism which links A and B, there is covariation between A and B. As a result, when people rely on covariation in identifying causes, we do not know whether it is the covariation information per se or the underlying mechanism information that was primarily used in inferring the causal relationship. One way of addressing this issue is to demonstrate that the mechanism information contains unique content not included in the covariation information. In Experiment 4 of Ahn et al. (1995), the actual covariation value of each piece of mechanism information was empirically measured. Then the subjects were provided with various combinations of mechanism information and/or its corresponding covariation statements as background information for the same event. The results showed that mechanism information was not redundant to covariation information and furthermore, the regression analysis indicated that the mechanism information was almost twice as influential as covariation information in isolating a cause of the event.

Using a similar logic, the current study focuses on reasoning with multiple causes (i.e., the conjunction and the discounting effects) and attempts to show that the two types of information are treated differently. The idea is that if the mechanism statements serve to convey only covariation information, then both types of statements will lead to similar phenomena. No one has yet shown conjunction and discounting effects using purely covariational explanations. As will become clear in the next section, we predict that conjunction and discounting effects will occur only with mechanism-based explanations and not with covariation-based explanations, even when the covariation information conveyed by the two types of explanations is equated.

Insufficiency of covariation information. Many researchers who support the covariation approach have explicitly stated that covariation is not sufficient in order to make causal inferences, although it is necessary (e.g., Cheng & Novick, 1992). Covariation cannot be equated with causality because causal relationships are only a subset of covariation. In addition, there should be constraints in selecting candidates for covariation analyses (Cheng, 1993). For example, in finding out why Kim had a traffic accident, we cannot compute all possible covariations including the one between the traffic accident and the flapping of an orange butterfly in Japan. Background knowledge certainly plays an important role in limiting or generating causal candidates. The contri-

bution of the mechanism approach is to further explicate this point and to show in what sense covariation information is insufficient.

Ahn et al. (1995) have shown that in information-seeking tasks, analysis of covariation information does not play a central role. The mechanism approach argues that when attempting to identify causes, people hypothesize about certain mechanisms based on their background knowledge. Then, they seek out information concerning whether or not the necessary preconditions for those mechanisms were satisfied by the target event. In explaining Kim's traffic accident, for example, people would ask such questions as "Was Kim drunk?" or "Was the road icy?" rather than "Did other people also have traffic accidents last night?" or "Does Kim usually have traffic accidents?" The subjects in Ahn et al.'s experiments were instructed to ask questions that they would like answered to aid them in explaining given events. The majority of the subjects' explanations referred to some mechanism responsible for the occurrence of the effect which was not present in the target event statements. There was a strong bias not to seek out information about patterns of covariation, and a tendency to focus on information which illustrated whether or not the preconditions for causal mechanisms were satisfied by the target event.

One might argue that the covariation approach is an output model rather than a process model. According to this interpretation, people act as if they compute covariation between presence/absence of a causal candidate and presence/absence of an event but they are not actually computing these probabilities. The product of people's causal reasoning is relatively well modeled by the covariation approach, as events linked by a causal mechanism entail a covariational relation. In this respect, the results from the information-seeking tasks do not undermine the covariation approach, because the previous tasks measured the intermediate processes of causal reasoning rather than the product of it. But the tasks used in the current study measure the output of causal reasoning; we investigate whether or not two well-known phenomena in causal reasoning, the conjunction and discounting effects, can occur as an output when only covariation information is given. If they do not, then this manipulation will again show covariation information to be insufficient. In the next section, we provide our account of the two effects and, additionally, describe why the covariation approach makes different predictions than does the mechanism approach.

ACCOUNT OF THE CONJUNCTION AND THE DISCOUNTING EFFECTS

The Conjunction Effect

We propose that the causal attribution process is equivalent to using information about mechanisms relating the cause(s) and the effect in order to create a coherent story. Now, consider a conjunctive explanation, such as, "Kim is nearsighted and there was a severe storm last night." These two explanations can be easily combined into a coherent model based on a single

mechanism. Most people can easily imagine that when poor vision is combined with a severe storm condition, a traffic accident is likely to occur due to the driver's inability to control the car appropriately. Compared to the single explanation, the conjunctive explanation fills in slots of the candidate mechanism with values that are more likely to lead to the observed event. Therefore, people would prefer the conjunctive explanations as the cause of the traffic accident to a single explanation.

Notice that our approach argues that the conjunction effect is not a nonnormative response. As a philosopher, Kim (1971) has argued, there are two senses of the word "and." When we say Arnold *and* Maria went to a Mexican restaurant, for example, we mean Arnold went to a Mexican restaurant and Maria went to a Mexican restaurant. When a conjunctive event is connected by this interpretation of "and," then judging the conjunctive event as more likely than its constituents is certainly a nonnormative response. However, there is the second sense of "and" as in "Arnold *and* Maria weigh 423 pounds," which implies that the two people together weigh 423 pounds. In this second interpretation of the conjunctive connective, it is quite rational to say that the conjunctive event is more likely than a single event: The probability of two people together weighing 423 pounds would be much higher than the probability of one person weighing 423 pounds and this would be a rational judgment. This second sense of "and" is the interpretation we propose subjects are making in judging the likelihood of conjunctive explanations. That is, Kim's nearsightedness and the bad weather condition together contribute to the occurrence of a traffic accident rather than Kim's nearsightedness led to one traffic accident and then the bad weather condition separately led to another traffic accident.

The mechanism approach's account for the conjunction effect also specifies conditions in which the effect will *not* occur. First, if people fail to combine multiple causes into a single mechanism-based story, conjunctive explanations will not be judged as better than a single explanation. Consider an event, "Charles had to leave school." If the conjunctive explanation is, "It is because he was 21 years old and the United Nations was unable to resolve the problems in the Middle East," then most people would have difficulty finding a mechanism or constructing a story consistent with the two causes, although these causes do not necessarily conflict. In this case, a single cause (e.g., "Charles was 21 years old") would more effectively construct a coherent mechanism-based story (e.g., "He is graduating and people leave school when they graduate") than would two causes. Consequently, the conjunctive explanation would usually receive a lower rating than, or at most, the same rating as its constituents.

Suppose, however, that people were provided with the right context to facilitate construction of a coherent story from two independent causes. In the above example, the context of "being drafted" might serve this purpose. Given this cue, people can easily come up with a story which relates both causes. Charles is old enough to be drafted in the Middle East and is leaving

school for that reason. Thus, when multiple reasons in the right context point to a reasonable, single mechanism, people will rate the conjunction as higher than when the two reasons are independent of each other in terms of causal mechanisms.

Secondly, the conjunction effect will not occur when the two explanations do not help people create a mechanism-based story of causal processes. When two explanations are both covariation-based (e.g., “Kim is more likely to have traffic accidents than other people are, and traffic accidents were more likely to occur last night than on other nights”), it is difficult to construe a coherent mechanism, resulting in no advantage of two explanations over a single explanation. Similarly, when one explanation is mechanism-based (e.g., “Kim who is nearsighted tends not to wear her glasses”) and the additional explanation is covariation-based (e.g., “Traffic accidents were more likely to occur last night than on other nights”), the additional explanation does not increase the rating of the conjunction because it does not provide further evidence for the mechanism suggested by the first explanation. In brief, the mechanism approach predicts that the determinant of the conjunction effect is whether or not the two explanations suggest a single mechanism by which the occurrence of the event becomes more likely than does a mechanism implied by a single explanation.

The Discounting Effect

How does the mechanism approach explain the discounting effect? We need to reconsider the small but crucial difference between the conjunction and the discounting tasks. In the discounting task, one cause is given to be true and another cause is given to be judged. When receiving one cause as the fact, people construct a mechanism-based story. When they receive another explanation to be judged, people examine how well the second cause fits with the initial story. If they conflict, the second cause would be judged to be less likely.

In our previous example of Kim’s traffic accident, suppose that the explanation, “Kim is nearsighted,” is given to be true. Then, people would construct a story in which Kim’s nearsightedness is severe enough to cause a traffic accident even under a normal weather condition. When the additional cause, “There was a severe storm,” is presented to be judged as a cause, it would not coincide with the initial simulation of the event where Kim’s nearsightedness was sufficient to lead to a traffic accident under a normal weather condition. Therefore, the additional cause is discounted or judged to be less likely than would be if it were presented without the preceding cause.

As in the conjunction effect, the degree of the discounting effect will depend on how the two causes interact and how the context biases the initial story. In our previous example about the context effect (e.g., “Charles had to leave school”), suppose one was told that it was because he was 21 years old. Then the explainer would infer the most available mechanism (e.g., Charles is graduating from a college). Suppose the person is later asked to

judge the likelihood of another cause, "The United Nations was unable to resolve the problems in the Middle East." This additional cause would be discounted because it is not coherent with the initial story.

As with the conjunction effect, however, the context can change the initial story. For example, suppose the "draft" context was initially provided for "Charles had to leave school because he was 21 years old." Then the initial story would be about Charles, who is old enough, getting drafted. The additional cause (e.g., the UN being unable to resolve the problems in the Middle East) actually serves as more evidence for the initial story. Therefore, the second cause is not necessarily discounted, as long as it receives support from the constructed context.

Again, the discounting effect will not occur when the two explanations do not refer to any specific causal mechanisms and, as a result, there is no conflict between the two explanations at the level of mechanism information. For example, suppose one knows that Kim had a traffic accident and it was because Kim was more likely to have a traffic accident than were others. There are many possible underlying mechanisms for this kind of covariation, such as she is very careless, she is a professional race car driver, etc. Then, given another explanation to be judged, "It was more likely to have a traffic accident last night than other nights," it is difficult to tell whether or not this additional explanation will conflict with the initial explanation, hence resulting in no discounting.

Summary of Predictions by the Mechanism Approach

To summarize, the mechanism approach argues that both conjunction and discounting effects derive from the tendency to explain events at the level of underlying mechanisms as opposed to covariation between causes and effects. The conjunction effect, according to this approach, occurs only when people can picture how the additional explanation can increase the likelihood of a conjectured mechanism. Therefore, if the second explanation is covariation-based (i.e., not adding any further support for a hypothesized mechanism) or if the explanations conflict at the mechanism level, the conjunction effect should not occur. The latter case of conflict would rather lead to the discounting effect.

The differences in the specifics of the tasks can also contribute to the perception of whether or not two explanations conflict at the mechanism level. The conjunction task involves a judgment of two pending explanations. Unless the two explanations conflict or are explicitly irrelevant to each other (e.g., "Charles had to leave school because he was 21 years old and the U.N. was having a trouble in the Middle East"), people can come up with a coherent mechanism underlying two explanations. Once it occurs, the conjunction effect occurs, as in "Kim had a traffic accident because she was nearsighted and there was a heavy snowstorm last night." On the other hand, the discounting task involves a judgment of one pending explanation given another explanation known to be true. With this initial explanation given to be true

(e.g., “Kim had a traffic accident because she was nearsighted”), people create a mechanism-based story which sufficiently leads to the effect (e.g., “Kim probably is severely nearsighted and would have had an accident in any normal weather situation”). Therefore, a mechanism involved in the additional explanation (e.g., “There was a heavy snowstorm last night”) conflicts with the initially established story, leading to the discounting effect. Due to this task difference, it is possible to simultaneously obtain the conjunction and the discounting effects, which were previously considered as conflicting.

Predictions of Covariation-Based Models

The covariation-based models are among the many models suggesting exclusiveness of the two effects. In this section, we describe the predictions of the most recent covariation-based model proposed by Cheng and Novick (1992). They argue that causal strength of a factor A increases as the probability of an event E given A (i.e., $P(E|A)$) increases and as the probability of E given the absence of A (i.e., $P(E|\bar{A})$) decreases. More formally, the causal strength of A equals $P(E|A) - P(E|\bar{A})$. According to Cheng and Novick (1992), if there is an additional cause for E (say, B), then $P(E|\bar{A})$ would increase because E would occur due to B when A is absent. As a result, the causal strength for A is decreased and hence A is discounted in the presence of B . However, this account of the discounting principle is inconsistent with the conjunction effect for the following reason. According to the model, the strength of a conjunctive cause, A and B , equals $P(E|A \& B) - P(E|\bar{A} \& \bar{B}) - P(E|A \& \bar{B}) + P(E|\bar{A} \& B)$. In order to obtain the discounting effect, $P(E|\bar{A} \& B)$ has to be increased, but this increase would reduce the strength of conjunctive causes. Therefore, these models predict that the simultaneous occurrence of the conjunction effects and the discounting principle cannot occur. Furthermore, the model does not make differential predictions for mechanism-based explanations as long as they have the same covariation values as covariation-based explanations. So while the two explanations that “Kim is nearsighted” and “Kim is a professional race car driver” have the same function in a covariation model as long as the two factors covary to the same degree with Kim’s having a traffic accident, the mechanism theory predicts differential strength for the two.

OVERVIEW OF EXPERIMENTS

Three experiments were conducted to test the following two main questions derived from the above discussion. First, can the discounting and the conjunction effect occur simultaneously with the same materials? In all three of the experiments, subjects received a conjunction task and/or a discounting task with the same materials. For the conjunction task, the subjects were asked to judge the likelihood of the conjunction of explanations compared to their constituents on the same event (but on different trials). For the discounting

task, the subjects estimated the strength of one cause with or without another cause already present.

Second, under which conditions do the discounting and the conjunction effects occur? In our previous discussion, we predicted that whether or not a single coherent mechanism underlies the two given explanations determines the amount and the direction of the two effects. The current experiments tested this prediction by manipulating the difficulty of mechanism-based story construction in various ways. Experiment 1 uses two different versions of explanations, one based on familiar mechanisms (e.g., traffic accidents, failing in exams, etc.) and the other based on abstract covariation information (e.g., Kim is more likely to have traffic accidents than others). We predicted that both the conjunction and the discounting effects would occur more with familiar mechanisms than with abstract covariation information, because it is easier to construct stories from familiar mechanisms. In Experiments 2 and 3, we manipulated the context and background knowledge and therefore the difficulty of constructing a coherent story from multiple causes. In Experiment 2, subjects received only mechanism-based explanations, but differentiations in context dictated the coherence of the explanations. We empirically measured how two explanations cohere with or without various contexts, and tested whether or not this measurement could predict the direction and amount of the conjunction and the discounting effect. Experiment 3 was similar to Experiment 2 except that it employed covariation-based explanations. The use of context manipulation in studying causal inferences is similar to the one used by Ackerman, Paine, and Silver (1991) who have recently provided developmental evidence showing the importance of initial concept accessibility in later causal inferences. They have found that the prominence of a concept early on in a story influenced the use of the concept in causal attributions in subjects as young as second-grade children. In Experiments 2 and 3, we employed a similar paradigm of manipulating the accessibility of concepts of causal mechanisms and examined the directions of the conjunction and the discounting effects.

EXPERIMENT 1

In Experiment 1, subjects received a series of event descriptions and performed either the conjunction or the discounting task on two versions of explanations: mechanism (e.g., Kim had a traffic accident because Kim who is nearsighted tends not to wear her glasses while driving) or covariation-based explanations (e.g., Kim had a traffic accident because Kim is much more likely to have traffic accidents than other people are). The mechanism approach does not necessarily argue that the conjunction and discounting phenomena are contradictory to each other. If people can formulate a coherent story from two reasons, the conjunction effect should occur. However, if the explanations are based on arbitrary and abstract covariation, people may have difficulty coming up with a single coherent story which merges both explanations, resulting in no conjunction effect. Similarly, the discounting

effect will occur with mechanism-based explanations because given one cause, people would construct a mechanism-based story which may not need the additional cause given later, resulting in the discounting of the second cause. In contrast, given covariation-based explanations without any mention of mechanisms, story construction would be difficult (there is no mechanism-based story to conflict with the second cause) and consequently the additional cause cannot be discounted. Although Experiment 1 does not test the specific nature of the story construction processes, comparing the two types of explanations (i.e., mechanism-based vs covariation-based) should provide indirect evidence for our processing account. In sum, we predicted both conjunction and discounting effects only from mechanism-based explanations and not from covariation-based explanations.

Method

Procedure. Subjects received a series of problems consisting of a target event description and a candidate explanation. For the conjunction task, the subjects were asked "to rate on a scale of 1 to 7 how probable it is that the explanation constitutes at least part of the actual explanation." This instruction was directly adopted from the original study by Leddo et al. (1984) showing the conjunction effect in causal explanations. Then, the subjects received a sample event, "Ellen didn't drink the French wine at dinner," followed by an explanation, "The French wine was cheap." In the example provided with the instructions, the subjects did not see multiple causes for the same event. For the discounting task, the subjects were asked "to rate the magnitude of the various possible causes of the event on a 7-point scale." This instruction was adopted from Morris and Smith (in preparation). Then the subjects received the same example event as was in the conjunction event, followed by the problem, "Estimate how cheap the French wine was." For both tasks, 1 on the scale indicated "very low," 7 indicated "very high," and the intermediate numbers indicated the intermediate values.

Each problem was presented on a computer screen and the subjects responded by pressing a number key. They were also instructed that throughout the experiment, the same event descriptions would be presented several times but with different possible explanations. They were asked to treat each problem separately (i.e., "an explanation given in one problem has nothing to do with an explanation given in another problem even when the event description is the same"). The order of the problems given to the subjects was randomized across all the subjects. The subjects performed the task at their own pace.

Design. There were two types of explanations (covariation-based and mechanism-based, see below) as a within-subjects variable. For half of the events, a subject received covariation-based explanations and for the other half, he/she received mechanism-based explanations. For the conjunction task, there were single explanations and conjunctive explanations for the same item as a within-subjects variable. For the discounting task, there were single explanations and conditional explanations as a within-subjects variable. (See below for more detail.)

Materials. A subset of materials used in Experiment 4 of Ahn et al. (1995) was used. In that experiment, event descriptions were developed to include person, stimulus, and occasion components (e.g., "Kim had a traffic accident last night"). For each event, two factors were chosen as candidate factors (e.g., Kim and last night in the above example). For each factor in question, we developed a sentence conveying mechanism information (e.g., "Kim is nearsighted and tends not to wear her glasses while driving"). See Appendix A for event descriptions and mechanism-based explanations. Then the covariation-based explanations were developed as follows.

Pretest in Ahn et al. (1995). For each mechanism sentence, Ahn et al. developed a corresponding covariation sentence by carrying out the following experiment. In this pretest, 28 subjects received a list of the mechanism sentences and were asked to rate each sentence according to

how much more or less likely the situation made the corresponding target event. For example, given that "There was a very severe storm and the roads were very slick last night," the subjects were asked "Compared to the average night, how likely were people to have a traffic accident last night?" The subjects answered these questions by rating on a 13-point scale marked with extremely less likely (-6), very much less likely (-5), much less likely (-4), somewhat less likely (-3), a bit less likely (-2), barely less likely (-1), about as likely (0), barely more likely (1), a bit more likely (2), somewhat more likely (3), much more likely (4), very much more likely (5), and extremely more likely (6). Subjects' mean ratings were calculated (rounding to the most extreme whole number). Covariation sentences were created using the phrase corresponding to the mean ratings. In the example above, if the mean rating was the closest to "much more likely," then the covariation sentence was "Traffic accidents were much more likely last night than on other nights." The covariation sentences are presented in Appendix A followed by "Covariation (the name of the corresponding factor)."

Appendix A shows the complete set of materials used in this experiment. For each problem, there were two types of explanations depending on the factor the explanation concerned. For example, for Event PO, one type of explanation concerns a "person" factor and the other type of explanation concerns an "occasion" factor. In Appendix A, the events are numbered in terms of which factors are involved in the given explanations (e.g., Event SP standing for Stimulus and Person factors). Three factors frequently used in the attribution area were adopted (i.e., person, stimulus, and occasion) and all possible combinations of these three factors appeared (i.e., PO, SP, and PS). For each combination (e.g., PO), two events were instantiated. In Appendix A, they are numbered as 1 and 2 (e.g., PO1 and PO2).

For the conjunction task, three problems were developed for each event description: ratings for (a) single explanation for Factor A ($P(A)$ henceforth), (b) single explanation for Factor B ($P(B)$ henceforth), and (c) conjunctive explanations ($P(A\&B)$ henceforth). For each subject, all three problems for each event were either the mechanism type or the covariation type. For example, given the event "Kim had a traffic accident last night," a subject had to judge the probability of a mechanism-based single explanation for Factor A, "Kim is nearsighted and tends not to wear her glasses while driving," the probability of a mechanism-based single explanation for Factor B, "There was a severe storm and the roads were very slick last night," and the probability of a mechanism-based conjunctive explanation, "Kim is nearsighted and tends not to wear her glasses while driving, and there was a severe storm which made the roads very slick last night."

Each subject received three events with two mechanism-based single explanations and one mechanism-based conjunctive explanation for a total of nine problems, and the other three events with two covariation-based single explanations and one covariation-based conjunctive explanation for a total of nine problems. Consequently, a single subject only saw one type of explanation (either mechanism-based or covariation-based) for any single event but during the experiment, the subject encountered both types of explanations for different events. There were five randomizations depending on which event involved covariation- or mechanism-based explanations.

For the discounting task, four problems were developed for each event: estimating (a) strength of factor A ($P(A)$ henceforth), (b) strength of factor B ($P(B)$ henceforth), (c) strength of factor A given factor B ($P(A|B)$ henceforth), and (d) strength of factor B given factor A ($P(B|A)$ henceforth). As in the conjunction task, for each subject, all four problems for the same event were either of the mechanism type (e.g., "Given that Kim, who is nearsighted, did not wear her glasses, estimate how likely there was a severe storm last night and the roads were slick") or of the covariation type (e.g., "Given that Kim was much more likely to have traffic accidents than other people, estimate how much more likely traffic accidents were last night than other nights"). Each subject received three sets of problems involving mechanism-based explanations and another three sets of problems involving covariation-based explanations, resulting in a total of 24 problems. Five different random combinations were used to determine which event description described which type of explanation.

Subjects. There were 67 subjects who were undergraduate students at the University of Michigan, participating in partial fulfillment of course requirements for introductory psychology. Thirty-

TABLE 1
Mean Ratings for the Conjunctive Task in Experiment 1

Type of explanation	Number of explanation(s)		Total
	Mean of $P(A)$, $P(B)$	$P(A \& B)$	
Covariation	3.34	3.33	3.33
Mechanism	4.80	5.22	5.01
Total	4.07	4.27	

one subjects were randomly assigned for the conjunction task and 36 subjects were assigned for the discounting task.

Results

The conjunction effect. Table 1 shows the mean ratings of each type of explanation (covariation or mechanism) for single and conjunctive explanations for the conjunctive task. An ANOVA was conducted with each subject's average ratings on each type of problem to test the effect of the number and the type of explanations. Overall, the conjunction effect was much stronger with mechanism-type explanations than with covariation-type explanations, shown by a reliable interaction between number and type of explanations, $F(1,30) = 4.92$, $p < .05$. More specifically, with covariation-type explanations, there was no difference between single and conjunctive explanations (3.34 and 3.33, respectively). With mechanism-type explanations, however, conjunctive explanations (5.22) were rated to be much higher than single explanations (4.80). In addition, there was a reliable main effect of the type of explanation with mechanism-type explanations being higher (5.01) than covariation-type explanations (3.33) regardless of the number of explanations, $F(1,30) = 10.28$, $p < .001$. There was no overall main effect of number of explanations. An item analysis showed a greater conjunction effect with mechanism-type than with covariation-type explanations in five out of six items.

TABLE 2
Mean Ratings for the Discounting Task in Experiment 1

Type of explanation	Number of explanation(s)		Total
	Mean of $P(A)$, $P(B)$	Mean of $P(A/B)$, $P(B/A)$	
Covariation	4.08	4.17	4.13
Mechanism	4.25	3.73	3.99
Total	4.16	3.95	

The discounting effect. The mean ratings for the discounting task are shown in Table 2. The discounting effect occurred with the mechanism-based explanations but not with the covariation-based explanations. An ANOVA was conducted with each subject's average ratings on each type of problem to test the effect of the number and the type of explanations. As in the conjunctive task, there was a significant interaction effect between type of explanation and number of explanations, $F(1,35) = 12.93, p < .001$. More specifically, with covariation-type explanations, there was no difference between single and conditional explanations (4.08 and 4.17, respectively). With mechanism-type explanations, however, conditional explanations (3.73) were rated to be much lower than single explanations (4.25). There was no reliable main effect of types of explanation, $p > .10$ but there was a reliable main effect of number of explanations, $F(1,35) = 7.98, p < .01$ with single explanations being higher (4.16) than conditional explanations (3.95).

A separate item analysis also showed results consistent with the interaction effect. For each item, two difference scores were obtained: one for $P(A/B)$ minus $P(A)$ and the other for $P(B/A)$ minus $P(B)$. The lower these scores are, the greater the discounting effect would be. Out of 12 possible scores (2×6 items) for each type of explanation, 10 were lower with mechanism-type explanations than with covariation-type explanations.

Discussion

Experiment 1 showed two important findings. First, as discussed in the introduction, some researchers have suggested (Einhorn & Hogarth, 1986; Zuckerman et al. 1986) that the conjunction effect and the discounting effect are paradoxical. Whereas the discounting principle implies that when two causes for an effect are available, one cause will be singly preferred, the conjunction effect implies that explanations with two causes are better than explanations with one cause. The results from Experiment 1, however, showed that the two effects could occur with the same materials.

Second, both effects occurred significantly more often with the mechanism-based explanations than with the covariation-based explanations. We have hypothesized that this phenomenon occurs because people have a tendency to reason at the level of underlying mechanisms when explaining events. With the conjunctive, mechanism-based explanations (e.g., "Kim who is nearsighted tends not to wear her glasses and there was a severe storm last night resulting in very slick roads), we can easily imagine a coherent scenario about how each factor would support the other. Conjunctive explanations have an advantage over single explanations because the former provide more evidence supporting the existence of a stronger mechanism linking the potential cause to the effect.

However, with conjunctive, covariation-based explanations, we conjecture that a coherent story cannot be easily constructed because the mechanisms are unknown and have to be inferred from the information given to the subject. People can easily list a number of reasons for why and how Kim would

have had more traffic accidents than other people. Furthermore, when two covariation-based explanations are combined, the number of possible stories is increased even more. The uncertainty involved in coming up with a single story might have led the subjects to rate the probability of the conjunctive covariation-based explanations at the same level as for the single covariation-based explanations. There was not much advantage of having multiple reasons in this case.

Similarly, there was much less discounting with the covariation-based explanations than with the mechanism-based explanations. Presumably this occurred because there was no conflicting mechanism inferred from two abstract covariation-based explanations. In contrast, a given mechanism-based explanation might have led subjects to construct a story incoherent with the additional mechanism-based explanation, resulting in the discounting effect.

A proponent of the covariation approach might argue that the covariation information provides evidence about possible causes but does not serve as an actual cause for an effect. Therefore, according to this claim, the instructions for the conjunction task (i.e., asking whether a covariation-based explanation constitutes part of a true explanation) might have been misleading. Experiment 1, as the initial test to obtain simultaneous conjunction and discounting effects, used the same instructions as the original conjunction fallacy experiments by Leddo et al. (1984) for the purpose of comparison. But these instructions might not have been applicable to the conjunction task, as they asked subjects to judge whether or not covariation was a cause. This argument, however, does not seem to undermine our interpretation of the results for the following reasons. First, if ill-formed instructions were the reason for not being influenced by covariation information in obtaining the conjunction effects, then it is not clear why subjects were not also influenced by covariation information in the discounting task. Second, and more importantly, the researchers supporting the covariation approach have explicitly claimed that covariation is a necessary condition for causality. If so, additional covariation information should have invariably influenced causal judgment at some level in the conjunction task. However, we observed the influence of additional covariation information in neither the conjunction nor the discounting tasks, suggesting that causal reasoning in these tasks was not primarily based on combining covariation information. Since it is still important to eliminate any possible alternative interpretations, in Experiment 3 we changed the instructions for the conjunction task for covariation-based explanations. The next two experiments directly test the hypothesis that causal reasoning is affected by covariation information only if it is related to stored background knowledge of underlying causal mechanisms.

EXPERIMENT 2

Experiment 2 tests the tendency to construct a coherent story given multiple causes by using a priming task. Through a pretest, we developed two independent explanations for each event in such a way that it is difficult to construct

a coherent story based on both explanations. Then we also developed three types of cues: unifying, biased, and no ("XXX" in the actual experiment) cues. In the pretest (Experiment 2-a), the unifying cues were judged to be very helpful in constructing a coherent story with both explanations. The biased cues were designed to provide a mechanism for only one of the explanations, making it difficult for the subjects to imagine a coherent situation involving both of the candidate explanations.

We hypothesized that in the situation where story construction is easy (i.e., with the unifying cues), the conjunction effect will be greater than in the situation where it is more difficult (i.e., with the biased cues). In contrast, the discounting effect will be greater with the biased cues which support only one of the explanations than with the unifying cues which support both explanations within one mechanism. As shown in Experiment 1 with the covariation-based explanations, we expected neither the discounting effect nor the conjunction effect in the situation where there are no common mechanisms available to support both explanations (i.e., with no cues).

Experiment 2-a presents a pretest and manipulation check of types of cues. Because we do not have a priori operationalization for the coherency measure, we conducted this separate experiment to use subjects' own intuition about coherency. Experiment 2-b is the main experiment where the three types of cues were used for the conjunction and the discounting task.

Experiment 2-a: Pretest for Stimulus Development and Manipulation Check

Method

Materials. The explanations were chosen to appear unrelated. But they could be united in order to explain the event, depending on how the given cue altered the context of the situation. There were three types of cues for each problem: a unifying, a biased, and no (i.e., XXX) cue. The unifying cues were designed to allow the two explanations for each event to fit well together in a coherent story. The biased cues favored one of the explanations over the other as to why the event occurred, thus eliciting a mechanism which excluded the second explanation. The no-cue condition was used as a baseline. For example, a given event is, "John came over to Mary's house." The two candidate explanations are "John was wearing greasy clothes" and "Mary had no air conditioning." In this example, the unifying cue is "handyman," favoring both explanations and the biased cue is "beggar," favoring only the former one.

Pretest. Twenty-two problems were initially developed by the authors. In a pretest, these problems were informally presented to six undergraduate students. They read each target event and two candidate explanations on paper and were then instructed to "judge on a 5-point scale how well the two explanations fit together in making a coherent story." After this rating, the subjects were verbally given the unifying and biased cues, one at a time in a random order. In brief, they gave three ratings, one for the coherency of explanations without the cues (N), one with the biased cue (B), and one with the unifying cue (U). The average ratings for each problem were used to determine which items out of the 22 should be used for Experiment 2-b. We selected the items that resulted in large differences between N and U (i.e., large effect of a unifying cue in constructing a story compared to no cue), and U and B (i.e., large effect of a unifying cue in constructing a story compared to a biased cue).

Procedure. The nine problems selected through the pretest (see Appendix B for the complete list) were presented to the subjects. Ten subjects were asked to judge on a 7-point scale how

TABLE 3
Mean Ratings for Coherency Judgment Given Each Cue Type in Experiment 2-a

Explanation type	Cue type				Total
	Biased for	Biased against	Unifying	None	
Single	5.92	1.83	5.22	3.36	4.08
Conjunction	3.64	3.64	5.84	3.53	4.34
Total	4.78	2.74	5.53	3.45	

coherent each of the single explanations was with the target event description given one of the three types of cues. The subjects always judged the coherency without any cue, followed by either a biased cue or a unifying cue in a random order. The order of nine problems was randomized across subjects. A separate group of 11 subjects were asked to judge on a 7-point scale how coherent the two explanations were with the target event. The rest of the procedure was the same as the above.

Subjects. There were 21 subjects who were undergraduate students at the University of Michigan, participating in partial fulfillment of course requirements for introductory psychology.

Results

Table 3 shows the subjects' mean ratings given each cue type. The higher the numbers are, the more coherent the explanations were judged. The results from the biased cue are broken down into the explanations that we initially selected to be supported by the biased cue (under "Biased for" in Table 3) and the explanations not supported by the biased cue (under "Biased against" in Table 3). For example, for the event, "Everybody was looking at Randy," the biased cue "CONCERT" supports the explanation "Randy was singing" but does not support the explanation "It was finals week."

Overall, the unifying cue greatly increased the coherency between single explanations and the event descriptions. The biased cue increased the coherency of only the biased-for, single explanations and not the coherency of the biased-against, single explanations compared to the same items in the no-cue condition.

For the conjunctive explanations, however, only the unifying cue increased the coherency. That is, the biased cue, compared to the no-cue condition, did not help people construct a coherent story from the conjunctive explanations.

In sum, Experiment 2-a obtained an independent measure of coherency given the three types of cues. Based on this measure, the results obtained from Experiment 2-b seem to be attributable to the differences in the degree of coherency.

Experiment 2-b: Main Experiment

Methods

Materials. There were nine sets of problems for each subject, along with five practice problems to familiarize them with the process. These materials were developed through the pretest described in Experiment 2-a.

Procedure. The subjects were randomly assigned to participate in either the conjunction or the discounting task. In the conjunction task, subjects received a series of problems consisting of a target

event description and a candidate explanation (either $P(A)$, $P(B)$, or $P(A \& B)$). The instructions to the problems were similar to the ones described in Experiment 1, except that there were further instructions concerning the cues. Before each problem was presented, subjects saw the target event description alone without the explanations. Immediately following the event description, a blank screen was shown for 300 msec. After that time, a one-worded cue appeared for 250 msec. Subjects were instructed to take the cue into account in that “the word may be helpful when you are rating how probable the given explanation constitutes a part of the actual explanation for the event.” After the cue disappeared, the screen became blank for 600 msec. The subjects then saw the target event with the candidate explanation (either single or conjunctive) and proceeded to rate the explanation. There was no time limit for the rating task.

The discounting task employed basically the same procedure as the conjunction task. The same events and explanations were used in both experiments, and the amount of time between the appearance of events, cues, and explanations was the same. In the discounting problems, however, the candidate explanations were either single explanations ($P(A)$, $P(B)$) or conditional explanations ($P(A|B)$, $P(B|A)$), as in Experiment 1. In Experiment 2, however, we slightly changed the wording of the questions for the following reason. In Experiment 1, the format of the questions was as follows: An event was stated, followed by a question “Given A , estimate the strength of B .” This wording can be misleading because subjects might try to predict the strength of B solely based on the occurrence of A and not based on the fact that A caused the target event. In Experiment 2, we explicitly combined the target event description with the cause which was given to be true (e.g., “Bob touched the animal because Bob likes animals”) and then asked the likelihood of the additional cause (e.g., “How likely is it that Bob touched the animal because it was also his job?”). For single explanation problems, the subjects received the target event (e.g., “Bob touched the animal”) plus the question about the likelihood of a cause (e.g., “How likely is it that Bob touched the animal because it was his job?”).

Design. Using a Latin-square design, each subject received one of three random combinations of which cue was given to each problem.² For the conjunction experiment, subjects received each target event with the two candidate explanations in conjunction, and the same event with each of the single candidate explanations shown separately. For all three types of explanations ($P(A)$, $P(B)$, and $P(A \& B)$), the cues and events remained constant for each subject. For example, if the unifying cue was used for the event “Bob touched the animal” when judging $P(A)$, then the same cue was used for judging $P(B)$ and $P(A \& B)$. But across the nine problems, the same subject encountered all three types of cues. The presentation order of each trial was randomized for each subject.

The design of the discounting task was the same as in the conjunction task except that there were four explanations ($P(A)$, $P(B)$, $P(A|B)$, and $P(B|A)$) to be judged for the same event.

Subjects. There were 60 subjects who were undergraduate students at the University of Michigan, participating in partial fulfillment of course requirements for introductory psychology. Half of the subjects were randomly assigned to the conjunction task and the other half were assigned to the discounting task.

Results

The conjunction effect. Table 4 summarizes the results from the conjunction task. A within-subject design ANOVA was conducted over each subject’s

² In one combination, “Bob,” “Lisa,” and “Charles” problems were preceded by neutral cues, “Julie,” “Kim,” and “John” problems by unifying cues, and “Students,” “Randy,” and “Rachel” by biased cues. For the other combination, the first set of problems was preceded by unifying cues, the second set by biased cues, and the third set by neutral cues. Finally for the third combination, the first set was preceded by biased cues, the second by neutral cues, and the third by unifying cues. Therefore, across all subjects, the data were collected for all three types of cues for all the problems and all subjects received all three types of cues but for different problems.

TABLE 4
Mean Ratings for the Conjunction Task in Experiment 2-b

Explanation type	Cue type				Total
	Biased for	Biased against	Unifying	None	
Single	4.24	2.74	4.03	3.37	3.59
Double	3.70	3.70	4.91	3.69	4.10
Total	3.97	3.22	4.47	3.53	

mean response on each type of question in order to test the effect of the Number of Explanations (single or conjunctive) and the effect of Cue Types. There was a reliable main effect of the Number of Explanations, $F(1,29) = 16.47$, $MSE = 9.80$, $p < .001$, a reliable main effect of the Cue Types, $F(3,87) = 18.59$, $MSE = 17.71$, $p < .001$, and a reliable interaction effect, $F(3,87) = 13.17$, $MSE = 7.20$, $p < .001$.

Further planned, paired t -tests were conducted between single and conjunctive explanations within each cue condition in order to test the main hypotheses of the study. As predicted, given the unifying cue, ratings on conjunctive explanations (4.91) were reliably higher than ratings on single explanations (4.03), $t(29) = 5.62$, $p < .001$. Furthermore, when the cue supports only one of the explanations as shown under "Biased for," the opposite of the conjunction effect occurred (4.24 for single explanations vs 3.70 for conjunctive explanations), $t(29) = 4.30$, $p < .001$. For example, given the event, "Everyone was looking at Randy," and the biased cue "CONCERT," the rating for the single explanation that was supported by the biased cue "because Randy was singing" was judged to be quite a bit more likely than the conjunctive explanations "because Randy was singing and it was finals week." Given no cue, the difference between conjunctive explanations (3.69) and single explanations (3.37) was not reliable, $p > .05$.

An item analysis also showed consistent results. The conjunction effect was greater given the unifying cue than the Biased-for cue for 8 out of 9 items. In addition, the opposite of the conjunction effect occurred for all 9 items given the Biased-against cue.

Additional evidence for coherent story construction in causal reasoning comes from a comparison across subjects' ratings on conjunctive explanations. Given the Unifying cue, the conjunctive explanations were rated to be reliably higher than those given other types of cues, $p < .001$.

The discounting effect. Table 5 summarizes the results from the discounting task. A within-subject ANOVA was conducted over each subject's mean response on each type of question in order to test the effect of the Number of Explanations (single or conjunctive) and the effect of Cue Types. There was a reliable main effect of the Number of Explanations, $F(1,29) = 5.13$, $MSE = 1.50$, $p < .05$, a reliable main effect of the Cue Types, $F(3,87) =$

TABLE 5
Mean Ratings for the Discounting Task in Experiment 2-b

Explanation type	Cue type				Total
	Biased for	Biased against	Unifying	None	
Single	4.21	2.66	3.75	3.28	3.47
Double	3.82	2.46	3.63	3.35	3.31
Total	4.02	2.56	3.68	3.31	

18.23, $MSE = 23.63$, $p < .001$, and a marginally reliable interaction effect, $F(3,87) = 26$, $MSE = 0.56$, $p = .08$.

Further planned t-tests were conducted between conditional and single explanations within each cue condition to test the main hypotheses of the experiment. The discounting effect occurred only when the Biased cue was given. Given the Biased cues, the ratings on single explanations which were supported by these cues (4.21) were reliably higher than the ratings on double explanations (3.82), $t(29) = 2.99$, $p < .01$. For all the other cue conditions, the differences between single and double explanations were not reliable, $p > .10$. This pattern of results holds for 6 out of 9 items.

Discussion

As predicted, conjunction and discounting effects could be manipulated through mechanisms suggested by the cues. When the subjects saw the cues which allowed them to construct a coherent story as measured by Experiment 2-a, the conjunction effect was the greatest. When the subjects were cued to construct a story supporting only one of the explanations, the discounting effect was increased.

Similar results were obtained by Schul and Burnstein (1985) who examined the conditions in which the discounting effect occurred. In the integrative condition of their experiments, the arguments were presented so that they could be elaborated on and stored together in a common structure. In the discrete condition, the arguments were presented so that each one was interpreted and stored separately. The subjects in the discrete condition demonstrated more of a discounting effect than those in the integrative condition. These results are consistent with the current finding that people show more discounting with the biased cue condition which emphasizes the difference between the two explanations than with the no-cue condition.

It is also interesting that when there was no cue, there was no conjunction and no discounting effect as in the covariation-based explanations of Experiment 1. Note that the explanations in Experiment 2-b were not explicit covariation statements. However, as shown by the coherency measure of Experiment 2-a in Table 3, the conjunctive explanations with no cue were not any more coherent than the single explanations with no cue. As a result, the subjects

had difficulty coming up with a single coherent mechanism for conjunctive explanations as with covariation-based explanations of Experiment 1, resulting in no conjunction effect. In order to maximize the effect of cues, we also intentionally developed each explanation not to be a "good" explanation. For example, "John came over to Mary's house because John wore greasy clothes" is not a good explanation without the aid of cues such as "BEGGAR," because the subjects failed to come up with an underlying mechanism for this explanation. The coherent measure data in Table 3 also illustrate this point. That is, the mean ratings for coherency judgment for single explanations was much lower given no cue than given the unifying or biased-for cue. Because of this failure to come up with coherent mechanisms, the additional explanation (e.g., "because Mary had no air conditioning") was not necessarily discounted. This phenomenon is very similar to the results obtained from the covariation-based explanations shown in Experiment 1; when there were no underlying mechanisms, there were no conjunction or discounting effects.

EXPERIMENT 3

There were two purposes for Experiment 3. First, we investigated whether or not the results of Experiment 2 could be generalized when using covariation-based explanations in contexts of varying coherency with respect to mechanisms. Experiment 1 found that the conjunction and the discounting effects occurred only with the mechanism-based explanations and not with the covariation-based explanations. However, one can criticize our results by saying that the wording of covariation-based explanations sounds too unnatural or too abstract to be used in everyday explanations of events. On the one hand, the criticism supports our position that purely covariation-based explanations do not reflect our natural level of explanations. On the other hand, it is important to show that the results which support the mechanism approach were not simply due to unfamiliarity of the wording. Our account of the results from Experiment 1 was that the existence of coherent mechanisms which support multiple explanations produced the varying effects. In other words, we believe that the differences in ratings between covariation and discounting explanations were not due to the wording of covariation-based explanations per se but rather to subjects' preference for underlying mechanisms as causal agents. Therefore, in Experiment 3, subjects only judged covariation-based explanations while we provided coherent, incoherent, or no mechanism information as a context for those same explanations. We predicted that both conjunction and discounting effects can occur with covariation-based explanations if the contexts provide a coherent mechanism. This control insures that the null effects from Experiment 1 in the covariation-based condition were not simply due to the unnaturalness or abstractness of the covariation-based explanations.

The second purpose of Experiment 3 was to obtain generality of the previous results across different instructions, materials, and procedures. As discussed earlier, Experiment 1 used the same instructions as the ones initially

used by other researchers investigating the conjunction and discounting effects. However, one can also point out that the covariation-based explanations are too abstract or unnatural to be treated as explanations. In addition, an advocate of the covariation approach might also claim that covariation information serves only as necessary evidence for causal judgments rather than the cause per se. Therefore, according to this interpretation, asking “How likely is it that the given explanation constitutes a part of the true explanation?” as in Experiments 1 and 2 may be unfair because the covariation information is not a true explanation but is instead some kind of evidence. Consequently, according to this argument, the null effect with covariation-based explanations in these experiments might be an artifact of unfair questions. Experiment 3 responded to this alternative interpretation in two ways. First, as discussed, we used only the covariation-based explanations across various context conditions. Furthermore, we used the same questions across all problems. Therefore, if we can obtain any significant conjunction and discounting effects in specific mechanism contexts, then the null results in the other context conditions cannot be attributed to the unfairness of questions. Second, in Experiment 3, we asked “How likely was it that ⟨target event description⟩ because ⟨candidate explanation⟩?” with ⟨target event description⟩ being replaced with specific target event descriptions, such as “Charles had to leave school” and ⟨candidate explanation⟩ being replaced with such descriptions as “Charles was more likely to leave school than other students are.” With this kind of question format, subjects do not necessarily have to assume that the “candidate explanation to be judged” is an explanation used in everyday conversation.

The format of Experiment 3 is similar to Experiment 2. We first conducted a pretest (Experiment 3-a) in order to obtain an independent measure of coherency of the two explanations with or without various contexts. In Experiment 3-b, the main experiment, the subjects performed the conjunction and the discounting tasks given various contexts.

Experiment 3-a: Pretest for Coherence Judgment Methods

Materials. Six event descriptions and two explanations for each description were developed. Among these six descriptions, two had explanations about person and occasion factors, two had explanations about person and stimulus factors, and two had explanations about stimulus and occasion factors. All of the explanations were about covariation between the target event and the factor involved. For example, given the event “Bob brought roses to the Humana building yesterday,” an explanation involving a person factor was “Bob was more likely to bring roses to the Humana building than other visitors were,” and an explanation involving a stimulus factor was “Bob is more likely to bring roses to the Humana building than to other office buildings.” (See Appendix C for a complete list of event descriptions and explanations.)

For each event description, two context sentences were developed. One context, called “Biased context,” provides a piece of mechanism information supporting only one of the two factors in the given explanations. In the above example, the context was “Bob delivers flowers,” which supports only the first explanation. The other context, called “Unifying context,” provides a piece of mechanism information that is coherent with both factors in the given explanations (e.g., “Bob is in love with Mary who works at the Humana building”). Appendix C provides

a complete list of these contexts. In Appendix C, the events are numbered using a notation indicating which two factors are involved in the given explanations (e.g., "PO" for person (P) and occasion (O), "SO" for stimulus (S) and occasion (O), etc.). In addition, the factor that is biased by the Biased context sentence is mentioned first. For example, "PO" indicates that the person factor is supported by the Biased context. In total, the six events were PO, OP, SO, OS, SP, and PS. Therefore, there were six events with explanations about all possible pairwise combinations of person, stimulus, and occasion factors and the Biased context supports each of the three factors equally frequently.

Procedure. Subjects received 18 problems, which are all possible combinations of the six events and three contexts (none, Biased, and Unifying). The order of the problems was randomized across all subjects with one constraint: problems with the Biased and the Unifying contexts should follow the no-context problems within each target event. This constraint would insure that subjects solving the no-context problems would not be affected by other contexts. In each problem, subjects saw a context sentence, followed by a target event description. (In the No context condition, there was no sentence preceding the target event description.) Following the target event descriptions, the subjects received two explanations. Then, they were told, "Given these explanations, you are to judge how coherent these two explanations are as a single story." Then, they were asked to rate their judgment on a 9-point scale where 9 indicated "Very Coherent" and 1 indicated "Very Incoherent."

The subjects were further provided with more elaborate instructions on the coherency judgment as follows.

Please keep in mind that the task is to judge coherency between the two explanations in explaining the event, and not the plausibility of explanations for the event. In other words, your judgment should not be based on how good the explanations are for the given event. Sometimes the explanations might look very unlikely, but the two explanations can be coherent with each other in explaining the event. For example, "Ron broke up with Judy because Ron's father didn't like the way Judy walked and because Ron cares a lot about his father's opinion" is a very unlikely situation but the two reasons can make a coherent story. Sometimes, the opposite can happen. For example, "Wendy failed in the final exam in Chemistry because she had a stomach flu that day and because the professor's lectures had been incomprehensible throughout the semester" can be good reasons for failing in the final exam but the two reasons might not form a coherent single story.

The subjects were told that the same event description would be repeated several times throughout the experiment but they should treat each problem separately.

Subjects. There were 20 subjects who were undergraduate students at University of Louisville, participating in partial fulfillment of course requirements for introductory psychology.

Results

The paired t-tests indicated that the mean rating from the Unifying condition (7.9) was reliably greater than that from the Biased condition (5.7), $t(19) = 7.58$, $p < .01$, and also greater than that from the None condition (4.8), $t(19) = 6.92$, $p < .01$. Therefore, we have obtained an independent measure indicating that two covariation-based explanations are more coherent under the Unifying context than under the Biased and the None context.

Experiment 3-b: Main Experiment

Methods

The six event descriptions and their explanations developed in Experiment 3-a were used. Each subject received 6 sets of problems, each set of which applies to the same event. Three sets were a conjunction task and the other three sets were a discounting task. For the conjunction task, there were three problems: two judgments on single explanations ($P(A)$ and $P(B)$) and one judgment on a conjunctive explanation ($P(A\&B)$). For the discounting task, there were four problems: two judgments on single explanations ($P(A)$ and $P(B)$) and two judgments on conditional explanations ($P(A|B)$, $P(B|A)$). In total, there were 9 questions for the conjunction task (i.e., 3 events \times 3 problems) and 12 questions for the discounting task (3 events \times 4 problems) for each subject.

For both tasks, subjects first received one of the three contexts, followed by the target event description. Then, the subjects were asked to make the judgment in the format of, "How likely was it that (target event description) because (candidate explanation)?" For example, "Lisa is a bank teller. Lisa gave the man thirty dollars when he asked. How likely was it that Lisa gave the man thirty dollars when he asked because Lisa was more likely to give the man thirty dollars than other people were?" For both conjunction and discounting tasks, the questions for $P(A)$ and $P(B)$ were exactly the same. For the conjunctive explanations in the conjunction task, (candidate explanation) was simply replaced with conjunctive explanations. For the conditional explanations in the discounting task, the target event description included a given explanation. Then, in the question, the subjects were asked to judge how likely the target event occurred *also* because of (candidate explanation). An example was, "Lisa is a bank teller. Lisa gave the man thirty dollars when he asked because Lisa was more likely to give the man thirty dollars on this day than on other days. How likely was it that Lisa gave the man thirty dollars *also* because Lisa was more likely to give the man thirty dollars than other people were?"

For all of the questions, subjects made a judgment on a 9-point scale where 9 indicated "Very likely" and 1 indicated "Very unlikely." The subjects were also told that the same event and explanations would be repeated several times but they would be presented with different contexts. Therefore, they were told not to pay attention to previous problems and treat each problem separately.

A Latin-square design was used to randomly assign which problems were used in different contexts and tasks. For example, using the notation shown in Appendix C, one randomization had SP for conjunction, None context, PO for conjunction, Biased context, OS for conjunction, Unifying context, PS for discounting, None context, OP for discounting, Biased context, and SO for discounting, Unifying context. In total, there were 6 randomized sets, each of which was used for 5 subjects. Within each set, the actual order of the problems was completely randomized for each subject.

Subjects. There were 30 subjects who were undergraduate students at University of Louisville, participating in partial fulfillment of course requirements for introductory psychology.

Results and Discussion

The mean scores for each context condition for each type of question are summarized in Tables 6 and 7. For both tasks, the rows for "single" indicate mean ratings on $P(A)$'s and $P(B)$'s. For the conjunction task, the rows for "double" indicate mean ratings on conjunctive explanations and, for the discounting, they indicate mean ratings on conditional explanations. For the "double" in the conjunction task, since $P(A\&B)$ were the same for the Unbiased and the Biased conditions, the same data points were used for these two cells.

Conjunction task. A within-subject ANOVA testing the number of explana-

TABLE 6
Mean Ratings for the Conjunction Task in Experiment 3-b

Explanation type	Cue type				Total
	Biased for	Biased against	Unifying	None	
Single	5.30	3.17	6.00	4.33	5.14
Double	4.07	4.07	6.57	4.03	5.03
Total	4.92	3.62	6.19	4.18	

tions and the type of context was conducted for each subject's average ratings on each type of problem in order to test the effect of Number of Explanations and the effect of Context. There was no main effect of Number of Explanations, $p > .10$, a reliable main effect of Context, $F(3,87) = 6.09$, $MSE = 48.64$, $p < .05$, and a reliable interaction effect, $F(3,87) = 4.98$, $MSE = 11.17$, $p < .01$.

Further planned, paired t -tests were conducted within each Context condition between single and conjunctive explanations. None of the conjunctive explanations was reliably higher than single explanations, $p > .10$. Unlike the ratings from Experiment 2-b, in the Unifying Context condition, the mean ratings of single explanations had already reached the ceiling (6.00 on a 7-point scale) and the mean for double explanations (6.57) also could not be increased much to make a significant difference. However, as in Experiment 2-b, the opposite of the conjunction effect occurred in the Biased Context condition. The rating of conjunctive explanations given the Biased context (4.07) was reliably lower than the rating of single explanations given the Biased context (5.30), indicating the reverse conjunction effect, $t(29) = 2.86$, $p < .01$. Again, as in Experiment 2-b, this result shows that conflict at the mechanism level actually leads to discounting effects even when the task was a conjunction task.³

TABLE 7
Mean Ratings for the Discounting Task in Experiment 3-b

Explanation type	Cue type				Total
	Biased for	Biased against	Unifying	None	
Single	5.70	3.53	6.43	4.30	4.99
Double	4.90	3.87	5.91	4.77	4.86
Total	5.25	3.70	6.17	4.54	

³ No item analyses were conducted for Experiment 3-b because there were not enough subjects ($N = 5$) for each item for each condition.

Another result to point out is the null difference between single and double in the None condition, $p > .10$. This result is a replication of the results from Experiment 1. Recall that the None condition in Experiment 3 used covariation-based explanations without providing any context for how these covarying factors would fit with target events in terms of known causal mechanisms. In Experiment 3, we changed the instructions, so clearly the no-conjunction effect from Experiment 1 was not an artifact derived from people's reluctance to accept covariation-based explanations due to their appearance as an awkward, nonpragmatic, conversational act.

Finally, another set of planned, paired t-tests was conducted among conjunctive explanations across various context conditions. The ratings on conjunctive explanations were always reliably higher given the Unifying Context than given any other contexts, $p < .01$.

Discounting task. A within-subject ANOVA was conducted for the discounting task results in order to test the effect of Number of Explanations and the effect of Context. There was a reliable main effect of Context, $F(3,87) = 7.07$, $MSE = 67.14$, $p < .01$, no main effect of Number, $F(1,29) = .32$, $MSE = 1.00$, $p > .10$, and a marginally reliable interaction effect between Context and Number, $F(3,87) = 2.50$, $MSE = 5.85$, $p = .06$.

As shown in Table 7, the discounting effect occurred only when the two explanations conflict at the level of mechanisms. First, comparing single and double explanations within each context condition produced only one reliable difference: within the Biased context. The rating on a single explanation (5.70) was reliably greater than the rating on double explanations (4.90), $t(29) = 2.15$, $p < .04$. All the other differences between single and double explanations were not reliable, $p > .10$.

A second result was obtained by comparing double explanations across various context conditions. The double explanation in the Unifying context was always reliably higher than those given other contexts, $p < .05$. Again, when the context was coherent at the level of mechanisms, the conjunction effect occurred even in the discounting task.

Finally, the result from the None condition again replicated the results from Experiment 1 in that purely covariation-based explanations did not lead to discounting effects. As in the conjunction task, we modified the instructions to take care of any alternative interpretations from Experiment 1. In Experiment 3, the subjects were asked to directly assess how likely the target event was to occur because of an additional factor. Not only did we fail to obtain the discounting effect from covariation-based explanations without the context of mechanism information, but also the general difference was in a reverse direction. The conditional probabilities were higher than the single probabilities.

GENERAL DISCUSSION

Summary of Results

The three experiments have shown conditions in which both the conjunction and the discounting effects are obtained. The two effects were both observed

with mechanism-based explanations (Experiments 1 and 2) and covariation-based explanations where the details of the underlying processes were known to the subjects through contexts (Experiment 3). The effects were essentially absent for combinations of covariation-based explanations (Experiments 1 and 3). The conjunction effect was increased when the context facilitated construction of a coherent story covering all available causes, and the opposite occurred when the context was biased toward only one of the available causes (Experiment 2). The discounting effect was increased when people were cued with a mechanism supporting only one of the explanations (Experiment 2). The same pattern was observed using covariation-based explanations (Experiment 3). The current results are consistent with the mechanism-based approach which argues that mechanism information rather than covariation plays crucial roles during causal reasoning.

Other Approaches

This section discusses whether other approaches to causal attribution can explain the current results.

Covariation-based models. The principle of covariation has been discussed earlier on in the introduction, and includes Kelley's ANOVA model and Cheng and Novick's probabilistic contrast model. These models, without additional assumptions, seem to have difficulty explaining the current data.

The discounting principle was initially proposed by Kelley (1972), but this principle is not a natural extension of his ANOVA model in that Kelley had to add additional assumptions concerning abstract causal schemata (e.g., people tend to believe that for most usual events a single cause is sufficient to cause the effect). Kelley postulated various causal schemas (1972), such as multiple necessary schemas where an event occurs due to conjunction of several necessary causes (i.e., conjunction effect) and multiple sufficient schemas where one cause explains away an event (i.e., discounting effect). Kelley's (1972) description of these various schemas implies that different schemas are employed with different events and, as a result, both effects cannot occur simultaneously as in our studies.

Similarly, we have earlier described why Cheng and Novick's model also predicts that the two phenomena are mutually exclusive.⁴ In addition, these

⁴ One might argue that the interactive cause used in the probabilistic contrast model is much more specific than the conjunctive causes used in the current study. According to this claim, the interactive cause in the contrast model refers to the case when two factors jointly operate together (only when they are together) but the subjects in our experiments could have estimated the likelihood of the effect of each group of individual causes (i.e., main effects) plus the interactive causes when they estimated the likelihood of conjunctive explanations. Then, the discussion we made earlier in the Introduction could be invalid because it was based on the assumption that the estimates of conjunctive explanations are the same as the contrast values for interactive causes. However, results from Experiments 2 and 3 show this was not the case. If conjunctive explanations were interpreted as a combination of two main effects plus an interactive effect, then ratings on conjunctive explanations should be always higher than those on single explanations, which was not the case in Experiments 2 and 3.

covariation-based models, in their current form, cannot explain why there are different levels of discounting and conjunction effects for mechanism-based and covariation-based explanations. According to these models, the presence of a specific mechanism in the potential explanations should make no difference in the assessment of causality when the covariation information was identical between the two types of the explanations. The probabilistic contrast model might account for the current results by employing the notion of "focal sets." According to Cheng and Novick, people use different focal sets from which different sets of samples are selected as necessary for the computation of covariation. Therefore, according to that model, the mechanism-based explanations in Experiment 1 and the various contexts in Experiments 2 and 3 serve to activate different focal sets. However, it is beyond the scope of the model to delineate how these focal sets are specifically determined. As discussed earlier, one contribution of the mechanism approach can be to demonstrate the insufficiency of the model and propose specific cases where the model might fail.

Knowledge structure approach. Since Kelley first proposed his ANOVA model, psychologists have claimed that people make causal attributions in accordance with a set of formal, syntactic rules, independent of other cognitive systems. Some researchers, however, doubted that inductive reasoning could proceed independent of a person's general world knowledge. Psychologists working in the knowledge-structure paradigm sought to imbed causal attribution in the more general process of understanding, using knowledge structures such as schemas, scripts, plans, and goals (i.e., detailed representations of the real world used to understand social events, Schank & Abelson, 1977). According to the knowledge structure approach, causal attributions are made by matching an event with the appropriate script. The quality of a causal explanation is a function of how well the explanation matches the underlying script (Leddo et al., 1984).

The knowledge structure approach has attempted to explain why people commit the conjunction effect. Knowledge structures often have more than one goal. Thus, explanations with multiple reasons are rated as more representative of the underlying knowledge structure and are subsequently rated higher than ones with single reasons (Tversky & Kahneman, 1983). Using similar logic, if a knowledge structure only had a single goal, then a single explanation would seem most representative, accounting for the discounting effect. As Leddo et al. (1984) stated, "People would then seek an explanation that would fill the frame to meet the explanatory demands of the situation. Having filled in this available slot, the explanation is complete. Adding more reasons would seem to be over sufficient and therefore less preferred (p. 941-942)." This scenario, however, would predict that the conjunctive effect and the discounting effect could not occur for the same stimuli. Rather, the internal structure of the script would determine whether given explanations would be more likely to demonstrate the conjunctive or the discounting effects.

Abnormal conditions focus model. Hilton and Slugoski (1986) also dis-

agreed with formal models of causal attribution (i.e., covariation-based models) because all covariational approaches to causal attribution allow for spurious correlations to be labeled as "causes" of events. Hilton and Slugoski (1986) proposed that using counterfactual reasoning, all of the necessary conditions are determined. From the list of necessary conditions, people contrast the target event with their pre-stored information on what is normal. The necessary conditions that are abnormal will be attributed as the cause.

The abnormal-conditions focus model can account for the conjunction effect: If two conditions are judged to be abnormal, then conjunctive explanations would be better than their constituents. Likewise, it can handle the discounting effect by claiming that if there is only one abnormal condition, then people would discount other reasons if they already have a sufficient explanation. But since a given target event can have only one set of abnormal conditions, it would be impossible for the same target event to produce single and multiple abnormal conditions on different occasions. Thus, the abnormal-conditions focus model excludes the possibility that the discounting and the conjunction effect could occur with the same stimuli.

Thagard's ECHO. Thagard (1989, 1992) presented a connectionist model of explanatory coherency based on several principles, such as symmetry (if propositions P and Q cohere, then Q and P cohere), explanation (if two hypotheses together explain a piece of evidence, then the hypotheses cohere with each other, and the amount of coherence is inversely proportional to the number of propositions required to explain the evidence), and competition (hypotheses that explain the same evidence compete with each other unless there is a reason to believe otherwise). In the actual connectionist simulation program, called ECHO, units are propositions representing hypotheses and empirical data. Units receive activation from other units connected to them in varying weights. When two propositions cohere, an excitatory link is established. When they incohere, an inhibitory link is established. Each of the principles of explanatory coherency is implemented in the network. For example, for symmetry, the weight between unit i and unit j is the same as the weight between unit j and unit i . For competition, the hypotheses that do not explain a piece of evidence together have inhibitory links and have to vie with each other for spreading of activation. When the network is run, activation spreads from the special unit connected to data units until the network settles down, at which point the hypotheses with the highest level of activation are chosen as the most preferred explanations. In various tests, ECHO has been shown to prefer simple explanations over complex ones, and explanations that are consistent with more data and other hypotheses. These features are also shown to be psychologically valid in Read (1993).

Thagard's ECHO is consistent with our account of the conjunction and discounting effects. When two hypotheses are coherent by supporting the same explanation for a piece of evidence, they receive more activation than when there is one hypothesis explaining the evidence. As shown in Experiments 2 and 3, two coherent explanations produce the conjunction effect. If,

however, multiple hypothesis (or causes for events in our case) are not part of the same larger hypothesis or part of each other, then they compete and one is rejected. In other words, if they do not form a coherent story, then multiple explanations are not preferred according to the Competition principle in ECHO. The conjunction effects can be explained by the principle of explanation: You can have multiple explanations to explain an event, but they must cohere with each other.

One potentially troubling idea is Thagard's notion of simplicity (i.e., the amount of coherency is inversely proportional to the number of propositions). Since conjunctive explanations involve two hypotheses, according to the simplicity principle, one explanation should be preferred. There are several remedies for this. First, ECHO mainly concerns scientific explanations. With everyday explanations involving social events, parsimony might not be a crucial factor. ECHO was run over two networks with varying simplicity parameters: one where Hypothesis 1 explains Evidence 1 and the other where Hypotheses 1 and 2 explain Evidence 1. When the simplicity parameter was decreased slightly, having two hypotheses led to a higher activation level than having one hypothesis. Therefore, it was possible to successfully model the conjunction effect by adjusting the simplicity parameter. Second, the simplicity principle can be interpreted as saying that a unified single explanation which incorporates both meanings of the conjunctive explanation would be preferred to the conjunctive one in its more complex form with two separate mechanisms, which is exactly what was observed in our experiments.

Other Related Studies

In the area of social cognition, many studies have shown that providing an explanation for a scenario makes people judge the scenario to be more likely (see D. Koehler, 1991, for a review). According to Koehler's account, previous findings, taken as a whole, suggest that "any task that prompts a person to temporarily accept the truth of a hypothesis will increase his or her confidence in that hypothesis (p. 502)." As shown in Koehler's review (1991), the effect of explanations in increasing likelihood judgment needs to be qualified. For example, Sherman et al. (1985) have shown that judgments of likelihood were mediated by the ease with which one can imagine the scenario. In their study, some subjects were asked to imagine that they would contract prevalent diseases whereas others were asked to imagine contraction of less familiar diseases. The easily imagined symptoms led to higher likelihood judgments than did the unfamiliar symptoms. These results are consistent with our studies; not all explanations led to the conjunction and discounting effects. We found that only the explanations with which subjects could easily simulate in their minds the occurrence of the effects led to judgment of greater likelihood. The covariation-based explanations are difficult to imagine because we cannot picture the underlying processes that went on between, for example, something special about Kim and Kim's having a traffic accident. Consequently, people cannot temporarily accept the explanation as being true.

Other phenomena showing base-rate neglect are closely related to people's bias to reason based on underlying mechanisms. Tversky and Kahneman (1980) had shown that people ignore base-rates of events in favor of representativeness. In their well-known cab problem, the subjects were told that a cab was involved in a hit-and-run accident at night. They were also told that 85% of the cabs in the city were Green and 15% were Blue. Finally, they learned that the witness identified the cab as a Blue cab when the witness had only 80% accuracy. When asked to estimate the probability that the cab involved in the accident was Blue rather than Green, the results showed that the subjects neglected the base rate or covariation information given in the problem. Although Jonathan Koehler's review (1996) on base-rate neglect indicates mixed reports, several studies had shown that increasing the causal relevance of base rates made subjects more likely to seek out base rates (e.g., Wolfe, 1992). This results is similar to our findings on the difference between mechanism-based explanations and the covariation-based explanations in Experiment 1.

Conclusion

The set of studies presented here poses difficulties for previous approaches to causal attribution. People consistently rate the probability of conjunctive explanations as more likely than the probabilities of each constituent explanation. At the same time, there is a tendency to discount all other causes when there is support that a given cause is already responsible for an event. As covariation theories assume that attribution is equivalent to the estimation of the strength of correlation between two factors, it is impossible for this normative paradigm to explain such contradictory processes. The three experiments described in this paper show that people do not rely solely on such covariation information. Instead, the attribution process entails using information about the actual mechanisms underlying the causes and the effect. As a result, when people deal with multiple explanations, the crucial information is whether or not these explanations cohere at the level of causal mechanisms.

APPENDIX A

Materials Used in Experiment 1

(*Note:* The target event descriptions are underlined. For each event, explanations involve two factors (two out of person, occasion, and stimuli). For each factor, there were two versions of explanations: mechanism-based (mech) and covariation-based (cov).

PO1: Kim had a traffic accident last night.

(mech, person): Kim is nearsighted and tends not to wear her glasses while driving.

(cov, person): Kim is much more likely to have traffic accidents than other people are.

(mech, occasion): There was a severe storm and the roads were very slick last night.

(cov, occasion): Traffic accidents were much more likely to occur last night than on other nights.

PO2: Joanne was really nervous when she was taking the exam last week.

(mech, person): Joanne does not know how to prepare for exams.

(cov, person): Joanne is much more likely than an average person to be nervous when taking exams.

(mech, occasion): It was finals week last week.

(cov, occasion): Last week people were much more likely to be nervous than they were other weeks.

SP1: Dave got sick to his stomach this morning after eating chicken last night at a local restaurant.

(mech, stimulus): The chef at the restaurant always undercooks chicken.

(cov, stimulus): People are much more likely to get sick after eating chicken at the restaurant than after eating other foods.

(mech, person): Dave's stomach lining is easily irritated.

(cov, person): Dave is much more likely than other people to get sick to his stomach.

SP2: Yesterday Al went to the Dragons' game at the Dragons' stadium.

(mech, stimulus): The Dragons are a really good team.

(cov, stimulus): People are much more likely to go to Dragons' games than to go to other games.

(mech, person): Al sells hot dogs at the Dragons' stadium.

(cov, person): Al is much more likely than other people to go to the Dragons' stadium.

OS1: Mary did not enjoy dancing with Fred at the annual office party this year.

(mech, stimulus): Fred is a poor dancer.

(cov, stimulus): People are much less likely to enjoy dancing with Fred than with other people.

(mech, occasion): The management invites a very bad band to the annual office party.

(cov, occasion): People are much less likely to enjoy dancing with Fred at the annual office party than at other parties.

OS2: Tom bought a coat at Briarwood mall last week.

(mech, stimulus): It was the kind of coat worn by a famous rock star.

(cov, stimulus): People are somewhat more likely to buy these coats than they are to buy other kinds of coats.

(mech, occasion): Last week was the coldest week of the year.

(cov, occasion): People were somewhat more likely to buy these coats last week than they were to buy them other weeks.

APPENDIX B

Materials Used in Experiment 2

(Note: Target event descriptions are underlined. Two cues (biased and unifying) are specified in parenthesis after each target event description. The

explanation which is supposed to be supported by the biased cue is labeled as “biased” in parenthesis. Conjunctive explanations were simply the conjunction of two single explanations.)

Bob touched the animal.

(bias: BUTCHER, unify: VETERINARIAN)

It was his job. (biased)

He likes animals.

Charles had to leave school.

(bias: GRADUATED, unify: DRAFTED)

He was 21 years old. (biased)

The United Nations was unable to resolve the problems in the Middle East.

John came over to Mary’s house.

(bias: BEGGAR, unify: HANDYMAN)

John wore greasy clothes. (biased)

Mary had no air conditioning.

Julie went to see a doctor yesterday.

(bias: LACTOSE, unify: DENTIST)

She couldn’t eat ice cream. (biased)

Julie had bad breath.

Kim did not feel well after eating a chicken tarragon sandwich at Glimpy Burgers.

(bias: HEAT STROKE, unify: SPOILED)

The restaurant was very hot inside. (biased)

Kim did not look inside the sandwich.

Lisa and Alan got divorced.

(bias: FRAUD, unify: ADULTERY)

Alan cheats on his taxes. (biased)

Elena is very attractive.

Rachel gave the man thirty dollars.

(bias: BANKER, unify: WAITER)

He came over to Rachel. (biased)

She was no longer hungry.

Everyone was looking at Randy.

(bias: CONCERT, unify: LIBRARY)

Randy was singing. (biased)

It was finals week.

The students left the classroom.

(bias: BELL, unify: FIRE)

The professor stopped talking. (biased)

The room was getting hot.

APPENDIX C

Materials Used in Experiment 3

PO: Lisa gave the man thirty dollars when he asked.

Biased context:

Lisa is a bank teller.

Unifying context:

Lisa is a charitable woman. It is a Christmas Day.

Explanations:

Lisa was more likely to give the man thirty dollars than other people were.

Lisa was more likely to give the man thirty dollars on this day than on other days when he asked.

OP: Charles left school that year.

Biased context:

Charles barely finished his senior year in college. He left school that year.

Unifying context:

Charles was drafted. He left school that year.

Explanations:

Charles was more likely to leave school than any other students in the same class.

Charles was more likely to leave school this year than at any other year.

SP: Harry ran over Judy on Hikes Lane.

Biased context:

Judy is blind.

Unifying context:

Harry wanted to murder Judy.

Explanations:

Judy was more likely to be run over by Harry than to be run over by another driver.

Harry was more likely to run over Judy than to run over other people.

PS: Bob brought roses to the Humana building yesterday.

Biased context:

Bob delivers flowers.

Unifying context:

Bob is in love with Mary who works at the Humana building.

Explanations:

Bob was more likely to bring roses to the Humana building than other visitors were.

Bob is more likely to bring roses to the Humana building than to other office buildings.

OS: Kim watched the evening TV news yesterday.

Biased context:

Kim's evening class was canceled yesterday.

Unifying context:

There was a severe flood in Texas.

Explanations:

Kim was more likely to watch the evening TV news than other evening TV shows.

Kim was more likely to watch the TV news on this occasion than on other occasions.

SO: Many people looked at Liz yesterday.

Biased context:

Liz is undoubtedly attractive. Many people looked at Liz yesterday.

Unifying context:

Liz had an epileptic seizure yesterday. Many people looked at Liz yesterday.

Explanations:

People were more likely to look at Liz than to look at anybody else.

People were more likely to look at Liz yesterday than on other days.

REFERENCES

- Ackerman, B. P., Paine, J., & Silver, D. (1991). Building a story representation: The effects of early concept prominence on later causal inferences by children. *Developmental Psychology*, *27*, 370–380.
- Ahn, W., Kalish, C. W., Medin, D. L., & Gelman, S. A. (1995). The role of covariation versus mechanism information in causal attribution. *Cognition*, *54*, 299–352.
- Braun, O. L., & Wicklund, R. A. (1989). When discounting fails. *Journal of Experimental Social Psychology*, *25*, 450–461.
- Cheng, P. W. (1993). Separating causal laws from causal facts: Pressing the limits of statistical relevance. In D. Medin (Ed.), *The psychology of learning and motivation* (Vol. 30), 215–264.
- Cheng, P. W., & Novick, L. R. (1992). Covariation in natural causal induction. *Psychological Review*, *99*, 365–382.
- Cheng, P. W., & Novick, L. R. (1991). Causes versus enabling conditions. *Cognition*, *40*, 83–120.
- Cheng, P. W., & Novick, L. R. (1990). A probabilistic contrast model of causal induction. *Journal of Personality and Social Psychology*, *58*, 545–567.

- Einhorn, H. J., & Hogarth, R. M. (1986). Judging probable cause. *Psychological Bulletin*, **99**, 3–19.
- Forbus, K., & Gentner, D. (1986). Learning physical domains: Towards a theoretical framework: In R. S. Michalski, J. Carbonell, & T. Mitchell (Eds.), *Machine learning: An artificial intelligence approach*, Vol. II (pp. 311–348). Los Altos, CA: Morgan Kaufmann.
- Franklin, N., & Tversky, B. (1990). Searching imagined environments. *Journal of Experimental Psychology: General*, **119**, 63–76.
- Gelman, S. A., & Wellman, H. M. (1991). Insides and essence: Early understandings of the non-obvious. *Cognition*, **38**, 213–244.
- Gentner, D., & Stevens, A. L. (Eds.) (1983). *Mental models*. Hillsdale, NJ: Erlbaum.
- Gigerenzer, G. (1991). From tools to theories: A heuristic of discovery in cognitive psychology. *Psychological Review*, **98**, 254–267.
- Hansen, R. D., & Hall, C. A. (1985). Discounting and augmenting facilitative and inhibitory forces: The winner takes almost all. *Journal of Personality and Social Psychology*, **49**, 1482–1493.
- Hewstone, M. R. C. (1989). *Causal attribution*, Cambridge, MA: Basil Blackwell.
- Hewstone, M. R. C., & Jaspars, J. M. F. (1987). Covariation and causal attribution: A logical model of the intuitive analysis of variance. *Journal of Personality and Social Psychology*, **53**, 663–672.
- Hilton, D. J. (1988). *Contemporary science and natural explanation: Commonsense conceptions of causality*. New York: New York Univ. Press.
- Hilton, D. J., & Slugoski, B. R. (1986). Knowledge-based causal attribution: The abnormal conditions focus model. *Psychological Review*, **93**, 75–88.
- Hume, D. (1978). *A treatise of human nature*. Oxford, England: Oxford Univ. Press. (Original work published 1739.)
- Johnson-Laird, P. N. (1983). *Mental models*. Cambridge, MA: Harvard Univ. Press.
- Kahneman, D., & Miller, A. (1986). Norm theory: Comparing reality to its alternatives. *Psychological Review*, **93**, 136–153.
- Kahneman, D., & Tversky, A. (1982). The simulation heuristic. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases* (pp. 201–208). NY: Cambridge Univ. Press.
- Kelley, H. H. (1967). Attribution theory in social psychology. In D. Levine (Ed.), *Nebraska symposium on motivation* (Vol. 15, pp. 192–238). Lincoln: Univ. of Nebraska Press.
- Kelley, H. H. (1971). *Attribution in social interaction*. Morristown, NJ: General Learning Press.
- Kelley, H. H. (1972). Causal schemata and the attribution process. In E. E. Jones, D. E. Kanouse, H. H. Kelley, R. E. Nisbett, S. Valins, & B. Weiner, *Attribution: Perceiving the causes of behavior*. Morristown, NJ: General Learning Press.
- Kelley, H. H. (1973). The processes of causal attribution. *American Psychologist*, **28**, 107–128.
- Kim, J. (1971). Causes and events: Mackie on causation. *Journal of Philosophy*, **68**, 426–441.
- Kintsch, W., & van Dijk, T. A. (1978). Toward a model of text comprehension and production. *Psychological Review*, **85**, 363–394.
- Koehler, D. J. (1991). Explanation, imagination, and confidence in judgment. *Psychological Bulletin*, **110**, 499–519.
- Koehler, J. J. (1996). The base rate fallacy reconsidered: Descriptive, normative and methodological challenges. *Behavioral and Brain Sciences*, **19**, 1–53.
- Lalljee, M., & Abelson, R. P. (1983). The organization of explanations. In M. Hewstone (Ed.), *Attribution theory: Social and functional extensions*. Oxford: Basil Blackwell.
- Lalljee, M., Lamb, R., Furnham, A., & Jaspars, J. M. F. (1984). Explanations and information search: Inductive and hypothesis-testing approaches to arriving at an explanation. *British Journal of Social Psychology*, **23**, 201–212.
- Leddo, J., Abelson, R. P., & Gross, P. H. (1984). Conjunctive explanations: When two reasons are better than one. *Journal of Personality and Social Psychology*, **47**, 933–943.
- Mandler, J. M., & Johnson, N. S. (1977). Remembering of things parsed: Story structure and recall. *Cognitive Psychology*, **9**, 111–151.

- McClure, J., Lalljee, M., & Jaspars, J. (1991). Explanations of extreme and moderate events. *Journal of Research in Personality*, **25**, 146–166.
- McArthur, L. A. (1972). The how and what of why: Some determinants and consequences of causal attribution. *Journal of Personality and Social Psychology*, **22**, 171–193.
- Medin, D. L., & Ortony, A. (1989). Psychological essentialism. In S. Vosniadou & A. Ortony (Eds.), *Similarity and analogical reasoning* (pp. 179–196). NY: Cambridge Univ. Press.
- Morris, M. W., & Smith, E. E. (in preparation). How much explanation does behavior require?: The paradox between discounting and the conjunction effects in attribution.
- Pennington, N., & Hastie, R. (1992). Explaining the evidence: Tests of the story model for juror decision making. *Journal of Personality and Social Psychology*, **62**, 189–206.
- Pennington, N., & Hastie, R. (1988). Explanation-based decision making: Effects of memory structure on judgment. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **14**, 521–533.
- Pennington, N., & Hastie, R. (1986). Evidence evaluation in complex decision making. *Journal of Personality and Social Psychology*, **51**, 242–258.
- Read, S. J. (1987). Constructing causal scenarios: A knowledge structure approach to causal reasoning. *Journal of Personality and Social Psychology*, **52**, 288–302.
- Read, S. J. (1993). Explanatory coherence in social explanations: A parallel distributed processing account. *Journal of Personality and Social Psychology*, **65**, 429–447.
- Robinson, J. A., & Hawpe, L. (1986). Narrative thinking as a heuristic process. In T. R. Sarbin (Ed.), *Narrative psychology: The storied nature of human conduct*. NY: Proegen.
- Rumelhart, D. E. (1975). Notes on a schema for stories. In D. G. Brown & A. Collins (Eds.), *Representation and understanding: Studies in cognitive science*. New York: Academic Press.
- Schank, R. C., & Abelson, R. P. (1977). *Scripts, plans, goals and understanding: An inquiry into human knowledge structures*. Hillsdale, NJ: Erlbaum.
- Schul, Y., & Burnstein, E. (1985). When discounting fails: Conditions under which individuals use discredited information in making a judgment. *Journal of Personality and Social Psychology*, **49**, 894–903.
- Sherman, S. J., Cialdini, R. B., Schwartzman, D. F., & Reynolds, K. D. (1985). Imagining can heighten or lower the perceived likelihood of contracting a disease: The mediating effect of ease of imagery. *Personality and Social Psychology Bulletin*, **11**, 118–127.
- Stein, N. L., & Policastro, M. (1984). The concept of a story: A comparison between children's and teachers' viewpoints. In H. Mandl, N. L. Stein, and T. Trabasso (Eds.) *Learning and comprehension of text*. Hillsdale, NJ: Erlbaum.
- Thagard, P. (1989). Explanatory coherence. *Behavioral and Brain Sciences*, **12**, 435–467.
- Thagard, P. (1992). *Conceptual revolutions*. Princeton Univ. Press, NJ.
- Thorndyke, P. S. (1977). Cognitive structures in comprehension and memory of narrative discourse. *Cognitive Psychology*, **9**, 77–110.
- Tversky, A., & Kahneman, D. (1980). Causal schemas in judgments under uncertainty. In M. Fishbein (Ed.), *Progress in social psychology* (pp. 49–72). Hillsdale, NJ: Erlbaum.
- Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review*, **90**, 293–315.
- Wells, G. L., & Gavanski, I. (1989). Mental simulation of causality. *Journal of Personality and Social Psychology*, **56**, 161–169.
- Wolfe, C. R. (1992). There's more than one reason for the base rate fallacy. Unpublished manuscript, Miami University.
- Zuckerman, M., Eghrari, H., & Lambrecht, M. R. (1986). Attributions as inferences and explanations: Conjunction effects. *Journal of Personality and Social Psychology*, **51**, 1144–1153.
- Zuckerman, M., Colwell, E. L., Darche, P. R., Fischer, S. A., Osmun, R. W., Spring, D. D., Winkler, B. A., & Wolfson, L. R. (1988). Attributions as inferences and explanations: Effects of discounting. *Journal of Personality and Social Psychology*, **54**, 748–757.