An experiment examined the potentially biasing effects of prior implicit personality theories on judgments about new empirical data related to the theory. In addition, the study examined the joint effects of prior theories and new data on final implicit personality theories. New data were presented to college student participants in scatterplot form. Results yielded strong evidence of biased assimilation in the judgments of the new data; that is, judgments of new data were systematically biased in the direction of prior implicit personality theories. However, judgments were also very sensitive to the covariation strength of new data. Finally, both prior theories and new data influenced final beliefs, providing evidence for both perseverance and change of initial beliefs. Discussion focuses on the conditions under which biased assimilation is likely to occur and on the conditions under which such biases constitute reasonable ways to deal with uncertainty.

Friendly people are not liars, or so our implicit personality theory holds. But occasionally, we are confronted with a lie perpetrated by someone we know to be friendly. How do we deal with this discrepancy?

Discrepant data pose serious epistemological problems for people. If there is only one piece of new discrepant information we may be tempted to ignore it, reinterpret it, or forget it. Scientists do much the same when faced with a datum that contradicts a well established or favorite theory (Kuhn, 1970; Mahoney, 1976). When the contradiction is rare or weak,
such biased processing of new information seems defensible, perhaps even desirable. A pregnant teen's claim of virginity, for example, is properly met with skepticism rather than a revamping of prior beliefs about the process that produces babies. However, a problem emerges when the new contradictory data are strong and frequent, or when the prior belief is ill-founded. In the social domain, the persistence of racial stereotypes is based in part on overreliance on ill-founded prior beliefs and underutilization of contradictory data.

The broad question concerning how people deal with such theory/data conflicts has been addressed by several different literatures. The two most relevant are the literatures on belief perseverance (Anderson, Lepper, & Ross, 1980; Ross, Lepper, & Hubbard, 1975; Jelalian & Miller, 1984) and on covariation detection (Alloy & Tabachnick, 1984; Crocker, 1981; Troler & Hamilton, 1986).

COVARIATION DETECTION

Covariation detection refers to the process by which organisms discover the relations between pairs of variables. This broad definition thus includes many paradigms with human and nonhuman subjects. Classical conditioning, operant learning, learned helplessness, and attribution theory all depend upon the subject being able to detect covariations (or lack of covariations) among various stimuli and events. For example, a basic assumption of all major attribution theories is that people can detect covariations among various possible causes and effects. Early on, Kelley (1973) noted that “An effect is attributed to the one of its possible causes with which it, over time, covaries.” (p. 108). There have been many refinements and additions to Kelley’s notions about the attribution process in recent years, but the ability to detect covariations remains a central assumption of each (e.g., Anderson & Weiner, 1992; Hewstone & Jaspars, 1987; Hilton & Sligoski, 1986; Novick, Fratianne, & Cheng, 1992).

Crocker (1981) identified the main steps necessary to detect covariation between a pair of variables. Briefly summarized, the person must perform six tasks. First, the person must decide what data are relevant. Second, cases must be sampled. Third, the sampled cases have to be interpreted. Fourth, the person must recall these data and estimate frequencies. Fifth, the recalled data must be integrated. Sixth, this integration must be used to make a judgment or decision. A little consideration of the complexities involved in each step produces the realization that accurate detection of true covariations in the naturalistic environment is a difficult task. Nonetheless, people (and other animals) do survive and do detect covariations, sometimes ones that are exceedingly complex.
BIASED ASSIMILATION

The first problem—biased assimilation—is the more widely studied of the two. Although people can accurately detect covariations when cognitive load is low and prior expectancies are absent (Alloy & Tabachnik, 1984), these ideal conditions seldom exist in covariation detection tasks faced by people in the social realm. Thus, it is not surprising to discover that under some circumstances people are not terribly accurate or even-handed in their assessments of new data.

Biased assimilation can itself take two forms. In one the person may accurately judge the direction and extremity of the new data, but may judge the quality or relevance of the data on the basis of their congruence with prior beliefs. For instance, Lord, Ross, and Lepper (1979) showed that people with different beliefs about the efficacy of capital punishment laws (pro vs. con) judged the quality of the studies of capital punishment very differently. Subjects examined studies of capital punishment that either clearly supported or clearly contradicted their positions, so there was no opportunity for distortion to occur in judging what the results were. However, both proponents and opponents of capital punishment judged the studies that supported their beliefs as methodologically better than the studies that contradicted their beliefs. This first form of biased assimilation does not always occur, though. Anderson and Sechler (1986) found that laboratory-created beliefs (using the hypothetical explanation procedure) did not produce systematic distortions in judgments of quality or relevance of new data that clearly supported or contradicted those newly created beliefs. We proposed in that work that the strength of the initial belief may be an important factor in determining whether or not biased assimilation will occur.

Of more direct relevance to the present study is the second form of biased assimilation, in which judgments about the direction and extremity of the new data are distorted. Research in domains as varied as illusory correlation (e.g., Chapman & Chapman, 1969; Hamilton & Rose; 1980; Slusher & Anderson, 1987) and cognitive perception (e.g., Lewicki, Hill & Sasaki, 1989; Posner, Goldsmith, & Welton, 1967) has shown that perceptions about what is in the data can be influenced by prior expectations. In the clinical domain, for instance, the Chapmans showed that students and practicing clinicians alike reported seeing correlations between patients’ symptoms and their drawings in draw-a-person tests, even when there were no correlations present. In the stereotype domain, Slusher and Anderson (1987) showed that occupational stereotypes produced increases in the judged frequency of stereotype congruent trait-occupation pairings in a memory task. In both of these cases, though, the new data were themselves difficult to process. The cognitive demands of the tasks were quite high, perhaps exacerbating whatever assimilation biases may exist when people judge new data. When it is difficult to recall how many supportive and contradictory cases have been seen, it may be both natural and normatively defensible to supplement one’s memory with prior beliefs.

But what happens when the new data are presented in a form that eliminates the memory load? Does biased assimilation occur in the judgments of strength/extremity of new data when those new data are clearly and presently available? Anderson and Kellam (1992) examined this question by manipulating subjects’ prior beliefs via a hypothetical explanation procedure. Next, subjects were exposed to scatterplot data that either clearly supported or clearly contradicted the manipulated belief, and the researchers obtained strength/extremity ratings of these new data. Even though the manipulation of initial beliefs was highly successful, and final beliefs were strongly influenced by the initial belief induction, the ratings of the new data yielded no evidence of biased assimilation. Once again, we speculated that relatively weak, newly created beliefs (compared to long-standing, naturalistically generated beliefs) may constitute an important boundary condition on biased assimilation processes.

Of course, an equally interesting alternative view of these and other occasional “unbiased” performances by human judges is simply that clearly supportive or clearly contradictory data are immune to biased assimilation (Troepe, 1986). The present experiment examines this issue by including two important features: (1) use of strong, long-held initial beliefs; (2) use of clear, unambiguous data in the covariation detection task. The new data were presented in the form of scatterplots, as in Anderson and Kellam, thus eliminating most of the difficult memory and interpretation tasks inherent in more naturalistic covariation detection tasks (Crocker, 1981). The initial beliefs were implicit personality theories about pairs of personality traits. The discovery of biased assimilation in judgments of strength in this context would broaden our understanding of the range and power of assimilation processes. On the other hand, discovery of unbiased judgments in these circumstances would suggest important—one might say severe—boundary conditions on biased assimilation processes.

SENSITIVITY

This second covariation detection problem—sensitivity of judgments of new data—refers to the extent to which empirically strong data (e.g., new data with a high correlation between the covariation detection variables) are judged as being stronger than empirically weak data (e.g., low correlation data). For instance, to what extent is a strong data set
(e.g., r = .8) on the relation between politeness and friendliness judged as being stronger than a weak data set (e.g., r = .3) on this same relation? In the extreme case of no sensitivity, the two judgments would not differ. As the judge gets more sensitive to the covariation differences, the two judgments diverge.

Lane, Anderson, and Kellam (1985) demonstrated that in the absence of any theory connecting two covariation detection variables, people judging positive covariation data sets were generally quite sensitive to differences in covariation strength. Specifically, whether examining bivariate tables or scatterplots the subjects in those studies were able to distinguish between weak, moderate, and strong covariations. Though informative, the Lane et al. studies differ in many ways from covariation detection situations involving people. For instance, in social domains the judge often has a prior theory relating the target variables. In addition, people often must judge the strength of covariations involving variables that are negatively related, not just those that are positively related. So, two sensitivity questions arise when we move to the social domain: (1) Are people sensitive to covariation strength when judging variables for which they have prior theories? (2) Are people as sensitive to negative relation data as to positive? These issues are also addressed by the present experiment.

COVARIATION COMPONENTS, SENSITIVITY, AND BIAS

An additional point of Lane et al. concerned the metric by which different sets of covariation data are classified. Most studies of covariation detection sensitivity and bias classify their stimulus sets on the basis of the Pearson correlation relating two variables. The assumption is that two such data sets with the same r are equivalent. Lane et al. noted that the Pearson r is itself composed of three components: slope relating x to y; the error of prediction (error variance), and the variance of x. Equation 1 illustrates these components and their combination into a Pearson r.

\[ r^2 = \frac{b^2 s^2_x + s^2_y}{b^2 s^2_x + s^2_y} \]  

Thus, a data set with slope, error variance, and variance of x values of 2, 1000, and 400 is statistically equivalent to one with values of 4, 4000, and 400 because each produces a Pearson r of .78. However, even though Pearson's particular combination of slope, error, and variance of x is extremely useful statistically, it is not the only way to combine these components. Different weightings could be given in a judgmental context. From a functional perspective, for instance, the error variance might be relatively more important because it is essentially a measure of how accurate one's predictions of y are, regardless of whether x actually contributed to the accuracy of the predictions. Functionally, it may be more important to know the likelihood that a person is lying to us (low error variance = accurate individual predictions) than it is to know whether the friendliness of the person helps us to predict lying behavior (high slope = friendliness helps predict lying). Thus, from a purely functional view one would predict that people would display relatively greater sensitivity to the error component. Interestingly, Lane et al. found that data sets with equivalent rs were judged to be stronger when the error variance was low than when it was high. In other words, the error component was more important than the slope or variance of x components. The present study examines whether this enhanced sensitivity to the error component of bivariate covariations occurs when prior social theories relate the two covariation variables, and does so with both positive and negative covariation data sets.

This componential approach also has important implications for the study of sensitivity and bias. In both types of studies, one must use stimulus data sets that equate not only on the basis of r, but on the basis of slope, error variance, and variance of x as well. Otherwise, one could inadvertently draw incorrect conclusions. Consider the following hypothetical study of biased assimilation. Each subject is to be presented with two data sets in scatterplot form. Each has been "equated" to have r = .8. The two cannot be the exact same plot because the subjects would recognize them as such and would become suspicious of the experimenter's intent. One scatterplot is paired with the variables "politeness" and "friendliness," whereas the other is paired with "politeness" and "liar." Subjects judge the strength of these new data sets to allow a test of whether or not prior beliefs influence judgments of new data, the biased assimilation hypothesis. If the "friendliness" scatterplot happens to be based on a lower error variance component than the "liar" plot, then the researchers could get evidence of biased assimilation that in actuality was produced by the componential structure of the plots rather than true bias. Alternatively, if the "friendliness" scatterplot happens to be based on a higher error variance component than the "liar" plot, then the componential structure of the plots could inadvertently hide a true bias. The present experiment controlled for this potential artifact by using scatterplot sets equated for each component as well as for overall correlation.

BELIEF PERSEVERANCE

Though biased assimilation and sensitivity issues are important in their own right, it is the resulting beliefs that are of most interest to most people. Beliefs guide subsequent behaviors, trigger particular emotions,
and influence subsequent cognitive processes. It matters not whether the processes leading up to the beliefs were biased or fair, or whether the judge was sensitive or insensitive to covariations in the data; anger born of judgmental error is no less likely to produce aggression than anger born of accuracy. So what happens when prior beliefs are pitted against contradictory data?

Past research has shown that when the data are weak, or ambiguous as to relevance or quality, prior beliefs tend to win the battle. This occurs even when the the beliefs themselves are based solely on hypothetical explanations of why the belief may be true (e.g., Anderson & Sechler, 1986). There is some laboratory evidence, however, that strong covariation data can produce some change in weakly held beliefs, even if it doesn’t completely override those prior beliefs (Alloy & Tabachnik, 1984). But the evidence for what happens when strong prior beliefs, such as the implicit personality theory that friendly people are not liars, are pitted against strong covariation data is less clear. Certainly, in the real world strongly held beliefs do sometimes change, but the persistence of extreme racial, sexual, occupational, and even national stereotypes suggests that strongly held initial beliefs will be resistant to change even in the face of clearly contradictory data. In other words, it was expected that subjects’ implicit personality theories would undergo some change after exposure to the new data, but that their final implicit personality theories would also show a residual impact of their initial theories.

OVERVIEW

When people with strongly held initial theories examine clearly supportive or clearly contradictory data, several interesting phenomena are likely to result. The present experiment examined biased assimilation, belief change, and covariation sensitivity issues. It did so using strong prior beliefs (implicit personality theories) and unambiguous new data (in scatterplots) that either clearly confirmed or clearly contradicted those initial beliefs. College students participated in a study on the “ability of nonexperts to judge relations in scatterplots.” The concepts of positive, negative, and zero covariations were carefully explained during the training phase of the study. Subjects then indicated their belief about the true relation between a pair of personality traits such as “polite” and “friendly.” Next, they examined and rated eight scatterplots of data relating the traits. Each plot consisted of nine points supposedly drawn from a sample of 396 people used in prior research. In actuality, the eight plots were constructed to be a factorial combination of high and low slope, high and low error, and high and low variance of x, as in Lane et al. (1985). Last, subjects indicated their final beliefs about the true relation between the two traits. This procedure—indicate initial implicit personality theory, examine new data, indicate final beliefs—was repeated a total of eight times with different trait pair/data set combinations. For half of the sets, the eight scatterplots all showed a positive relation between the two target traits; half of the sets showed a negative relation. Crossing this data type manipulation was a manipulation of the type of trait pair. This four-level factor was manipulated by changing the x and y axis labels. One level was the null trait pair type, in which the axes were labelled as trait X and trait Y. These two conditions (one each with positive and negative relation data) constituted control conditions, used for comparisons with judgments made in the other conditions. For the other three levels (the verbal label conditions), trait pairs were chosen such that most people would tend to see them as positively related, negatively related, or unrelated.

Of primary interest was the relation between initial beliefs and the covariation strength judgments in the verbal label conditions. This was examined by computing for each subject a regression line relating his or her initial beliefs to the corresponding strength judgments. This was done separately for the positive and negative data conditions. The resulting slopes thus indicated the extent to which prior theories influenced covariation strength judgments. The resulting intercepts indicated the extent to which the new data influenced covariation judgments. Similar analyses were used to examine the effects of prior theories and new data on final beliefs. Finally, individual graph ratings were examined to test predictions about the effects of the three covariation components on judgments of data strength.

These analyses provided answers to five questions about biased assimilation, belief perseverance and change, and covariation detection sensitivity: (1) Do strong prior theories bias covariation assessments of unambiguous new data? (2) Are final beliefs a function of one’s prior theory, the covariation data, or both? (3) Are people sensitive to the 3 components of Pearson’s r when social variables are used? (4) Are the 3 components equally weighted? (5) Are the above effects the same for judgments based on negative versus positive relation data? 1

METHOD

Design, Stimuli, and Equipment

The basic design was a 2 (Data Type) x 4 (Trait Pair Type) within subjects factorial. Additionally, the 8 scatterplots within each set can be seen as

1. The additional cognitive and linguistic complexity of negative concepts and negative empirical relations suggested that biased assimilation, sensitivity, and belief change effects might be weaker when the new data depict negative relations (cf., Clark & Clark, 1977; Gilbert, 1991).
a factorial combination of slope, error variance, and variance of x (high vs. low in each case, see Lane et al., 1985). Table 1 displays the characteristics of the eight scatterplots within each set, as well as contrast weights corresponding to the various sensitivity measures described later.2

Four different positive scatterplot sets from Lane et al. were used in the main experiment. These can be labeled A, B, C, and D. Recall that each set of eight plots has the same statistical characteristics, but the sets differ in particular form. The four negative sets were simply mirror images of the four positive sets. Each subject judged each of the four sets twice, once in the positive form, once in the negative form.

A between subjects factor concerned the specific choices of trait labels in the various conditions and their pairings with the different scatterplot sets. In essence, two complete replications were conducted to reduce the possibility that any effect of interest resulted from a particular choice of traits or a particular scatterplot set. The two between subject conditions used different trait pairs for the trait pair type manipulations, based on their raw correlations in the Anderson and Sedikides (1991) implicit personality theory research. Condition 1 used polite/friendly (r = .71), talkative/depressed (r = -.01), and thoughtful/narrow-minded (r = -.70) for the verbal label conditions. Condition 2 used insincere/conceited (r = .69), liar/emotional (r = -.01), and honest/unreliable (r = -.70). All analyses collapsed across the two between subjects conditions, essentially treating them as uninteresting but useful counterbalancing controls. All stimuli were presented and all dependent variables were obtained via a Macintosh SE computer.

Subjects

Seventy-three university undergraduates participated in the experiment and received extra course credit. Data from eight were deleted because their initial beliefs did not display sufficient range to allow reasonable tests of prior theory effects (see below). The final sample thus consisted of 65 subjects, 46 females and 19 males.

Procedure

Subjects first completed consent forms and a brief background questionnaire. The experimenter then explained that the experiment as involving people's ability to accurately estimate the strength of the relation between two variables. A detailed explanation of covariation detection and scatterplots was given. This was done via computer, though the experimenter was available to answer questions. Examples of positive, negative, and zero relations were presented both verbally and visually. In addition, examples of a perfect positive and a perfect negative relation were presented. Subjects were encouraged to ask questions throughout this phase, and were repeatedly instructed in the use and interpretation of scatterplots until they appeared to understand all the basic points. Subjects then made some practice judgments, again on the computer. After any remaining confusions had been resolved, subjects proceeded with the main tasks. All remaining instructions, stimuli, and tasks were presented and answered via computer.

For each set, the following events occurred in the same order. First, the two traits being examined in the set were described. Second, subjects indicated their initial belief about the relation (except for the null trait pair type sets, of course). Third, the eight "new data" plots were presented one at a time. Subjects judged each plot before the next one was presented. Figure 1 presents a sample plot. Fourth, subjects gave their overall summary judgment of the data presented in the eight plots. Finally, subjects indicated their personal belief about the true relation between the two target traits (except for the null trait pair type sets). This sequence was repeated for all eight sets. Order of the eight sets was randomly determined for each subject.

Dependent Variables

Initial Beliefs. For the six sets containing verbal labels on the x and y axis, subjects indicated their initial beliefs on a scale anchored at perfect negative relation (-100), no relation (0), and perfect positive relation

<table>
<thead>
<tr>
<th>TABLE 1. Characteristics of the Stimulus Scatterplot Sets: Component and Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error Variance*: High</td>
</tr>
<tr>
<td>Variance of X**: High</td>
</tr>
<tr>
<td>Slope*: Low</td>
</tr>
<tr>
<td>Pearson's Correlation</td>
</tr>
<tr>
<td>Error Variance Sensitivityd</td>
</tr>
<tr>
<td>Variance of X Sensitivityd</td>
</tr>
<tr>
<td>Slope Sensitivityd</td>
</tr>
<tr>
<td>Overall Sensitivityd</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Note</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>High = 4000; Low = 1000.</td>
<td></td>
</tr>
<tr>
<td>Low = 100; High = 400.</td>
<td></td>
</tr>
<tr>
<td>Low = 2; High = 4.</td>
<td></td>
</tr>
<tr>
<td>To put these sensitivity scores on the proper scale, each must be divided by 4.</td>
<td></td>
</tr>
<tr>
<td>To put this sensitivity score on the proper scale, it must be divided by 12. This is the same as the average of the three component sensitivity scores.</td>
<td></td>
</tr>
</tbody>
</table>
High

polite

Low

Final Beliefs. For the sets containing verbal (trait) labels on the x and y axis (i.e., all sets except the Null sets), subjects also indicated their Final Beliefs concerning the true relation between the target pair of traits.

RESULTS

Equivalence of Prior Theories in Positive and Negative Data Conditions

The various counterbalancing and trait selection procedures were used, in part, to guarantee that the initial beliefs in the positive and negative data conditions would be equivalent and would average about zero. If successful, this would facilitate comparisons across data types. The procedures were successful. The average initial beliefs were practically identical in the positive and negative data conditions, Ms = -0.9 and -1.0, respectively. These means did not differ from each other, ps > .7. In addition, the average ranges of initial beliefs were essentially the same in the positive and negative data conditions, Ms = 120.7 and 121.0, respectively. These means did not differ from each other, p > .9.

ANALYSIS STRATEGY

The basic hypothesis that a person's prior beliefs can influence judgments about new data is a regression hypotheses. Specifically, the prediction is that the slope relating a person's prior theory to his or her judgments about the strength of new data will be positive—the more positive the prior theory, the more positive (or less negative) the judged relatedness of new data. Recall that each subject was presented with three trait pairs associated with statistically equivalent (in terms of correlation and covariation components) positive relation data plots. For each subject, evidence of biased assimilation would appear as a positive slope between that subject's prior theories and his or her strength judgments, across those three trait pairs. If prior theories do not influence subsequent data judgments, then the slopes should, on average, be close to zero. The same reasoning applies to the subject's prior theories and subsequent judgments concerning the three trait pairs that were later associated with negative relation data plots.

In addition to these two slopes, one can compute for each subject the corresponding intercepts, which indicate the average judgment when the prior theory is zero. A comparison of the intercepts obtained from

3. Negative scores were possible; they would indicate that the component had been used exactly backwards in making judgments. Such scores did not occur.
positive versus negative data conditions indicates the average effect of the data on the judgments. If the data significantly influenced judgments, then the average intercepts for positive versus negative data conditions should be significantly different from each other, and significantly different from zero.

The same analysis can be applied to the effects of prior theories and new data on final beliefs. That is, one can get slopes and intercepts relating prior theories to final beliefs for the positive and negative data conditions separately.

Figure 2 presents the “overall” judged strength and prior theory estimates for one subject. In addition, the regression lines relating these variables in the positive and negative data conditions are presented. As can be seen, for this subject both slopes were positive and equivalent in size, suggesting that some biased assimilation occurred with both types of data. In addition, the intercepts were quite different, indicating that the new data had a major impact on judged strength.

Effects of Prior Theories and Data Type on Strength Judgments

Two measures of judged strength were obtained from subjects. One was the “overall” judgment made after examining and rating the eight scatterplots; the other was the average of the eight scatterplot ratings.

Figure 3 presents the averaged regression lines from the “overall” judgments. The positive slopes revealed that biased assimilation occurred in both positive and negative data type conditions, \( Ms = .173 \) and \( .102 \), \( ts(64) = 4.55 \) and \( 2.36, ps < .0001 \) and .03, respectively. These mean slopes did not differ from each other reliably, \( t(64) = 1.56, p > .1 \). Overall, when subjects had a prior theory their judgments about new data relevant to that theory were systematically biased in the direction of supporting the theory.

4. Examination of Figure 2 highlights an additional crucial requirement for testing biased assimilation process issues. If a given subject does not have prior theories that vary, there can be no reasonable estimate of slope or intercept. The trait pairs selected for use in this research were picked to maximize the likelihood that subjects would indeed have sizeable ranges of prior theories within each of the two data type conditions (positive and negative). This was generally true; however, several subjects gave very similar estimates for all of their prior belief estimates. A criterion was needed to determine which subjects had sufficiently varied prior theories to allow accurate testing of biased assimilation issues. It was decided to delete any subject whose range of prior theory scores for either the positive or the negative data conditions was less than 20% of the possible range, which was 200 (+100 to -100). In other words, to be included in the analyses, a subject had to have indicated initial beliefs that had a range of at least 40 scale points (out of 200) for their three trait pairs later associated with positive data and for their three trait pairs later associated with negative data. This resulted in a loss of eight subjects, as indicated earlier. This same criterion resulted from a more statistically guided process as well. Specifically, the lower boundary of the 90% confidence interval on the range on prior theories was 40.8. To get an idea of how specific the reported results were to this criterion, I also reanalyzed the slope and intercept data using a more extreme minimum range of 50. Data from an additional seven subjects failed to meet this criterion. The results were essentially the same.
TABLE 2. Effects of Prior Beliefs and New Data on Overall Strength Judgments, Averaged Strength Judgments, and Final Beliefs

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Verbal Label Conditions</th>
<th>Null Theory Conditions</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Strength Judgments</td>
<td>Slope</td>
<td>Intercept</td>
<td>Mean</td>
</tr>
<tr>
<td>Positive Data Plots</td>
<td>.173**</td>
<td>38.4**</td>
<td>37.5**</td>
</tr>
<tr>
<td>Negative Data Plots</td>
<td>.102**</td>
<td>-37.6**</td>
<td>-37.3**</td>
</tr>
<tr>
<td>Averaged Strength Judgments</td>
<td>Positive Data Plots</td>
<td>.092**</td>
<td>34.6**</td>
</tr>
<tr>
<td>Negative Data Plots</td>
<td>.063**</td>
<td>-33.6**</td>
<td>-33.8**</td>
</tr>
<tr>
<td>Final Beliefs</td>
<td>Positive Data Plots</td>
<td>.296**</td>
<td>31.6**</td>
</tr>
<tr>
<td>Negative Data Plots</td>
<td>.280**</td>
<td>-31.5**</td>
<td>na</td>
</tr>
</tbody>
</table>

All means are significantly different from zero at: *p < .05 **p < .001

The intercepts revealed that the overall strength judgments were also affected by the type of new data. The intercepts for the positive and negative data conditions were both significantly different from zero, ts(64) = 14.02 & -13.35, ps < .0001, respectively. The positive and negative data seemed to influence overall strength ratings about the same amount, just in opposite directions. Reversing the sign on the negative data intercepts, and testing the two means against each other, confirmed this observation, t(64) < 1.00.

The means of the overall strength judgments for the positive and negative null theory conditions were similar to the corresponding intercepts from the verbal label conditions, as shown in Table 2. The interaction in a 2 (positive vs. negative data type) x 2 (verbal labels [intercepts] vs. null theories) repeated measures ANOVA did not approach significance, F(1, 64) < 1.00.

Parallel analyses on the "averaged strength" judgments yielded the same results. As can be seen by the positive slopes in Table 2, biased assimilation occurred in both data type conditions, ts(64) = 4.48 and 4.6, ps < .0001 & .02, for the positive and negative data conditions respectively.

5. Instead of examining average intercepts, one could analyze the average actual strength judgment, averaged across the three trait pairs in each data type condition. As one might expect from the fact that the average initial beliefs were essentially zero in both the positive and negative data conditions, the average actual strength judgments were practically identical to the average intercepts, and therefore produced practically identical results. The intercepts are more relevant theoretically, because they would more accurately estimate the true effects of data type if the average initial beliefs had systematically differed from zero or had differed between the positive and negative data conditions.

These slopes did not differ from each other reliably, t(64) = 1.02, p > .3. Averaged strength judgments were also strongly affected by the type of new data, as shown by the intercepts in Table 2, each of which differed significantly from zero, ts(64) = 17.95 and -17.81, ps < .0001, for the positive and negative data conditions respectively. Once again, the absolute magnitude of the effects of positive and negative data types did not differ, t(64) < 1.00. Finally, the averaged strength judgments for the positive and negative null theory conditions were quite similar to the corresponding mean intercepts. The apparent similarity in the size of the data type effect was confirmed by the nonsignificant interaction, F(1, 64) < 1.00.

Overall the strength results strongly supported the hypothesis that even relatively objective judgments of the relations between variables are susceptible to the biasing influence of prior theories. Scatterplots are particularly useful to data analysts of all types precisely because they are easy-to-read displays of raw information. Compared to the typical covariation detection task faced by the social perceivers, the present scatterplot task was a piece of cake (Crocker, 1981). There were no interpretation demands, no memory load demands, and no data selection demands. Yet, judgments of the strength of the data were biased by prior theories. So, the answer to the first of the five questions posed earlier is a clear "yes"—strong prior theories can produce biased covariation assessments of unambiguous data. The biased assimilation effects appeared to be slightly stronger for the judgments of positive data plots than the judgments of negative data plots; the slopes were slightly steeper. But these differences were not statistically reliable. Finally, the intercept results revealed that subjects were sensitive to the direction of the new data plots, equally so in both the positive and negative data conditions.

Effects of Prior Theories and Data Type on Final Beliefs

The second question concerns subjects' final beliefs. What happens when new data support or contradict strong prior theories? If theories are impervious to new data, then we should see little systematic change in beliefs as a function of whether the new data are supportive or contradictory. If theories are completely malleable with respect to new clear data, then prior theories should have little impact on final beliefs. For an individual faced with contradictory new data, though, the most reasonable decision may well be to compromise, allowing one's final beliefs to be influenced by both initial theory and new data.

In the present study, the measure of final beliefs was taken shortly after the new data had been examined and rated, and used the exact same rating scale (-100 to +100). Anderson and Kellam (1992) found that this combination maximized use of the new data and minimized use of prior
theory. Thus, finding an effect of prior theory on final beliefs in the present study would attest to the strength of initial beliefs to withstand contradictory data.

The slope and intercept procedure used in analyses of strength judgments was also used to analyze the effects of prior theories and new data on final beliefs. As expected, final beliefs were strongly influenced by both factors, as shown by the means presented in Table 2. For both positive and negative data type conditions, the average slopes relating prior theories to final beliefs were positive and reliably different from zero, \( t(64) = 5.49 \) & \( 4.58, p < .0001 \), respectively. These two slopes did not differ from each other, indicating that the prior theory effect on final beliefs was essentially the same regardless of whether the intervening data plots displayed positive or negative new data, \( t(64) < 1.00 \).

The intercepts revealed that the new data also had a big impact on final beliefs, as can be seen in Table 2. Both the positive and the negative data condition intercepts were significantly different from zero, \( t(64) = 11.59 \) & \( -10.14, p < .0001 \), respectively. Once again, the absolute magnitude of the effects of positive and negative data types did not differ, \( t(64) < 1.00 \).

Covariation Detection: Sensitivity

The effects of data type (positive versus negative) reported in the previous sections revealed that subjects were at least somewhat sensitive to the covariation information contained in the new data plots. However, those analyses did not directly address all relevant sensitivity questions. As noted earlier, the relation between two variables (\( x \) & \( y \)) can be broken down into three components: the slope, the error variance, and the variance of \( x \). The analyses in this section examine the extent to which people are sensitive to each of these components within each of the two data types.

The first sensitivity question concerns whether people are sensitive to the each component. Recall that three sensitivity scores, one for each component, were calculated for each of the six sets of scatterplots with trait labels. Because the particular trait pairs used in these conditions have no bearing on sensitivity issues, the scores were averaged across the three trait pairs within each data type. The signs were reversed for the negative data conditions so that in all cases positive scores indicated that subjects were sensitive to the component in the proper direction. An overall sensitivity score was also computed for each data type by averaging the three component scores.

Figure 4 presents the resulting means. As expected, each individual component in each condition of the experiment had a significant effect, all \( t > 13, p < .0001 \). In other words, subjects were quite sensitive to covariation differences in the plots for each component of covariation.

The second sensitivity question is whether people are differentially sensitive to the three components. To examine this, a 2 (data type) x 3 (component) repeated measures ANOVA was conducted on the sensitivity scores. Consistent with the functional analysis presented earlier, people were most sensitive to the error component. The component main effect was highly significant, \( F(2, 128) = 20.38, p < .0001 \).

This same analysis also revealed that subjects were equally sensitive to covariation differences in positive and negative data type conditions, \( F(1, 64) < 1.00 \). The overall sensitivity means are displayed in Figure 4 as well. However, there was also a significant interaction effect, indicating that the sensitivity pattern was not quite the same for the two data types, \( F(2, 128) = 3.81, p < .03 \). The main pattern in this interaction is that sensitivity to error and variance of \( x \) was slightly higher in the positive data condition, whereas sensitivity to slope was slightly higher in the negative data condition. This interaction is quite small when compared to the main effect of component. Therefore, it seems prudent to avoid overinterpreting it without further replication.

DISCUSSION

The present results add to the judgment literature in numerous ways. It is now clear that people are sensitive to all three covariation components, whether examining data in scatterplot or tabular form (Lane et al., 1985), whether there are strong prior theories (the present experiment) or not
(Lane et al., 1985), and whether the data display a positive or negative relation between the target variables (the present experiment). Furthermore, this study makes it clear that people do not weight slope, error variance, and variance of x in the same proportions as Pearson’s r. The predominant deviation appears to be heightened sensitivity to error variance, a deviation that makes sense from a functional view that it is often more important to be able to predict outcome (error variance) than it is to know the effect of the predictor (slope). Additional work, in which the sensitivity issues are assessed in systematically more natural covariation detection tasks, would help establish the generality and the boundary conditions of these phenomena. One could, for instance, present new covariation data in the form of brief videotaped episodes in which the target traits are displayed.

The present study also demonstrates that even when prior theories are quite strong, as in one’s own implicit personality theories, exposure to new data produces large changes in beliefs, at least temporarily. People are sensitive to the implications of data and do modify their beliefs in response to them. Of course, the change may be relatively task-dependent or short-lived; further research is needed in which final beliefs are assessed in different ways and with some passage of time between the examination of new data and the assessment of final beliefs.

An additional contribution of this study is the extension of biased assimilation phenomena to cases where the new information is clear and unambiguous. Even though the data were presented in an uncommonly easy-to-assess format, prior implicit personality theories produced systematic shifts in judgments about the data. This suggests that such theory driven biases are common across many types of tasks and domains. A related contribution is that the assimilation bias displayed in the present experiments is of a different type than that demonstrated in previous research. For example, Lord’s studies of capital punishment beliefs (Lord et al., 1979; 1984) demonstrated bias in judgments of the quality or relevance of new contradictory data, whereas the present studies demonstrated bias in perceptions of the strength of the data themselves. Finally, although the finding that prior beliefs can influence final beliefs is not a new one, this study additionally demonstrated that this effect can occur even in the face of clearly contradictory data.

A BAYESIAN VIEW

At first glance, both the biased assimilation results and the effects of prior theories on final beliefs suggest that people are committing judgmental errors. A closer look reveals that we should be wary of such a conclusion.

In the case of strong theories, at least, normative rules of inference do not demand a total shift in beliefs to match the new data. As any good Bayesian knows, one’s final beliefs in a given domain should always be responsive to prior beliefs except: (1) when the prior beliefs are known to be totally invalid, or; (2) when the new data are known to be perfectly valid. Prior implicit personality theories presumably have some validity to them, at least from the theory-holder’s perspective. In most cases, certainly in the present study, the theory-holder also has good reason to suspect that the new data are not perfectly valid.

Similarly, even though the scatterplot task presented clear data in a relatively simple way, there still was room for interpretation. A Bayesian (or similar) analysis of normativeness in decision making certainly allows for prior beliefs to influence judgments of strength of new data except in rare circumstances where prior beliefs have no validity or the new data are perfectly clear. Thus, it can be entirely correct to allow prior theories to influence judgments of new data as well as final beliefs.

THEORETICAL IMPLICATIONS

Broad theories relying on the assumption that people can detect covariations with some degree of accuracy, such as all current models of the attribution process, gain some strength from the present findings. People did detect differences in covariation strength and did use all three covariation components. The differential use of covariation components suggests that more specific models of covariation detection processes need to be developed. It also suggests that even studies of covariation detection that are not specifically concerned with underlying processes need to use stimuli constructed very carefully so that supposedly equal stimulus sets are in fact equivalent. Equating covariation stimulus sets on Pearson’s r is not an adequate safeguard. They also need to be equivalent on the three components, or else one runs the risk of introducing systematic bias into the judgment data.

The fact that people are sensitive to all three components of covariation fits well with Nisbett’s work on statistical heuristics (e.g., Nisbett, 1993). That work has shown that people are sensitive to a variety of statistical principles such as the law of large numbers, that people use these abstract rules in a variety of circumstances, and that training on these abstract rules improves performance on a wide variety of reasoning problems. Sensitivity to covariation components appears to be another case where people have some intuitive understanding of complex statistical principles. Can brief training in these abstract principles further improve people’s abilities at a range of covariation detection tasks?
Although the long history of thought in psychology and education, reflected in both the Piagetian and the learning traditions, denies the possibility of improving reasoning through formal training, recent work by Nisbett and his colleagues demonstrates clearly that such formal training can have major effects on reasoning. Perhaps similar effects can occur in the covariation detection domain.

PRACTICAL IMPLICATIONS

From the classroom to the boardroom to the courtroom, people are called upon to examine new data, judge the relatedness of variables, and act on those judgments. Very often, the person who has gathered the data is trying to persuade others that some relation does exist between two variables. One might be presenting data on the predictive validity of some employment exam, or on differences in pay as a function of race or sex of employee. How does one convince an audience composed of statistical novices? Very often, scatterplots are presented. The current findings regarding the differential weightings of covariation components suggest that certain scatterplots will be more effective than others, even though the data are identical. A host of practical issues involving persuasion arise from these findings, all revolving around the question of how best to present one’s data to convince an audience that there is (or in some cases, is not) a relation between the target variables. The present studies suggest some preliminary answers, but more importantly they demonstrate that additional work in this area is likely to yield significant theoretical and practical contributions.

REFERENCES


