

## The Role of Inference in Attribute Framing Effects

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### ABSTRACT

Previous research has shown that a speaker's choice between logically equivalent frames is influenced by reference point information, and that listeners draw accurate inferences based on the frame. Less clear, however, is whether these inferences play a causal role in generating attribute framing effects. Two experiments are reported, which suggest that frame-dependent inferences are sufficient to generate attribute framing effects, and that blocking such inferences may block framing effects. Experiment 1 decomposed the typical framing design into two parts: One group of participants saw a target described in one of two attribute frames and reported their estimates (inferences) of the typical attribute value. These estimates were then given to a second group of yoked participants, who evaluated the target. Although this latter group was not exposed to different attribute frames, they nevertheless exhibited a "framing effect" as a result of receiving systematically different inferences. In contrast, Experiment 2 shows that experts—who are familiar with an attribute's distribution and are therefore less likely to draw strong frame-based inferences—exhibit a diminished framing effect. Together, these findings underscore the role of inferences in the generation and attenuation of attribute framing effects. Copyright © 2017 John Wiley & Sons, Ltd.

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KEY WORDS framing effect; inference; information leakage; rationality; expertise

Framing effects occur when people's judgments or choices systematically depend on which logically equivalent description of outcomes or objects is presented to them. The present article focuses on attribute framing, in which a single attribute of an object is described in one of two ways. One frame is usually positive and one negative, and a robust finding is that the object is evaluated more favorably in the positive frame than the negative frame (a "valence-consistent shift" in preference; Levin, Schneider, & Gaeth, 1998). Ground beef is rated as better tasting and less greasy when described as "75% lean" rather than "25% fat" (Levin & Gaeth, 1988), a basketball player's performance is rated higher when described in terms of the percentage of shots "made" rather than "missed," and a medical treatment is more likely to be recommended when described in terms of "survival" rather than "mortality" rate (see Table 3 in Levin et al., 1998).

Several competing explanations for these intriguing effects have been proposed. Levin and colleagues suggested an associative account (Levin, 1987; Levin et al., 1998). Positive frames are assumed to evoke positive associations, negative frames evoke negative associations, and these associations influence the evaluation of the object. Thus, ground beef described as "75% lean" is evaluated more favorably because "lean" evokes positive associations, which in turn color the perception of the ground beef. A second account, query theory, posits that frames influence the order in which people retrieve supporting evidence (Hardisty, Johnson, & Weber, 2010). According to this account, the initial query generates more retrievals, and hence different query orders result in a different balance of evidence. People evaluating

ground beef in a "lean" frame, for example, begin by retrieving favorable evidence before considering unfavorable evidence, and this order results in more favorable evidence being retrieved overall. Both the associative account and query theory are consistent with the common view of attribute framing effects as irrational biases, because surface associations and query order are unrelated to the value of the evaluated item.

An alternative, rational account of attribute framing focuses on the information content of frames (McKenzie & Nelson, 2003; Sher & McKenzie, 2006, 2008). According to this "information leakage" account, a speaker's choice among logically equivalent frames can "leak" relevant information beyond the chosen frame's literal content. For example, comparisons to a known reference point (the initial, typical, or expected level of an attribute) may influence a speaker's frame selection. In particular, speakers are more likely to frame options in terms of attributes that exceed a salient reference point. In one demonstration, McKenzie and Nelson (2003) found that "speaker" participants were more likely to describe a cup with liquid at the halfway mark as "half empty" rather than "half full" when the cup had initially been full (and was therefore relatively empty). "Listener" participants, in turn, consciously or unconsciously "absorbed" the information leaked by the speaker's choice of frame and were more likely to infer that a cup was originally full (rather than empty) when it was described as "half empty" (rather than "half full"). That is, listeners' inferred reference points matched the actual reference points that guide speakers' frame selection. Logically equivalent frames can thus implicitly convey different information. This speaker–listener framework has been used to help explain behavior in other framing contexts such as medical treatment outcomes (McKenzie & Nelson, 2003), time and work on a

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project (Teigen & Karevold, 2005), and ground beef advertisements (Keren, 2007).

In the information leakage framework, attribute framing effects can arise from the different inferences drawn by listeners exposed to different frames. In particular, high evaluations in a positive frame reflect comparisons with an inferior inferred reference point (e.g., ground beef described as “75% lean” is good because typical ground beef is inferred to be less lean), whereas low evaluations in a negative frame reflect comparisons with a superior inferred reference point (e.g., ground beef described as “25% fat” is bad because typical ground beef is inferred to be less fatty). Note that while the listener’s updated beliefs reflect her or his attunement to a subtle linguistic cue, this basis for her or his inference need not be consciously accessible to her or him. Indeed, as Sher and McKenzie (2006) point out, the inferential processes at play are likely to be largely implicit: If the non-equivalence of the information contained in logically equivalent attribute frames was self-evident, these framing effects would hardly have been regarded as problematic for rational models of decision making.

By showing that reference points influence speakers’ frame selection, and that frames influence the inferences that listeners draw regarding a speaker’s reference point, previous research offers considerable evidence that is consistent with this account. It has not, however, established a causal role of inferences in generating attribute framing effects. In this article, we provide strong evidence for this missing link between frames, inferences, and evaluations by demonstrating that reference point inferences are sufficient for generating attribute framing effects, and that when inferences are likely weaker or absent, framing effects are weaker or absent.

To demonstrate the sufficiency of reference point inferences, Experiment 1 employs a yoking procedure recently developed by Sher and McKenzie (2014) to examine how changes in context lead to different beliefs and how these different beliefs subsequently affect evaluations. We used this procedure to break a standard attribute framing design into two parts. In the first part, we presented “modeler” participants with the target attribute in either one of two frames. They were not asked to form evaluations, however, but to state inferences about the typical value of the attribute. We expected that the positive frame would yield lower estimates of the typical value, in line with findings of McKenzie and Nelson (2003) and Sher and McKenzie (2006). In the second part, each modeler participant was individually yoked to a “recipient” participant who was presented with the modeler’s inference about the typical attribute value as part of the background information. The recipients then evaluated the target attribute which, crucially, was always described by *both* frames. In other words, the target attribute was not selectively framed for recipients. Information leakage predicts that these “unframed” recipients should nevertheless exhibit a framing effect in their evaluations: A positive frame presented to a modeler should, by way of the modeler’s inference, lead the yoked recipient to provide a more favorable evaluation. Because recipients are provided with different (modeler) inferences, but not different attribute frames, such

an effect would indicate that frame-based inferences are sufficient to generate an attribute framing effect.

Whereas Experiment 1 asks whether inferences are sufficient to generate attribute framing effects, in Experiment 2, we examine the converse prediction that blocking inferences should block framing effects. To this end, we measured participants’ knowledge in a specific content domain (basketball) and investigated their reactions to attribute frames both in that domain and in an unrelated domain (medical treatments). Those who know more about the content domain should be less influenced by framing in that domain, as their stronger prior beliefs about the typical attribute value limit the scope of frame-dependent inferences. At the same time, knowledge in a specific domain should not preclude participants from being influenced by framing in the unrelated domain. Together, the experiments indicate that the presence of frame-based inferences can generate an attribute framing effect, while their absence can greatly attenuate the effect.

## EXPERIMENT 1

Participants read a framing scenario about recruiting a basketball player. “Modeler” participants were presented with the target player’s performance framed as either shots “made” or shots “missed” and then reported their estimates (i.e., their inferred “models”) of the typical player’s performance. “Recipient” participants then received these reference point inferences as part of their background information, and they evaluated the target player described in a neutral (“unframed”) manner. To establish a baseline for the framing effect, we also included control conditions, in which participants simply provided evaluations after receiving one frame. The study was designed to test two main predictions. First, we expected that, replicating prior findings (McKenzie & Nelson, 2003; Sher & McKenzie, 2006), different frames would lead modelers to draw systematically different inferences about typical performance. Second, the critical question is then whether the different inferences drawn from the different frames are sufficient to reproduce the “framing effect” among recipients, who all receive the same, neutrally framed description. Finally, although this experiment was not specifically tailored to test the role of knowledge, we asked participants to report their level of general basketball knowledge, expecting those with more knowledge to show a reduced framing effect.

### Method

The participants were 414 University of California, San Diego, undergraduate students ( $M_{\text{age}} = 20.3$ , one participant did not report age; 68% female) who received partial course credit. This sample was obtained by collecting data for a pre-determined period of time (the duration of an academic quarter). The experiment was part of a larger series of unrelated experiments lasting less than an hour. Participants were run at individual computer stations in groups of up to six.

Participants were randomly assigned to one of six conditions. In the two Control conditions (Figure 1a), participants read a scenario involving the performance of a basketball player (based on Levin et al., 1998). In the “made” frame condition, participants were asked to

Imagine that you are a recruiter for a college basketball team. Your job is to search for promising high school basketball players and try to recruit them to your college. You are looking through files for players from local high schools, and you are especially interested in players who can score many points.

The file you are currently looking at shows a player whose performance is quite unusual. This player made 40% of his shots last season.

In the “missed” frame condition, the last sentence instead stated “This player missed 60% of his shots last season.” Afterward, participants were asked “How valuable do you think this player would be to your basketball team?” and answered by adjusting a continuous slider scale with a low anchor (*Not at all valuable*) and a high anchor (*Extremely valuable*) (Figure 1a). The numerical value corresponding to a slider position was not visible to participants, but their responses were recorded from 0 to 10 to two decimal places.

The four remaining conditions comprised the yoked design. The two Modeler conditions were exactly the same as the two Control conditions, except that participants reported an inference about the typical player’s performance, rather than rating the target player (Figure 1b). Specifically, modelers in the “made” frame condition completed the statement “Typical high school basketball players on average make \_\_\_\_ % of

their shots.” Modelers in the “missed” frame condition completed the same statement except that the word “make” was replaced with “miss.” Thus, the frame condition determined whether the estimate was elicited in terms of “make” or “miss,” and this frame matched the one used to describe the target player’s performance in the scenario. Participants responded by typing a number ranging from 0 to 100 and were instructed to make their best guess if they were unsure.

The target player’s performance was described as “quite unusual” in the scenario because we wanted to discourage modelers from simply restating that player’s performance (made 40% or missed 60%) for their inference. The “quite unusual” phrase might also amplify any effect of frame, in both the Modeler and Control conditions, because it indicates that a typical player is far from making 40%/missing 60% of his shots, and the frame is expected to influence the direction in which the inferred reference point is displaced (e.g., if the “made” frame suggests above-average performance, the “quite unusual” phrase would further suggest well-above-average performance).

The two Recipient conditions were identical to the two Control conditions except for two differences (Figure 1c). Each recipient was now provided with a modeler’s estimate as part of the background information, and this estimate, along with the target player’s performance, was described in a “double frame.” Specifically, the sentence “Typical high school basketball players on average make \_\_\_\_ % of their shots and miss \_\_\_\_ % of their shots” was inserted into the background scenario just before the sentence that mentions the target player’s performance as “quite unusual,” and the target player’s performance was described as “This player made 40% of his shots and missed 60% of his shots last

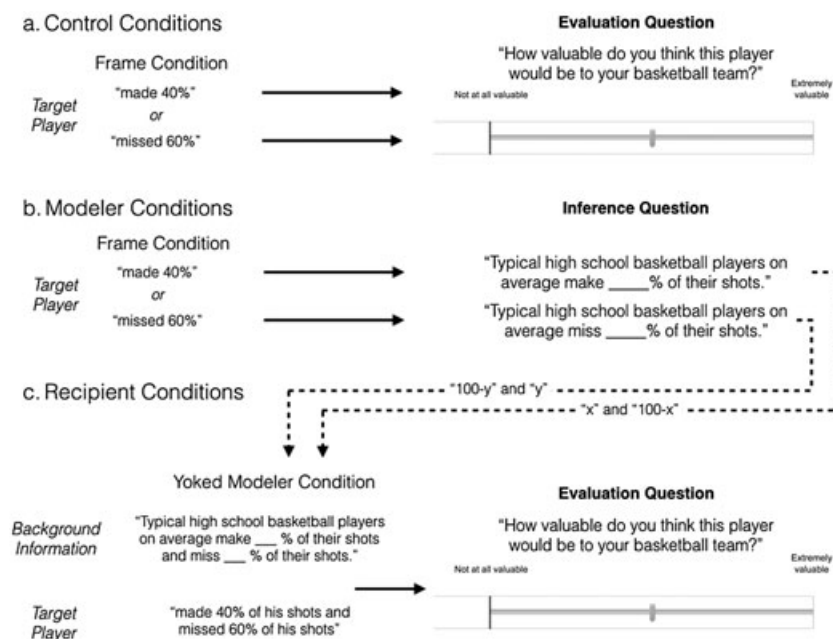


Figure 1. In the Control conditions (a), participants saw the target player described either in the “made” or “missed” frame and evaluated the player. In the Modeler conditions (b), participants saw the target player described in one of the two frames and made an inference about a typical player’s performance rather than evaluating the target player. These inferences were then given to yoked participants in the Recipient conditions (c) as part of their background information. For recipients, both the typical and target player’s performance were now described in double frames (in the order “made,” then “missed”). Recipient participants then evaluated the target player in the same way as in the Control conditions

season.” The blanks were filled in with the yoked modeler’s estimate. For example, if a modeler were in the “made” frame condition and reported that the typical player makes 25% of his shots, then, for the recipient, the respective blanks would be filled in with “make 25%” and “miss 75%.” The yoking was implemented such that each modeler’s estimate was provided to the next recipient who completed the experiment on the same computer. Thus, the source of the inference (i.e., the frame condition of the yoked modeler) was the only difference between the two Recipient conditions. Recipients were asked to judge how valuable the target player is by using the same slider scale as in the Control conditions.

Demographic information was collected at the end of the experiment. At this stage, participants were also asked “In general, how knowledgeable are you about basketball?” and selected one of four answers (*Not at all knowledgeable*, *Slightly knowledgeable*, *Somewhat knowledgeable*, or *Very knowledgeable*).

## Results

Figure 2a shows the mean ratings in the Control conditions by frame. We obtained a standard valence-consistent shift, with the target player judged as more valuable when his or her performance was described in the “made” frame than in the “missed” frame,  $M_s = 4.93$  and  $3.42$ ,  $t(136) = 4.75$ ,  $p < .001$ ,  $d = 0.81$ .

Next, we analyzed the inferences that modelers drew from the different frames. Although we attempted to discourage modelers from restating the target player’s performance by describing it as “quite unusual,” eight participants nevertheless provided that as their estimate of the typical player’s performance. Their data were excluded from the following analyses because their judgments created an inconsistency in the background blurbs provided to their yoked recipients (i.e., the resulting blurbs described the target player’s performance as both typical and unusual). Figures 3a and 3b show the distributions and boxplots of the modelers’ estimates of the typical player’s performance in the “made” and “missed” frame condition respectively. To facilitate comparisons between the two frame conditions, we transformed the estimates in the “missed” frame condition into estimates of shots *made* by subtracting them from 100. As predicted by the information leakage account, 55% (38/69) of the modelers in the “made” frame condition provided an estimate lower than the target player’s performance of 40% shots made, compared with only 28% (17/61) of those in the “missed” condition,  $\chi^2(1, N = 130) = 8.73$ ,  $p = .003$ ,  $\phi = .260$ . The mean estimates also exhibited the predicted pattern, with a higher mean estimate in the “missed” frame condition than in the “made” frame condition,  $M_s = 49.03$  and  $42.06$ ,  $t(128) = 2.02$ ,  $p = .046$ ,  $d = 0.36$ .

For the recipient analyses, the data for those yoked to the eight modelers who were excluded in the previous analyses were also excluded. We first confirmed that recipients were affected by the modeler estimates they received. Collapsing across the two modeler conditions, higher estimates of

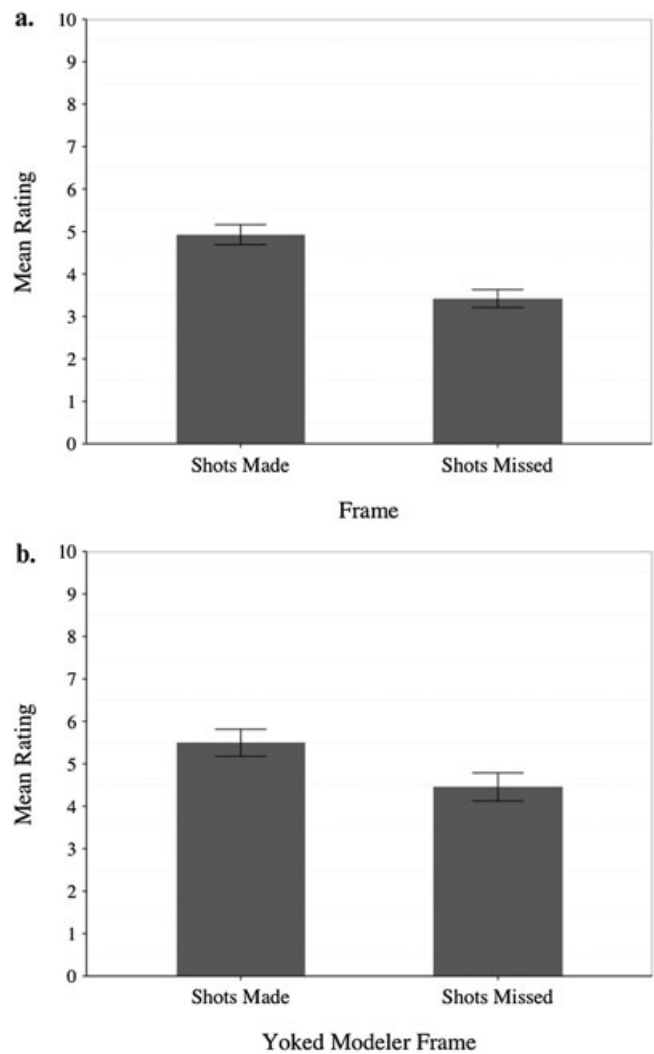


Figure 2. Mean rating of the target player (a) as a function of frame in the control conditions and (b) as a function of the frame condition of the yoked modeler in the recipient conditions. Standard error bars are shown

typical shooting performance led to lower recipient evaluations of the player,  $r(128) = -.767$ ,  $p < .001$ .

Thus frames influenced modeler estimates, and modeler estimates influenced recipient evaluations. Putting these two effects together, Figure 2b shows that recipients yoked to modelers in the “made” condition on average judged the target player to be more valuable than recipients yoked to modelers in the “missed” condition,  $M_s = 5.50$  and  $4.46$ ,  $t(128) = 2.26$ ,  $p = .025$ ,  $d = 0.40$ . Even though the information they received was not subjected to the typical attribute framing manipulation, recipients nevertheless exhibited a “framing effect.” This novel effect was somewhat smaller ( $d = 0.40$ ) than was the standard framing effect observed in the control conditions ( $d = 0.81$ ). To more directly compare the two effects, we performed a 2 (Condition: control vs. recipient) by 2 (Frame: made vs. missed) analysis of variance. This analysis revealed a main effect of condition,  $F(1, 264) = 8.42$ ,  $p = .004$ ,  $\eta_p^2 = .031$ , with higher overall ratings in the recipient conditions. This may in part be due to the use of a double frame for recipients, which has been found to



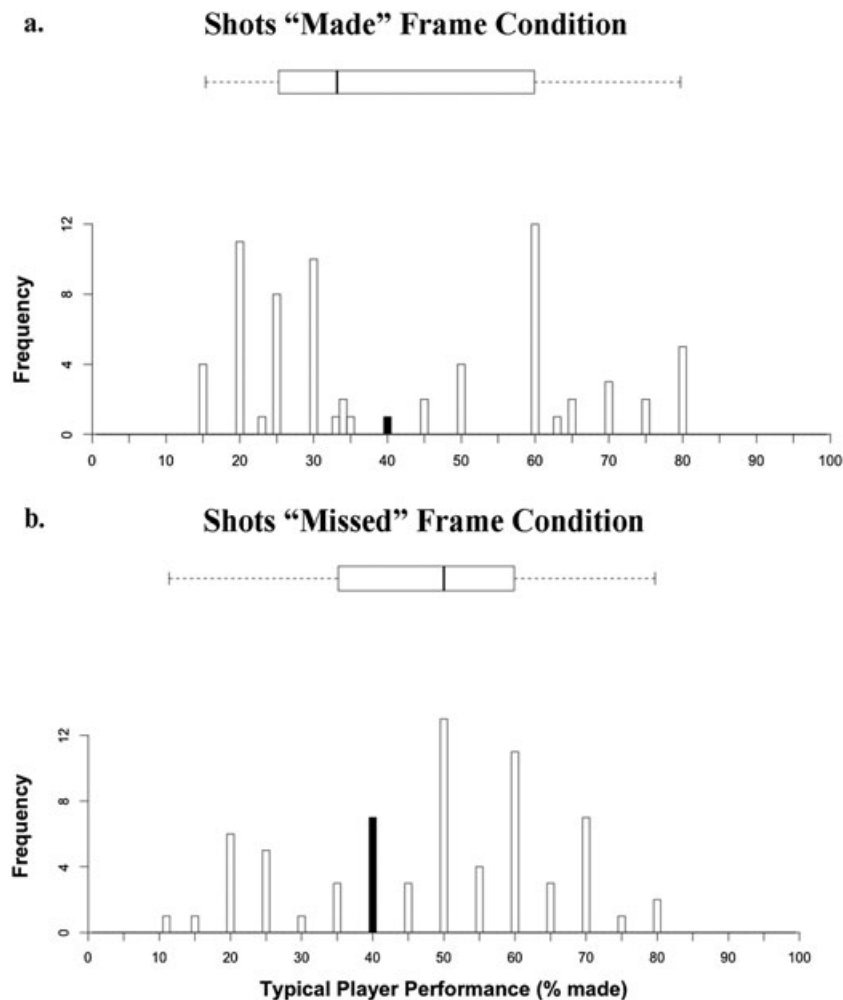


Figure 3. The distribution of modelers' estimates of the typical player's performance in (a) the shots "made" frame condition and (b) the shots "missed" frame condition. The boxplots do not include the eight estimates that are equal to 40

lead to relatively favorable evaluations (Kreiner & Gamliel, 2016). There was also a main effect of frame,  $F(1, 264) = 21.21, p < .001, \eta_p^2 = .074$ . Compared with their shots "missed" frame counterparts, participants gave higher ratings in the "made" frame (control conditions) or when the inferences came from a modeler presented with the "made" frame (recipient conditions). Importantly, however, the Condition  $\times$  Frame interaction was not significant,  $F(1, 264) = .71, p = .402, \eta_p^2 = .003$ . That is, the effect resulting from frame-based inferences is not significantly different from the effect resulting from the frames themselves.<sup>1</sup>

We also analyzed whether the participant's general basketball knowledge interacts with their judgments and inferences. The percentage of participants in the overall sample who self-reported their knowledge as *Not at all*

*knowledgeable*, *Slightly knowledgeable*, *Somewhat knowledgeable*, and *Very knowledgeable* are respectively 26%, 41%, 24%, and 9%. A 2 (Frame: made vs. miss) by 4 (Knowledgeable: not at all vs. slightly vs. somewhat vs. very) analysis of variance was performed separately for the control conditions, modeler conditions, and recipient conditions. In each of these analyses, the interaction between frame and knowledge was not significant ( $ps > .20$ ).

### Discussion

We replicated the typical attribute framing effect in our basketball scenario: Participants in the two Control conditions judged the target player as more valuable when his performance was described in the "made" frame than in the "missed" frame. Crucially, participants in the two Recipient conditions, who all received the same wording, also exhibited the framing effect. The only difference between the two Recipient conditions was the source of the inferences: Each recipient saw the inference from a modeler who had seen the target player described in either the "made" frame or the "missed" frame. As predicted by information leakage, modelers who saw the "missed" frame inferred a higher

<sup>1</sup>Including the data from the eight modelers and the recipients yoked to these modelers in the analyses do not qualitatively change any of the results except for one. The difference in the mean estimate of the typical player's performance for modelers in the two frame conditions changed from being significant to being marginally significant,  $M_{\text{missed}} = 48.10$  vs.  $M_{\text{made}} = 42.03, t(136) = 1.86, p = .065, d = 0.32$ .

reference point, or typical performance level, than do modelers who saw the “made” frame. Compared with recipients who were provided with inferences from modelers in the “missed” frame, recipients provided with inferences from modelers in the “made” frame evaluated the target player as more valuable. In sum, the different reference point inferences drawn from the different frames were sufficient to reproduce the attribute framing effect.

Experiment 1 tested for an effect of basketball knowledge on (basketball) attribute framing, and we did not find evidence for such an effect. However, our ability to detect this effect, if it does exist, was limited, as only very few of our participants reported being “Very knowledgeable” about basketball (35/398, or 9%). Moreover, the high school context and the description of the target player’s performance as “quite unusual” may have discouraged knowledgeable participants from applying their knowledge to our scenario. These limitations are addressed in our next experiment.

## EXPERIMENT 2

While Experiment 1 demonstrated that frame-based inferences are sufficient for attribute framing effects, the goal of Experiment 2 was to examine whether these inferences are necessary for the effect. The prediction is that “turning off” frame-based inferences will attenuate or even abolish attribute framing effects. Experiment 1 attempted to address this question by examining self-reported levels of basketball knowledge, with the expectation that greater prior knowledge would limit the scope of frame-based inferences and hence the size of the framing effect. Though there was no evidence that knowledge affected inferences or target player evaluations, the categorical self-report measure we employed was crude, there were very few “Very knowledgeable” participants, and, as noted above, the special context and “unusual” background description may have discouraged those participants from applying their general knowledge.

Experiment 2 overcomes these shortcomings to provide a proper test of a moderating role of expertise in attribute framing effects. In particular, we recruited participants with varied degrees of basketball knowledge, including a sizeable subset of highly knowledgeable participants. Furthermore, we made two contextual changes to our basketball scenario. First, we adapted the scenario to an NBA context because we assumed that people generally know more about basketball statistics in that setting. Second, we now described the target player’s performance in terms of free throw shooting, because we expected that free throw shooting percentages would be more readily interpretable to experts than generic shooting percentages.<sup>2</sup> Those who are knowledgeable should

<sup>2</sup>The generic shooting percentage previously used may be difficult to interpret owing to differences in playing positions (e.g., guard vs. center), which relate to how often players attempt shots and the distance they shoot from the basket. Using free throw percentage mitigated these problems because all players shoot under the same circumstances (namely, from the free throw line). Also note that the number in the shooting percentage was changed to “made 60%” and “missed 40%” for the two frames.

recognize the target player’s performance as poor relative to the actual distribution of free throw performance, while those who are not knowledgeable may not.<sup>3</sup> We also measured basketball knowledge via an NBA trivia quiz, which provided an objective measure of knowledge in place of the self-report method used in Experiment 1. Finally, participants were presented with two attribute framing scenarios, one in which basketball knowledge is relevant and another in which it is not. This allowed us to test the specificity of the role of knowledge across different domains.

We expected more knowledgeable participants to show an attenuated framing effect in their domain of expertise. Those who know more about basketball should both score higher on our quiz and have a better idea of what constitutes a typical free throw shooting percentage. They should then be less likely to draw different inferences—and by extension form different evaluations—when performance is described with different frames. In particular, knowledgeable participants should recognize the specific free throw percentage we used to describe the target player as very low for the NBA, regardless of the frame. Finally, knowledge should only be associated with a reduced framing effect in the relevant domain (basketball) and not in an irrelevant domain (medical treatments).

## Method

Participants were recruited on Amazon Mechanical Turk in two batches, with a target sample size of 200 for each. After excluding 45 participants with missing responses and duplicate IP addresses, we were left with a final sample of 364. In the first batch ( $N = 198$ ,  $M_{\text{age}} = 34.8$ , one participant did not report age; 35% female), we specifically targeted those who are knowledgeable about NBA basketball. In particular, we requested that “We are looking for NBA fans to read some short scenarios and answer questions about them. Do not accept this HIT if you do not watch the NBA or know about basketball.” In the second batch ( $N = 166$ ,  $M_{\text{age}} = 36.7$ , 58% female), we removed this request and did not target any particular population. Recruitment was conducted in this way to help obtain a larger sample of participants knowledgeable in NBA basketball. Data collection for the second batch started 2 days after data collection was completed for the first batch, and those who participated in the first batch were not allowed to participate in the second batch.

Each participant was presented with two framing scenarios in counterbalanced order, one about NBA basketball and the other about a medical treatment. The frame conditions in the two scenarios were orthogonally manipulated (i.e., participants were randomly assigned to one of the four combinations of frames across the two scenarios). For the

<sup>3</sup>In the NBA regular season 2015–2016 (during which Experiment 2 was run), only six out of 122 players had a free throw percentage below 60% ([http://espn.go.com/nba/statistics/player/\\_stat/free-throws/sort/freeThrowPct/seasontype/2/order/false](http://espn.go.com/nba/statistics/player/_stat/free-throws/sort/freeThrowPct/seasontype/2/order/false)). If participants are knowledgeable about the true underlying distribution of free throw percentage, then they should recognize that a free throw percentage of made 60% or missed 40% is very poor.

basketball scenario, participants in the “made” condition were instructed to

Imagine that you are a scout for an NBA team. Your job is to search for promising basketball players and to draft them to your team. You are looking through the files for potential players in the upcoming draft, and you are only interested in players who are good free throw shooters.

The file you are currently looking at shows a player who, last season, made 60% of his free throws.<sup>4</sup>

In the “missed” condition, the last sentence instead stated that the player “missed 40% of his free throws.” Afterward, participants evaluated how valuable the target player is in the same way as the Control conditions in Experiment 1. Also note that, in contrast to Experiment 1, the target player’s performance was no longer described as “quite unusual” in this scenario.

The medical treatment scenario we used was based on McKenzie and Nelson (2003). Participants in the “survive” frame condition were instructed to

Imagine a rare disease that leads to many unpleasant symptoms and can even cause death. The method by which this disease is contracted has been studied, but scientists have yet to identify the exact cause. For the past 20 years, the same treatment has been used in patients with the disease.

A new experimental treatment has been tested, and it has several advantages and disadvantages. In terms of outcome, 85% of patients undergoing this new treatment survive at least 5 years.

In the “die” frame condition, the last sentence instead stated “In terms of outcome, 15% of patients undergoing this new treatment die within 5 years.” Afterward, participants rated the effectiveness of the new treatment using the same slider scale as in the basketball scenario except that the low anchor was changed to *Not at all effective* and the high anchor to *Extremely effective*.

After providing a rating for each of the two framing scenarios, participants answered an NBA trivia quiz with six multiple-choice questions, three regarding aspects of the league and three regarding the rules of the game (see Supporting Information). To discourage participants from looking up the answers, they had 10 seconds to respond for each question.

## Results and discussion

We first checked whether our targeted recruitment was successful in obtaining a larger proportion of participants knowledgeable about NBA basketball. Figure 4 shows the percentage of participants who received each of the seven possible scores on our quiz in each recruitment batch. As expected, participants recruited in the first batch scored higher on the quiz than did those in the second batch,  $M_s = 3.91$  and  $2.72$ ,  $t(362) = 6.37$ ,  $p < .001$ ,  $d = 0.67$ .

<sup>4</sup>Note that we assume participants would evaluate the target player’s free throw percentage according to NBA standards even though that player has yet to play in the NBA.

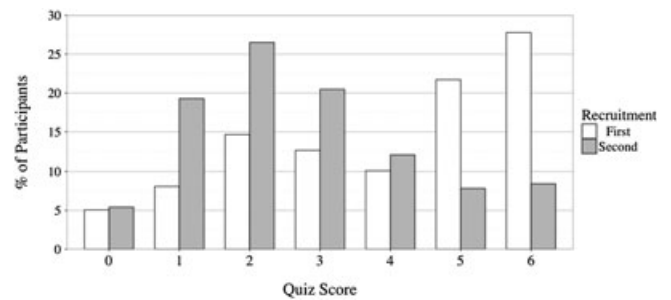


Figure 4. Percentage of participants in the two recruitment batches who received each of the seven possible quiz scores. The sample sizes for the first recruitment and second recruitment are 198 and 166, respectively. The question format on the quiz was multiple choice with four possible answers, and the expected number of correct answers by chance alone is 1.50

Next, we analyzed how basketball knowledge affected the framing effect in the two scenarios. Starting with the basketball scenario, we regressed the ratings of how valuable the target player is on frame and quiz score. Frame was dummy coded with 0 indicating the “missed” frame and 1 indicating the “made” frame, and quiz score indicates the number of correct answers. We predicted that participants with the least basketball knowledge would rate the target player as more valuable in the “made” frame than in the “missed” frame,

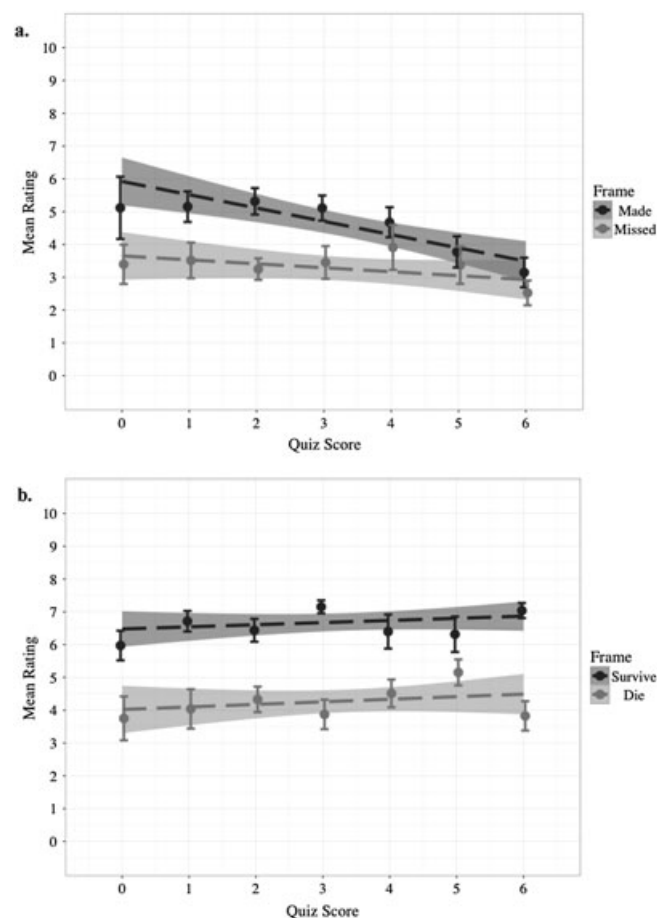


Figure 5. Fitted regression lines and group means as a function of frame and quiz score for (a) the basketball scenario and (b) the medical treatment scenario. Shaded regions represent the 95% confidence interval of the regression lines, and standard error bars for the mean ratings are shown

and that this framing effect would decrease for participants with higher quiz scores. Figure 5a shows the fitted regression lines, as well as mean ratings, as a function of quiz score and frame. For participants who did not answer any of the quiz questions correctly, we found a framing effect,  $b_{\text{frame}} = 2.27$ ,  $t(360) = 4.35$ ,  $p < .001$ , and this framing effect decreased as performance on the quiz increased,  $b_{\text{frame} \times \text{quiz}} = -0.28$ ,  $t(360) = -2.10$ ,  $p = .036$ . That is, the model predicts a difference of 2.27 in rating between the two frames for participants with the least basketball knowledge, but a difference of only 0.56 for those with the most knowledge. As predicted by information leakage, the participants with little basketball knowledge thus exhibited a sizeable framing effect, and the effect was greatly attenuated for those participants knowledgeable about basketball.<sup>5</sup>

We analyzed the role of basketball knowledge in the medical treatment scenario in the same way. Our dependent variable was the new treatment's rated effectiveness, and frame was dummy coded with 0 indicating the "die" frame and 1 indicating the "survive" frame. We predicted that participants would rate the treatment as more effective in the "survive" condition than in the "die" condition, and that this framing effect would be independent of quiz score. Figure 5b illustrates that participants in the "survive" frame consistently provided higher effectiveness ratings than those in the "die" frame, regardless of their basketball knowledge. As predicted, we found a framing effect for participants who did not answer any of the quiz questions correctly,  $b_{\text{frame}} = 2.46$ ,  $t(360) = 6.20$ ,  $p < .001$ , and the framing effect did not change depending on the level of basketball knowledge,  $b_{\text{frame} \times \text{quiz}} = -0.01$ ,  $t(360) = -0.11$ ,  $p = .91$ . The regression model thus predicts a difference of 2.46 in rating between the two frames for participants with the least basketball knowledge, and it predicts a similar difference of 2.38 for those with the most knowledge. Participants more knowledgeable about NBA basketball exhibited a reduced framing effect in the basketball framing scenario, but an unaltered, sizable framing effect in the medical treatment framing scenario.<sup>6</sup> This indicates that it is their basketball expertise, and not something else about the knowledgeable participants, that attenuates the framing effect they exhibit in the basketball scenario.

Finally, we note that the attenuation of the framing effect in the basketball scenario could also be explained "mechanistically" if participants with more basketball knowledge were simply extremely consistent in their judgments: If knowledge constrained the range of experts' judgments, it would also constrain the range of a potential framing effect, whether or

not this framing effect is caused by inferences. According to this potential alternative explanation, the responses of participants with higher quiz scores should be less variable than the responses of participants with lower quiz scores, which would lead to heteroskedastic errors in our regression model. We tested for this possibility by performing a White test but did not find evidence against the homogeneity of variance,  $\chi^2(4, N = 364) = 1.93$ ,  $p = .75$ . Alternative Breusch–Pagan tests that directly assessed heteroskedasticity due to linear or quadratic effects of quiz scores led to the same conclusion ( $ps > .25$ ). These results suggest that the reduction in the framing effect is not merely due to less variability in the responses of the more knowledgeable participants.<sup>7</sup> However, an inferential account naturally explains the full pattern of results.

## GENERAL DISCUSSION

In the information leakage framework, attribute framing effects occur because people draw systematically different inferences from different frames. While previous research has demonstrated that frames influence inferences, the causal connection between inferences and framing effects has not been established. In this article, we report two experiments that provide evidence for such a causal relation by establishing that frame-dependent inferences are sufficient to produce an attribute framing effect (Experiment 1), and that expertise, which presumably renders the inferences unnecessary, reduces the effect (Experiment 2). The results of our experiments are not readily explained by an associative account or query theory. Instead, they implicate inferences in the generation and attenuation of attribute framing effects.

Experiment 1 showed, using a yoked design, that inferences from frames are sufficient to generate a standard attribute framing effect. Modeler participants presented with a target player described in the "made" frame, rather than the "missed" frame, inferred that the typical shooting percentage was lower. These results replicate and extend previous findings (e.g., McKenzie & Nelson, 2003; Teigen & Karevold, 2005). Yoked recipient participants then received these inferences as part of their background information, and those yoked to modelers who saw the "made" frame evaluated the fully described (i.e., unframed) target player as more valuable than those yoked to modelers who saw the "missed" frame.

While the results of Experiment 1 provide strong support for an inferential explanation, they are not necessarily inconsistent with an associative account or query theory. For example, if one makes the ancillary assumption that positive associations in the "made" frame lead participants to infer that the typical performance levels are below those of the "positively tagged" target player, then affective associations would be contributing to the inferences that participants draw. However, because strong reference point inferences have been demonstrated in non-evaluative domains (such as rolls of a die or the level of a cup of water; McKenzie & Nelson, 2003; Sher & McKenzie,

<sup>5</sup>At the suggestion of a reviewer, we conducted additional, unplanned analyses to examine the effect of gender (see Supporting Information for details). Male participants in our sample on average scored higher on the basketball quiz than did female participants, and when gender and its interactions were added to the regression model, we found a significant three-way interaction. This suggests that the effect of knowledge on the framing effect differed between women and men. Additional analyses revealed that the predicted pattern was obtained for women but not for men, who did not show a framing effect regardless of quiz performance. Importantly, these gender effects do not affect our theoretical conclusions—the information leakage account predicts that, if there are group differences in framing, the group that exhibits the framing effect should also exhibit the frame by knowledge interaction, which is what we find.

<sup>6</sup>See Supporting Information for additional regression analyses on recruitment batch.

<sup>7</sup>Also see Supporting Information for a table with the means and standard deviations as a function of frame and quiz score for the basketball scenario.



2006), affective associations or query orders are unlikely to be essential for the pattern of reference point inferences found here. While contributions from other sources cannot be ruled out, the most parsimonious explanation of the full body of findings is that listeners are implicitly attuned to regularities in how speakers select frames: The reference point affects a speaker's choice of frame, and the frame accordingly affects a listener's beliefs about the reference point.

These results on the role of frame-based inferences in attribute framing complement recent findings on the role of sample-based inferences from options in joint–separate reversals (JSRs). JSRs occur when an option that is superior on a difficult-to-evaluate attribute receives high ratings when judged jointly with the alternative option and low ratings when judged in isolation (Hsee, 1996). In a study resembling Experiment 1, Sher and McKenzie (2014) presented modeler participants two options either separately or jointly and then asked them to estimate the mean and range of the difficult-to-evaluate attribute. Modelers drew very different inferences across joint and separate evaluation conditions, and these different inferences were sufficient to reproduce the JSR in recipients, all of whom evaluated only a single option. These results provided support for an “options-as-information” model, according to which JSRs occur not because of different attribute weighting in different “evaluation modes” (joint vs. separate) but because of the different inferences that are drawn from different option samples (Sher & McKenzie, 2014). Sample-based inference likely also contributes to the asymmetric dominance effect (Prelec, Wernerfelt, & Zettelmeyer, 1997; Sher, Müller-Trede, & McKenzie, 2016) and can lead to intransitive behavior in multi-attribute choice (Müller-Trede, Sher, & McKenzie, 2015). When prior knowledge is limited, people appear to draw inferences both from the set of available options and from the way in which those options are framed. Such inferences can, in turn, generate both context effects and framing effects.

Information leakage also predicts that framing effects should be attenuated when frame-based inferences are eliminated. Experiment 2 showed that expertise abated a framing effect in the relevant content domain (NBA basketball) but did not alter a second framing effect in an irrelevant content domain (medical treatments). Decision makers should only draw frame-based inferences about reference points insofar as their prior knowledge of the relevant attribute distribution is limited. Expertise concerning specific attributes reduces framing effects for those attributes. The results of Experiment 2 cannot be easily explained by the associative account or query theory, as it is not clear why frame-based associations or query orders should depend on basketball knowledge.

We note that while expertise reduced the relevant framing effect in Experiment 2, other research has found mixed effects of expertise on judgment and decision making tasks. Some researchers have argued that experts rely on the same heuristics and exhibit the same biases as non-experts (e.g., Tversky & Kahneman, 1971), while others have found that relevant knowledge attenuates biases (e.g., Wilson, Houston, Etling, & Brekke, 1996). Note, however, that from an information leakage perspective, the question is not who exhibits more or less bias, as both non-experts (who fill in the gaps in

their imperfect knowledge via frame-based inferences) and experts (who, thanks to their prior knowledge, need not rely as much on frame-based inferences) are behaving reasonably. Seemingly more relevant are studies showing that medical students and even physicians are affected by how treatment outcomes are framed in choice under uncertainty (e.g., McNeil, Pauker, Sox, & Tversky, 1982; McNeil, Pauker, & Tversky, 1988). However, the hypothetical scenarios used in these studies provide minimal context, making it difficult for physicians to apply their domain-specific knowledge. Furthermore, whenever they lack detailed relevant knowledge about specific attributes within the domain, experts, like novices, may rely on the provided frame to fill in the gaps. Domain expertise thus need not attenuate all framing effects broadly related to that domain. Instead, expertise should only attenuate framing effects when specific prior knowledge pre-empts specific inferences that would otherwise be drawn from a speaker's choice of frame.

We further note that, from an information leakage perspective, knowledge of an attribute's distribution should reduce, but need not completely eliminate, attribute framing effects. Related work has generalized the information leakage framework from signaling a speaker's reference point (e.g., whether ground beef is relatively lean) to signaling a speaker's attitude toward the object—a type of implicit recommendation (Sher & McKenzie, 2006). For instance, speakers were more likely to describe a research and development (R&D) team in terms of its “failure” rather than its “success” rate when the team was obviously inept rather than stellar. Moreover, listeners are sensitive to this framing when making decisions about allocating R&D funds. Duchon, Dunegan, and Barton's (1989) participants allocated fewer funds to R&D teams described in terms of their number of unsuccessful projects rather than their number of successful projects. The notion that frames signal implicit recommendations has also been used to explain default effects, because people expect policy makers to select their favored course of action as a default (McKenzie, Liersch, & Finkelstein, 2006). Because frames may signal implicit recommendations in addition to reference points, even experts who are highly familiar with the distribution of a framed attribute may be sensitive to a speaker's choice of frame. Echoing the preceding discussion, this observation supports the general prediction that domain-relevant expertise should often reduce, but not necessarily eliminate, attribute framing effects.

Framing effects have often been regarded as compelling evidence for incoherence and irrationality in human decision making. The underlying assumption is that an option or outcome is the same regardless of how it is described, and thus decision makers should not make different choices or judgments when different descriptions are used. But subtle changes in wording and context may provide task-relevant information, particularly when prior knowledge is limited, and decision makers have been shown to be sensitive to these implicit cues (e.g., Hilton, 1995; Payne, Bettman, & Johnson, 1993; Schwarz, 1994). The experiments reported here suggest that frame-based inferences can account for both the generation and attenuation of the valence-consistent shift. These findings, together with recent work on JSRs (Sher &

McKenzie, 2014) and intransitive choice behavior (Müller-Trede et al., 2015), point to an important role for inferences in context and framing effects.

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