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Research Article

The Format in Which Uncertainty Information Is Presented Affects Decision Biases

Daniel A. Gottlieb, Talia Weiss, and Gretchen B. Chapman

Department of Psychology and Center for Cognitive Science, Rutgers University

ABSTRACT—We examined how the format in which uncertainty information is presented affects two biases in humans' choice behavior. In a computer task, participants were given four common-ratio effect and four common-consequence effect problems in each of four different formats. In these problems, uncertainty information was described, as percentages (e.g., 80%) or as frequencies (e.g., 16/20), or was experienced, either serially (20 outcomes shown one at a time) or simultaneously (20 outcomes all shown at once). Presenting information as percentages attenuated the common-ratio effect and augmented the common-consequence effect, which suggests that these biases have different underlying mechanisms. Participants' percentage estimates of outcome likelihoods did not differ according to the format in which the information was presented; however, participants' nonverbal estimates of outcome likelihoods differed across formats. The results suggest that uncertainty information presented as percentages is processed differently than the same uncertainty information presented in other formats.

The world is predictable, but only probabilistically so. Choices rarely lead to certain outcomes, and an important part of an organism's life involves assessing an option when multiple outcomes are possible. Foraging animals must allocate time across locations, even though there is no guarantee that any one location will provide sustenance at any given time. People must choose which route is likely to be fastest, which course of action is most likely to provide relief from back pain, and which job will provide the best balance of money, security, and enjoyment.

In all these choices, there is an element of uncertainty as to which particular outcome will occur, and how this uncertainty is represented and processed determines the choices organisms make.

In studies of decision making under uncertainty in humans, people receive information about the value of an outcome and its likelihood of occurrence before being asked to make a decision based on that information. Typically, information is given in a summarized form that includes probabilities and payouts (e.g., "Lottery A pays \$5 with a probability of .75"), and less frequently information is presented as frequencies or in graphical form (E.U. Weber, Shafir, & Blais, 2004). However, as Hertwig, Barron, Weber, and Erev (2004) pointed out, uncertainty information outside the laboratory must often be gathered from personal experience. In addition, direct experience with environmental contingencies is the only way in which nonverbal animals can gather uncertainty information. It is clear that both humans and nonverbal animals are able to extract this information from experience in order to behave adaptively. It follows that a question of primary importance is how decision making varies as a function of how uncertainty information is presented.

Humans exhibit decision-making biases in which their choices are inconsistent with normative principles. One might wonder whether such decision biases reflect the functioning of core cognitive mechanisms that are likely present across species or rather result from the use of the more recently developed and uniquely human capacity to represent probabilistic information in symbolic form. This article focuses on how two decision-making biases, the common-ratio effect and the common-consequence effect, are influenced by the format in which uncertainty information is presented.

Consider the following choice:

Low-risk, high-probability option: 100% chance of \$3,000

High-risk, high-probability option: 80% chance of \$4,000

Address correspondence to Daniel Gottlieb, Department of Psychology, Sweet Briar College, Sweet Briar, VA 24595, e-mail: dgottlieb@sbcc.edu.

People typically choose the low-risk option over the high-risk option, even though the expected value (probability multiplied by payout) of the low-risk option is lower. Consider now a different choice:

Low-risk, low-probability option: 25% chance of \$3,000

High-risk, low-probability option: 20% chance of \$4,000

In such cases, people typically choose the high-risk option over the low-risk option (Allais, 1953; Kahneman & Tversky, 1979), even though these low-probability options are generated from the previous high-probability options by dividing the two probabilities by a constant value. This preference reversal, termed the common-ratio effect, is nonnormative because it cannot be explained by a computation that uses unbiased estimates of outcome probabilities. Rather, people act as if they are using a nonlinear probability-weighting function when determining the value of an option.

A similar preference reversal is seen in the common-consequence effect (Allais, 1953; B.J. Weber & Chapman, 2005). Consider the following choice:

Low-risk, high-probability option: 100% chance of \$2,400

High-risk, high-probability option: 66% chance of \$2,400 and 33% chance of \$2,500

Again, people typically choose the low-risk option over the high-risk option, even though the expected value of the low-risk option is lower than the expected value of the high-risk option. Consider now a different choice:

Low-risk, low-probability option: 34% chance of \$2,400

High-risk, low-probability option: 33% chance of \$2,500

In this case, people typically choose the high-risk option over the low-risk option (Kahneman & Tversky, 1979). Notice, however, that this time a common payout (a 66% chance of \$2,400) was subtracted out of the two high-probability options in order to obtain the low-probability options. Like the common-ratio effect, this preference reversal is nonnormative because it cannot be explained by a computation that uses unbiased estimates of outcome probabilities.

In order to accommodate the common-ratio effect, the common-consequence effect, and other phenomena, descriptive theories propose that people multiply the subjective value of a payout by a weighted function of objective probability in order to determine the value of an option (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). It is typical of the hypothesized weighting function that low probabilities are overweighted, middle and high probabilities are underweighted, and the function is steepest near probabilities of 0 and 1. It is this

overweighting of certainty that is thought to be responsible for the common-ratio effect and the common-consequence effect.

FORMAT OF PRESENTATION AND DECISION-MAKING BIASES

There have been relatively few studies investigating whether decision biases are influenced by the way in which information is acquired. Recently, however, Barron and Erev (2003) and Hertwig et al. (2004) presented evidence showing that the common-ratio effect reverses when uncertainty information is not presented symbolically as probabilities, but rather must be extracted from experience. Barron and Erev used a task in which, after each choice, participants received feedback about whether a small outcome had been won or not. Hertwig et al. used a task in which participants sampled outcomes from two lotteries until they were ready to choose one of the lotteries from which to gain a randomly selected outcome. It is noteworthy that these two studies used quite different procedures, one involving feedback and multiple decisions, the other involving a single decision without feedback, but obtained similar results (but see Battalio, Kagel, & MacDonald, 1985, and MacDonald, Kagel, & Battalio, 1991, for reports of a common-ratio effect in barpressing rats).

Both Barron and Erev (2003) and Hertwig et al. (2004) explained their results as due to the underrepresentation of rare events in small samples. The number of low-probability events in a given sample size is described by the binomial distribution, which becomes increasingly skewed as sample size decreases. This skew means that rare events are more likely to be underrepresented than overrepresented, and to a larger degree as sample size decreases.

According to Barron and Erev (2003), when their participants accumulated information across time, they weighted recent events more strongly than earlier events. This effectively decreased the sample size from which to make likelihood estimates, leading to an underrepresentation of rare events. In addition, participants in the study by Hertwig et al. (2004) were allowed to stop sampling from the different lotteries whenever they liked. Because they sampled a relatively small number of times, rare events were measurably underrepresented. In one condition, 18 out of 25 participants never encountered a rare event that occurred 1 time in 10.

Underrepresenting rare events should lead to an attenuation or reversal of the common-ratio effect. Consider, again, the choice between a \$3,000 payout 100% of the time and a \$4,000 payout 80% of the time. The rare event is the \$0 payout that occurs 20% of the time in the second option. Insofar as this outcome is underrepresented, participants should overvalue that option. This might lead subjects to prefer the risky option in the high-probability choice, thus attenuating or reversing the common-ratio effect.

In the current study, we built on the work of Hertwig et al. (2004) and aimed to extend previous findings in four ways. First, we investigated decision making in common-ratio effect problems in which uncertainty information was acquired through trial-by-trial experience but recency effects and sampling biases were minimized by constraining both sampling and the sequence of sampled outcomes. Second, we extended the paradigm to the common-consequence effect, which is thought to result from the same mechanisms that lead to the common-ratio effect. Third, we included three additional presentation formats for uncertainty information: In a second experience condition, all information was presented simultaneously, and in two descriptive conditions, information was presented either as frequencies or as percentages. Finally, we investigated whether format-dependent differences in choice behavior reflect differences in the underlying representations of uncertainty or in how those representations are used in a forced-choice setting (i.e., differences in the probability-weighting functions).

We predicted that the decision-making biases would be most apparent when likelihoods were explicitly described as percentages and least apparent when likelihoods had to be extracted from trial-by-trial experience. This prediction stemmed from the assumption that behavior will be more normative when information is presented in a format that is readily interpreted by core cognitive mechanisms than when it is presented in a format that can only be interpreted with the help of more recently evolved abstract reasoning mechanisms. Indeed, Gigerenzer and Hoffrage (1995) reported a series of studies generally consistent with this idea: Inferences were more normative when probability information was presented as natural frequencies than when it was presented as probabilities or standardized frequencies.

METHOD

One hundred twenty-eight Rutgers University students completed a computer task consisting of 16 consecutive cycles. Within each cycle, participants were given information about the contents of two decks of cards, each card having a value ranging from 0 to 9 points. The decks were presented in four formats (see the top of Fig. 1). In the one-by-one format, subjects sampled the 20 cards in each deck one at a time by using a mouse to click on the decks. In the simultaneous format, the computer screen showed all 20 cards in both decks simultaneously in two 5×4 grids. In the frequency format, subjects were told the frequency of cards that had each payout (e.g., “16 out of 20 cards have a point value of 4”). In the percentage format, subjects were told the percentage of cards that had each payout (e.g., “80% of the cards have a point value of 4”). After learning about the two decks, participants chose the deck from which the computer program would randomly draw a card on their behalf; this card and its corresponding point value were concealed until all cycles were complete. Participants were told to accrue as

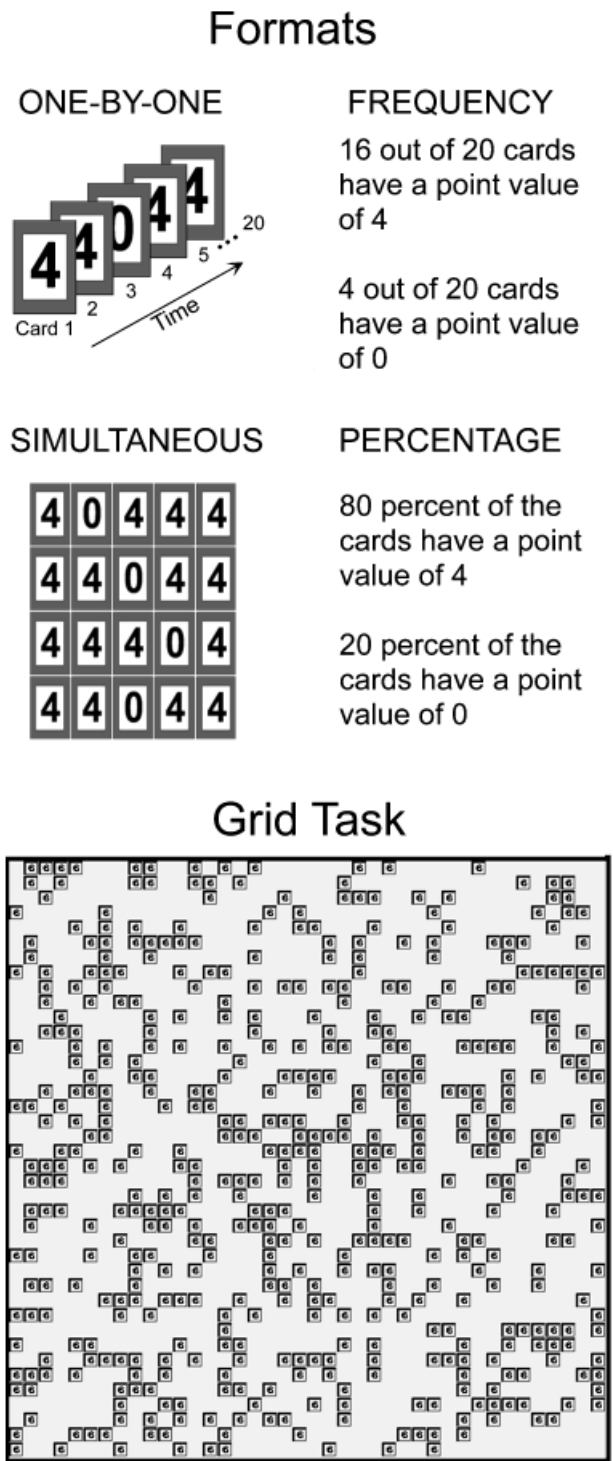


Fig. 1. Depictions of the four different presentation formats (one-by-one, simultaneous, frequency, and percentage) and of the grid task. This sample grid has 32% of the possible spaces filled with small images of the card with a value of 6. Participants adjusted the proportion of the target card in the cells of the grid to match the proportion of that card in the deck.

many points as possible, as the sum of their points would determine their compensation. Each point was worth \$0.10.

We used eight problems (see Table 1), so that in a within-subjects design, all participants were given one common-ratio

TABLE 1
Problems Used in the Experiment

Decision problem	High-probability options		Low-probability options	
	High risk	Low risk	High risk	Low risk
CR1	4 (.8), 0 (.2)	3 (1.0)	4 (.2), 0 (.8)	3 (.25), 0 (.75)
CR2	7 (.75), 0 (.25)	5 (1.0)	7 (.15), 0 (.85)	5 (.2), 0 (.8)
CR3	6 (.75), 0 (.25)	4 (1.0)	6 (.3), 0 (.7)	4 (.4), 0 (.6)
CR4	7 (.6), 0 (.4)	4 (1.0)	7 (.15), 0 (.85)	4 (.25), 0 (.75)
CC1	5 (.75), 8 (.2), 0 (.05)	5 (1.0)	8 (.2), 0 (.8)	5 (.25), 0 (.75)
CC2	4 (.7), 7 (.2), 0 (.1)	4 (1.0)	7 (.2), 0 (.8)	4 (.3), 0 (.7)
CC3	6 (.8), 9 (.15), 0 (.05)	6 (1.0)	9 (.15), 0 (.85)	6 (.2), 0 (.8)
CC4	3 (.65), 5 (.25), 0 (.1)	3 (1.0)	5 (.25), 0 (.75)	3 (.35), 0 (.65)

Note. Each cell depicts the payouts and probabilities (in parentheses) for one deck of cards. For example, “4 (.8), 0 (.2)” means that 80% of the cards had a payout of 4 points, and 20% of the cards had a value of 0 points. CR = common-ratio problem; CC = common-consequence problem.

effect problem and one common-consequence effect problem in each of the four formats. Because every problem had two separate versions, a high-probability version and a low-probability version, there were 16 cycles total (the two versions of a problem were presented in the same format for a given subject). The sequence of problems was fixed, as follows (CR = common-ratio problem, CC = common-consequence problem): CR1, CC1, CC2, CR2, CR3, CC3, CC4, CR4, CC1, CR1, CR2, CC2, CC3, CR3, CR4, CC4. For each problem, presentation format was counterbalanced across participants using a Latin square design. Also, whether the high-probability or low-probability version of a problem was presented first or second was counterbalanced. In the one-by-one condition, the cards were sampled in fixed sequences in which the rare events were evenly distributed on a global level but irregularly distributed at a more local level. For example, if a deck contained 15 cards with a point value greater than 0 and 5 cards with a value of 0, every block of 4 cards contained 1 card with a value of 0.

At the end of each cycle, after making the choice, participants were asked to estimate the likelihood that each possible card would be chosen from its corresponding deck. They performed this task either by stating the likelihood as a percentage (e.g., ___% of cards were worth 4 points) or by using the up and down arrow keys to adjust the density of small images of the card (each approximately 0.5 × 0.5 cm), randomly dispersed on a grid (see the bottom illustration in Fig. 1). A full grid contained 1,600 (40 × 40) images of a particular card. The amount of change in grid density was not constant for each key press; rather, the amounts increased with repetitions of either key and decreased with switches from one key to the other.¹ For half of the prob-

lems, participants gave percentages, and for the other half, they used the grid.

RESULTS AND DISCUSSION

Figure 2 shows the main choice results as the proportion of high-risk choices. A common-ratio effect or common-consequence effect is indicated by more high-risk choices in the low-probability than in the high-probability version of a given problem.

Figure 2 indicates that the common-ratio effect was largest in the experience conditions and smallest when information was given as percentages. Indeed, a reliable common-ratio effect was seen in the one-by-one, simultaneous, and frequency formats, but not in the percentage format, $\chi^2(1, N = 128) = 18.57, p < .0001, p_{\text{rep}} > .999, OR (\text{odds ratio}) = 2.58; \chi^2(1, N = 128) = 5.37, p = .02, p_{\text{rep}} = .95, OR = 1.68; \chi^2(1, N = 128) = 4.19, p = .04, p_{\text{rep}} = .93, OR = 1.53; \text{ and } \chi^2(1, N = 128) = 0.10, p = .76, p_{\text{rep}} = .59, OR = 1.07, \text{ respectively. In contrast, the figure indicates that the common-consequence effect was manifest only in the percentage condition. Statistical tests confirmed this observation: one-by-one condition, } \chi^2(1, N = 128) = 0.25, p = .61, p_{\text{rep}} = .64, OR = 1.11; \text{ simultaneous condition, } \chi^2(1, N = 128) = 0.06, p = .80, p_{\text{rep}} = .57, OR = 1.06; \text{ frequency condition, } \chi^2(1, N = 128) = 0.23, p = .63, p_{\text{rep}} = .63, OR = 1.11; \text{ and percentage condition, } \chi^2(1, N = 128) = 6.27, p = .01, p_{\text{rep}} = .96, OR = 1.78.$

The results were further quantified in a 4 × 2 × 2 repeated measures logistic regression, with presentation format, problem type, and version of the problem (low or high probability) as the three factors, and choice as the dichotomous dependent variable. The three-way interaction was significant, $\chi^2(3, N = 128) = 9.60, p = .02, p_{\text{rep}} = .95$;² the effect of presentation format

¹Actually, half of the participants used a grid with increments in equal 5% steps, and half used the unequal-increment grid. Because participants in the equal-increment condition reported learning the increment, it was unclear whether this was really a nonverbal task. Thus, graphs and analyses related to the grid task include only data points from participants who used the unequal-increment grid.

²Because there were four formats, the three-way interaction had three odds ratios. With the simultaneous format as the baseline, the odds ratios were 0.68, 1.15, and 2.66 for the one-by-one, frequency, and probability formats, respectively.

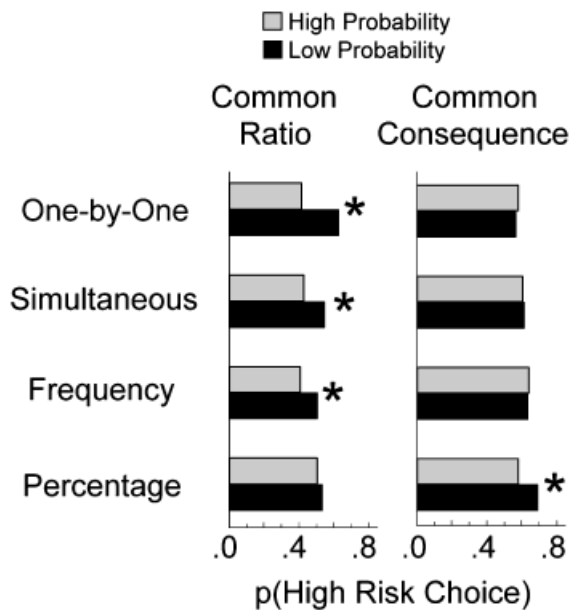


Fig. 2. Probability of a high-risk choice for each presentation format and problem type (common ratio or common consequence), combined for all four problems of each type. Choices in the high-probability and low-probability versions of the problems are shown separately. Asterisks indicate reliably more high-risk choices in the low-probability versions than in the high-probability versions for the indicated format.

varied by problem type. Figure 2 suggests that this interaction reflects different responding in the percentage condition compared with the other conditions.

Some of the preference reversals may seem somewhat small in magnitude. One of the reasons for this is that not all the problems led to biases. The third common-ratio effect problem (see Table 1), for which high-probability outcome likelihoods were divided by the smallest value (2.5) to get the corresponding low-probability outcome likelihoods, did not yield a common-ratio effect in any one of the formats, or when results for all four formats were combined. Similarly, two of the common-consequence effect problems did not yield evidence for a common-consequence effect in any format or across formats. These were the problems with the highest chance of a 0 outcome (10%) in one of the high-probability options, as well as the greatest difference in likelihoods (10%) between the two low-probability options. When these problems were removed from the analysis, the patterns illustrated in Figure 2 remained, but the magnitudes of the effects increased.

Several conclusions can be drawn from these results. First, presentation format affects choice behavior in decision biases. Second, despite the results of Hertwig et al. (2004), it is possible to obtain a common-ratio effect when uncertainty information is acquired through trial-by-trial experience, if the effects of recency and sampling biases are minimized. Third, the common-consequence effect is attenuated when information is acquired through experience or represented in frequency format.

This study also investigated whether differences in choice behavior reflect different underlying representations of uncertainty or simply differences in subsequent use or weighting of this information. To answer this question, we asked participants to quantify their uncertainty estimates either by stating percentages or by adjusting the density of squares on a grid to match the outcome probabilities. The upper row of graphs in Figure 3 shows participants' percentage estimates as a function of the objective percentages. The graph for each presentation format shows the raw data and the first-, second-, or third-order polynomial that is the most likely model of the data.³ For all formats, a linear model is most likely (14 to 42 times more likely than either a second- or a third-order polynomial). The linear fits accounted for 82, 80, 68.5, and 72% of the variance in the four conditions, respectively, and the best-fitting third-order polynomial was at most able to account for 0.3% of additional variance.

The lower row of graphs in Figure 3 shows participants' subjective estimates of outcome probability as measured by the grid task as a function of the objective percentages. The graph for each presentation format shows the raw data and most likely third-order polynomial. Only the curve for the frequency format is linear. The other three curves are all fit by second-order polynomials, and it appears that the greatest deviation from linearity is in the percentage condition. The second-order polynomials for the one-by-one and simultaneous conditions were only 1.3 and 6.5 times as likely as the next-best model (linear), but for the percentage condition, the second-order polynomial model was more than 943,000 times more likely than the linear model. This pattern is also reflected in the additional amount of variance accounted for by the second-order polynomials, as compared with the linear models. The linear models accounted for 59.2, 62.4, 54.2, and 53.7% of the variance for the one-by-one, simultaneous, frequency, and percentage conditions, respectively. Only in the percentage condition did a second-order polynomial account for more than an additional 1% of the variance—in this case, an additional 3.3%. It is of particular interest that these best-fitting second-order polynomials re-

³A third-order polynomial always fits the data better than a first-order polynomial, yet the four curves in the top of Figure 3 are linear. This is because the additional parameters needed to describe higher-order polynomials are not justified. To determine whether additional parameters were justifiable, we computed the odds in favor of particular functions using an equation proposed by Schwartz (1978):

$$\text{odds}_{\text{model}1} = \exp[LL_{\text{model}1} - LL_{\text{model}2} - \frac{1}{2}(d_1 - d_2) \log(n)],$$

where LL_i refers to the maximum log likelihood for model i , d_i refers to the number of free parameters in model i , and n refers to the number of total observations in both models. This equation represents a basic likelihood analysis with the addition of a mathematically justified correction for number of free parameters. This correction is necessary to assess the relative likelihoods of models that differ in complexity (Glover & Dixon, 2004; Kass & Raftery, 1995). It is important to remember that this type of analysis tells which of several models is most likely (the primary issue), not which model accounts for the most variance.

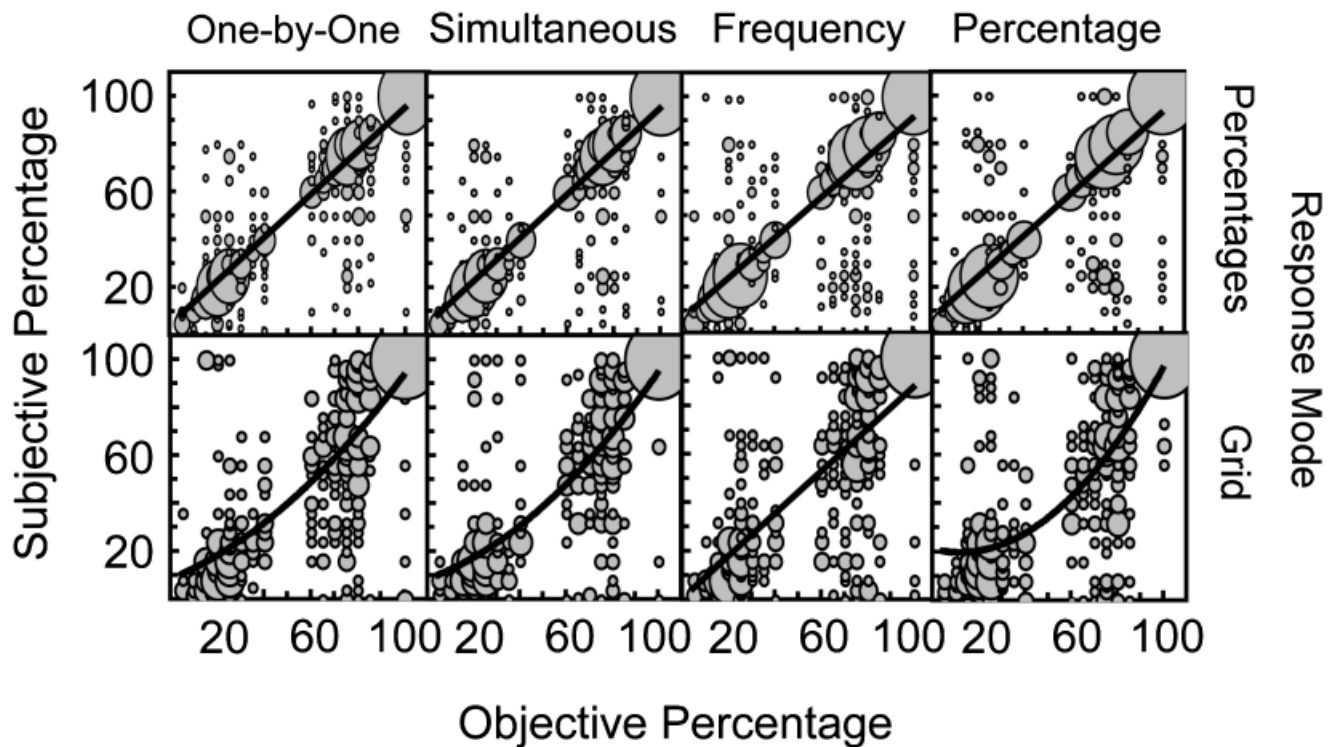


Fig. 3. Subjective likelihoods as a function of objective percentages, for the four presentation formats. The size of the plotted circles corresponds to the number of identical data points. The solid lines depict the most likely third-order polynomials describing the relation between the objective likelihoods and subjective estimates. The top row shows results for subjective estimates given by percentages, and the bottom row shows results for subjective estimates as determined by the nonverbal task of adjusting the density of squares on a grid.

seem the hypothesized probability-weighting function that has been used to explain the common-ratio and common-consequence effects, as well as other decision-making phenomena.

Overall, results from this experiment suggest that uncertainty information is processed differently when it is presented in a percentage format than when it is presented in other formats. Percentage information led to choice behavior that minimized the common-ratio effect and maximized the common-consequence effect (see Carlin, 1990; Erev, 1992; and Keller, 1985, for changes in presentation format that reduce the common-consequence effect; see Keller, 1985, for a change in presentation format that reduces the common-ratio effect). It also led to the greatest deviation from linearity in nonverbal estimates of uncertainty. Interestingly, Peters et al. (2006) reported a study in which risk estimates did not differ across frequency and percentage formats except in low-numeracy participants, who underweighted low percentages. That study suggests that the systematic differences observed in the percentage condition of the current experiment might have resulted from a subset of our population that was below average in general ability to process basic probabilistic information. Unfortunately, we did not collect numeracy data on our participants and cannot check this possibility.

One of our initial hypotheses was that there is an important distinction between uncertainty information extracted from

experience and explicitly described uncertainty information. However, our results suggest that not all forms of explicitly described uncertainty information should be grouped together (also see Gigerenzer & Hoffrage, 1995). Rather, the overall pattern of results suggests that frequency information is processed more similarly to information extracted from experience than to percentage information. One important way in which percentages differ from frequencies and experienced information is that percentages, like probabilities, are unitless and contain no information about the number of times an individual event occurred.

We also predicted that the decision-making biases would be minimized when information was directly extracted from trial-by-trial experience. This was the case for the common-consequence effect, but not for the common-ratio effect. If anything, the common-ratio effect was augmented when information was extracted from experience. This pattern is problematic for the view that the common-ratio effect and common-consequence effect are both certainty effects and share an underlying mechanism. If these two biases derive from common mechanisms, that is, mechanisms that underweight high probabilities and overweight certainty, then factors that augment one of the biases should also augment the other. For example, one might explain the finding of a common-consequence effect in the percentage condition by assuming that percentages are mapped

to nonverbal representations of uncertainty before those estimates are used to decide between options. Because the mapping of percentages to nonverbal estimates of uncertainty leads to the greatest underweighting of high probabilities, the common-consequence effect should be largest in the percentage condition. However, this line of reasoning would also predict the largest, not the smallest, common-ratio effect in the percentage condition. The fact that the pattern of results for the common-ratio effect was essentially the opposite of the pattern of results for the common-consequence effect suggests that the two phenomena have different underlying mechanisms, despite the fact that they both appear to illustrate a certainty effect. Results from B.J. Weber and Chapman (2005) point to a similar conclusion.

In summary, we found a common-ratio effect in humans when uncertainty information had to be extracted from experience. However, uncertainty information extracted from experience did not lead to a common-consequence effect, even though the bias was observed when the same information was expressed as percentages. This interaction of presentation format and type of bias suggests that the common-consequence effect and the common-ratio effect do not share the same underlying mechanism. The across-format differences in choice behavior were not the result of the transformation of nonverbal representations of uncertainty into symbolic representations, as percentage estimates of uncertainty did not vary across formats. However, nonverbal estimates of uncertainty did vary as a function of format of presentation. Most notable was a nonlinearity in the transformation of percentages into nonverbal magnitudes that was reminiscent of the hypothesized probability-weighting function. Deviation from linearity was less apparent in transformations involving the other presentation formats. Overall, it appears that percentage information is processed differently than other forms of uncertainty information.

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