The Visual Communication of Risk

Isaac M. Lipkus, J. G. Hollands

This paper 1) provides reasons why graphics should be effective aids to communicate risk; 2) reviews the use of visuals, especially graphical displays, to communicate risk; 3) discusses issues to consider when designing graphs to communicate risk; and 4) provides suggestions for future research. Key articles and materials were obtained from MEDLINE® and PsychInfo® databases, from reference article citations, and from discussion with experts in risk communication. Research has been devoted primarily to communicating risk magnitudes. Among the various graphical displays, the risk ladder appears to be a promising tool for communicating absolute and relative risks. Preliminary evidence suggests that people understand risk information presented in histograms and pie charts. Areas that need further attention include 1) applying theoretical models to the visual communication of risk, 2) testing which graphical displays can be applied best to different risk communication tasks (e.g., which graphs best convey absolute or relative risks), 3) communicating risk uncertainty, and 4) testing whether the lay public's perceptions and understanding of risk varies by graphical format and whether the addition of graphical displays improves comprehension substantially beyond numerical or narrative translations of risk and, if so, by how much. There is a need to ascertain the extent to which graphics and other visuals enhance the public's understanding of disease risk to facilitate decision-making and behavioral change processes. Nine suggestions are provided to help achieve these ends. [Monogr Natl Cancer Inst 1999; 25:149–63]

Communicating risk to the public poses formidable challenges *(1–4).* Chief among them is helping the public understand risk, especially low-probability events (e.g., probabilities <.1). In most situations, risk is conveyed numerically (e.g., percentages or probabilities), and the literature is increasing on how different numerical expressions affect perceived risk (i.e., how people view risk) and decision-making processes [e.g., *(5–10)*]. However, visual displays, such as graphs and pictures, can be used in lieu of numbers or as adjuncts to aid in the further understanding of numerical risks. Unfortunately, little is known about how visual displays of risk independently, or in combination with numerical or narrative translations, affect perceived risk, decision-making processes, and, ultimately, behavior. Understanding how visual displays of risk affect these processes will become increasingly important as communication aids, especially with the accumulating evidence that a significant proportion of people have difficulty grasping and using numerical risk [i.e., are innumerate *(11–13)*].

This review has several objectives. First, we discuss how graphical displays can improve the communication of risk. We focus primarily on graphical displays because they are commonly used to transmit risk information. [Results pertaining to pictorials and other visual displays (e.g., posters or media) will be discussed when relevant.] Second, we discuss criteria to evaluate the effectiveness of graphical displays for communicating risk. Third, we summarize how graphical displays of risk affect risk perception, most notably risk magnitude. To narrow the focus, we review studies that experimentally tested how the addition of graphical displays to numerical or verbal text affected risk perception and other outcomes (e.g., intentions) or that used focus groups or one-on-one interviews to evaluate graphical displays of risk. Then, on the basis of findings in visual and graphical perception, we highlight issues to be considered when designing graphical displays to communicate risk. Last, we provide recommendations to advance the state of the art in visually communicating risk.

How Visual Displays Can Enhance the Communication of Risk

Visual displays (e.g., graphics) have desirable properties that can enhance the understanding of (numerical) risk. We propose that graphics possess at least three desirable properties for communicating risk.[1]

First, graphics reveal data patterns that may go undetected otherwise *(14–17).* For example, line graphs are excellent for conveying trends in data *(17–20),* whereas pie charts and divided bar graphs are the best choice for depicting proportions *(18,21–23).* Second, specific graph types may evoke automatically specific mathematical operations *(21,22).* People use graphical schemas to assist in viewing and interpreting the numerical information depicted in graphs *(24,25).* Given a particular task (e.g., comparing risks), certain graphs allow the observer to process more effectively information than when numbers are presented alone. Third, unlike numbers, graphs can attract and hold people's attention because they display information in concrete, visual terms. [For a review of how vividness effects may affect attentional processes, *see (26,27).*]

Criteria to Evaluate the Effectiveness of Visual Displays for Communicating Risk

What standards should be used to determine whether a visual display is useful for communicating risk? When possible, visual displays of risk should be evaluated on the basis of the following seven criteria suggested by Weinstein and Sandman *(28).* Their criteria are 1) comprehension (do people understand the message and suggestions contained in the message?), 2) acceptance (do people agree with the interpretation and recommended action?),

Affiliations of authors: I. M. Lipkus, Duke University Medical Center, Durham, NC; J. G. Hollands, Defence and Civil Institute of Environmental Medicine, Toronto, Canada.

Correspondence to: Isaac M. Lipkus, Ph.D., 905 W. Main St., Box 34, Durham, NC 27701 (e-mail: Lipku001@mc.duke.edu).

See "Notes" following "References."

3) dose-response consistency (do perceptions of risk and intentions vary according to the magnitude of the risk, such that increasing levels of risk are perceived as such within a hazard?), 4) hazard-response consistency (do people facing a hazard that is higher in risk perceive the risk as greater, show greater readiness to take action, or both than people exposed to a hazard of lower risk?), 5) uniformity (do people with the same exposure level interpret and react similarly to the information?), 6) audience evaluation (do people find the communication to be clear and helpful?), and 7) direction of communication errors (when interpretations and action plans depart from those intended, is it because people overreact and underreact?). In addition, if visuals affect risk perceptions by making a hazard easier to imagine, then measures that capture the ease of visualizing the risk(s) should be incorporated.

Studies Examining the Visual Communication of Risk

In this section, we review studies that used graphical displays to affect risk perceptions and other outcomes (e.g., intentions), focusing on risk ladders, stick or facial displays, line graphs, dots or marbles, pie charts, and histograms [*see (29)* for other examples]. Examples of these displays are illustrated in Fig. 1.

To be useful, graphs must communicate different risk characteristics, such as 1) risk magnitude (i.e., how large or how small is the risk), 2) relative risk (i.e., comparing magnitude of two risks), 3) cumulative risk (i.e., observing trends over time), 4) uncertainty (e.g., estimating amount of variability and range of scores), and 5) interactions (e.g., synergy), among risk factors. We review how graphs have been used to communicate these

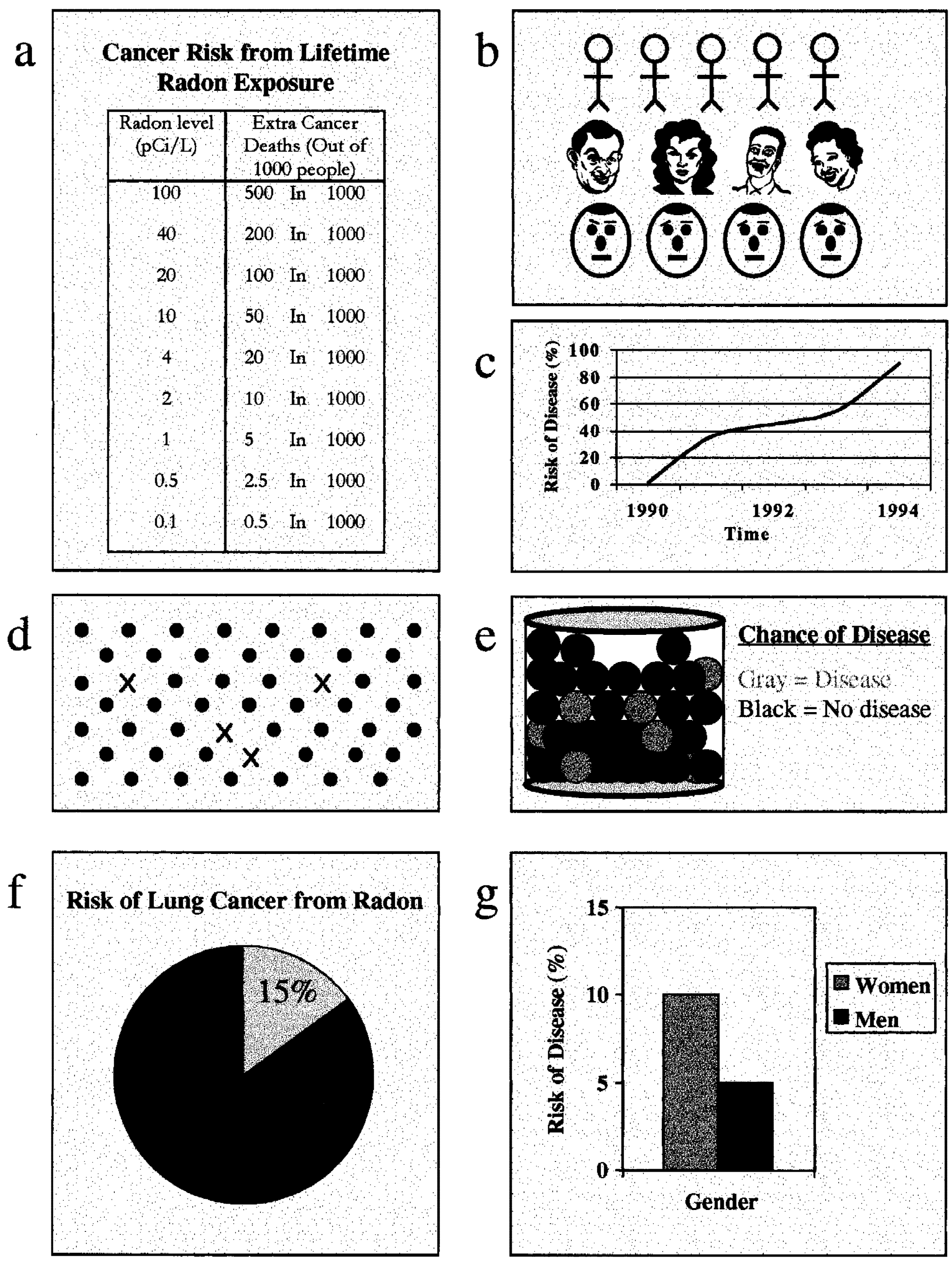

Fig. 1. Examples of visual displays that have been used to communicate risk. Researchers have used the following to illustrate risk: (*a*) risk ladder; (*b*) stick, human, and Chernoff faces; (*c*) line graph; (*d*) dots and Xs in which the Xs represent those affected by the hazard; (*e*) marbles; (*f*) pie chart (data are fictitious); and (*g*) histogram.

characteristics, beginning with the use of risk ladders. Because of the rarity of studies testing visual aids to communicate risk and of differences in design and outcomes among studies that tested visuals to communicate risk, detailed summaries pertaining to each graphical format are nearly impossible to compile. Rather, an overall summary of the extant literature is provided after the review.

Risk Ladder and Related Formats

The risk ladder has been used most extensively to describe environmental hazards [e.g., radon or asbestos *(30–38)*]. Typically, the risk ladder displays a range of risk magnitudes such that increasing risk is portrayed higher up on the ladder. Often, as a further aid, the risk in question is compared with other, perhaps more familiar, risks to encourage comprehension of small-probability events *(30,33–35,38)*. For example, the risk ladder used by Weinstein et al. *(33)*, and displayed in Fig. 2, equates different radon levels with quantities of cigarettes smoked and the extra number of cancer deaths. Therefore, the risk ladder communicates both risk magnitude and relative risk. In addition, the ladder can include other information, such as an action standard (i.e., a level at which a hazard poses a threat to be acted on, e.g., 4 pCi/L) and advice specifying how to help interpret the risk and what action to take, if any (*see* Fig. 2).

Extensive experimental research testing the utility of the risk ladder has been performed by Weinstein and colleagues who examined the communication of asbestos and radon risk [*(33,34,36,39); see (40)* for summary report]. There also are focus group impressions of the risk ladder *(41)*. In a series of studies *(33,34,36)*, Weinstein and colleagues presented homeowners with brochures with hypothetical test results of radon and asbestos that used different formats. For example, formats varied with respect to 1) location of risk on the ladder (i.e., radon or asbestos risk was high or low on the ladder), 2) the addition of a comparative risk (i.e., smoking; *see* Fig. 2), whether an action standard or advice (e.g., how soon you should act to remove radon) was presented,[2] 3) magnitudes of risks, and so forth. Although several outcomes were measured across studies (e.g., clarity or helpfulness of material and acceptance of action recommendations), we highlight two: perceptions of threat (composite measure of perceived risk, seriousness of level of risk, and concern and fear) and mitigation intentions (e.g., willingness to spend $1000 to reduce risk of radon or asbestos to 0; intention to take action).

There are four relevant findings. First, people's perceptions of threat were influenced by location of the risk on the ladder; people saw threat as greater at the top of the ladder. If the goal is to affect perceived risk, placing a risk closer to the top of ladder should increase people's perceived risk. Second, adding a risk ladder to a written action standard reduced perceived threat and mitigation intentions relative to the use of an action standard alone. Hence, if the goal is to lessen panic, a risk ladder may achieve this goal by allowing people to judge where they stand along a range of risk. People can compare other levels with their own. Third, the addition of a risk comparison (i.e., quantities of cigarettes smoked) did not affect perceived threat, mitigation intentions, or help people distinguish what is a high or low risk beyond that provided by an action standard or advice. However, adding a risk comparison made people feel that the information was more helpful and that they understood their risk better. Thus, trying to improve people's understanding of unfamiliar risks by comparing them with familiar risks may not strengthen the relationship between a person's actual risk and responses to that risk, although people may view the inclusion of the information as useful. Fourth, as shown in Fig. 2, having a risk ladder that includes risk probabilities (e.g., number of additional deaths because of radon or asbestos at different exposures), a risk comparison (i.e., cigarettes), an action standard (i.e., 4 pCi/L), and advice seems best to help people 1) distinguish between different risk levels for a single hazard, 2) develop appropriate mitigation intentions in accordance with their level of risk (i.e., people's intentions to pay for or take action to reduce a risk correspond with the actual level of risk such that mitigation intentions are greater at higher risks and vice versa), and 3) feel confident that they understand the risk.

In a study by Johnson and Slovic [*(42)*, study 2], college students were provided with information about the additional lifetime risk of getting cancer from a fictitious water contaminant presented as written text with or without a graph. The graph was a vertical line conveying cancer risk magnitudes of 0, 1 in 1000, to 1 in 100 at the bottom, middle, and top of the graph, respectively. Therefore, their risk ladder visually depicted a range of risks from low to high (0 to 1/100). The main outcomes were whether the addition of a graph affected how well people 1) noticed a range of risk estimates (e.g., are more apt to acknowledge that a risk can have different values ranging from low to high) assessed on a 4-point scale from seeing no risk to a great range of risk, 2) perceived trust in governmental agencies, and 3) perceived risk. Overall, the addition of a graph 1) increased the perceived *range* of risk (i.e., from no to great range) but did not affect perceived risk, and 2) decreased the perceived trustworthiness of the information. In addition, focus groups (study 3) reacted positively toward the visual portrayal of risk, claiming that the graph made the story clearer and more salient.

In sum, the risk ladder effectively helps people "anchor" a risk to upper- and lower-bound references points. Perceived risk is influenced by the location of risk perhaps more so than the actual numbers *(34,36)*. The efficacy of the risk ladder (e.g., to promote behavior change, understand one's risk, etc.) can be enhanced by the addition of an action standard and advice relevant to different risk levels *(33,35,37)*. Action standards and advice may influence significantly whether any actions to advert the risk are taken *(37)*. However, questions about its use remain *(40)*. For example, should the scales be logarithmic versus linear? What should the range of risk values be?

Stick and Facial Figures

Stick and facial figures have been used most extensively to aid relative risk judgments. In in-depth analyses of visual displays of risk, Stone et al. *(9)* examined how well stick and other visuals (bar graph or asterisks) communicated low-probability events (e.g., tire blowouts and serious gum disease).

Three studies were performed. In study 1, participants were shown the risks of a tire blowout using standard or improved tires in which the risk was reduced by half (i.e., 30 versus 15 serious injuries per 5 000 000 drivers for standard and improved, respectively). The risks were presented numerically or with added stick figures depicting the number injured (e.g., 15 or 30). A similar presentation was made for a standard and improved toothpaste. In study 2, participants were randomly assigned to

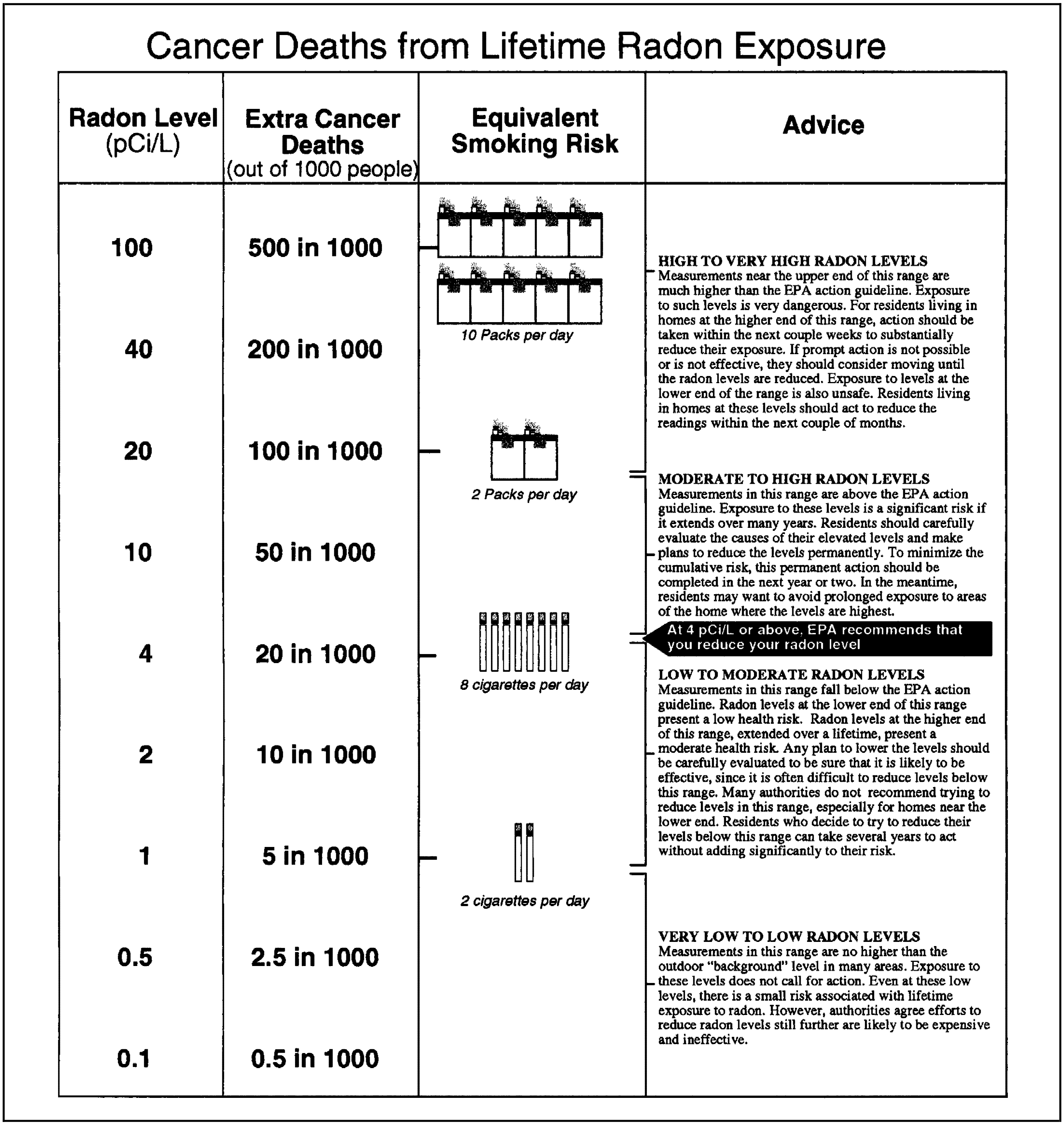

Fig. 2. Example of a risk ladder conveying the risks of radon. Radon levels are being compared with the number of cigarettes smoked and the number of extra cancer deaths. **On the right,** the ladder displays an action standard (pointing arrow of 4 pCi/L), along with advice on how to interpret radon levels and the action that is required, if any. Reprinted with permission of author *(33)*.

one of four conditions: 1) risk magnitude presented as numbers, 2) risk magnitude presented as numbers with stick figures—replicating the two experimental conditions in study 1, 3) replacing stick figures with asterisks, or 4) replacing stick figures with a bar graph. In study 3, participants were presented with stick figures or human faces. In each study, the main outcome was willingness to pay for the product (i.e., improved tires or toothpaste).

Overall, participants were more willing to pay for an improved product when graphics (stick figures, asterisk, or bar graph) were added to the numerical presentation (studies 1 and 2, respectively). That is, participants became more risk averse with the addition of a graphical figure. Willingness to pay was not affected by the kind of displays examined in studies 2 and 3. In sum, the studies by Stone et al. suggest that graphical displays of comparative risk increase risk aversion relative to presenting numbers alone. However, visual displays did not produce greater risk aversion for higher-probability events [e.g., .40 *(43)*].

Stephenson and Witte *(44)* tested whether vivid facial displays can promote skin protective behaviors through fear appeals related to skin cancer. College students randomly received a text message alone or with accompanying visuals (e.g., pictures of people with advanced skin cancer)—how effective sun block was at reducing skin cancer was also manipulated. Participants in the latter condition expressed greater intent to take preventive measures to protect their skin, but there were no differences in perceptions of fear and threat (i.e., risk by severity interaction) between the text and the text with visuals. Thus, the use of high threat visuals may not enhance the effectiveness of fear appeals, as the literature on vividness effects would suggest [for reviews, *see (26,27)*], but behavioral intentions can be modified without necessarily evoking fear.

Stick and facial figures have also been used to illustrate how many women, out of a certain number, are expected to get breast cancer. Such displays have been used to show the relationship between breast cancer risk and age and the effects of tamoxifen and hormone replacement therapy. This approach assumes that showing relative frequencies will maximize women's understanding of (low magnitude) risks by focusing, for example, on the numerator (showing the number of women affected) versus the denominator (how many women in the background are not affected).

There is a lack of research testing the effectiveness of communicating breast cancer risk using stick figures or women's faces compared with other visuals.[3] Pilot data obtained from the Duke Risk Communication Laboratory suggest that women may not prefer the former mode of communicating risk. Participants were presented with 100 female figures on a 8½ × 11 page. Figures with breast cancer had "X"s across them. Women thought the picture was too complex, or "busy," and did not like the idea of having women who were affected "X"ed out. However, results from the study by Stone et al. *(9)* discussed earlier would suggest that presenting breast cancer risk via the use of stick figures or faces versus numbers only would induce risk aversion, which may, in turn, increase the likelihood of breast cancer screening or genetic testing.

In sum, similar to other visuals (e.g., asterisks or histograms), stick figures and facial displays may affect perceived risk for smaller probabilities, leading people to be risk averse. Preliminary evidence suggests that people do not desire these displays to convey the risks and consequences of events like cancer. Thus, stick figures or facial displays may affect behavioral change despite the unappealing nature of the risk information.

Line Graphs

Line graphs are effective for communicating trends in data *(17–20)*. Explicit tests of whether the addition of a line graph to numerical or written text improves people's understanding of risk over time (e.g., cumulative risk) are unavailable. However, Mazur and Hickman *(45)* tested how physicians', medical students', and patients' treatment preferences for a serious yet unidentified medical condition were influenced by three 5-year survival curves that differed with respect to the amount of area under the curve. Overall, unlike physicians and medical students, patients' treatment preferences were most influenced by the location of the immediate (year 0) and end point (year 5) data. Medical students' and physicians' treatment preference was also influenced by the shape of the curve pertaining to years 2 to 4.

Dots and Related Formats

A few experimental studies have tested the efficacy of using a field of dots to communicate different probabilities of disease.[4] Kaplan et al. *(46)* informed 240 college undergraduates of one of three probabilities of having a negative reaction (i.e., nerve damage) to a flu vaccine (Guillian-Barré syndrome). The probabilities were 1/1000, 1/10 000, and 1/100 000. Half the participants were provided with a probability only; the other half were provided with a visual display of dots representing one of the three risks. Visually, those who reviewed a risk of 1/1000 saw 1/10th of a page covered with 1000 dots, those who reviewed a risk of 1/10 000 saw a page covered with 10 000 dots, and those who reviewed a risk of 1/100 000 saw 10 pages covered with 10 000 dots per page. Participants were asked how likely they were to get vaccinated. Regardless of the probability of side effects, the visual display increased the likelihood that participants would take the vaccine.

Weinstein et al. *(47)* performed an extension and attempted to replicate the results of Kaplan et al. In study 1, college students were presented with two decisions. The first decision was whether to get vaccinated against the flu given the risk of possible nerve damage—thus replicating the influenza scenario of Kaplan et al. The second decision was whether to move out of a dormitory to avoid the risk of minor nerve damage from improperly applied pesticides. Two levels of risk for side effects were used: 1 in 50 or 1 in 10 000. These risks were presented as odds, odds plus a grid of dots to represent the denominator of the odds ratio (i.e., total population), and a condition whereby an "X" was included among the dots to represent the numerator (the number affected) of the odds ratio (*see*, for example, Fig. 1, d). In addition, to more powerfully test whether participants are more influenced by the numerator or denominator of the odds ratio, a third condition was added involving a risk of 200 in 10 000, represented using each of the three formats described above. Format did not affect intentions or perceived threat. In study 2, four formats illustrating the risk of having a side effect from a flu vaccine (1 in 10 000) were used: 1) odds only; 2) odds plus a grid of 10 000 dots; 3) odds plus a grid of 10 000 dots plus a single dot on a separate page; and 4) a format identical to format 2, except that the dilemma, format, and questionnaire assessing risk and intention to act were presented one page at a time. Format did not affect intention; however, format 3 elicited more perceived threat than format 4. Overall, in neither study did any visual display differentially affect threat perception and intention compared with the odds-only format.

Similar to dots, marbles have been used to convey the risk of getting breast cancer (*see*, for example, Fig. 1, e). Baty et al. *(48)* presented women who had the BRCA1 mutation with the cumulative risk (i.e., aggregated risk over time) of getting breast cancer and ovarian cancer by age, using different colored marbles randomly distributed in a jar. These women also were presented with the cumulative risks of getting breast cancer and ovarian cancer for women without the mutation, again using marbles in a jar. Baty et al. reported that these displays helped several women understand the effects of carrier status on getting breast cancer and ovarian cancer. However, they pointed out that some women may be disturbed by this presentational style, in comparison with tabular information.

Pie Charts

Pie charts are effective for conveying proportions *(18,21–23)*. Fig. 3 shows a visual developed by the National Cancer Institute that depicts the risk of getting lung cancer as a function of smoking and radon exposure *(49)*.[5] Several participants in focus groups found the visual confusing, because they lacked knowledge about radon. In addition, although participants understood that the graph showed several risk factors linked to smoking and that smoking was a greater risk than radon exposure, some felt it was too complex (i.e., its main idea was not clear). Furthermore, a study by Hampson et al. *(50)* showed that the use of three pie charts failed to help communicate the synergistic (i.e., interactive) effects of smoking and radon exposure on lung cancer risk. Participants were shown a slice of a pie, specifying the total risk of getting lung cancer from radon exposure and smoking, that was *greater* than the sum of the pie slices for each risk factor displayed separately. These results suggest that 1) relatively straightforward visuals are easily misinterpreted and 2) visuals should be accompanied by brief captions that state the take-home message(s), especially for unfamiliar risks.

Devousges and colleagues *(31,41)* used focus groups to pilot test the effectiveness of using several pie charts—which they called probability or risk circles—to portray environmental risks. Participants were presented with two probability circles. One portrayed the risk of exposure to an environmental hazard, and the second portrayed the risk that exposure would produce detrimental effects (*see* top two circles in Fig. 4). Therefore, participants had to first imagine being exposed to an environmental hazard (i.e., landing on the pie slice that represented being exposed) and then similarly imagining the risks of harm if exposed. Through group discussions, participants expressed their difficulties understanding 1) how the shaded part of the pie conveyed chance (i.e., risk) and 2) exposure and effect as separate events or effect being contingent on first being exposed. Consequently, a third pie chart was added that displayed combined risk (i.e., exposure and effect; *see* bottom of Fig. 4). This third pie chart aided their understanding of the distinct probabilities. Therefore, a pie chart showing joint probabilities is more effective than two pie charts, each showing single-risk probabilities.

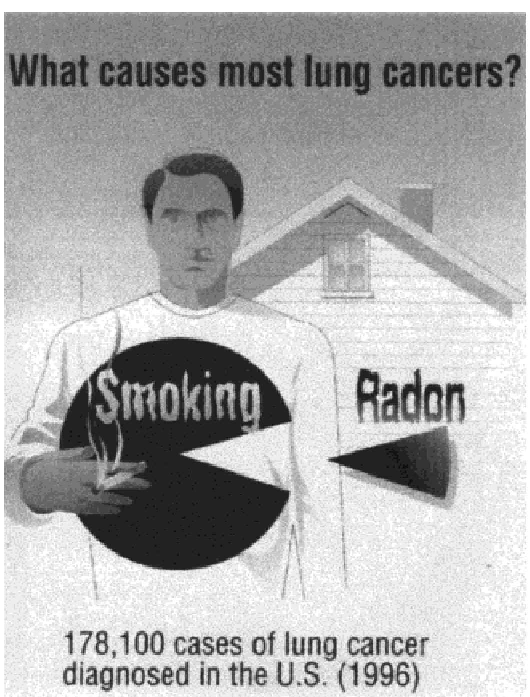

Fig. 3. Pie chart developed by the National Cancer Institute and evaluated by focus groups to depict lung cancer risk as a function of smoking and radon exposure. Reprinted with permission from the National Cancer Institute *(49)*.

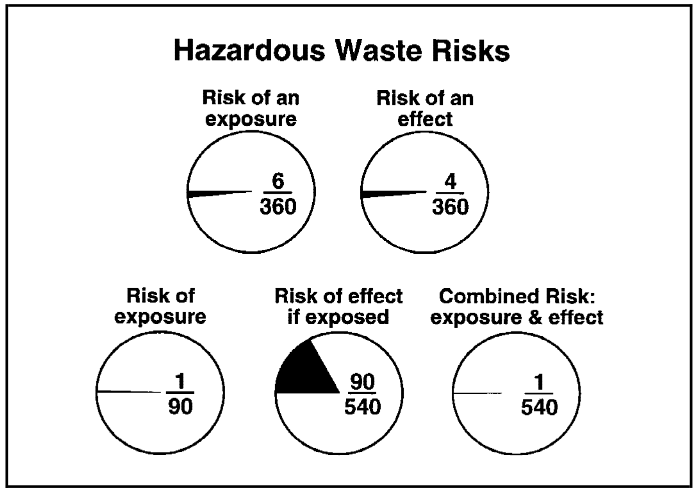

Fig. 4. Examples of risk circles, or probability circles, to illustrate risk of environmental hazard. The **top two circles** were less understood than the **bottom three circles.** The addition of the circle that combined the probabilities of exposure and effect aided comprehension. Reprinted with permission from the author *(31)*.

Histograms

Histograms have been used to convey smoking-related diseases in cessation manuals, such as the American Cancer Society's *Pathways to Freedom: Winning the War Against Tobacco.* This cessation manual portrayed the leading causes of death for African-Americans (i.e., homicide, car crashes, smoking-related diseases, drug abuse, and acquired immunodeficiency syndrome) in a histogram. Pilot testing of this graph at the Duke Risk Communication Lab showed that all participants understood that smoking was the leading cause of death for African-Americans and were quite alarmed by this fact.

The National Cancer Institute *(49)* used focus groups to test reactions toward a histogram to convey breast cancer risk (*see* Fig. 5). The histogram plotted the number of cases of breast cancer for different age categories (e.g., 40–49 years, etc.). Overall, the histogram was well received and understood. Women appreciated the gray shading to highlight the age groups at greatest risk. However, some participants were disturbed by the numbers and questioned their validity (e.g., why were the statistics of the number of women affected by breast cancer not more up to date?).

Although the research linking histograms with perceptions of risk is sparse, it appears that people readily understand and find histograms helpful and that they may induce risk aversion compared with numbers alone *(9)*. Whether risk perception is more affected by numerical risks or the height of the bars *(33)* remains to be tested—this can be determined by showing risk data using other graphical formats as well as the histogram.

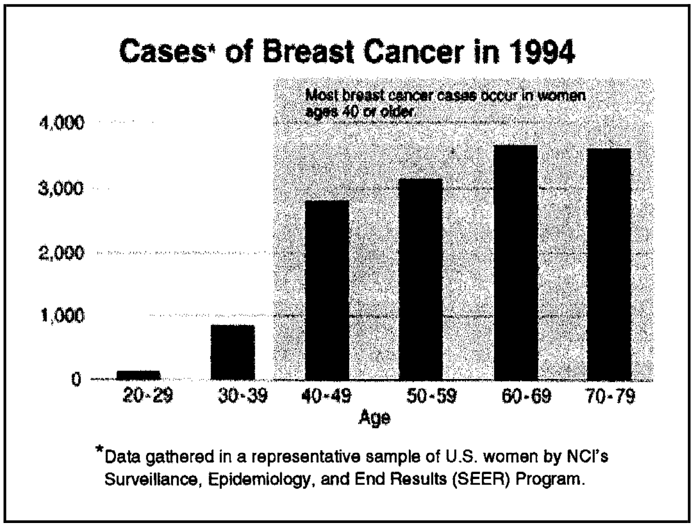

Fig. 5. Histogram developed by the National Cancer Institute and evaluated by focus groups to depict breast cancer risk as a function of age. Reprinted with permission from the National Cancer Institute *(49).*

Miscellaneous Visuals

A few studies have assessed how variability in data (i.e., distribution of data points) is perceived. Although these data do not address risk perceptions per se, they provide some insights into how people respond to variability in data. We review these few studies below.

Lathrop *(51)* replicated and extended research by Hoffstatter [cited in *(51)*], who found that, when people were asked to judge the variability associated with a bundle of sticks, they appeared to weigh the standard deviation by the reciprocal of the mean. That is, as values increase, perceived variability decreases. Lathrop showed cards depicting a set of lines to subjects and varied the order of presentation. Some cards had lines that alternated radically between long and short, whereas others did not. He found that the sequencing of the lines affected variability estimates, even when subjects were told to ignore the sequence. These results suggest that, if risk data are presented visually in different sequences, they may affect perceived variability, which can subsequently affect subjective probabilities and how these probabilities are combined (e.g., greater variability may lead to inflated probability estimates).

Legge et al. *(52)* examined how observers detect differences in variances between pairs of datasets sampled from Gaussian distributions. These data were displayed in three formats: tables, scatterplots, and luminance-coded displays. Performance was best for scatterplots and worst for tables.

Ibrekk and Morgan *(53)* examined how educated and semitechnical participants used nine visual formats showing quantitative distributions. The nine displays included an error bar, pie charts, histograms, conventional probability density plots, Tukey Box, and a cumulative probability plot. For the first of a two-part questionnaire study, the displays depicted meteorological information about snowfall. Participants were shown the nine displays and asked to indicate for each display 1) the best estimate of how much snow would fall, 2) the chance that more than 2 inches of snow would fall, and 3) the chance that the amount of snowfall would be between 2 and 12 inches. In part 2, participants were presented with these displays and asked similar questions to predict amount of water depth from a flood. In part 2, the questionnaire also contained a series of nontechnical explanations of the meaning and use of each of the displays in the context of predicting water depth from a flood.

When the task was to convey a single best estimate (e.g., amount of snowfall), graphs that explicitly portrayed the mean produced the most accurate responses (i.e., error bar and modified box plot; *see* Fig. 6, a and b). When the task was to estimate the probability that a quantity exceeded a certain amount (e.g., probability of snowfall greater than 2 inches) or fell within certain amounts (e.g., probability of more than 2 inches but less than 12 inches of snow), performance was best for estimating probabilities using a plot with a cumulative distribution function (CDF) (*see* Fig. 6, c) after explaining how it should be used—the pie chart was superior to the CDF but only before explanation. Ibrekk and Morgan *(53)* speculated that the combined use of cumulative probability and density plots would be most effective for communicating uncertain quantities (*see* Fig. 7), although this idea has not been explicitly tested.

Summary of Visual Displays of Communicating Risk

Despite the urging of several risk communication researchers [e.g., *(1,54,55)*], little research has tested the efficacy of visual formats for communicating risk per se. In this section, we summarize the research of the studies reviewed above.

Visuals May Help

Most risk information is portrayed as numbers alone (e.g., in tables) or as numbers with narrative translations. Visuals are assumed to help individuals understand and summarize risk in-

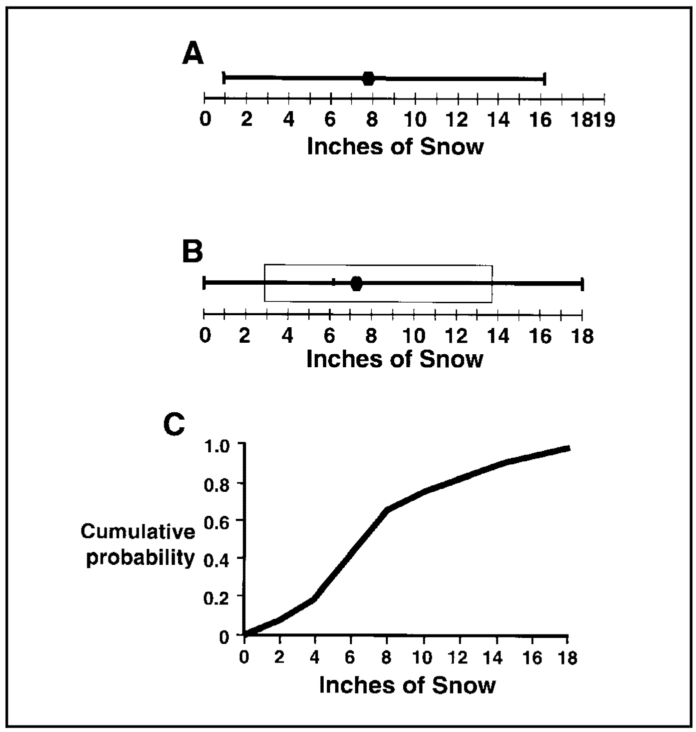

Fig. 6. Graphics that effectively convey point estimates and uncertainty data. **A**) error bar and **B**) modified box plot were most effective for communicating a single estimate (e.g., mean estimate of amount of snowfall), as indicated by the dot on the line. **C**) The cumulative probability plot was most effective for communicating the probability that an amount would exceed or be between certain values. Reprinted with permission from Risk Analysis *(53).*

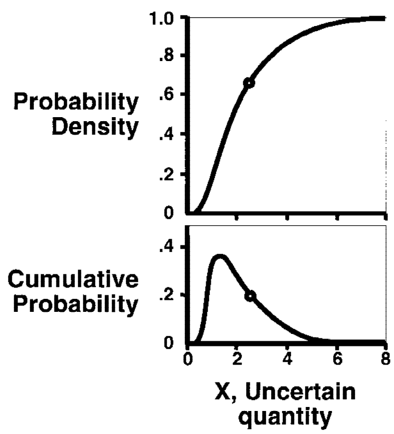

Fig. 7. Ibrekk and Morgan's recommended graphical plots to communicate quantitative uncertainties. This example of a cumulative distribution function is plotted directly below the probability density function with the same horizontal scale and with the location of the mean marked by a **dot.** Reprinted with permission from Risk Analysis *(53).*

formation. Most, but not all [e.g., *(47)*], of the preliminary *experimental* evidence suggests that combining visuals with numerical and written information does affect several outcomes, such as the perceived helpfulness of the information, perceived risk (e.g., threat), mitigation intentions, and trust in government officials *(9,35–37,39,42,46).* The tentative conclusion that visuals are useful for communicating risk is based on limited experimental studies that involved different hazards (e.g., radon or asbestos, product risks), risk magnitudes, type of risk being communicated (i.e., absolute versus relative risk), format of communicating risk (e.g., risk ladder, stick figures, or dots), and outcomes.

Despite Their Popularity, Experimental Tests of the Effectiveness of Visuals Are Few

The mass media (e.g., newspapers) and health communication researchers often use graphics to communicate risk, assuming that these displays will improve the public's understanding of risk and act accordingly. There is still little experimental research testing whether the lay public's perceptions and understanding of risk vary by graphical format and whether the addition of graphical displays improves comprehension significantly beyond numerical or narrative translations of risk and, if so, by how much.

Research Is Largely Atheoretical

With few exceptions *(9,31,33–35,39),* most research using graphs and other visuals specifically to communicate risk has been atheoretical. It is not clear why particular graphs or visuals are chosen. For research in this area to advance, the application of theory and findings from other fields (e.g., visual perceptions and psychophysics, human factors, or visual persuasion) may be useful. Nonetheless, hypotheses have been put forth with respect to 1) how stick and other visuals may induce risk aversion (e.g., willingness to pay) when added to numerical risk information *(9);* 2) how the placement of risk information on a risk ladder affects perceived risk and intentions *(33,36,37);* 3) how an action standard and advice, when added to a risk ladder, affect perceived risk, understanding, intentions, and behaviors *(34–37);* and 4) how visually distinguishing the numerator from the denominator of an odds ratio affects perceived risk and intentions when added to numerical information *(46,47).*

Overall, it is still unclear why the addition of a visual display to numerical risk information would induce greater risk aversion *(9).* Similarly, results are inconclusive whether visually emphasizing the numerator and denominator of an odds ratio (e.g. showing "X"s to represent number affected versus dots to represent total population) affects perceived risk and intentions. People are sensitive to placement of risks on the risk ladder. Furthermore, as discussed previously, adding an action standard and advice affects perceived risk, intentions, and possibly behavior. Nonetheless, a comprehensive theoretical model linking visuals to risk communication that can incorporate these findings is needed.

Impact of Task Is Ignored

The use of particular visuals has not been linked explicitly to specific risk communication tasks. The most extensive research examining the effectiveness of visuals has examined the use of the risk ladder and the testing of stick and facial figures, primarily for the communication of absolute and relative risks. What is known is that 1) risk ladders are effective at conveying magnitude and range of risk, based on the positioning of the hazard(s) on the ladder; 2) stick figures, faces, asterisks, and histograms are roughly equivalent in their ability to induce risk aversion when added to numbers, although it is unclear whether people's understanding of relative risk is improved comparing visuals displays with numbers only *(9);* and 3) people have difficulty understanding low-probability events, even with the aid of visuals.

Research that examines which graphics and visuals are best matched to particular risk communication tasks is needed. The graphical perception literature shows that certain graphs are well suited for particular tasks (e.g., evaluating trends in risk over time, judging proportions, etc.). We discuss this research and its applications to risk communication in a later section.

Few Visuals Are Known to Be Effective at Communicating Uncertainty

While a few attempts have been made to visually communicate the quantitative uncertainties of environmental health risks, we have yet to begin testing visuals for communicating uncertainties about cancer risk per se. What is known is that placing the upper and lower bound of risk on a vertical scale, akin to a risk ladder, helps people understand that the risk of an adverse outcome can take on high and low values (i.e., see a range of risk) and that scatterplots are effective for conveying variability (i.e., dispersion) in data. In addition, if a series of data is presented whereby the ordering of the magnitudes differs substantially (e.g., have an alternating sequence of presenting low and high risk), people's perceptions of variability and perhaps risk may be affected. However, it is not clear how perceived variability would affect perceived risk. For example, if variability is perceived as uncertainty or instability, people may perceive the information as less trustworthy and consequently be less inclined to alter their risk perception and actions. If the goal is to communicate probabilities for a range of outcomes (e.g., probability that we will get rain in the amount of 1 to 4 inches), the combined cumulative and probability density plots suggested by

Ibrekk and Morgan [*(53); see* Fig. 7] might prove useful after explaining to people how to use them.

Few Standards Used to Evaluate Visual Representations of Risk

To date, visuals have been evaluated on the basis of their ability to affect primarily people's perceptions of risk magnitude and relative risk and intentions to modify risk-related behaviors (e.g., test for radon). Little is known about how visuals affect other outcomes as part of the risk communication processes, as discussed in the section on criteria used to evaluate the effectiveness of visual displays to communicate risk. The work by Weinstein and colleagues *(33,34,36),* pertaining to communicating risks of exposure to radon or asbestos, ideally exemplifies the explicit use of these criteria.

Adding Reference Points to Graphs Affect Risk Perceptions and Intentions

Graphs that contain a reference point (e.g., action standard, colors that highlight level of risk, or arrow showing high risk) to indicate level of hazard threat (i.e., low, moderate, or high risk) affect risk perceptions, intentions, and possibly behaviors *(33–35,37).* When possible, graphs should contain a reference point indicating when a hazard reaches a level requiring action (i.e., an action standard) along with advice about what action to take at that level. Information also should be included about how to interpret risk below and above the action standard and what, if any, appropriate action is needed at these levels. Indeed, it is relatively easy to incorporate a reference point and some descriptions into some graphs, and different graphical formats make it easier to compare a particular quantity with a reference point *(56).*

Guidelines for Maximizing the Effectiveness of Graphs

In the previous sections, we provided general conclusions about the use of graphical displays but provided no guidelines to maximize their effectiveness. In this section, we discuss seven guidelines pertinent to graphical depiction of risk data. [Readers interested in further guidelines for construction should consult Gillan et al. *(57).*]

No single graphical format will perform optimally in all situations. Rather, the effectiveness of a display will be affected by several factors, such as 1) the display characteristics (e.g., use of colors, width of lines, or type and spacing of legends), 2) conditions of presentation (e.g., lighting or time pressure), 3) data complexity (e.g., number of data points or configuration of the display), 4) the task (i.e., purpose, for example, to assess trends), 5) user characteristics (e.g., cognitive styles), and 6) the criterion for choosing the display (e.g., speed of performance or accuracy) *(19).* In our discussion, we assume that risk data can be plotted graphically similar to other data (e.g., finances, sports, or weather). Furthermore, we assume that what is known generally about graphical perception should apply specifically to the graphical depiction of risk data.

Avoid Areas or Volumes to Depict Quantities

People make errors when judging graphs. That is, people overestimate or underestimate quantities compared with their true values. These biases may be because of optical illusions [e.g., Poggendorf illusion *(58)*], distortion in memory (e.g., remembering more symmetry than exists [*see (59)* for review]), or perceptual limitations in estimating the magnitudes of certain kinds of stimuli (e.g., area and volume). The key point is that graph designers should avoid using graphical elements that lead to perceptual biases. We briefly review a few biases that are relevant to presenting risk data.

Individuals show biases in estimating physical magnitudes of objects. According to Stevens and Gallanter *(60)* and Stevens *(61),* the relationship between perceived and actual magnitude is described by the power function $p(x) = cx^{\beta}$, in which $p(x)$ is the perceived magnitude of the object, c is a constant, x is the actual magnitude, and $^{\beta}$ is an exponent. When the exponent is 1, there is no bias in the perceived magnitude; when the exponent is greater than 1, each incremental increase in the physical magnitude results in greater and greater estimates of perceived magnitude, producing a positively accelerated function (i.e., response expansion). When the exponent is less than 1, each incremental increase in physical magnitude results in smaller and smaller increases in perceived magnitude, producing a negatively accelerated function (response compression). In particular, response compression has been shown for estimates of areas and volume (dimensions often used to code variables in graphs), so that large areas and volume are underestimated. In contrast, lengths are usually perceived without bias. Illustrations of these biases are depicted in Fig. 8.

In addition, the biases described by Stevens's law appear to affect more complex judgments when multiple quantities are used, such as judgments of proportion (i.e., what proportion is *A* of *B*?). When using graphs depicting proportions (e.g., pie charts or stacked bar graphs), people show a cyclical bias pattern, such that proportions of 0–.25 and .50–.75 are overestimated and proportions of .25–.50 and .75–1 are underestimated [*see* Fig. 8, B–D, and *(56,62)* for review]. This bias can be reduced by adding reference points, such as tick marks, to the graph. For example, as shown in Fig. 8, D, placing a tick at 0, 90, 180, and 270 degrees of a pie chart has been shown to reduce errors in estimating proportions *(56).* Therefore, researchers who wish to illustrate proportional judgment of risk (e.g., proportion of breast cancer relative to all cancers) may reduce error by adding reference points to a pie chart. In sum, making errors in relative judgment can be reduced by 1) avoiding the use of stimuli whose Stevens's exponents differ from 1, and 2) increasing the use of reference points (e.g., tick marks) in the graph.

Consider the Task

What are graph readers being asked to do with the information depicted in the graph—to read the exact value of a risk estimate, compare the value of two risks, assess trends, or judge proportions? Consistent with Sparrow's *(63)* notion of task or display compatibility, a display should provide the relevant information such that it minimizes the amount of computational effort and transformations needed to perform these tasks.

To assist in this endeavor, Carswell *(64)* devised a taxonomy, incorporating the following four basic graphical tasks: 1) point reading, 2) local comparisons, 3) global comparisons, and 4) synthesis. In point reading, the observer judges the value of a single graphical element (e.g., what is the value of risk expressed in a histogram?). In local comparisons, the observer compares two graphical elements (e.g., which person, *A* or *B,* has a higher risk of getting breast cancer?). For global comparisons, the ob-

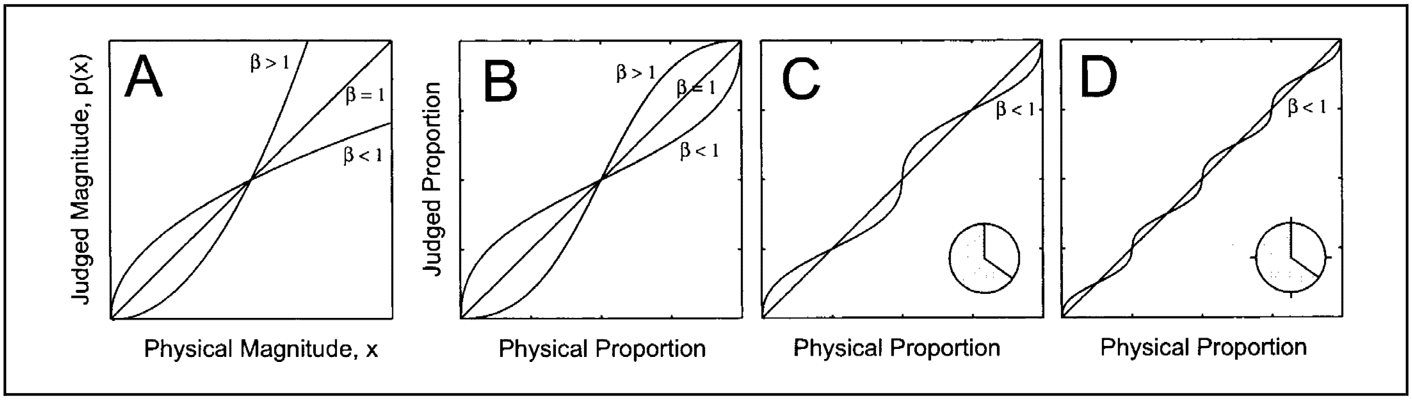

Fig. 8. Bias in perceptual judgment. **Panel A** shows the bias in single estimates of magnitude described by Stevens's law. β <1 when judging areas or volumes, β = 1 when judging lengths. **Panels B, C,** and **D** show the cyclical bias in proportion judgments that is because of the bias in the estimate of each single quantity. The patterns in **panels C** and **D** are seen when reference points at halves or quarters are used, respectively. The pattern in **panel C** is seen with common graph types, such as pie charts and divided (stacked) bar graphs. Error in judgment can be reduced by adding tick marks to a pie chart at the quarters, resulting in the pattern shown in **panel D.**

server compares quantities derived from other quantities shown in the graph (e.g., is person *A*'s risk for breast cancer less than that of *B*'s over two time periods?). For synthesis judgments, the observer needs to consider all data points to make a general, integrative judgment (e.g., is person *A*'s risk of breast cancer increasing or decreasing over time?).

Carswell's taxonomy can be applied to consumer risk information. A consumer might wish to extract the following types of information: 1) risk magnitude (i.e., how large or small the risk is), 2) relative risk (i.e., comparing the magnitude of two risks), 3) cumulative risk (i.e., observing trends over time), 4) uncertainty (e.g., estimating amount of variability or range of scores), or 5) interactions (e.g., synergy) among risk factors. Applying Carswell's taxonomy, the estimation of risk magnitude would be an example of point reading. Comparison of two risk magnitudes would constitute local comparisons, whereas assessing cumulative risk, uncertainty, and interactions among risk factors would most likely constitute global comparisons and synthesis judgments. Of import, point reading and local comparisons can be considered fairly low level, focused tasks, whereas global comparisons and synthesis judgments involve integrating several pieces of information (e.g., how variables are related) to see the "big picture." Some graphical displays are better suited for focused rather than integrated tasks, and we discuss these below.

When the task is to communicate a precise risk magnitude (i.e., point reading) or to compare two risks (i.e., local comparisons), two fairly low level focused tasks, the graph designers should make use of the ranking of elementary perceptual tasks as proposed by Cleveland and McGill *(16,65).* According to Cleveland and McGill, individuals are least accurate at extracting information using 1) position along a common aligned scale (e.g., bar charts, histograms, or dot charts); 2) position on a common nonaligned scale (e.g., polygon displays with reference axes or scatterplots); 3) length (e.g., polygon displays without reference axes); 4) angle or slopes (e.g., pie charts, disks or meters); 5) area (circles or blobs); 6) volume, density, or color saturation (e.g., cubes); and 7) color hue (e.g., statistical maps with color coding). Therefore, if people are asked to evaluate the magnitude of a risk or asked to compare risks, line graphs, bar charts, histograms, and dot charts are likely to lead to greater accuracy in estimation than are other graphical formats. For example, the effectiveness of the risk ladder is probably because of its resemblance to a divided bar chart, which capitalizes on position along a common scale. If the task is to make proportional judgments of risk, a focused task that is served well using area to illustrate quantities, pie charts should be used *(18,21–23).* Nightingale roses also may be effective for proportion judgments. Like pie charts, Nightingale roses are circular and segmented; however, they differ from pie charts in one important way. In a pie chart, each segment shares a common radius but has a central angle that varies as a function of the data. In a Nightingale rose, each segment subtends the same central angle, but the length of the segment differs as the square root of the radius *(66)* as shown in Fig. 9.

Overall, the ranking of elementary perceptual tasks by Cleveland and McGill *(16,65)* serves us well for focused risk communication tasks (e.g., point reading, comparing two risk magnitudes along a common scale, etc.). However, their rankings do poorly for addressing integrative tasks that require seeing the "bigger picture" *(64).* A model for visual display design, called the proximity compatibility principle, makes predictions about which task–graph combinations should be most effective for focused and integrative tasks *(67).*

According to the proximity compatibility principle, there are two important components to consider: display proximity and processing proximity. Display proximity relates to how similar graphical elements are to each other. Graphical elements will be

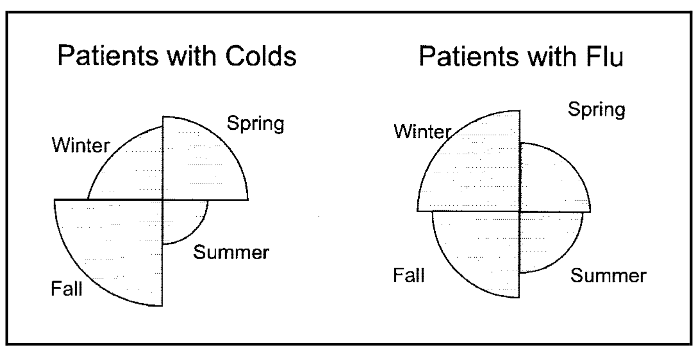

Fig. 9. Example of a Nightingale rose. For each rose, a circle is divided into multiple regions of equal angle; the radius of each slice is used to depict the quantity of interest. Because the data for each season are in the same position in each rose, it is easy to compare them. The data are fictional.

perceived as more similar to the extent that they are close together, share the same colors, use the same physical dimensions (e.g., length or height), or use the same code (e.g., both are digital or both are analog). Graphical elements that are viewed as similar and integrated have high display proximity. Processing proximity refers to whether two or more informational sources are used within the same task. Tasks that require integrating several pieces of information are said to require high processing proximity (e.g., estimate whether there is an increase or decrease in the slope of a scatterplot). Tasks that do not require the integration of several information sources are low in processing proximity (e.g., determine the value of a symbol in a graph). Hence, on the basis of these two dimensions, tasks that require high processing capacity (e.g., local comparison or synthesis tasks) should have high display proximity (e.g., integrate features of the graph to make them appear as one unit so that it is easier for the observer to use all the information, e.g., line graphs). Tasks that require low processing proximity (point reading or local comparisons) should have low display proximity (e.g., create graphs that highlight specific informational elements).

The proximity compatibility principle is in agreement with Cleveland and McGill's ranking system for focused tasks. However, the proximity compatibility principle makes different predictions than Cleveland and McGill's ranking system for integrative tasks, because these tasks are best preformed with integrated displays that often use area and volume to communicate quantities. Hence, for integrative risk communication tasks (e.g., global comparison or syntheses tasks), it is best to use displays that 1) highlight emergent features of the display, such as symmetry, area, and linearity, and 2) increase the spatial proximity among elements. For example, tasks that require seeing changes in several variables at once may benefit from facial displays in which different facial characteristics (e.g., eyes or mouth) convey different levels of multivariate data [e.g., Chernoff face displays *(68–70); see* Fig. 1, c, bottom row). Thus, facial displays may be useful for displaying synergy among risk factors, where specific features can be used to designate type and level of risks. In addition, integrative tasks are served well by such formats as line graphs *(71)*. Line graphs should be used when the main tasks are to assess trends in risk over time or to view the interaction between variables.

Minimize Number of Mental Operations

When a graph reader reviews a graph, he or she will perform a sequence of perceptual operations, cognitive operations, or both. A graph designer should select the graph and arrangement of information to reduce the number of operations performed. Several researchers have proposed models of mental operations for graph reading—a detailed review of this literature is beyond the scope of this paper [*see (18,21,22,25,64,72–76)*]. For example, Hollands and Spence *(18)* found that trends are best analyzed with line graphs than with a series of pie charts. When estimating trends with line graphs, people can use a slope estimation procedure; with pie charts, they must perform multiple size discriminations between pie slices. However, when estimating proportions, a person performs a ratio estimation task with pie charts, but must perform multiple summation operations before estimating the ratio with line graphs. In addition to preattentive perceptual processes [e.g., detection, discrimination, and identification *(77)*], ratio and summation operations are likely to be common mental operations. In sum, reducing the number of operations will help reduce errors in judgment and in the time needed to perform the task.

Data–Ink Ratio

According to Tufte *(14)*, the amount of ink used to display features other than data should be kept at a minimum. For example, Fig. 10 shows a low data–ink ratio—there is more ink devoted to background and other variables than to the data. In agreement with the recommendations by Tufte *(14)*, Gillan and Richman *(78)* found that participants had faster response times and were more accurate when the data–ink ratio was high than when it was low. In addition, integrated tasks (e.g., global comparisons or synthesis judgments) appear to be more affected by the data–ink ratio than are focused tasks (e.g., selecting the value of a data point). These results suggest that graphs depicting risk data should avoid background or elements that divert attention away from the data (e.g., illustrating the health risks associated with smoking and having a house in the background as shown in Fig. 3). This need to highlight the most relevant data is in keeping with Tufte's other recommendations that are to 1) erase nondata ink, within reason; 2) erase redundant data–ink, within reason; and 3) maximize data density and the size of the data matrix (i.e., how many data points), within reason.

Use of Multiple Graphs

Thus far, our discussion has centered on the construction of single graphs. However, at times, sets of related data must be communicated—when there are several outcomes affected by a single factor (e.g., how smoking affects lung cancer, heart disease, stroke, etc.). In these situations, the graph designer must focus on the relationship between successively viewed graphs, in addition to optimizing the format for each graph. Keep in mind the following three issues:

- *Highlight differences.* Help the observer see the changes or differences from graph to graph in the legends or symbols. For example, if different outcomes (*y*-axis) are presented as a function of the same factor (*x*-axis), the designer should highlight the label related to the outcomes.

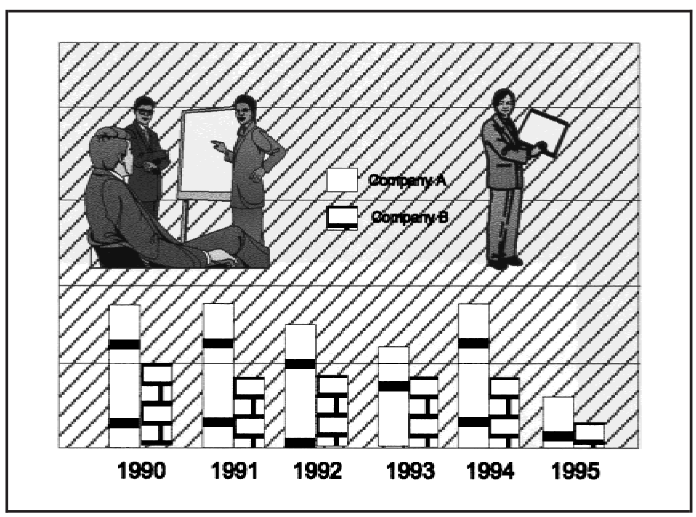

Fig. 10. A graph with a low data–ink ratio. Notice the amount of ink devoted to objects that do not contain the data of interest (pictures, busy background, horizontal grid lines, patterned fills on the bars, etc.).

- *Use distinctive legends.* Legends of similar graphs should highlight their distinctive features.
- *Be consistent.* When plotting the same data in different ways or plotting different data as a function of the same variables, keep elements of the graphs (e.g., colors and legends) consistent. For example, if a variable is highlighted with a particular color in one graph, the same color should be used to depict that variable in another graph.

In addition to the above guidelines, the graph designer should consider at least two additional issues.

Problem of Communicating Small-Probability Events Visually

Although people may have an intuitive understanding of everyday probabilities (e.g., .50), they may fail to comprehend the magnitude of small-probability events (e.g., .0003). One solution is to change probabilities into frequencies (e.g., 3 out of 10 000). Frequency information conforms more readily to people's intuitive assessment of probabilistic occurrences in nature [*see (79)* for review].

Moreover, given that most risk events that threaten our lives have a low probability of occurrence during any particular month or year, it may be more meaningful to communicate aggregate (i.e. cumulative) risk over time *(80)*. For example, whereas the chance of being injured in an automobile accident is roughly about 1 in 10 000 each time a person drives, the chance of being injured at least once during a lifetime of driving is about 1 in 3 *(7)*.

Audience

Knowing the characteristics of the audience is vital to the success of risk communication efforts *(81)*. A critical question is whether the audience can comprehend the communication [e.g., reading level or preferred method of communication *(81,82)*]. In this respect, two variables may be potentially important: familiarity and experience with graphical displays and how facile people are with mathematical operations and concepts [i.e., numeracy *(11–13)*].

The ability to decipher and comprehend graphs may differ as a function of a person's greater familiarity and working experience with a display. Although performance with graphs and other visuals should improve with experience and some studies *(19,53)* support this, other studies *(16,65)* show that technical training has no effect on the audience's performance using graphs. Until further research clarifies these relationships further, decisions to use a specific graph to communicate risk should not be based largely on the audience's familiarity with the graph, but more by how well the graph is suited to the task.

In addition, numeracy has been shown to affect risk perceptions. For example, less numerate individuals overestimate personal risks of dying of breast cancer and are less able to accurately gauge the magnitude of risk reduction from mammograms than do more numerate individuals *(11,13)*. Less numerate individuals may stand to benefit more from the visual communication of risk magnitudes and uncertainties than more numerate individuals. However, empirical tests of such effects have yet to be conducted.

Recommendations for Future Research

The visual communication of cancer risk is still in its infancy. In this section, we suggest areas of research that should aid our understanding of these processes.

Conduct Research Linking Graphical Perception to Risk Perception

Research on graphical perception has identified basic graphical forms that should be ideally suited to convey risk information. This research would first identify how basic graphical forms affect risk perceptions along such dimensions as magnitude and accuracy of risk. For example, does varying the size of pie charts and their constituent parts (e.g., number and size of slices) affect perceived risk? This work would capitalize on and integrate findings in the disciplines of psychophysics and graphical perception. Subsequent research could identify how varying graphical elements such as type of numbers (e.g., percents versus frequencies), labels, color, and so forth influences perceived risk.

Determine Effects of Preference for and Experience With Displays on Risk

This information may prove useful when tailoring risk messages to a particular person or audience [*(83); see* also Rimer and Glassman *(84)*, in this monograph]. Ideally, individuals should prefer graphical formats that are consistent with the computational algorithm (e.g., judging magnitude or proportion) suited to a particular graph or visual. People should prefer graphical and visual displays that are consistent with their schemas of what a particular graph or visual is supposed to do.

Establish How Graphs Affect Perceived Severity and Risk

Hazards are often examined with respect to two main components: the nature of the adverse event (i.e., severity, e.g., number of lives lost) and the probabilities that adverse consequences will occur *(85)*. Therefore, it is important to determine how the visual will affect the perceived severity, the probabilities, or both. For example, graphs that appeal to our emotions and arouse thoughts and feelings related to experienced or imagined negative events may initially and most powerfully affect perceived severity. In turn, severity may affect perceived risk by increasing the ease with which negative events are imagined to occur *(86)*.

If the aim of the risk communication is to persuade and initiate behavior change, then it will become important, from a theoretical perspective, to disentangle these effects. For example, several models of health behavior suggest that behavioral change can be predicted by a severity-by-risk interaction, such that hazards that are both severe and highly probable should instigate greater behavior change than hazards that are not very severe and highly probable or very severe and not highly probable [*see (87)* for review].

Establish How Risk Characteristics Interact With Visual Displays to Affect Risk Perceptions

Research using the psychometric paradigm has examined several characteristics of perceived risk, such as whether the risk is voluntary or involuntary, chronic or catastrophic, common or dreaded, injurious or fatal, controllable or not controllable, and old or new [*see (88)* for review]. Perception of risk is greater for those events in which adverse risks are dreaded, uncontrollable, catastrophic, fatal, and that affect future generations. In what ways might these characteristics of risk interact with graphical displays? Perhaps graphs that display such risks might receive more detailed scrutiny (i.e., are more salient), changing the kinds of mental operations applied to the display. Do displays that communicate dreaded, uncontrollable, catastrophic, or fatal risks engender greater imagery and then affect the risk depicted in a graph?

Determine the Range of Probabilities Conveyed Most Effectively

Are graphical displays most effective for communicating small probabilities, or are they effective at communicating risk at all ranges (i.e., probabilities from 0–1)? For example, the work by Stone et al. *(43)* revealed that visual displays affected how risk-averse participants were via willingness to pay for products using small but not larger probabilities. This study suggests that graphical displays may be powerful aids for conveying the risk of an unlikely event, and people may prefer to have a graphical display in those contexts.

Determine Which Visuals Are Most Effective to Communicate Cancer Risk Uncertainty

We have yet to begin researching how providing visual displays of cancer risk per se affects risk perception, decision-making processes, and, ultimately, behavior. For example, does the addition of a visual display increase or decrease the credibility of the information? Are people less likely to take action when uncertainty information is provided in a graphical format compared with when it is not? Given the various definitions and sources of uncertainty *(89,90)*, this issue deserves more attention.

Use Standard Criteria

To better understand how the addition of graphs improves on other modes of communicating risk (e.g., narratives or numbers only), there is a need for standard evaluation criteria [e.g., those devised by Weinstein and Sandman *(28)*]. Standard criteria would allow conclusions to be drawn across various studies.

Need Multidisciplinary Research

Given the multidimensionality of risk, collaborations between various disciplines and organizations are needed. Working collaboration between experts in human factors, psychology, sociology, psychophysics, graph perception, and the mass media is likely to lead to more integrative and novel approaches than research within a single discipline.

Provide Detailed Accounts of Materials Used to Communicate Risk Visually

In this endeavor, we hope editors will increase the number of graphical and other visuals that can be added to journal articles and book chapters. This increase should enhance tremendously the ability to make comparisons between graphical displays.

Conclusions

The graphical perception literature shows that certain graphs are well suited for specific tasks and provides insight into what to avoid (e.g., use of volume or area and low data–ink ratio). Admittedly, this extant literature has not been applied specifically for communicating cancer risk information and should be explored within this context. Indeed, there is a small but growing amount of experimental literature showing that graphs can affect perceived risk, intentions, and possibly behaviors. For example, the use of the risk ladder shows promise. It is now time for researchers of risk communication to step forward to advance the field of visual risk communication. We hope that this review provides insight into the issues that should be considered when visually displaying risk and spurs researchers to meet the challenges posed by the field of visual risk communication.

References

(1) Covello VT, von Winterfeldt DV, Slovic P. Risk communication: a review of the literature. Risk Abstr 1986;3:171–82.

(2) Fischhoff B. Risk perception and communication unplugged: twenty years of process. Risk Anal 1995;15:137–45.

(3) National Research Council. Improving risk communication. Washington (DC): National Academy Press; 1989.

(4) Slovic P. Informing and educating the public about risk. Risk Anal 1986; 6:403–15.

(5) Halpern DF, Blackman S, Salzman B. Using statistical risk information to assess oral contraceptive behavior. Appl Cogn Psychol 1989;3:251–60.

(6) Siegrist M. Communicating low risk magnitudes: incidence rates expressed as frequency versus rates expressed as probability. Risk Anal 1997;17: 507–10.

(7) Slovic P, Fischhoff B, Lichenstein S. Accident probabilities and seat belt usage: a psychological perspective. Accid Anal Prev 1978;10:281–5.

(8) Stone ER, Yates JF, Parker AM. Risk communication: absolute versus relative expressions of low-probability risks. Organ Behav Hum Decis Process 1994;60:387–408.

(9) Stone ER, Yates JF, Parker AM. Effects of numerical and graphical displays on professed risk-taking behavior. J Exp Psychol Appl 1997;3: 243–56.

(10) Yamagishi K. When a 12.86% mortality is more dangerous than 24.14%: implications for risk communication. Appl Cogn Psychol 1997;11: 495–506.

(11) Black WC, Nease RF, Tosteson AN. Perceptions of breast cancer risk and screening effectiveness in women younger than 50 years of age. J Natl Cancer Inst 1995;87:720–31.

(12) Paulos JA. Innumeracy: mathematical illiteracy and its consequences. New York (NY): Vintage Books; 1990.

(13) Schwartz L, Wolosin S, Black WC, Welch HG. The role of numeracy in understanding the benefits of screening mammography. Ann Intern Med 1997;127:966–72.

(14) Tufte ER. The visual display of quantitative information. Cheshire (CT): Graphics Press; 1983.

(15) Tufte ER. Envisioning information. Cheshire (CT): Graphics Press; 1990.

(16) Cleveland WS, McGill R. Graphical perception: theory, experimentation, and application to the development of graphic methods. J Am Stat Assoc 1984;70:531–54.

(17) Shamo MK, Meyer J, Gopher D. Predicting values from tables and graphs. Proceedings of the 40th annual meeting of the Human Factors and Ergonomics Society; 1996 Sept 2–6; Philadelphia. Santa Monica (CA): Human Factors and Ergonomics Society; 1996. p. 1151–4.

(18) Hollands JG, Spence I. Judgments of change and proportion in graphical perception. Hum Factors 1992;34:313–34.

(19) Meyer J, Shinar D, Leiser D. Multiple factors that determine performance with tables and graphs. Hum Factors 1997;39:268–86.

(20) Schutz HG. An evaluation of formats for graphic trend displays (experiment II). Hum Factors 1961;3:99–107.

(21) Hollands JG, Spence I. Judging proportion with graphs: the summation model. Appl Cogn Psychol 1998;12:173–90.

(22) Simkin D, Hastie R. An information processing analysis of graph perception. J Am Stat Assoc 1987;82:454–65.

(23) Spence I, Lewandowsky S. Displaying proportions and percentages. Appl Cogn Psychol 1991;5:61–77.

(24) Kosslyn SM. Understanding charts and graphs. Appl Cogn Psychol 1989; 3:185–226.

(25) Pinker S. A theory of graph comprehension. In: Freedle R, editor. Artificial intelligence and the future of testing. Hillsdale (NJ): Erlbaum; 1990. p. 73–126.

(26) Eagly AH, Chaiken S. The psychology of attitudes. Fort Worth (TX): Harcourt Brace College Publishers; 1993.

(27) Nisbett RE, Ross L. Human inference: strategies and shortcomings of social judgment. Englewood Cliffs (NJ): Prentice-Hall; 1980.
(28) Weinstein ND, Sandman PM. Some criteria for evaluating risk messages. Risk Anal 1993;13:103–14.
(29) Henderson M. Living with risk: the choices, the decisions. Chicester (UK): John Wiley and Sons; 1987.
(30) United States Environmental Protection Agency. Indoor air and radiation. In: A citizen's guide to radon. 3rd ed. Washington (DC): Environmental Protection Agency; 1992 Sept; Report No.: EPA 402K92001.
(31) Smith VK, Desvousges WH, Freeman AM. Valuing changes in hazardous waste risks: a contingent valuation analysis. Vol. I: Draft interim report. EPA Cooperative Agreement No. CR-811075: The benefits of hazardous waste management regulations using contingent valuation. Washington (DC): The U.S. Environmental Protection Agency; 1985. Section 8, p. 13–47.
(32) Covello VT. Risk comparisons and risk communication: issues and problems in comparing health and environmental risks. In: Kasperson RE, Stallen PJM, editors. Communicating risks to the public: international perspectives. Dordrecht (The Netherlands): Kluwer Academic Publishers; 1991. p. 79–124.
(33) Weinstein ND, Sandman PM, Roberts NE. Communicating effectively about risk magnitudes, Phase 1. New Brunswick (NJ): Environmental Communication Research Program, Cook College, Rutgers University; 1989.
(34) Weinstein ND, Sandman PM, Miller P. Communicating effectively about risk magnitudes, Phase Two. New Brunswick (NJ): Environmental Communication Research Program, Cook College, Rutgers University; 1991.
(35) Smith VK, Desvousges WH, Johnson FR, Fisher, A. Can public information affect risk perception? J Policy Anal Manage 1990;9:41–59.
(36) Sandman PM, Weinstein ND, Miller P. High risk or low: how location on a "risk ladder" affects perceived risk. Risk Anal 1994;14:35–45.
(37) Smith KV, Desvouges W, Payne JW. Do risk information programs promote mitigation behavior? J Risk Uncertainty 1995;10:203–21.
(38) Fisher A, McClelland GH, Schulze WD. Communicating risk under Title III of the SARA; strategies for explaining very small risks in a community context. J Air Pollut Control Assoc 1989;39:271–6.
(39) Sandman PM, Weinstein ND, Hallman WK. Communications to reduce risk underestimation and overestimation. Risk Decis Policy 1998;3:93–108.
(40) Sandman PM, Weinstein ND. Communicating effectively about risk magnitudes: bottom line conclusions and recommendations for practitioners. Washington (DC): Environmental Protection Agency; 1994 Aug; Report No.: 230.
(41) Desvouges SH, Smith VK. Focus groups and risk communication: the 'science' of listening to data. Risk Anal 1988;8:479–84.
(42) Johnson BB, Slovic P. Presenting uncertainty in health risk assessment: initial studies of its effects on risk perception and trust. Risk Anal 1995; 15:485–94.
(43) Stone ER, Rush CJ. Risk communication: the effectiveness of graphical modes depends on the risk magnitude. Poster presented at the annual meeting for the Society for Judgement and Decision-making; 1997 Nov; Philadelphia (PA).
(44) Stephenson MT, Witte K. Fear, threat, and perceptions of efficacy from frightening skin cancer messages. Public Health Rev 1998;26:147–74.
(45) Mazur DJ, Hickman DH. Patients' and physicians' interpretations of graphic data displays. Med Decis Making 1993;13:59–63.
(46) Kaplan RM, Hammel B, Schimmel LE. Patient information processing and decision to accept treatment. J Soc Behav Pers 1985;1:113–20.
(47) Weinstein ND, Sandman PM, Hallman WH. Testing a visual display to explain small probabilities. Risk Anal 1994;14:895–7.
(48) Baty BJ, Venne VL, McDonald J, Croyle RT, Halls C, Nash JE, et al. BRCA1 testing: genetic counseling protocol development and counseling issues. J Genet Couns 1997;6:223–44.
(49) National Cancer Institute, Office of Cancer Communications. How the public perceives, processes, and interprets risk information: findings from focus group research with the general public. Bethesda (MD): National Cancer Institute; 1998 June; Report No.: POS-T086.
(50) Hampson SE, Andrews JA, Lee ME, Foster LS, Glasgow RE, Lichtenstein E. Lay understanding of synergistic risk: the case of radon and cigarette smoking. Risk Anal 1998;18:343–50.
(51) Lathrop RG. Perceived variability. J Exp Psychol 1967;73:498–502.
(52) Legge GE, Gu YC, Luebker A. Efficiency of graphical perception. Percept Psychophys 1989;46:365–74.
(53) Ibrekk H, Morgan GM. Graphical communication of uncertain quantities to nontechnical people. Risk Anal 1987;7:519–29.
(54) Keeney RL, von Winterfeldt D. Improving risk communication. Risk Anal 1986;6:417–24.
(55) Fiskel J. The impact of artificial intelligence on the risk analysis profession. Risk Anal 1987;7:277–80.
(56) Hollands JG, Dyre BP. Bias in proportion judgments: the cyclical power model. Psychol Rev. In press 1999.
(57) Gillan DJ, Wickens CD, Hollands JG, Carswell CM. Guidelines for presenting quantitative data in HFES Publications. Hum Factors 1998;40: 28–41.
(58) Poulton EC. Geometric illusions in reading graphs. Percept Psychophys 1985;37:543–8.
(59) Tversky B. Distortion in memory for visual displays. In: Ellis SR, Kaiser MK, Grunwald AJ, editors. Pictorial communication in virtual and real environments. London (UK): Taylor and Francis; 1991. p 61–75.
(60) Stevens SS, Galanter EH. Ratio scales and category scales for a dozen perceptual continua. J Exp Psychol 1957;54:377–411.
(61) Stevens SS. Psychophysics: introduction to its perceptual, neural, and social prospects. New York (NY): John Wiley and Sons; 1975.
(62) Varey CA, Mellers BA, Birnbaum MH. Judgments of proportions. J Exp Psychol Hum Percept Perform 1990;16:613–25.
(63) Sparrow JA. Graphical displays in information systems: some data properties influencing the effectiveness of alternative forms. Behav Inf Technol 1989;8:43–56.
(64) Carswell CM. Choosing specifiers: an evaluation of the basic tasks model of graphical perception. Human Factors 1992;34:535–54.
(65) Cleveland WS, McGill R. An experiment in graphical perception. Int J Man-Mach Stud 1986;25:491–500.
(66) Wainer H. Visual revelations: graphical tales of fate and deception from Napoleon Bonaparte to Ross Perot. New York (NY): Copernicus; 1997. p. 104–10.
(67) Wickens CD, Carswell CM. The proximity compatibility principle: its psychological foundation and relevance to display design. Hum Factors 1995;37:473–94.
(68) Chernoff H. The use of faces to represent point in K-dimensional space graphically. J Am Stat Assoc 1973;68:361–8.
(69) Jacob R, Egreth HE, Bevan W. The face as a display. Hum Factors 1976; 18:189–200.
(70) MacGregor D, Slovic P. Graphical representation of judgmental information. Hum-Comput Interact 1986;2:179–200.
(71) Carswell CM. Graphical information processing: the effects of proximity compatibility. Proceedings of the Human Factors and Ergonomics Society 34th annual meeting; 1990 Oct 8–12; Orlando. Santa Monica (CA): Human Factors and Ergonomics Society; 1990. p. 1494–8.
(72) Casner SM. A task-analytic approach to the automated design of graphic presentations. ACM Trans Graphics 1991;10:111–51.
(73) Gillan DJ. Visual arithmetic, computational graphics, and spatial metaphor. Hum Factors 1995;37:766–80.
(74) Gillan DJ, Lewis R. A componential model of human interaction with graphs: 1. Linear regression modeling. Hum Factors 1994;36:419–40.
(75) Gillan DJ, Lewis R. A componential model of human interaction with graphs II. Effects of the distances among graphical elements. Proceedings of the Human Factors and Ergonomics Society 36th annual meeting; 1992 Oct 12–16; Atlanta. Santa Monica (CA): Human Factors and Ergonomics Society; 1992. p. 365–8.
(76) Lohse GL. A cognitive model for understanding graphical perception. Hum-Comput Interact 1993;8:353–88.
(77) Winn W. Contributions of perceptual and cognitive processes to the comprehension of graphics. In: Schontz W, Kulhavy RW, editors. Comprehension of graphics. Amsterdam (The Netherlands): North-Holland; 1994. p. 3–27.
(78) Gillan DJ, Richman EH. Minimalism and the syntax of graphs. Hum Factors 1994;36:619–44.
(79) Gigerenzer G, Hoffrage U. How to improve Bayesian reasoning without instruction: frequency formats. Psychol Rev 1995;102:684–704.
(80) Doyle JK. Judging cumulative risk. J Appl Soc Psychol 1997;27:500–24.
(81) Lundgren RE. Risk communication: a handbook for communicating

environmental, safety, and health risks. Columbus (OH): Batelle Press; 1994.
(82) Health literacy: report of the Council on Scientific Affairs. Ad Hoc Committee on Health Literacy for the Council on Scientific Affairs, American Medical Association. JAMA 1999;281:552–7.
(83) Rimer BK, Glassman B. Tailored communications for primary care settings. Methods Inf Med 1998;37:171–7.
(84) Rimer BK, Glassman B. Is there a use for tailored print communications in cancer risk communication? J Natl Cancer Inst Monogr 1999;25:000–00.
(85) Hannson SO. Dimensions of risk. Risk Anal 1989;9:107–12.
(86) Tversky A, Kahneman D. Availability: a heuristic for judging frequency and probability. Cogn Psychol 1973, 5:207–32.
(87) Weinstein ND. Testing four competing theories of health-protective behavior. Health Psychol 1993;12:324–33.
(88) Slovic P. Perceptions of risk: reflections on the psychometric paradigm. In: Krimsky S, Golding D, editors. Social theories of risk. Westport (CT): Preager; 1992. p. 181–216.
(89) Rowe WD. Understanding uncertainty. Risk Anal 1994;14:743–50.
(90) Babrow AS, Kasch CR, Ford LA. The many meanings of uncertainty in illness: toward a systemic accounting. Health Commun 1998;10:1–23.
(91) Messaris P. Visual persuasion: the role of images in advertising. Thousand Oaks (CA): Sage Publications; 1997.
(92) Apaiwongse TS. Facial display of environmental policy uncertainty. J Bus Psychol 1995;10:65–74.
(93) Denes-Raj V, Epstein S. Conflict between intuitive and rational processing: when people behave against their better judgement. J Pers Soc Psychol 1994;66:819–29.
(94) Denes-Raj V, Epstein S, Cole J. The generality of the ratio-bias phenomenon. Pers Soc Psychol Bull 1995;21:1083–92.
(95) Kirkpatrick LA, Epstein S. Cognitive-experiential self-theory and subjective probability: further evidence for two conceptual systems. J Pers Soc Psychol 1992;4:534–44.

NOTES

[1]For a discussion as to how visuals other than graphics (e.g., pictures) might be used to persuasively communicate disease risk, the reader is referred to the text titled *Visual Persuasion: The Role of Images in Advertising (91).* For example, pictures may be effective, because they realistically capture, and hence provide, convincing data pertaining to real-life examples related to risk (e.g., disease severity).

[2]Smith et al. *(35,37)* tested how six formats to communicate radon risk affected risk perceptions and mitigation intentions. Of import, they varied in two formats the advice (i.e., tone) given in terms of how homeowners should interpret their actual radon levels. In the Command version, homeowners were told to follow the Environmental Protection Agency (EPA) guidelines for levels warranting action. For the Cajole version, participants were encouraged to use their own judgments and evaluations and used several standards (e.g., National Council on Radiation Protection), including the EPA's, to evaluate their radon levels. Similar to the results of Weinstein and colleagues *(33),* their outcomes suggest that providing directive advice encourages mitigation.

[3]Although not applied to risk communication, some researchers have made use of Chernoff face displays for portraying complex multivariate data *(68–70)* and as a method of conveying attitudinal uncertainty toward environmental policies *(92).* In these displays, facial features (eyes, nose, and mouth) vary with the magnitude of the variable they display.

[4]In decision-making trials, some researchers have used different colored jelly beans, rather than dots, to represent probabilities. One common observation is the ratio–bias phenomenon. People judge the occurrence of a low-probability event as less likely when the same probabilities are presented by the ratio of smaller (e.g., 1 in 20) than larger (e.g., 10 in 200) numbers *(93–95).*

[5]The National Cancer Institute *(49)* also used focus groups to test others visuals depicting the relative risks linking lung cancer with smoking. These visuals used blackened lungs and hospital beds to illustrate that smokers are significantly more likely (i.e., 10 times more likely) to get lung cancer than nonsmokers. Although most participants understood that smoking was linked with lung cancer, several interpretative problems emerged. The reader is referred to the publication by the National Cancer Institute *(49)* for the detailed results.

Supported by Public Health Service grant 5U19CA72099-03 from the National Cancer Institute, National Institutes of Health, Department of Health and Human Services.

We thank Eric Stone, Paul Slovic, Frank Yates, Caryn Lerman, Kerry Smith, William Desvousges, Melody Carswell, Joachim Meyer, and Neil Weinstein for providing suggestions, resources, and references. We thank Jimmy Rosen for his help in creating some of the graphics. We thank Barbara Rimer for her comments on an earlier version of this manuscript.