Policy Insights from the
Behavioral and Brain Sciences
2015, Vol. 2(1) 147–156
© The Author(s) 2015
DOI: 10.1177/2372732215601442
bbs.sagepub.com
SAGE

Meeting Three Challenges in Risk Communication: Phenomena, Numbers, and Emotions

Tim Rakow[1], Claire L. Heard[2], and Ben R. Newell[3]

Abstract

Risk communication takes many forms, can serve a number of different purposes, and can inform people about a wide variety of risks. We outline three challenges that must often be met when communicating about risk, irrespective of the form or purpose of that communication, or the type of risk that this involves. The first challenge is how best to help people understand the *phenomenology* of the risks that they are exposed to: The nature of the risk, the mechanism(s) by which they arise, and, therefore, what can be done to manage these risks. Each risk has its own phenomenology; therefore, rather than offering generic guidance, we illustrate with the case of climate change risk how evidence from behavioral science can guide the design of messages about risk. The second challenge is how best to present *quantitative risk information* about risk probabilities. Here, there is potential for: Ambiguity, difficulty in evaluating quantitative information, and weak numeracy skills among those being targeted by a message. We outline when each of these difficulties is most likely to arise as a function of the precision of the message and show how messages that cover multiple levels of precision might ameliorate these difficulties. The third challenge is the role played by people's emotional reactions to the risks that they face and to the messages that they receive about these risks. Here, we discuss the pros and cons of playing up, or playing down, the emotional content of risk communication messages.

Keywords

risk, risk communication, numeracy, emotions, climate change

Tweet

3 **T**'s for risk communication messages: **T**est alternative ways of explaining; **T**une the quantitative precision; **T**weak the emotional content.

Key Points

- Ignorance of risks is dangerous, so those exposed to a risk should know something about its phenomenology (cause and impact).
- Because risks are varied in their nature, testing the efficacy of explanations of risk phenomena should be done on a case-by-case basis.
- Imprecise statements about risk exposure are often ambiguous, while precise statements are often difficult for people to interpret and use.
- Messages that operate at multiple levels of precision may reduce ambiguity and improve comprehension for quantitative risk information.
- Emotional reactions to messages about risk influence people's perception of risk.
- The emotional component of a message needs to be taken into account in the design and delivery of risk communication messages.

Three Challenges in Risk Communication

In an effort to understand a "risk," risk analysts and risk managers often consider its constituent parts: What can go wrong (the event) and why (the hazard); what might the consequences be (severity or utility); what the probabilities of the event are; and—should the event occur—what probabilities are associated with each level of consequence (the outcome distribution). Risk communications often focus on some of these constituent parts. Thus, someone might be told that his or her current consumption of red meat (hazard) elevates his or her 5-year risk of stroke (event) to 20%; in turn, 1 in 50 strokes lead to death, 1 in 3 stokes have severe long-term consequences, and so on. This is a highly intellective approach and presents two broad kinds of challenge: understanding the

[1]King's College London, UK
[2]University of Essex, Colchester, UK
[3]University of New South Wales, Sydney, Australia

Corresponding Author:
Tim Rakow, Department of Psychology, Institute of Psychiatry, Psychology & Neuroscience, King's College London, Box PO77, Henry Welcome Building, De Crespigny Park, London, SE5 8AF, UK.
Email: tim.rakow@kcl.ac.uk

phenomenology of the risk (what it is, what can cause it, what can happen) and understanding the *quantification of risk* (measures of severity, probabilities). Another challenge in risk communication is that *emotional responses* to hazards and events also shape people's perception of risk, sometimes leading to reactions that differ from what would be expected based on what is known, or communicated, about a risk. In the first part of this article, we explain the importance of these three challenges (understanding phenomena, comprehending numbers, and the role of emotions). Drawing on research from the cognitive, social, and decision sciences, the second part of our review sets out how to address these challenges when communicating risk.

Why the Phenomenology Matters

Few of us are experts in disease processes, the modus operandi of burglars and thieves, the physics of highway collisions, or the forces of nature that bring about storms; yet we have every incentive to understand enough about these risks to protect ourselves and our property. Thus, a suitable understanding of risk phenomena can contribute to our *physical security* and *economic well-being* and, arguably, to meeting basic *psychological needs* for autonomy and control of the environment. Indeed, one way that people make sense of, and begin to cope with, disease is to learn about their medical condition: its nature, cause, likely progression, consequences, and how it can be controlled (Leventhal, Mayer, & Nerenz, 1980).

Not only do (many) people *want* to understand risk; arguably we *need* to understand risk because—put bluntly—*ignorance can kill*. For example, Doll and Hill's (1954) study, which is credited with establishing smoking as a *cause* of cancer, targeted all male physicians in the United Kingdom above 35 years of age, and only 12.7% of their sample of 24,389 were *non*-smokers. Such figures shock us now, but without knowledge of a risk, or understanding of the mechanism behind it, there is no reason, or means, to manage that risk. Likewise, many have speculated that deficits in lay understanding of the mechanisms of global warming contribute to the failure to take seriously the risks of severe and detrimental changes to our climate (e.g., Bord, O'Connor, & Fisher, 2000; Clark, Ranney, & Felipe, 2013; Newell, Kary, Moore, & Gonzalez, in press; Ranney, Clark, Reinholz, & Cohen, 2012; Sterman, 2008)—an issue we examine later in our review.

In addition, lack of knowledge or understanding about a risk can, itself, influence the perception of that risk. In numerous studies, Paul Slovic and colleagues have shown that risks which people judge to be "known" (i.e., risks known to science and to those exposed to these risks) are also generally perceived to be voluntary risks which can be controlled. Accordingly, "unknown" (involuntary and uncontrollable) risks are generally perceived as more serious and more in need of regulation (Fischhoff, Slovic, Lichtenstein, Read, & Combs, 1978; Slovic, 1987). This means that someone who misunderstands the nature of a risk (e.g., *incorrectly* assuming that the mechanism behind it is unknown to scientists) may misestimate the probability and/or severity of its adverse consequences.

Why the Numbers Matter

A major purpose in risk communication is to provide information, so that people need not estimate risk themselves and can make informed decisions about managing risk. However, this brings particular challenges because probabilities and numeric measures of outcome often prove difficult to understand. For example, despite the ubiquity of percentages in everyday communications, Gigerenzer, Hertwig, Van Den Broek, Fasolo, and Katsikopoulos (2005) found that the statement "a 30% chance of rain tomorrow" was often interpreted as meaning it will rain 30% of the time, or in 30% of the area, and was less commonly taken to mean (closer to the intended meaning) that it will rain on 3 of every 10 days with conditions like tomorrow's. Those low in numeracy may find it particularly difficult to use numeric risk estimates effectively. Indeed, they are less likely to extract correct information from graphs and plots that quantify the risks associated with medical intervention (Rakow, Wright, Bull, & Spiegelhalter, 2012; Rakow, Wright, Spiegelhalter, & Bull, 2015) and are more likely to make decision errors (Peters et al., 2006). And this may be no "tip-of-the-iceberg" issue: Studies in countries with well-developed education systems (e.g., United States, Germany) find that from one quarter to nearly one half of participants cannot change a "1-in-1000 probability" into a percentage (Galesic & Garcia-Retamero, 2010; Weller et al., 2013).

Such findings highlight that quantified risks can often be expressed in different, though mathematically equivalent, ways: Thus, a 1-in-5 chance can be expressed as a probability (.2), percentage (20%), or relative frequency (2 in 10, 200 in 1,000, etc.). However, equivalent expressions are not always treated as such; therefore, it is often difficult to know which type of expression is best (e.g., for facilitating informed decision making). For example, Slovic, Monahan, and MacGregor (2000) found that forensic practitioners with experience of risk assessment and risk management were more likely to discharge a patient into the community when his risk of violent offending was expressed as 2 in 10, compared with when it was expressed as a 20% chance. Those authors' preferred explanation is that these alternative expressions create different mental images, which change the emotional character of the message—suggesting we must sometimes look beyond the numbers to understand how people *feel* about the risks communicated to them.

Why Emotions Matter

When situations are emotionally charged (or “affect-rich”; Rottenstreich & Hsee, 2001), strong initial (anticipatory) emotional responses (e.g., fear, worry, dread) are experienced (Loewenstein, Weber, Hsee, & Welch, 2001) often leading people to overestimate risk (relative to risk estimates from data). Prominent examples include public perceptions of the risks from nuclear power (Slovic, 1987; Slovic, Flynn, & Layman, 1991) and parents’ perceptions of the risks from asbestos in school buildings (Rosenbaum, 2014); whereas, the data suggest that for these cases, the probability of accident, or cancer, respectively, is extremely low. Research by Slovic and colleagues suggests that “fear” and “dread” drive such overestimations of risks. When a potential for catastrophe is perceived—such as when an event could cause mass damage or many fatalities—a substance, technology, or activity is usually perceived to be “high risk” irrespective of the probability of catastrophe (Slovic, 1987; Slovic, Fischhoff, & Lichtenstein, 1981; Slovic & Weber, 2002).

Emotions can also influence the estimated benefit associated with an activity. Seemingly, people often base their evaluations on overall “gut” reaction such that if feelings are positive, benefits are judged high and risks low, and if feelings are negative, the opposite occurs (Alhakami & Slovic, 1994; Slovic, Finucane, Peters, & MacGregor, 2004). Supporting this “affect heuristic” account, Finucane, Alhakami, Slovic, and Johnson (2000) found that providing information about *either* benefits *or* risks not only altered people’s overall evaluation but also changed their evaluation for whichever entity (viz., risks or benefits) they had not received information. Thus, knowledge that increased positive affect decreased perceived risk, whereas knowledge that increased negative affect increased perceived risk. Lloyd, Hayes, Bell, and Naylor (2001) reported an instance where negative affect (e.g., anxiety) may actually *increase* the perception of benefit. They found that patients’ estimates of the benefits associated with their cardiovascular surgery were significantly *higher* the day before this major operation than they had been some weeks previously—presumably reflecting that one might make sense of the anxiety associated with impending surgery by focusing on (and even inflating) its hoped-for benefits.

These effects of emotion on risk perception are thought to occur because affect changes how we process information. For decisions about affect-poor outcomes (e.g., money), people use more calculation-based strategies (e.g., expected value calculations). For affect-rich outcomes (e.g., involving adverse health side effects), the outcomes themselves take precedence over probability information (Loewenstein et al., 2001). Pachur, Hertwig, and Wolkewitz (2013) found further support for this distinction between affect-rich (outcome-based) and affect-poor (calculation-based) decisions by tracking what information people collect in a laboratory decision task. In affect-poor situations (e.g., decisions about money), participants divided their time equally between acquiring outcome and probability information; in affect-rich situations (e.g., decision about medical treatment side effects), however, participants acquired outcome information more frequently than probability information. The emotional *content of labels* (as distinct from the event itself) has also been shown to influence decision processes. Sinaceur, Heath, and Cole (2005) found that, while probability information was taken into account when a scientific label was used (“Creutzfeldt-Jakob disease”), decisions about beef consumption were based primarily on their emotional reactions when an affect-rich label (“mad cow disease”) was used. In sum, when emotions run high, *what is possible* takes precedence over *how probable* that possibility is (Rottenstreich & Hsee, 2001; Sunstein, 2002).

How to Think About These Challenges

There is no magic bullet in risk communication, and so we do *not* offer a list of one-size-fits-all solutions to the difficulties inherent in communicating risk. Rather, we illustrate what we believe are helpful ways of thinking through the three challenges that we have outlined above.

Phenomenology: Exploring the Relationship Between Knowledge and Risk Perception

Different risks have different causes; therefore, one *cannot* say, “*This* is how to explain risk phenomena.” However, behavioral science offers a system for testing what helps people understand different risk phenomena, and we illustrate this evidence-based approach via a case study. This shows how behavioral science experiments can inform the design of messages designed to empower people with knowledge of an entity or system that places them at risk. We focus on lay understanding of the carbon cycle, accurate knowledge of which is, arguably, fundamental for understanding the mechanism of global warming.

The basic carbon cycle can be thought of as a dynamic system that involves “stocks” and “flows.” A stock (e.g., total amount of accumulated carbon do-oxide [CO_2] in the atmosphere) is some entity amount that is accumulated over time by inflows (e.g., anthropogenic CO_2 emissions) and depleted by outflows (e.g., CO_2 uptake by plants). When inflow exceeds outflow, the stock will increase; when outflow exceeds inflow, the stock will decrease; and when inflow equals outflow, the stock will stabilize. Despite their apparent simplicity, research using stock-flow reasoning tasks suggests that lay people’s understanding of these relationships is poor—even among those with backgrounds in science, engineering, or mathematics (Cronin, Gonzalez, & Sterman, 2009; Dutt & Gonzalez, 2012a, 2012b; Guy, Kashima, Walker, & O'Neill, 2013; Moxnes & Saysel, 2009; Newell et al., in press; Sterman & Booth-Sweeney, 2007).

For instance, Sterman and Booth-Sweeney (2007) showed participants a hypothetical plot in which the accumulated concentration of atmospheric CO_2 rises steadily until the year 2000 and then remains stable for the next century. The same participants were then shown an inflow function with CO_2 emissions increasing up to 2000, together with an estimate of current outflow. Notably, current outflow was shown to be substantially *below* inflow levels. Participants were asked to estimate the pattern of emission inflow that would be necessary to achieve stability in accumulated CO_2. Assuming a static level of outflow, the correct response is that emissions must be cut dramatically to a level equal with the outflow. However, most participants sketched emissions trajectories that either maintained current levels or increased them—thereby preventing stabilization. It seems that participants reason that the output of a system should "look like" its inputs (Cronin et al., 2009; Sterman, 2008). Thus, because the accumulated CO_2 stock gradually rises and then stabilizes, people think CO_2 emissions (inputs) should follow a similar pattern. They fail to realize that a stock accumulates its inflows *minus* its outflows.

In an effort to improve performance on the CO_2 task, some researchers have turned to analogies. Analogical reasoning involves identifying a common relation between two situations and generating inferences based on these commonalities. Analogies can help people integrate the presumably unfamiliar information about the climate system into existing knowledge structures (Dutt & Gonzalez, 2012a, 2012b; Gonzalez & Wong, 2012; Guy et al., 2013; Moxnes & Saysel, 2009; Newell et al., in press). This work shows promise, but it can be improved. For example, Guy et al. (2013) tested the usefulness of a "bathtub analogy" whereby participants were invited to think about the stock of CO_2 as water entering a bathtub from a tap ("emissions") and leaving via the plughole ("absorptions"). However, even when provided this analogical context, few participants gave the precisely correct answer. Newell et al. (in press) reformulated the CO_2 accumulation problem as one involving management of personal financial debt. They found that although more participants drew accurate inferences about the relations between debt, money earned, and money spent, there was little evidence of analogical transfer of conceptual understanding to the climate problem. In both of these investigations, there was also some evidence that depicting the relationships between stocks and flows in the climate problem graphically actually hindered performance (compared with only providing a text description).

These studies on stock-flow analogies for the carbon cycle suggest a need for more theoretically driven analogies and perhaps the need for more explicit analogical comparisons. For example, rather than just thinking about the carbon cycle in terms of analogies to other systems, participants could be invited to list similarities and differences between two problems—thereby encouraging consideration of both the surface *and* the deeper structural or behavioral similarity across different stock-flow analogical contexts (see, for example, Gentner, Loewenstein, & Thompson, 2003; Gonzalez & Wong, 2012). Another possible method for improving understanding of the carbon cycle (or other complex systems) is to allow participants to experiment and interact with virtual systems or simulations to learn how the components inter-relate (e.g., Dutt & Gonzalez, 2012a, 2012b; Sterman et al., 2012).

Development of clear methods for communicating the mechanisms of the carbon cycle will permit further work exploring the effect of such interventions on climate change risk perception. Although it would appear self-evident that increased knowledge and understanding of a problem should lead to higher risk perception, documenting such a direct relationship has not been straightforward (Newell, McDonald, Brewer, & Hayes, 2014). For example, Brody, Zahran, Vedlitz, and Grover (2008) found no significant relationship between climate change knowledge and risk perception; Kellstedt, Zahran, and Vedlitz (2008) found a negative association; and Malka, Krosnick, and Langer (2009) found that increased knowledge affected concern about climate change for liberals but not conservatives (see Kahan et al., 2012, for similar results). A comprehensive recent assessment by van der Linden (2015) does, however, find that in a large sample (N = 808) of U.K. residents, people tend to perceive climate change as a higher risk when they have knowledge about the causes of climate change, knowledge of what the likely impacts are, as well as information about appropriate response behaviors. That is, knowledge of *causes, impacts*, and *responses* are positively and significantly related to climate change risk perception. Van der Linden suggests that it is this delineation into different types of knowledge that permits clearer assessment of the role that improved understanding plays in risk perception.

Interestingly, knowledge of *causes* contributed least to explained variance in van der Linden's climate change risk-perception model, suggesting that even if the "perfect" method for improving reasoning about the carbon cycle were developed, it may be less successful than interventions that educate people about *impacts*, perhaps via appeal to more vivid emotion-laden messaging (van der Linden, 2015; Weber, 2006). Indeed, the *holistic affect* people associated with climate change explained more variance than any other single factor in van der Linden's risk-perception model.

Table 1. A Seven-Category Taxonomy for the Degree of Precision in Uncertainty Statements.

Category	Statement Specifies	Examples
Possibility	What event(s) can/might occur	Sea levels may rise. You are at risk of stroke.
Comparative possibility	Which of two events is more likely	Floods are more likely here than there. Surgery will reduce your risk of stoke.
Categorical possibility	How likely an event is (verbal label)	This is a high-risk area for flooding. You have a low risk of stroke.
Relative probability	Comparison of risks (numeric ratio)	Floods are 3 times as frequent here as there. Surgery will halve your risk of stroke.
Absolute probability	Numeric probability of a risk	There is a 1-in-75 annual risk of flooding. Your 5-year risk of stroke is 8%.
Comparative probability	Absolute probabilities for different risks	The annual risk of flood is 1 in 25 here, but 1 in 75 there. Surgery reduces your 5-year stroke risk from 8% to 4%.
Incremental probability	Probability difference between risks	The annual flood risk is 2.7% higher here than there. Surgery reduces your 5-year stroke risk by 4%.

Source. Adapted from Zikmund-Fisher (2013).
Note. Categories are ordered from least to most precise.

Numbers: Getting the "Right" Level of Detail

Zikmund-Fisher (2013) set out a taxonomy for categorizing statements about the (un)certainty of outcomes, according to the precision with which they communicate risk (Table 1). We use Zikmund-Fisher's seven-category taxonomy to unpack some implications of the different approaches to communicating risk probabilities and outcome distributions. One approach to addressing people's difficulties with understanding and using numbers is to communicate risk *without* using numbers, for example, simply stating what *can happen*, which of two things is *more/less likely*, or whether something has a *high/low chance* of occurring. These three kinds of statement represent the three lowest levels of precision in Zikmund-Fisher's taxonomy: *possibility, comparative possibility*, and *categorical possibility*. Such statements serve a purpose, being sufficient to alert people to a risk (possibility), to help people know how to decrease their risk exposure (comparative possibility), or get a sense of their current exposure to risk (categorical possibility).

However, the interpretation of verbal labels varies widely between individuals (Budescu, Broomell, & Por, 2009), is variable for a given individual (Dhami & Wallsten, 2005), and is highly context dependent. For example, Wallsten, Fillenbaum, and Cox (1986) found that most people interpreted a "slight chance" to mean a probability of .1 or lower when it referred to the probability of severe life threatening side effects from a flu shot, but everyone in their study inferred probabilities of .1 or above when "slight chance" referred to the probability of an ankle sprain. In addition, overestimating risk is more common with verbal labels than with numeric formats (Peters, Hart, Tusler, & Fraenkel, 2014). Moreover, statements such as "high/low" or "higher/lower" risk often imply points of comparison (e.g., high = "above average") that may not be well understood. For example, a pregnant woman may undergo a "low" risk diagnostic procedure (amniocentesis) because a screening test indicates she has "high" risk of giving birth to child with Down syndrome. Yet the U.K. National Health Service estimates the probability of the "small associated risk of miscarriage" with amniocentesis performed 15 to 20 weeks into pregnancy to be around 1 in 100 (NHS Choices, 2015a) while labeling a screening test that shows any probability above 1 in 150 of having a baby with Down syndrome a "higher-risk result" (NHS Choices, 2015b). Thus, even within the context of a single conversation about risk, "higher" may actually be *lower* than "low."

Quantifying risk for a single event increases the precision of communication, relative to comparative or categorical probabilities. However, the use of *relative probability* statements that compare risks (e.g., "A is twice as likely as B") is often criticized because it obscures one's risk exposure in either situation (e.g., Gigerenzer, 2002). At the extreme, we might be unnecessarily worried about a doubling of risk from 1-in-a-million to 2-in-a-million. *Absolute probability* statements are more precise but are not necessarily straightforward to interpret: If my 5-year risk of stroke is 8%, is that "good" or "bad"? This is important, because a sizable literature in experimental psychology shows that people base their decisions on other (more easily evaluated) information when they do not know how to evaluate numbers from a numeric scale (for reviews, see Hsee, Loewenstein, Blount, & Bazerman, 1999; Hsee & Zang, 2010). For instance, Slovic and Peters (2006) found *less* support for a safety measure that would save 150 lives than for one that saved 98% of 150 lives (presumably, because we "know" that 98% is almost as good as it gets). This is consistent with the notion that, in isolation, it is hard to know how "good" an intervention is that saves 150 lives.

Comparative probability statements that give absolute probabilities for two or more risks, and *incremental probability* statements that specify differences between risks, represent the highest levels of precision in Zikmund-Fisher's taxonomy (Table 1). These offer better opportunities for comparing different courses of action, but, by themselves, they may not fully address people's difficulties with evaluating the meaning of numbers on an unfamiliar scale. Moreover, while greater precision affords further calculation of risks, this is something that even some highly educated people struggle with (Lipkus, Samsa, & Rimer, 2001), including those in numerate professions such as medicine (Casscells, Schoenberger, & Grayboys, 1978; Hoffrage, Lindsey, Hertwig, & Gigerenzer, 2000), let alone those with lower levels of numeracy.

Our review highlights three issues to work through when designing communications about quantified risks: the potential for *ambiguity* in the message, the *evaluability* of any quantitative information included, and the *numeracy* of the people you are communicating with. Using Zikmund-Fisher's (2013) taxonomy, we can see that the prominence of these issues shifts according to the precision of the message. The potential for ambiguity is greatest at lower levels of precision that avoid the use of numbers (i.e., *possibility* statements; Table 1) because language is often polysemous, and at intermediate levels of precision (i.e., *relative* and *absolute probability*) because the point of comparison, or reference class, may not be clear. The difficulties of evaluating quantities are particularly acute when communicating at an intermediate level of precision. However, the problem is not necessarily solved by using higher levels of precision (i.e., *comparative* and *incremental probability*) because people may still have difficulty in evaluating unfamiliar measures of impact or severity. With greater precision in risk communication comes the responsibility to recognize the variability in, or limits of, the numeracy of your audience—and to know what strategies, tools, and decision aids can help to communicate the particular type of risk(s) that your communication concerns (e.g., for reviews relating to health/medical risks, see Ancker, Senathirajah, Kukafka, & Starren, 2006; Fagerlin, Zikmund-Fisher, & Ubel, 2011).

Research by Peters and colleagues points to the potential benefits of a "twin-track" approach to describing risks whereby risk messages cover multiple levels of Zikmund-Fisher's (2013) taxonomy. Peters et al. (2009) had people evaluate hospitals from several numeric quality indicators (e.g., treatment survival rate, percentage of patients receiving the recommended treatment). When labels designed to make the numbers easier to evaluate ("poor," "fair," "good," "excellent") were included alongside each number, people made more use of the indicators in their evaluations. Peters, Dieckmann, Dixon, Hibbard, and Mertz (2007) also presented quantitative information about several hospitals and asked participants to select the best hospital to deliver treatment if they had heart failure. Presenting icons (e.g., "traffic light" colors) that signaled average or above/below average values of an indicator encouraged people to use quality indicators (e.g., death rate) when evaluating a hospital, though among those with low numeracy participants, this seemed to encourage the use of arguably less important indicators (e.g., cost).

A twin-track approach can also be used to improve communications that include verbal statements about quantities. Working within the guidelines for communicating uncertainty used by the Intergovernmental Panel for Climate Change (IPCC), Budescu and colleagues found that adding numeric range information to verbal probability labels (e.g., "very unlikely, <10%") improved several aspects of communication (Budescu et al., 2009; Budescu, Por, & Broomell, 2012). Adding the numeric range information increased people's ability to differentiate between terms (e.g., "unlikely" vs. "very unlikely"), reduced the variability in interpreting these terms, and brought people's interpretation more in line with those intended by the IPCC. This benefit of dual labeling occurred even when people had previously been shown a table giving the IPCC's intended meaning of these terms. Overall, providing messages about risk at multiple levels of precision is an approach with promise.

Emotions: Playing Up Versus Playing Down the Emotional Content

Many risk communications fall on a continuum between "warning" and "informing": ranging from attempts to discourage people from putting themselves or others in danger, to providing information about risks and benefits to facilitate informed decision making. This *warning-informing continuum* for message *purpose* is mirrored in a similar *affective communication continuum* for message *emotionality*, which is characterized by the extent to which risk communicators "play up" or "play down" the emotional content of a message.

One side of this *affective communication continuum* reflects the "nudge" philosophy, which works on framing information so as to encourage (nudge) people (perhaps unknowingly) toward particular behaviors or responses (Thaler & Sunstein, 2008). Thus, those presenting messages about risk may capitalize on the effect that emotions have on perceptions of risk (described above) and play up the emotional content of their message—particularly if it is believed that people are under-estimating risk or under-responding to it. Often, for risks to health, safety, or security, this is done via fear-based messages, which use emotive language (e.g., see above for emotive labels such as "mad cow disease"; Sinaceur et al., 2005). Although these can work, in some cases, attempts to change behavior through "scary" messages or "shocking" imagery can be ineffective—because people can react against attempts to change their attitude or behavior that they regard as "heavy handed" (O'Neill & Nicholson-Cole, 2009; Ruiter, Abraham, & Kok, 2001). When considering such emotional nudges, it is important that policy makers consider whether this is (ethically) appropriate or whether it represents undue manipulation and a hindrance to informed decision making (Bovens, 2009).

Visual imagery is another common tactic for emphasizing risk and is most clearly illustrated by the gruesome pictures that several countries place on cigarette packets (Peters, 2011). The effectiveness of visual images in changing risk perceptions is supported by data from Keller, Siegrist, and Gutcher (2006) who found that showing people photographs of flooded houses increased their perception of the danger of living in a flood zone (compared with those shown pictures of other houses) even though all participants in this study received information and warnings about flood risk.

Using images to arouse emotions typically lessens the impact of "non-emotional" information that may be relevant to a decision. For example, Hsee and Rottenstreich (2004) found people's willingness to give money to save endangered animals was unaffected by the number of animals at risk when they were shown photographs of those animals, while people were sensitive to the number of animals at risk when a less emotive representation of these animals was used (dots representing each animal). While such effects are widely reported, Shaffer, Owens, and Zikmund-Fisher (2013) found that including patient narratives in a web-based patient decision aid *increased* the amount of additional information that people sought out—an effect which was stronger if that narrative was from a patient speaking on video. This illustrates that the effect of vivid messages can be difficult to predict—here, one would have anticipated that "personal" (affect-rich) video narratives would *reduce* the appetite for effortful decision making (Loewenstein et al., 2001; Small, Loewenstein, & Slovic, 2007; Sunstein, 2002).

Understanding the effects of emotion on risk perception and decision making is key to operating at the other end of the affective communication continuum. Here, the goal is to reduce the role played by emotions not only by seeking to eliminate emotive language and affect-rich images but also by seeking to reduce the room for emotions to enter any decision that relies on the risk information contained in a message. One such approach was described earlier, namely, the evidence suggests that making any numbers which quantify risk more straightforward to evaluate increases the appropriate use of those numbers, thereby reducing the opportunity for emotions to drive the decision (Hsee et al., 1999; Hsee & Zang, 2010; Peters et al., 2007, 2009). Studies of health care decisions by Fagerlin, Wang, and Ubel (2005) highlight how the clear presentation of quantitative information reduces the influence of emotive messages and so facilitates informed decision making. Their participants received statistical information in text and read anecdotes about treatment outcomes from hypothetical patients that were either representative or unrepresentative of actual cure rates. Some participants also received a pictograph illustrating the statistical information—which is often an effective aid when communicating probabilities (e.g., Galesic, Garcia-Retamero, & Gigerenzer, 2009). Unlike participants in a control condition (who received no pictograph), the decisions of those given the pictograph were relatively unaffected by the anecdotal information.

Conclusions and Policy Implications

Policy makers would not dream of presenting risks to the public that did not have an empirical basis. The same principle should apply to the *means of communication* that policy makers use to covey those risks to the public. When explaining the phenomenology of a risk, policy makers can often look to research by science educators to inform how best to explain the risk—but for "new" risks, it may be essential to examine, or commission, new behavioral science research to determine what works best. Getting the right level of detail when communicating quantitative risk estimates presents a sizable challenge: Imprecise communications breed ambiguity, but precise communications can be difficult to understand. Our main message, here, is that one size does *not* fit all: Messages delivered at multiple levels of precision may be an effective means of reducing ambiguity and misunderstanding, and messages need to take account of the variation in numeracy levels across the general public. Finally, the emotional content of messages must be managed: When emotions run high, the phenomenology and the numbers can be expected to take a back seat while emotions drive people's behavior. And while it is tempting to use emotions to drive behavior down a positive route, this will not always work as intended and can sometimes be challenged on ethical grounds.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study received no direct funding; however, the second and third authors receive funding for their on-going research. Claire Heard is supported by the UK Economic and Social Research Council and the University of Cambridge. Ben Newell is supported by an Australian Research Council Future Fellowship (FT110100151) and an Australian Research Council Linkage Project Grant (LP120100224).

References

Alhakami, A. S., & Slovic, P. (1994). A psychological study of the inverse relationship between perceived risk and perceived benefit. *Risk Analysis*, *14*, 1085-1096.

Ancker, J. S., Senathirajah, Y., Kukafka, R., & Starren, J. B. (2006). Design features of graphs in health risk communication: A systematic review. *Journal of the American Medical Informatics Association*, *13*, 608-618.

Bord, R. J., O'Connor, R. E., & Fisher, A. (2000). In what sense does the public need to understand global climate change? *Public Understanding of Science*, *9*, 205-218.

Bovens, L. (2009). The ethics of nudge. In T. Grüne-Yanoff & S. O. Hansson (Eds.), *Preference change: Approaches from philosophy, economics and psychology* (pp. 207-219). Dordrecht, The Netherlands: Springer.

Brody, S. D., Zahran, S., Vedlitz, A., & Grover, H. (2008). Examining the relationship between physical vulnerability and public perceptions of global climate change. *Environment and Behavior*, *40*, 72-95.

Budescu, D. V., Broomell, S., & Por, H. H. (2009). Improving communication of uncertainty in the reports of the Intergovernmental Panel on Climate Change. *Psychological Science*, *20*, 299-308.

Budescu, D. V., Por, H. H., & Broomell, S. B. (2012). Effective communication of uncertainty in the IPCC reports. *Climatic Change*, *113*, 181-200.

Casscells, W., Schoenberger, A., & Grayboys, T. (1978). Interpretation by physicians of clinical laboratory results. *New England Journal of Medicine*, *299*, 999-1000.

Clark, D., Ranney, M. A., & Felipe, J. (2013). Knowledge helps: Mechanistic information and numeric evidence as cognitive levers to overcome stasis and build public consensus on climate change. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Proceedings of 35th Annual Meeting of the Cognitive Science Society* (pp. 2070-2075). Austin, TX: Cognitive Science Society.

Cronin, M. A., Gonzalez, C., & Sterman, J. D. (2009). Why don't well-educated adults understand accumulation? A challenge to researchers, educators, and citizens. *Organizational Behavior and Human Decision Processes*, *108*, 116-130.

Dhami, M. K., & Wallsten, T. S. (2005). Interpersonal comparison of subjective probabilities. *Memory & Cognition*, *33*, 1057-1068.

Doll, R., & Hill, A. B. (1954). The mortality of doctors in relation to their smoking habits. *British Medical Journal*, *328*, 1451-1455.

Dutt, V., & Gonzalez, C. (2012a). Decisions from experience reduce misconceptions about climate change. *Journal of Environmental Psychology*, *32*, 19-29.

Dutt, V., & Gonzalez, C. (2012b). Human control of climate change. *Climatic Change*, *111*, 497-518.

Fagerlin, A., Wang, C., & Ubel, P. A. (2005). Reducing the influence of anecdotal reasoning on people's health care decisions: Is a picture worth a thousand statistics? *Medical Decision Making*, *25*, 398-405.

Fagerlin, A., Zikmund-Fisher, B. J., & Ubel, P. A. (2011). Helping patients decide: Ten steps to better risk communication. *Journal of the National Cancer Institute*, *103*, 1436-1443.

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, *13*, 1-17.

Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is safe enough? A psychometric study of risk attitudes towards technological risks and benefits. *Policy Sciences*, *9*, 127-152.

Galesic, M., & Garcia-Retamero, R. (2010). Statistical numeracy for health. *Archives of Internal Medicine*, *170*, 462-468.

Galesic, M., Garcia-Retamero, R., & Gigerenzer, G. (2009). Using icon arrays to communicate medical risks: Overcoming low numeracy. *Health Psychology*, *28*, 210-216.

Gentner, D., Loewenstein, J., & Thompson, L. (2003). Learning and transfer: A general role for analogical encoding. *Journal of Educational Psychology*, *95*, 393-408.

Gigerenzer, G. (2002). *Reckoning with risk*. London, England: The Penguin Press.

Gigerenzer, G., Hertwig, R., Van Den Broek, E., Fasolo, B., & Katsikopoulos, K. V. (2005). "A 30% chance of rain tomorrow": How does the public understand probabilistic weather forecasts. *Risk Analysis*, *25*, 623-629.

Gonzalez, C., & Wong, H. (2012). Understanding stocks and flows through analogy. *System Dynamics Review*, *28*, 3-27.

Guy, S., Kashima, Y., Walker, I., & O'Neill, S. (2013). Comparing the atmosphere to a bathtub: Effectiveness of analogy for reasoning about accumulation. *Climatic Change*, *121*, 579-594.

Hoffrage, U., Lindsey, S., Hertwig, R., & Gigerenzer, G. (2000). Communicating statistical information. *Science*, *290*, 2261-2262.

Hsee, C. K., Loewenstein, G. F., Blount, S., & Bazerman, M. H. (1999). Preference reversals between joint and separate evaluations of options: A review and theoretical analysis. *Psychological Bulletin*, *125*, 576-590.

Hsee, C. K., & Rottenstreich, Y. (2004). Music, pandas, and muggers: On the affective psychology of value. *Journal of Experimental Psychology: General*, *133*, 23-30.

Hsee, C. K., & Zang, J. (2010). General evaluability theory. *Perspectives on Psychological Science*, *5*, 343-355.

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., & Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature Climate Change*, *2*, 732-735.

Keller, C., Siegrist, M., & Gutcher, H. (2006). The role of affect and availability heuristics in risk communication. *Risk Analysis*, *26*, 631-639.

Kellstedt, P. M., Zahran, S., & Vedlitz, A. (2008). Personal efficacy, the information environment, and attitudes toward global warming and climate change in the United States. *Risk Analysis*, *28*, 113-126.

Leventhal, H., Mayer, D., & Nerenz, D. (1980). The common sense representation of illness danger. In S. Rachman (Ed.), *Medical psychology* (Vol. 2, pp. 7-30). New York, NY: Pergamon Press.

Lipkus, I. M., Samsa, G., & Rimer, B. K. (2001). General performance on a numeracy scale among highly educated samples. *Medical Decision Making*, *21*, 37-44.

Lloyd, A., Hayes, P., Bell, P. R. F., & Naylor, A. R. (2001). The role of risk and benefit perception in informed consent for surgery. *Medical Decision Making*, *21*, 141-149.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*, 267-286.

Malka, A., Krosnick, J. A., & Langer, G. (2009). The association of knowledge with concern about global warming: Trusted information sources shape public thinking. *Risk Analysis*, *9*, 633-647.

Moxnes, E., & Saysel, A. K. (2009). Misperceptions of global climate change: Information policies. *Climatic Change*, *93*, 15-37.

Newell, B. R., Kary, A., Moore, C., & Gonzalez, C. (in press). Managing the budget: Stock-flow reasoning and the CO2 accumulation problem. *Topics in Cognitive Science*.

Newell, B. R., McDonald, R. I., Brewer, M., & Hayes, B. K. (2014). The psychology of environmental decisions. *Annual Review of Environment and Resources*, *39*, 443-467.

NHS Choices. (2015a). *Amniocetesis*. Retrieved from www.nhs.uk/conditions/Amniocentesis/Pages/Introduction.aspx

NHS Choices. (2015b). *Screening for Down's, Edwards' and Patau's syndromes*. Retrieved from www.nhs.uk/conditions/pregnancy-and-baby/pages/screening-amniocentesis-downs-syndrome.aspx

O'Neill, S., & Nicholson-Cole, S. (2009). "Fear won't do it": Promoting positive engagement with climate change through visual and iconic representations. *Science Communication*, *30*, 355-379.

Pachur, T., Hertwig, R., & Wolkewitz, R. (2013). The affect gap in risk choice: Affect-rich outcomes attenuate attention to probability information. *Decision*, *1*, 64-78.

Peters, E. (2011). Affect and emotion. In B. Fischhoff, N. T. Brewer, & J. S. Downs (Eds.), *Communicating risks and benefits: An evidence-based user's guide* (pp. 89-99). Silver Spring, MD: Food and Drug Administration.

Peters, E., Dieckmann, N. F., Dixon, A., Hibbard, J. H., & Mertz, C. K. (2007). Less is more in presenting quality information to consumers. *Medical Care Research and Review*, *64*, 169-190.

Peters, E., Dieckmann, N. F., Västfjäll, D., Mertz, C. K., Slovic, P., & Hibbard, J. H. (2009). Bringing meaning to numbers: The impact of evaluative categories on decisions. *Journal of Experimental Psychology: Applied*, *15*, 213-227.

Peters, E., Hart, S., Tusler, M., & Fraenkel, L. (2014). Numbers matter to informed patient choices: A randomized design across age and numeracy levels. *Medical Decision Making*, *34*, 430-442.

Peters, E., Västfjäll, D., Slovic, P., Metrtz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science*, *17*, 407-413.

Rakow, T., Wright, R. J., Bull, C., & Spiegelhalter, D. J. (2012). Simple and multi-state survival curves: Can people learn to use them? *Medical Decision Making*, *32*, 792-804.

Rakow, T., Wright, R. J., Spiegelhalter, D. J., & Bull, K. (2015). The pros and cons of funnel plots as a risk communication aid for individual decisions about medical treatment. *British Journal of Psychology*, *106*, 327-348.

Ranney, M. A., Clark, D., Reinholz, D., & Cohen, S. (2012). Changing global warming beliefs with scientific information: Knowledge, attitudes, and RTMD (Reinforced Theistic Manifest Destiny theory). In N. Miyake, D. Peebles, & R. P. Cooper (Eds.), *Proceedings of the 34th Annual Meeting of the Cognitive Science Society* (pp. 2228-2233). Austin, TX: Cognitive Science Society.

Rosenbaum, L. (2014). Invisible risks, emotional choices: Mammography and medical decision making. *The New England Journal of Medicine*, *314*, 1549-1552.

Rottenstreich, Y., & Hsee, C. K. (2001). Money, kisses and electric shocks: On the affective psychology of risk. *Psychological Science*, *12*, 185-190.

Ruiter, R. A. C., Abraham, C., & Kok, G. (2001). Scary warnings and rational precautions: A review of the psychology of fear appeals. *Psychology & Health*, *16*, 613-630.

Shaffer, V. A., Owens, J., & Zikmund-Fisher, B. J. (2013). The effects of narratives on information search in a web-based patient decision aid: An eye-tracking study. *Journal of Medical Internet Research*, *15*, e273.

Sinaceur, M., Heath, C., & Cole, S. (2005). Emotional and deliberative reactions to a public crisis: Mad cow disease in France. *Psychological Science*, *16*, 247-254.

Slovic, P. (1987). Perception of risk. *Science*, *236*, 280-285.

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2004). Risk as analysis and risk as feeling: Some thoughts about affect, reason, risk and rationality. *Risk Analysis*, *24*, 311-322.

Slovic, P., Fischhoff, B., & Lichtenstein, S. (1981). Facts and fears: Societal perceptions of risk. *Advances in Consumer Research*, *8*, 497-502.

Slovic, P., Flynn, J., & Layman, M. (1991). Perceived risk, trust, and the politics of nuclear waste. *Science*, *254*, 1603-1607.

Slovic, P., Monahan, J., & MacGregor, D. G. (2000). Violence risk assessment and risk communication: The effects of using actual cases, providing instruction and employing probability versus frequency formats. *Law and Human Behavior*, *24*, 271-296.

Slovic, P., & Peters, E. (2006). Risk perception and affect. *Current Directions in Psychological Science*, *15*, 322-325.

Slovic, P., & Weber, E. U. (2002, April). *Perception of risk posed by extreme events*. Conference paper: "Risk management strategies in an uncertain world." Retrieved from https://www.ldeo.columbia.edu/chrr/documents/meetings/roundtable/white_papers/slovic_wp.pdf

Small, D. A., Loewenstein, G., & Slovic, P. (2007). Sympathy and callousness: The impact of deliberative thought on donations to identifiable and statistical victims. *Organizational Behavior and Human Decision Processes*, *102*, 143-153.

Sterman, J. D. (2008). Risk communication on climate: Mental models and mass balance. *Science*, *322*, 532-533.

Sterman, J. D., & Booth-Sweeney, L. (2007). Understanding public complacency about climate change: Adults' mental models of climate change violate conservation of matter. *Climatic Change*, *80*, 213-238.

Sterman, J. D., Fiddaman, T., Franck, T., Jones, A., McCauley, S., Rice, P., . . . Siegel, L. (2012). Climate interactive: The C-ROADS climate policy model. *System Dynamics Review*, *28*, 295-305.

Sunstein, C. R. (2002). Probability neglect: Emotions, worst cases, and law. *The Yale Law Journal*, *112*, 61-107.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth and happiness*. London, England: Penguin.

van der Linden, S. (2015). The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *Journal of Environmental Psychology*, *41*, 112-124.

Wallsten, T. S., Fillenbaum, S., & Cox, J. A. (1986). Base rate effects on the interpretation of probability and frequency interpretations. *Journal of Memory and Language*, *25*, 571-587.

Weber, E. U. (2006). Evidence-based and description-based perceptions of long term risk: Why global warming does not scare us (yet). *Climatic Change*, *77*, 103-120.

Weller, J., Dieckmann, N. F., Tusler, M., Mertz, C. K., Burns, W. J., & Peters, E. (2013). Development and testing of an abbreviated numeracy scale: A Rasch analysis approach. *Journal of Behavioral Decision Making*, *26*, 198-212.

Zikmund-Fisher, B. J. (2013). The right tool is what they need, not what we have: A taxonomy of appropriate levels of precision in patient communication. *Medical Care and Research Review*, *70*, 37S-49S.