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Communicating Numerical Risk: Human Factors That Aid Understanding in Health Care

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Abstract

In this chapter, we review evidence from the human factors literature that verbal and visual formats can help increase the understanding of numerical risk information in health care. These visual representations of risk are grounded in empirically supported theory. As background, we first review research showing that people often have difficulty understanding numerical risks and benefits in health information. In particular, we discuss how understanding the meanings of numbers results in healthier decisions. Then, we discuss the processes that determine how communication of numerical risks can enhance (or degrade) health judgments and decisions. Specifically, we examine two different approaches to risk communication: a traditional approach and fuzzy-trace theory. Applying research on the complications of understanding and communicating risks, we then highlight how different visual representations are best suited to communicating different risk messages (i.e., their gist). In particular, we review verbal and visual messages that highlight gist representations that can better communicate health information and improve informed decision making. This discussion is informed by human factors theories and methods, which involve the study of how to maximize the interaction between humans and the tools they use. Finally, we present implications and recommendations for future research on human factors in health care.

Keywords

human factors; presentation format; graphs; visual information; risk communication; numeracy; decision making; categorical risk; class inclusion

Risk communication is the interactive process of providing information about risk (Fischhoff, 2009; Reyna, 2008; Sleath & Goldstein, 2011). The communication process is particularly important in the context of health care, in which crucial decisions regarding prevention often hinge on understanding probabilities and health outcomes (Reyna, Nelson, Han, & Dieckmann, 2009). However, the word *communication* is often reserved for situations in which information is *understood*. This research has shown that limited understanding of risk, in particular, of numerical risks, can be harmful in the context of health prevention, detection and diagnosis of disease, and treatment and disease management options (see also Fischhoff, Brewer, & Downs, 2011). For example, an insulin-dependent diabetic must carefully monitor blood sugar levels and manage medication accordingly because improper evaluation of blood sugar levels could translate into incorrect dosage or nonadherence to medication, which could eventually increase complications of disease. This information is often expressed numerically. However, without the aid of good

communication, people may have a difficult time understanding benefits from adherence to medication as well as risks of complications from diabetes and other chronic diseases.

In this chapter, we discuss how people understand risk information and propose ways to format or visually present risk information that can help to increase the understanding of the risk being communicated. This discussion is informed by human factors theories and methods, which involve the study of how to maximize the interaction between humans and the tools they use. Specifically, we present relevant research that accounts for the difficulty people have in understanding information about numerical risk in health care and discuss how risk communication can enhance (or degrade) health judgments and decisions. We then discuss presentation displays designed to mitigate these difficulties, based on theoretical and empirical evidence. In particular, we highlight how different visual representations are best suited to communicating different risk messages (i.e., their gist). Finally, we present implications and recommendations for future research on human factors in health care.

HOW PEOPLE UNDERSTAND RISK

In order to understand how the visual display of information about risk affects health decisions, it is necessary to first discuss the mechanisms behind how people understand risks. Understanding risks that are communicated in health contexts is key for how people encode information and decide about health-promoting choices, because lack of understanding can lead to under- or overestimation of risk, which often results in poor choices (Fischhoff, 2009; Reyna, 2012b; Reyna et al., 2009). For example, people may overestimate the small chance of complications from a vaccination and choose not to get vaccinated, even though the actual risk is small and complications are unlikely to occur. In other circumstances, people may underestimate risks, such as the risk of sexual behaviors and the chance of contracting sexually transmitted infections. Much information about health risks is communicated numerically, such as the effectiveness of treatments (e.g., percentage of treated patients who survive for 5 years), the benefits of lifestyle (e.g., reduction of cardiovascular risk), and the chance of side effects (e.g., probability of death, discomfort, and disability). Therefore, we focus on understanding (and later in this chapter on visual presentation) of numbers, which is a particularly difficult form of information to communicate.

Further, research and standardized testing show that people vary in how they understand numerical risk, which has major implications regarding health care (Reyna & Brainerd, 2007). These differences have been found to influence how patients interact with health care professionals and understand their risk. For example, less numerate patients have been shown to be worse at interpreting risk information about medication side effects (Gardner, McMillan, Raynor, Woolf, & Knapp, 2011) and were demonstrated to be more influenced by mood than by objective probabilities in judging hospital quality (Peters et al., 2009). There are other factors that influence how people understand risk, including age, level of education, culture, and gender (Reyna, 2011; Reyna & Brainerd, 2007). However, because the focus of this chapter is on how numbers are presented, we will not discuss the role of individual differences other than numeracy (for a review, see Brust-Renck, Royer, Reyna, &

Corbin, in press; also see the chapter by Mitzner, McBride, Barg-Walkow, & Rogers, in this volume).

This ability to use and understand numbers (i.e., numeracy) plays an important role in how risk information should be displayed and communicated in health settings, which will be discussed in a later section. Research on numeracy has shown that people often do not understand numbers and thus fail to use them properly to make healthy (and other) decisions (Reyna et al., 2009). This lack of numeracy (or innumeracy) is particularly concerning when information is communicated about health risk. For some people, numbers may communicate information precisely, but for others, numbers are ciphers (Peters et al., 2006; Reyna et al., 2009). However, it is important to distinguish precision from meaning; precision alone cannot convey meaning (Reyna, 2008). That is, understanding whether a risk is low or high requires more than processing a number precisely; rather, it requires understanding the context and content to which the number applies (Reyna & Adam, 2003).

In this section, we discuss the ability of people to understand risk in health-related contexts, in particular, how they understand risk from numbers through a focus on theory and empirical evidence. Specifically, we discuss traditional dual-process approaches to numeracy that identify better reasoning (as opposed to affect and intuition) with enhanced numerical (computational) abilities, followed by a new conception of numeracy that is supported by research on fuzzy-trace theory, in which numeracy hinges on better understanding of the meaning (gist) of numbers. Both approaches distinguish numeracy as a dual dimensional construct, in which separate processes contribute to high- and low-level numerical thinking. We present an overview of each theory, describing the core principles that are relevant to understanding risk in health care, as well as illustrative evidence.

Traditional Approaches to Numeracy: dual-Process Theories

Dual-process theories assume two competing processes: intuition and reason. These theories have ties to Cartesian dualism and Freud's psychodynamic distinction between primary and secondary processes (see Epstein, 1994; Reyna, in press). The intuitive process (also called associative, experiential, affective, or System 1) is described as fast, impulsive, and reactive (e.g., Epstein, 1994; Evans, 2011; Kahneman, 2003, 2011; Sloman, 1996; Stanovich, 1999; Stanovich, West, & Toplak, 2011). The analytic process (also called reason, rule-based, rational, deliberative, or System 2) is slow, is computational, and uses effortful deliberative reasoning, in contrast to "quick-and-dirty" intuition (e.g., Kahneman, 2011). The intuitive process is also considered to be primitive, whereas the analytic process is more advanced. Although both processes can produce bad and good performance, analysis is assumed to be the source of logical and rational thought, whereas fallacies and biases spring from the more error-prone process of intuition. According to this view, biases are reduced by avoiding heuristics (which are intuitive processes of System 1) in favor of deliberative analysis.

Traditional dual-process approaches to numeracy involve mapping intuitive and analytical processes into low and high ability to understand numbers (e.g., Peters et al., 2006). Thus, high numeracy is an example of high deliberative and analytical (i.e., exact computation) processing and low intuitive processing, whereas low numeracy reflects high primitive intuition and low analytical processing (Epstein, 1994; Lipkus & Peters, 2009; Peters, 2008;

Peters, Slovic, Västfjäll, & Mertz, 2008). The key rationale for traditional dual-process theories is that intuitive thinking causes systematic biases, because it is fast, associative, and has an affective (or *experiential*) component (for a discussion of dual-process mechanisms, see Slovic, Finucane, Peters, & MacGregor, 2004).

For example, in a study about how adult men understand lifetime risk of prostate cancer informed by genetic testing, Rolison, Hanoch, and Miron-Shatz (2012) compared the interpretations of risk of 174 adult males older than 46 years. All subjects read two statements about the lifetime risk of prostate cancer associated with different risk groups: (a) a group who had a risk-promoting gene (48% to 80% higher) and (b) a group who smoked but had no gene associated with cancer (24% to 60% higher). In each group, the subjects were asked to estimate the number of men who would develop prostate cancer out of 1,000. Those with higher numeracy were more likely to answer correctly, though only about 37% of the subjects interpreted risk estimates correctly. Because accuracy was related to numeracy, these results can be interpreted as showing that reliance on analytical and not intuitive processing predicted better performance (see also Miron-Shatz, Hanoch, Graef, & Sagi, 2009).

As noted, given this standard view, biases should be more likely among those lower in numeracy because they rely on intuitive thinking more than other forms of rational thought. For example, people who rely heavily on intuitive thinking are predicted to make more errors due to framing effects. Framing effects happen when quantitatively equivalent risk options are treated differently on the basis of their presentation, such as choosing to take a medication when the chance of having no severe side effects is 80% but not choosing to take a medication when the chance of having a severe side effect is 20% (e.g., Kahneman, 2003; Porcelli & Delgado, 2009). (Note that 80% and 20% are complementary.) This is an important concern for the communication of health risks to a patient, because small changes in the wording of a potential risk can change the interpretation of those risks (O’Keefe & Jensen, 2007).

Peters et al. (2006) demonstrated that judgment biases can be influenced by how people understand numbers. This finding was established by having subjects rate final exam scores of hypothetical students on a 7-point Likert scale from *very poor* to *very good*. Exam scores were presented in terms of positive or negative framing. For example, if one student was described as having 74% correct answers in the positive frame, the negative frame would indicate this same student had 26% incorrect answers. Performance ratings were a function of framing and numeracy, because less numerate subjects showed a stronger framing effect (i.e., rated performance better when problems were framed positively [percentage correct] than when they were framed negatively [percentage incorrect]) than did more numerate subjects. Peters et al. suggest that highly numerate subjects are able to transform numbers and compare magnitudes and are, therefore, less susceptible to changing their preference on the basis of superficial differences in wording. However, some research has not shown the predicted link between low-analytical, high-intuitive processing and framing effects (Shiloh, Salton, & Sharabi, 2002; see Reyna & Brainerd, 2008, for a review).

Dauids, Schapira, McAuliffe, and Nattinger (2004) also showed that subjects with low numeracy were more biased in that they overestimated their risk of breast cancer (compared to epidemiological data) more than did subjects with high numeracy. However, those who were high in numeracy were not consistently accurate in estimating risk. In another study, Schapira, Dauids, McAuliffe, and Nattinger (2004) showed that both low- and high-numerate subjects neglected to account for the time difference between a 5-year versus a lifetime risk when asked to estimate risk. Subjects gave similar risk estimations for both periods. (Note that this result is an example of denominator neglect, which will be later discussed in this chapter.)

As the results of confusing 5-year and lifetime risk illustrate, traditional dual-process theories' prediction that more numerate people perform better in decision tasks is not always corroborated in the literature. For example, in the Peters et al. (2008) study, subjects were asked to hypothetically donate money from a charitable foundation to one of three research institutions, which had all submitted proposals on how their institution could help reduce death from a disease. Institution X could reduce deaths from 15,000 per year to 5,000 per year, Institution Y could reduce deaths from 160,000 per year to 145,000 per year, and Institution Z could reduce deaths from 290,000 per year to 270,000. Institution Z would save the greatest number of lives (20,000) and thus has the objectively best proposal, despite a small proportion of lives saved (6.9%). Highly numerate people tended to choose Institution X, the option that saved the greatest proportion of lives (66.7%) but fewest people overall (10,000) (Reyna et al., 2009). Contrary to the standard view, *less* numerate people were more likely than more numerate people to select Institution Z, which is the normatively correct option because more lives are saved (Peters et al., 2008).

These studies suggest that highly numerate people may not consistently make the best decisions about risk because of their focus on numbers (e.g., on ratios even when ratios are not relevant to the decision). In health settings, a doctor could communicate that three treatments for a certain disease have been used in the past with the same success rates as Peters et al.'s (2008) study (i.e., Treatment X reduced deaths from the disease from 15,000 to 5,000 per year, Treatment Y reduced deaths from 160,000 to 145,000 per year, and Treatment Z reduced deaths from 290,000 per year to 270,000). If provided with these numbers, previous research suggests, a highly numerate person would make a better decision about which treatment to undergo than would a less numerate person (see also Peters, Kunreuther, Sagaara, Slovic, & Schley, in press; Slovic et al., 2004). That is, if individuals have a disease, clearly Treatment X is more effective than Treatment Z. However, simply performing ratio computations, as measured by most numeracy tests, is not sufficient, as the charity problem demonstrates. In sum, contrary to traditional dual-process theories, those high in numeracy do not consistently better understand probabilities or make superior decisions (for additional examples, see Reyna et al., 2009).

However, on the whole, better numerical skills are useful in preventing basic errors, such as misunderstanding place value. In order to better communicate risk, patients' levels of numeracy need to be understood by health care providers. If patients do not understand place values or the meanings behind percentages, health care providers will be ineffective at communicating risk. However, it is also a problem if individuals are too focused on

irrelevant aspects of numbers and miss the true meaning of health risks. In the following section, we discuss a new approach to risk communication that places meaning at the core of information processing and accounts for results that are not predicted by traditional dual-process approaches (see Reyna & Brainerd, 2008).

A New Approach to Numeracy: Fuzzy-Trace Theory

A new conception of numeracy based on fuzzy-trace theory was proposed by Reyna and Brainerd (2008), who attempt to better explain the paradoxes that traditional dual-process theories cannot explain, such as the preference of more highly numerate individuals for options with lower numerical values. This conception of numeracy can further address the challenges involved in understanding health risks. Fuzzy-trace theory is a dual-process theory that contrasts two types of thinking: verbatim and gist based (Reyna & Brainerd, 1995, 2011). Analytical processing operates on verbatim representations of information—the *surface* form of information. Intuitive processing operates on gist representations of information. This type of processing is impressionistic, is usually quick for familiar knowledge domains, and incorporates factors that affect the gist meaning of information, such as culture and experience (e.g., Reyna, 2012b, in press; Reyna & Adam, 2003). Unlike other approaches' conceptions of intuitive thought processes, gist processing is not thought to be primitive. Rather than involving attempts to process fewer pieces of information, gist processing takes information and extracts its essence, facilitating efficient but higher-order processing. For example, when given the choice of two medications, whereby Medication A has the same outcomes as Medication B except that A has fewer side effects, gist processing would simply favor using Medication A without compensatory analysis of details. Subtle tests comparing fuzzy-trace theory to prospect and expected utility theories have been performed (Reyna, 2012a).

In contrast to traditional dual-process approaches, fuzzy-trace theory highlights the importance of understanding the bottom-line meaning (gist) of numbers (e.g., Reyna, 2008; Reyna & Brainerd, 1992, 1995, 2011). According to the theory, better numeracy is explained as one's ability to extract the gist of numbers, instead of mindless (verbatim) calculation (Liberali, Reyna, Furlan, Stein, & Pardo, 2011; Nelson, Reyna, Fagerlin, Lipkus, & Peters, 2009; Reyna et al., 2009; Reyna & Brainerd, 2007, 2008). This focus on gist is justified by experiments isolating simple gist representations in health decision making, as opposed to detailed verbatim representations. Thus, fuzzy-trace theory's conception of numeracy emphasizes that people who rely on precise (verbatim) representation of numbers could very well choose the worse option given certain scenarios, such as the charity problems described earlier when computation was rote (see Reyna et al., 2009, for a review).

When interpreting risks, according to fuzzy-trace theory, people who properly understand the situation will often extract the categorical gist of a risk. These basic categories of risk include differentiating no risk versus some risk and “will happen” versus “will not happen” (Reyna, 2012a; Reyna & Brainerd, 1991; Kühberger & Tanner, 2010; see also Kahneman & Tversky, 1979; Mather et al., in press). However, health options sometimes require greater precision, in which case people revert to ordinal (e.g., higher or lower risks) and precise interval-level representations (i.e., exact numerical representations) as the requirements of

the task at hand change (Mills, Reyna & Estrada, 2008; Reyna et al., 2011). People do not rely on more precise mental representations of numbers simply because a health option is more complex (involves more steps or is harder)—the key is what level of precision is required to perform the task. For example, knowing only that one medication has fewer side effects than another (all else equal) is sufficient to choose between them. However, exact ratio representations are needed to calculate how many 5-mg pills are equal to one 15-mg pill.

Hence, intuitive gist judgments are based on qualitative distinctions. Such judgments incorporate relative comparisons (e.g., high risk relative to a norm or in the context of a terrible consequence) rather than literal computation based on quantitative (verbatim) information. According to this new conception of numeracy—gist numeracy—people often rely on the qualitative (gist) content of information (e.g., what low or high risk *means*) in order to make decisions, even when a decision seems to involve the manipulation of quantitative (verbatim) information (i.e., calculation).

For example, fuzzy-trace theory accounts for risky choices in framing effects by assuming that people use the most basic gist form of a number, the categorical distinction between *some* quantity and *none* (Kühberger & Tanner, 2010; Reyna & Brainerd, 1991, 1995, 2011). For example, Eraker and Sox (1981) gave subjects a series of scenarios in which they were asked to make health decisions based on choices between two options. In one scenario, subjects were told to imagine that they were suffering from a terminal disease, choosing between Drug A, in which all people who took the drug lived 1 extra year, or Drug B, in which two thirds of the people who took the drug would live an extra 1.5 years but one third of the people who took the drug would live no extra years. When asked to choose between the two drugs in terms of years of life (i.e., positive frame), people tended to be risk averse and preferred Drug A, the sure option, rather than Drug B, the gamble. According to fuzzy-trace theory, this preference is because the choice is interpreted as a chance of living *some* time longer for sure versus a chance of living *some* time longer and a chance of not extending life at all (*none*). Because gaining *some* life extension is better than *none*, the sure option is preferred.

The presence of the “zero complement” (i.e., the later part of the risky option in which no life is added) in the presence of numerically equivalent (at a verbatim level) alternatives (i.e., calculation of the expected time of extra life given the probability; $1.5 \text{ years} * 2/3 \text{ chance}$) is critical to one’s decision according to fuzzy-trace theory (Kühberger & Tanner, 2010; Reyna, 2008; Reyna & Brainerd, 1991). That is, the reason people showed a preference for the sure option in the gain frame is because they are risk averse regarding the qualitative possibility of not extending life. In traditional decision-making theories, the zero complement of the probability is ignored (because it has a numerical value of zero). In contrast, according to fuzzy-trace theory, the zero complement is responsible for the aversion to risk. Analogous interpretations of the loss frame (as a choice between losing some years of life for sure versus maybe losing some years of life and maybe not losing any) produce preferences for the gamble (i.e., risk-seeking decision), because losing *no* years is better than losing *some* years.

However, categorical gist (i.e., *some* or *none*) is not the only way to understand risk. In situations in which mental representations of categories of information are not sufficient, people will move to an ordinal, interval, or ratio understanding of the gist (Reyna, 2008). For example, if a patient has a temperature of 100°, the categorical understanding of the number would be that their temperature is *high*. This representation becomes insufficient if the temperature rises to 101°, 102°, 103°, 104°, and then 105° in a short period of time, all of which satisfy the categorical gist of *high*. The clinically significant issue in the latter case is the pattern—the increasing trend—in the temperature, making 105° even more concerning than it would ordinarily be. To understand the proper relation among these numbers, the ordinal gist of increasing magnitude needs to be understood. The ordinal distinction captures that 105° is *higher* and therefore should be understood as a worse outcome in the context of a rapid increase (despite all of the numbers being categorically high). The ability to understand the ordinal gist of these numbers is important in clinical settings and in communicating the risk to patients. If all patients know is that a temperature is high, they will not understand the importance of context and why the same number is more dangerous in the context of rapid change.

According to fuzzy-trace theory, emotion affects the understanding of information about risk (Reyna & Rivers, 2008). Health issues often lead to emotional reactions from patients, and health care providers need to understand how to communicate risks effectively even when the perspectives are colored by emotion. According to fuzzy-trace theory, emotion shapes the mental representations of information (Rivers, Reyna, & Mills, 2008). For example, the chance of becoming infected with HIV/AIDS is objectively *small*, but many still have a gist representation of that risk being *high* because of its categorical meaning, which is influenced by emotion. This distinction is reflected in agreement with the categorical gist survey item “It only takes once” to get HIV/AIDS (Mills et al., 2008; Reyna et al., 2011).

Similarly, a 10% chance of survival from a cancer diagnosis can be given the categorical gist representation of “possible survival” (Reyna, Nelson, Han, & Pignone, 2012). Although many theorists would claim that emotion leads to an overestimation of survival, research on fuzzy-trace theory suggests that people can encode both the verbatim risk objectively and the categorical gist of possible survival. In other words, patients can appreciate both the verbatim and gist perspectives on risk at the same time. However, emotions have a strong impact on the gist interpretation of risks (Rivers et al., 2008). These interpretations may not be detrimental, but they can lead to changes in how risk is understood, which can alter decision making (Rivers et al., 2008; Wood & Bechara, in press). Understanding how emotion can alter the interpretation of risk is particularly relevant when communicating health risk.

Even when people are not emotional and they have the requisite knowledge about risks, they may not retrieve what they know without the proper cues. For example, Reyna and Adam (2003) asked physicians with different levels of domain knowledge, other health care professionals, and medical students about risk behaviors associated with sexually transmitted infections (STIs). In particular, when asked about the risk of STIs in general (i.e., the *packed* condition), respondents would report a risk estimation that did not account for all of the STIs. However when asked about STIs and given examples of STIs (i.e., the

unpacked condition), respondents would give more accurate predictions of risk. Results were consistent with this prediction that the *unpacked* condition provided more specific retrieval cues that improved accuracy of risk. Specifically, subjects gave lower risk estimates of STI infection when only asked about the risk of STIs in general. However, when the same question about risk was *unpacked* by simply adding examples as reminders, they gave a higher and more accurate estimate. So, when the category of STIs was unpacked, subjects retrieved more information about risk; knowledge was triggered and they were able to adjust their risk estimates. Retrieval failure occurred despite the fact that the health care providers understood the risk of STIs and, with prompting, could retrieve the correct information immediately after the cue (see also Adam & Reyna, 2005; Reyna & Lloyd, 2006).

Summary

In this section, we discussed how people understand information about health risks through the perspectives of traditional dual-process approaches and a new theoretical conception: fuzzy-trace theory. In particular, we delved into evidence regarding how difficult it is for people to understand health risk communicated in numerical terms, which leads to uninformed decision making. As Reyna et al. (2009) discuss, low numeracy is pervasive and impairs risk communication, limiting prevention efforts among those most vulnerable to health problems. Because health risk is commonly presented numerically, the ability to understand numbers is vital for making informed decisions (Boase, Mason, Sutton, & Cohn, 2012; Reyna & Hamilton, 2001). This ability is particularly important when judgments involve information regarding risk and outcomes of treatments and disease management. The particular human factors that matter differ across theories. However, according to traditional dual-process theory and fuzzy-trace theory, these individual differences in numeracy can be mitigated if human factors of risk communication are taken into account and information is formatted in a way that allows people to understand the risk. Proper communication of information (e.g., meaningful visual displays) can make risk information understandable for people both high and low in numeracy.

RISK COMMUNICATION IN HEALTH CARE

Communication options between patients and health care providers have changed substantially in the last quarter century. When people have to make health decisions, they no longer have to passively wait for information to reach them, nor is the only option to learn relevant information from their health care provider. Instead, when making decisions involving risk, such as whether to take a specific medication, patients have access to a myriad of expert sources that give information about risk, such as social media (Fischhoff, 2009). As a result, health care providers and patients may have different beliefs about how likely or rare a risk is. For example, although a health care provider may communicate information that suggests a specific side effect of a medication is unlikely, the patient may be more persuaded by a friend who took the medication and had a severe reaction (but see Nisbett & Ross, 1980, for examples of experts' susceptibility to this bias).

In this example, the health care provider has a better understanding of the risk of not taking the medication, whereas the patient is being triggered by a particular example (Slovic,

Fischhoff & Lichtenstein, 1979). This has become a greater concern with the advent of the Internet and social media, because patients can now look up information about potential risk factors and encounter personal anecdotes, before even speaking with a health care provider (Betsch et al., 2012). Even though people have access to a great deal of information that can help them make healthy risk-reducing decisions, complications can arise when the risk information is communicated through multiple sources that vary in reliability. Because people often think that they are an exceptional case and are less likely to experience a risk, or they overestimate the effect of their own risk-mitigating behavior compared to others, unreliable information that is seized on in the service of an optimistic bias may be an even greater concern (Fischhoff, 2009; Reyna & Farley, 2006).

Building on the background of research on numeracy (and risk estimation) from different perspectives, in this section, we focus on how communication plays a role in informed decisions in health care. In particular, we present two theoretical frameworks that are relevant to health care, followed by empirical evidence. The first framework represents the view of traditional approaches to risk communication and has a focus on providing people with the exact facts that they will need in order to make a health decision. Then, we present a new conception of risk communication based on gist-based presentation of meaningful messages. According to this approach derived from fuzzy-trace theory, risk communication should convey the bottom-line (gist) message of risk rather than only the facts to help people make informed decisions.

Telling the Facts: Traditional Approaches to Risk Communication

Traditional approaches to risk communication in health care and medical decision making emphasize telling the facts in order to facilitate informed decisions when risk is involved (Fischhoff, 2009). In particular, these theories suggest communicating risk requires presenting detailed and precise information as well as targeting misperceptions, which is assumed to be necessary to change someone's beliefs or behavior toward risk avoidance (Brewer, 2011; Fischhoff, 2011; Stone, Yates, & Parker, 1997). This traditional view includes major explanatory models of risky decision making, including health-belief models that adhere to a *rational* behavioral decision-making framework that stresses deliberate, quantitative trading off of risk and benefits, such as the behavioral decision-making framework (Fischhoff, 2005, 2010; see also Reyna & Farley, 2006). (Approaches to risk communication include emotional appeals, as opposed to dry facts by themselves; however, the ideal course of action is usually determined by a reasoned or rational analysis, which emotion then promotes; see Fischhoff et al., 2011.)

According to this view, the goal of risk communication is to “bridge gaps” between a normative ideal and descriptive reality (Fischhoff, 2009; Fischhoff & Kadvany, 2011). Whereas the normative ideal indicates how people should make decisions, the descriptive reality is how individuals actually make those decisions (Fischhoff, 2005, 2010). A prescriptive analysis mediates the conflict between ideal and reality and makes recommendations to improve understanding. In the context of health care, this perspective implies that risk communication should provide accurate, detailed information that would help people reach their own conclusions. In other words, the prescriptive analysis

recommendation is to tell the facts, not to tell people what to do, but tailoring health communication to each person (Petty & Cacioppo, 1986). The patient is responsible for “connecting the dots” between what is communicated and making his or her own decisions between Treatments X and Y or Drugs A and B or even whether to get regular screenings for cancer.

One of the hurdles in providing correct information and letting people connect the dots is counteracting negative existing information that is potentially incorrect and can inhibit people from making informed decisions that could benefit their health. For example, Brewer and Fazekas (2007) conducted a review of the literature on human papillomavirus (HPV) vaccine acceptability with the intent of understanding public opinion of the HPV vaccine and, further, how those opinions are formed. Twenty-eight relevant U.S. studies were found. Of the parents surveyed, 55% to 100% were willing to give the HPV vaccine to their adolescent children despite the fact that, across studies, an average of 42% of subjects had never heard of HPV. Even fewer subjects knew how common HPV is or how HPV is transmitted. Only 21% to 46% of subjects believed they had a chance of becoming infected. This lack of knowledge and belief of perceived likelihood made it difficult for the researchers to determine how acceptable the HPV vaccine really was. As shown in this study, communication about the risk of HPV and the benefits of taking the vaccine were not adequately explained to the population at risk or their families. If people do not know what the risks of HPV are, they will not be able to make an adequate decision about how to protect themselves and their children, nor will they be able to determine if the use of an HPV vaccine is truly acceptable.

In an attempt to facilitate communication of correct information to patients and improve their acceptability of the risk information, Grime, Blenkinsopp, Raynor, Pollock, and Knapp (2007) examined patients’ preferences for written communication from their health care providers and whether the communication was effective at conveying information about health outcomes. The authors conducted a review of 70 studies that contained information on the role, value, and effectiveness of written information for patients. Not everyone wanted written information, but those who did wanted sufficient detail to meet their needs, which varied across patients.

The success of traditional health care approaches relies on the idea that pertinent information is being communicated to the patient (Brewer, 2011). However, in this model, interpretation of risk is left to the patient, which can lead to a lack of understanding and poor decisions (e.g., refusing to take worthwhile medication or vaccines). With insufficient efforts to “bridge the gap” between normative ideals and descriptive reality, patients may not always choose the best option. Most recommendations in health care are grounded in empirical data, but this is not true of deciding how to communicate risk. The basic question remains about how to best communicate those data, such as whether to communicate through words alone, numbers alone, or visual aids (e.g., Grime et al., 2007; Stone et al., 1997). More fundamentally, traditional approaches emphasize the nondirective provision of both risks and benefits of alternative courses of action, rather than directing people toward a particular meaningful resolution of the facts.

Meaningful Messages: A Fuzzy-Trace Theory Approach to Risk Communication

From a fuzzy-trace theory perspective, communication about risk in health care involves identifying the most relevant facts from messages and making their meaning comprehensible to patients, not just sharing information (Reyna, 2012b). The goal of health risk communication, then, is to facilitate people's understanding of the meaning of numbers in context by distilling their simplest qualitative essence (Reyna, 2004; 2012b; in press; Severtson & Vatovec, 2012). Previous research based on fuzzy-trace theory has shown that people prefer to make decisions based on the least precise gist interpretation that will allow them to make an informed decision (e.g., Reyna & Hamilton, 2001; Reyna & Brainerd, 1995; Reyna & Lloyd, 2006; Wilhelms & Reyna, 2013). Informed decisions depend on being given accurate information and truly comprehending its meaning. Therefore, patients need to understand the correct gist of their situation when making an informed decision about risk.

Fuzzy-trace theory also suggests that risk communication and decision support should begin with the message in mind (Reyna, 2008, 2012b). In other words, the first step in communicating risks is to identify the gist that is meant to be communicated, the functionally significant "bottom line" of the information in as integrated a form as possible. One question that this recommendation prompts is, how do we know if we have the correct gist?

We have previously discussed that people often do not understand numbers and, therefore, cannot extract meaning from numbers on their own. In addition, there are usually multiple messages that can be extracted from numbers, and expert knowledge is important in unveiling the correct meaning. For example, Brewer, Richman, DeFrank, Reyna, and Carey (2012) investigated how to communicate the chance of breast cancer recurrence based on analysis of genetic risk. Merely presenting numbers to patients might generate confusion about how to judge the threshold for *high* risk; a risk of 30%, for instance, would be *low* in other circumstances familiar to the patient (e.g., chances of rain) in which 30% is a small chance. However, experts classified the meaning of 30% chance of breast cancer recurrence as *high* risk.

For health care professionals, judging recurrence risk and similar information can be automatic and routine, but patients are not experts and cannot rely on background knowledge of the risk when trying to make decisions. This becomes an issue when health care providers fail to give crucial information to their patients about a potential risk. In Young, Bell, Epstein, Feldman, and Kravitz's (2006) study, none of the 152 physicians studied gave his or her patients all of the important information about a drug being prescribed for a mental health disorder, including what to do if a dose was missed or what the purpose of the drug was. Similarly, Sleath, Tulskey, Peck, and Thorpe (2007) found that only 16% of patients continuing antidepressant treatment were asked by their physicians how the medication was working despite the fact that 19% of them reported having an issue with their medication and 22% were having difficulties remembering to take their medication. Further, only 2 of the 40 subjects asked their physicians a single question about the medication they were being prescribed.

These studies suggest that lack of communication between health care providers and patients is a common occurrence and can lead to patients not fully understanding the decisions they are being asked to make about health risks. Patients have been found to be reluctant to ask questions of their health care providers (Sleath, Roter, Chewning, & Svarstad, 1999; Street, Gordon, Ward, Krupat, & Kravits, 2005), and some health care providers neglected to discuss important aspects of medication, such as drug interactions and side effects, with their patients (Sleath et al., 2007; Sleath & Goldstein, 2011). There is evidence that Federal Drug Administration (FDA)–mandated written medication information available from pharmacies do not effectively compensate for provider/patient discussion given they are not well remembered (Morrow et al., 2005; Wolf et al., 2012). However, it is not clear how well package inserts that accompany prescription medications effectively compensate for this lack of discussion.

In many instances, health care providers may wonder which information is relevant for an informed decision. This uncertainty can be addressed if health care providers are trained to properly convey the gist of the risk to their patients. Although gist representations are subjective, and thus differ across individuals, they are not arbitrary. The process of identifying health-related gist often involves experts and experienced patients. It is not a matter of translating risks into simple conclusions but, rather, conveying the bottom-line, relevant meaning of information. Usually, a small number of gist representations encompass most people's interpretations of risks for the same information—especially if those people share background knowledge (Reyna, 2008). Experienced patients and providers can provide iterative drafts of proposed gist representations, which naturally should be informed by the most rigorous scientific evidence. Deciding the relevant gist to be communicated requires a subtle interpretation of risk that can be presented in a meaningful way to patients, omitting peripheral details.

Consider the example of the measles, mumps, rubella (MMR) vaccine. Official information about vaccines can be provided in very complex numerical terms, and much information someone may want to know is available online for consultation. Downs, Bruine de Bruin, and Fischhoff (2008) have demonstrated that such health communications from official sources are usually cryptic for people with little or no background knowledge, whereas antivaccination messages tell a compelling and plausible story. According to fuzzy-trace theory, websites that communicate more coherent and meaningful gist will be more influential on decision making, which can be a challenge for health care (Betsch et al., 2012; Reyna, 2012b). Antivaccination messages have associated MMR with the development of autism because of a supposed presence of mercury. Antivaccination messages sound plausible because the actual causes of autism are mysterious, even among researchers, and its onset is roughly at the same time as MMR vaccine (Betsch et al., 2012). However, if people really understand how vaccines work (i.e., MMR vaccine is a live vaccine and the presence of mercury would kill it), there should be less reason to avoid the MMR vaccine in most circumstances (Reyna, 2012b).

In sum, according to fuzzy-trace theory, giving information to a patient so that the pertinent gist is intuitively clear is necessary in order for differences in options to be effectively communicated and decisions to be informed. Knowing how people interpret risk and the

relevance of a meaningful representation of information—not as precise numbers but, rather, as categorical or ordinal gists (e.g., *low* or *high*)—is important when communicating risks (Reyna & Brainerd, 2008; Reyna et al., 2009). In other words, fuzzy-trace theory provides useful guidelines for how gist-based intuition can inform human factors methods to better communicate risks in health care.

Summary

In this section, we discussed the role of risk communication in informed decisions in health care through the perspective of traditional approaches as well as a new, meaning-based approach—fuzzy-trace theory. Specifically, we discussed how numerical risk about health care is communicated. As Brewer et al. (2007) discuss, there is a consistent association between how people perceive risk and their actual behavior. The link between risk perception and behavior highlights the importance of effective health risk communication in order for people to correctly interpret and respond to risk. However, researchers often suggest that the same risks should be communicated in a variety of ways. For example, Fagerlin and Peters (2011) suggest that information should be communicated by providing numerical likelihoods of risks, using visual aids, and framing information in multiple ways in order to give different perspectives so that patients can make informed decisions. As we shall discuss in the next section, some ways of communicating risk are a better fit for specific risk messages than other ways of communicating.

HUMAN FACTORS IN RISK COMMUNICATION

As discussed in the previous section, health care providers generally understand health risk better than their patients, despite being subject to biases, but that does not necessarily imply that they can communicate those risks. Still, a shared decision-making process requires that health care providers communicate risk to the patient, and the way that health care providers share information with their patients is important to how patients understand, interpret, and respond to this information. Visual displays, such as graphs and pictures, can be used to aid communication of risk and, in particular, health risks (Lipkus & Hollands, 1999). For example, Garcia-Retamero and Cokely (2011) showed that adding a visual aid to health messages in a sexual health information brochure increased healthy behavioral intentions (e.g., using condoms) to avoid health risks (e.g., contracting STIs).

In this section, we take advantage of advances in research derived from fuzzy-trace theory regarding how people understand and communicate risk, to provide user-friendly resources that can aid risk communication. The recommendations follow Lipkus and Hollands' (1999) criteria of effective visual displays for communicating risks in terms of comprehension, acceptance, dose-response consistency (i.e., variance according to the magnitude or risk), hazard-response consistency (i.e., at risk people perceive hazard as greater than other people), uniformity in interpretation, clarity evaluation, and direction of people's reaction. In addition, visual displays can be constructed in specific ways to be consistent with specific evidence (e.g., Reyna, 2008). The rationale is that communicating risk meaningfully, not just telling the facts, can improve understanding regardless of numeracy level. We present three frameworks (informed by human factors research) of how to communicate risk that are relevant to health care based on fuzzy-trace theory: (a) verbal distinctions that extract

meaning from complex numerical options—from the most crude to the most fine-grained level of precision, (b) intuitive visual representation to convey specific meanings, and (c) presentation formats that disentangle classes to facilitate complex probability judgments.

Breaking Down Risk: Simplest Gist

In the previous section, we discussed communicating relevant risks. However, understanding health risks requires patients to have some background knowledge of numbers and health or to be motivated to seek out reliable sources of information and guidance. This difference in background knowledge can lead to less numerate patients making worse decisions about health risks than other patients, despite being given potentially helpful information. Reyna (2008, 2012b) argues that health care providers can help most patients (with either high or low numeracy) make better decisions by presenting the relevant information in the most intuitive way, which has been defined explicitly in prior research (see Reyna, 2008, 2012a, 2012b). In this section, we discuss the process of extracting meaning from numerical risk information presented in a verbal or written format.

Biases in risk communication can be a result of misrepresentation of information (Bruine de Bruin, Downs, Fischhoff, & Palmgren, 2007; Reyna, 2012b). To avoid misrepresentation, according to fuzzy-trace theory, information should be presented in an intuitive, user-friendly format, in which meaning is straightforward (e.g., categorical when appropriate), to help reduce risk-taking behaviors and intentions, teach individuals to engage in gist-based thinking (e.g., “Even low risks happen to someone”), and retrieve gist principles and relevant values from information (e.g., “It only takes once to get HIV/AIDS”; “Better to be safe than sorry”; Reyna, 2004, 2008). The process of communicating risks can be effective even when information is presented in a way that allows people to mentally represent their risk without deliberative thinking. When gist values and principles are effectively communicated through meaningful representations of risk (which do not require mindless memorization), they can then be practiced sufficiently to be automatically retrieved in context to avoid (or at least reduce) risk (Reyna, 2008, 2011).

Similar to the Brewer et al. (2012) example discussed earlier, if a woman is trying to decide which medication is best for her and her doctor tells her that her risk of a severe side effect from the medication most successful in treating her disease is 10%, the woman may see it as a *low* risk because the risk is substantially less than 50% (i.e., it probably will not happen; Brewer et al., 2009). However, if this woman lacks the background knowledge that the risk of the severe side effect for an alternative medication is 2%, she may perceive a 10% risk as *high*. The role of the health care provider in this case is to guide how the gist of the risk estimate of 10% could be interpreted, as high or low, depending on the nature of the side effects as well as its likelihood (Fagerlin, Zikmund-Fisher, & Ubel, 2011).

According to fuzzy-trace theory, gist extraction can happen at multiple levels (or hierarchies) that roughly correspond to levels of measurement, from the most crude to the most fine-grained level of precision (Reyna, 2004, 2008, 2012a; Reyna, Lloyd, & Brainerd, 2003). The simplest, crude level of gist for quantities (e.g., numerical probability of developing side effects from a medication) corresponds to the simplest distinctions about quantities, namely, nominal or categorical level (e.g., “The risk for developing a severe side

effect is high”). The same information can also be communicated at an ordinal level of precision (e.g., “The risk of a severe side effect is higher than average”) and then again at yet more precise levels, such as interval or ratio levels (e.g., “The risk is 1 in 5 people”).

Communication of health risk can be *gistified* by translating arbitrary facts into meaningful messages (e.g., deciding which facts are essential to decision making, explaining the reasons behind the essential facts, integrating facts, and deleting irrelevant details) in order to improve message effectiveness. In order to choose the right gist, experts and long-term patients can use their expertise to evaluate expressions that communicate risks and benefits. In some cases, someone else can generate the gist (e.g., experimenter or other health care providers); however, the gist should be validated on the basis of experts’ (including experienced patients’) opinions. The meaning (gist) of the message should express the nature of the risk (e.g., whether an option is safe or risky, low or high) in addition to the objective (verbatim) number.

Consider an example of risk communication from the field of oncology. The situation requires deciding whether a patient with rectal cancer should choose a radiotherapy treatment that has a reduced recurrence rate of 5%—at the expense of substantial side effects (50% more sexual dysfunction and 30% more bowel control problems)—or chemotherapy that is associated with an 11% recurrence rate (i.e., percentage of people who have a recurrence of the disease) and the same survival rate (i.e., percentage of people who survive the disease). Even though radiotherapy has a lower recurrence rate, note the risk that a patient will die (i.e., not survive) from both treatment options is the same. Thus, the quantitative difference between 5% and 11% does not matter for the bottom line of survival.

It is important in the interpretation of these options to ignore the verbatim numbers and get the right meaning out of the facts (i.e., that there is the same survival with and without radiotherapy—but radiation is qualitatively worse due to greater side effects). Even though numbers are relevant, they can be misleading (e.g., recurrence rates in this example), and patients may have a hard time reaching the conclusion to undergo chemotherapy. In this example, health care providers could communicate that chemotherapy is better because it has fewer side effects and that, otherwise, the two treatment options are quantitatively the same. With this overall meaningful interpretation of the risks in mind, patients can make better-informed decisions about which treatment option to choose.

In addition to the simplicity of focusing on simple meaning and on causal understanding of that meaning, one of the main reasons to categorize risk is to avoid the all-or-none precipice (Mills et al., 2008; Reyna et al., 2011). Certain behaviors can result in bad outcomes from which there is no going back to the original status (e.g., death due to alcohol poisoning or getting HIV/AIDS from unprotected sex). Initial results from a variety of interventions have been surprisingly successful in communicating this all-or-none risk. For example, Reyna, Mills, and Estrada (2008) developed an intervention based on fuzzy-trace theory to teach adolescents about the risks of pregnancy and STIs from unprotected sex. The gist-based intervention was implemented as part of a randomized control trial with 734 adolescents comparing it to (a) a standard multicomponent intervention (“Reducing the Risk”; Reyna, Adam, Poirier, LeCroy, & Brainerd, 2005) and (b) an unrelated control group. All three

interventions consisted of 14-hr classes in small groups of high school students in either school settings or after-school programs. Effectiveness of the interventions was assessed via testing that occurred prior to the intervention, immediately after the intervention, and at 3, 6, and 12 months later.

The gist-based intervention included the same content as the standard intervention, but risk was communicated in a gist format (e.g., “Even low risks happen to someone”), and subjects were also taught to identify and automatically retrieve gist values (e.g., “Avoid risk”; “Better to not put my partner at risk”). Subjects were encouraged to understand the gist of information about risky behaviors (gist lasts longer in memory compared to memorization of verbatim details), recognize risky situations rapidly, retrieve relevant values, and engage in automatic gist-based thinking (that is faster than verbatim and deliberative analysis of risk; Reyna, 2008; Reyna et al., 2008). Results comparing the three interventions (i.e., gist-based, standard, and control) demonstrated that the fuzzy-trace theory curriculum produced significant improvements (relative to controls) for 17 out of 26 outcomes and was more effective than the others across a range of outcomes (e.g., knowledge, attitudes, and behaviors), lasting as long as 12 months after program delivery (Reyna et al., 2008; also Reyna & Farley, 2006, Table 4).

When communicating risks such as unprotected sex—which puts people at risk of contracting STIs, including HPV and HIV infection—meaningful representation of risk helps respondents understand why HIV/AIDS infection is not curable (i.e., “It is a virus” and “Viruses are not curable”) as opposed to mindless memorization that does not rely on comprehension (Reyna & Adam, 2003). One reason to rely so much on meaningful understanding is because it facilitates greater transfer of knowledge from the concrete example being taught to similar situations (in comparison to mindless memorization or compliance). The idea is that this transfer of understanding will lead to more healthy behaviors. For example, other viral STIs, such as herpes, do not have a cure for the same reason that HIV is incurable—it is a virus. Once people understand that all incurable STIs share the common feature of being viruses (HIV, HPV, and herpes) and they understand what being a virus means, they realize that these diseases cannot be cured with antibiotics and should be avoided. Connecting the dots across these different diseases allows people to infer a gist that has important ramifications for protecting their health (Adam & Reyna, 2005; Mills et al., 2008; Reyna, 2004; Reyna & Adam, 2003).

In summary, as predicted by fuzzy-trace theory, use of categorical gists (e.g., “No risk is better than some risk”) has been associated with effective risk communication in health care (compared to verbatim information). Extracting the relevant, correct gist requires knowledge, which laypeople and inexperienced patients often do not have, but this knowledge can be supplied through risk communication that focuses on essential meaning. Thus, health care providers can endow patients with appropriate gist that can lead to improved health communication and outcomes.

Intuitive Visual Representations to Communicate Health Risks

In the previous section, we discussed how gist-based representations of risk support understanding, which informs decision making and behavior. Another important set of

human factor concepts that can help patients (both low and high numerate) understand health risks are graphic representations of the risks, which will be discussed in this section. Graphic representations are particularly helpful for low-numerate individuals and can facilitate more accurate decisions about risk (Garcia-Retamero & Galesic, 2010). The primary focus is not just to present information graphically in a direct and salient format (e.g., Robertson, Czerwinski, Fisher & Lee, 2009), because the same data can be presented in different formats. The goal is to discuss how each format is best conveys specific meanings (gists) to provide sufficient information for an informed decision based on evidence in support of fuzzy-trace theory. We therefore present a series of visual aids that are recommended for conveying specific meanings (gists; see Table 6.1 for an overview).

Use of graphical illustrations with distinct features has been shown to be an effective and user-friendly tool to communicate risk (Ancker, Senathirajah, Kukafka, & Starren, 2006; Feldman-Stewart, Brundage, & Zotov, 2007; Galesic & Garcia-Retamero, 2011; Lipkus & Hollands, 1999; Reyna, 2004, 2008; Stone, Yates, & Parker, 1994; Stone et al., 2003). These illustrations can be used as a human factor method that can increase the understanding of risk communication if used correctly to facilitate meaningful comprehension. However, some people have difficulty interpreting graphs and other visual aids (Galesic & Garcia-Retamero, 2011), and not all visual aids are helpful (Reyna, 2008). For example, shaded maps (in which shades of the same color represent different levels of risk) translate a clear ordinal gist because saturation represents “more of” in a meaningful way, whereas a complex table conveying the same information is more difficult to understand (Severtson & Henriques, 2009; Severtson & Vatovec, 2012).

Reyna (2004, 2008) highlights that efficient communication requires information to be presented in formats that encourage decision makers to automatically extract specific gist representations. According to fuzzy-trace theory, presenting information visually in a meaningful way improves extraction of the relevant gist. In other words, meaningful formats can help differentiate superficially similar aids that seem helpful (but are not) from those that are efficacious (Reyna, 2008). The first step in deciding how to communicate risk is to know the message to be conveyed (Table 6.1). Once the risk to be communicated is clear, the appropriate presentation format can be selected on the basis of its fit to this message.

In addition, it is worth noting that not any visual aid will improve understanding, as shown by Gaissmaier et al. (2012). For example, numerical (verbatim) information that is more concrete and presents vivid details fades more over time than more abstract (gist) information. In this study, risk of medication or smoking was communicated in five graphical formats that varied in terms of concreteness. Results for 275 subjects demonstrated that some visual aids do not allow simple gists to be apprehended. Consistent with fuzzy-trace theory’s account, selection of visual aids should not be random, but each format should highlight specific relations, such as “more than” or “increases over time” (see also Severtson & Henriques, 2009).

One example of how numbers can be visually represented to introduce meaning is the use of stacked bar graphs (e.g., Stone et al., 1994). Stacked bar graphs are useful when attempting to avoid denominator neglect because they give attention to both the denominator and the

numerator and separate the two (Reyna, 2008). According to fuzzy-trace theory, stacked bar graphs can also convey the gist of absolute risk, for example, when denominators shift (e.g., 100 out of 400 people survive in the treatment group vs. 200 out of 1,000 people in the control group). In the example used in Figure 6.1, a stacked bar graph is used to show that two treatment options have little absolute difference in effectiveness relative to a large sample of 2,000. The smaller bars representing absolute risk of getting sick are so small that they can barely be distinguished from the larger bars representing the total number of people who get healthy. This avoids overestimation of small probabilities (Reyna, 2008). Note, however, that for side effects with deadly impact, such as small chances of dying, even small differences can matter.

A good way to convey relative differences between two magnitudes (e.g., which treatment is the most effective or puts one more at risk) is to use simple bar graphs (Reyna, 2008). Simple bars positioned side by side (Figure 6.2) will make the relative gist more salient by making the difference between options clear as opposed to an absolute difference (Figure 6.1). Figures 6.1 and 6.2 show the differences between the gists of the two graphical illustrations, despite the fact that both graphs convey the same numbers. Both graphs show the number of patients who remain sick after being treated for heart disease with either Treatment X or Treatment Y. In Figure 6.1 (i.e., stacked bar graph), Treatment X and Treatment Y appear to be effectively the same, with both treatment options treating the majority of patients. However, Figure 6.2 (i.e., simple bar graphs) conveys a completely different gist by showing that Treatment X results in fewer patients with disease than Treatment Y. When the difference between treatments is relevant, the message should be presented in relative terms (Figure 6.2) so that the gist that the risk in Treatment X is smaller than the risk in Treatment Y would be salient (and presumably Treatment X should be chosen, all else equal). Note that information can be misleading when the range of values is too small on the y-axis and the size of the bars seems bigger than it really is. For example, using a range of 0.002 to 0.009 on the y-axis may give the appearance of a large change; however, in reality, it may be insignificant (Reyna, 2008).

The contrast between Figures 6.1 and 6.2 illustrates that the same numerical information can be represented visually to convey different messages. The choice of how to display risk information graphically should be made on the basis of what gist is ultimately judged to be most important; this choice cannot be resolved by numbers or graphs. The message must be selected first. Then, an appropriate format can be selected to emphasize meaningful differences and deemphasize trivial ones.

In an attempt to compare how well each of these presentation formats, such as stacked and simple bar graphs, communicated chance of survival and chance of side effects of a series of diseases, Feldman-Stewart et al. (2007) presented information about risk to 217 subjects from the community older than 50 years. Presentation format varied within subjects in six ways: vertical bars, horizontal bars, systematic icons, random icons, pie charts, and digits. Subjects were also randomly assigned to one of three add-on conditions accompanying the presentation format: (a) numbers (percentage), (b) scales, and (c) numbers and scales. The relative size of the quantity the subject was to choose (whether chance of survival was smaller or larger for a specific target) varied within subjects along with the size of the

difference between quantities being evaluated. Results showed that a vertical stacked bar, horizontal stacked bar, and systematic icon array were more accurate at communicating relative risk than were random icons, pie charts, and digits. In addition, errors increased for formats with scales only for pie charts and random icons. Vertical stacked bars with scales were the most accurately processed, followed by horizontal stacked bars and systematic icons.

Other examples of graphical displays, such as pie charts and icons, used in the Feldman-Stewart et al. (2007) study illustrate specific relationships among numbers, which could explain the results (Reyna, 2004, 2008). Similar to simple bar graphs, pie charts and icons are useful for helping patients judge relative magnitude. However, they are more useful when presenting multiple diseases at a time. Each color in pie charts can be used to represent a specific condition, such as prevalence of a disease in different racial groups, although naturally saturation of a single color (or bar graphs arranged in order of magnitude as stair steps) would be better to convey ordinal risk.

Figure 6.3 shows an example of a pie chart that shows the risk of potentially fatal side effects from a drug throughout different age ranges. The pie chart helps show the gist that risk for side effects becomes much greater as the patient ages. If the doctor is trying to convey that a patient should not take this medication when he or she is older, this chart can help communicate the information that more than half of all side effects occur for people in the oldest group (65 or older). Reyna and Brainerd (1994) highlight that even 4-year-old children can perceive the difference between two magnitudes from a pie chart (e.g., red area is bigger than blue area), even though they cannot estimate the exact value.

In a study with 104 patients who had rheumatoid arthritis (Table 6.1), Fraenkel et al. (2012) communicated information about risks through the presentation of simple graphs about benefits (e.g., from different medications) and adverse effects (e.g., risk of developing diabetes). They used the three types of graphs explained previously. Based on fuzzy-trace theory, each graph was used to communicate the essential gist of benefits and risks identified by experts and patients. Two bars positioned side by side for easy comparison were used to demonstrate the incremental benefit of adding a specific biologic to a traditional disease-modifying antirheumatic drug (clear language, such as “higher bar is better,” was used). Pie charts (for adverse events with a risk of 1% or greater) were used to describe risks, that is, the relative frequency of side effects. Exact numbers, such as “2% (2 out of 100 people) will experience adverse events,” was also provided in case a patient wanted to extract his or her own meaning. However, a panel of experts and patients provided interpretations of these numbers, such as “small chance.”

Although we have focused on mental representations of risks, people must also retrieve personal and social values and apply them to those representations in order to make decisions (Reyna, 2008; Reyna et al., 2011). Hence, Fraenkel et al. (2012) also presented patients with simple values (such as the ones discussed in the previous section) that they could endorse, such as “It is important to reduce my chances of becoming disabled, even if it means taking medications with a risk of serious side effects,” followed by feedback to each patient regarding whether his or her endorsement of such values showed that he or she might

be “interested in changing their medications to better control their arthritis.” Results showed that the intervention increased knowledge, patient willingness to escalate care, and the likelihood of making an informed choice in a pre- and post-test comparison. With the use of presentation formats to communicate risk based on fuzzy-trace theory, the proportion of patients making an informed, value- concordant choice increased substantially from 35% to 64%.

Simple bar graphs and pie charts readily convey gist-based relative magnitude judgment, but other graphical displays can be useful visual formats that can help highlight specific relationships among numbers. For example, icons in pictographs can visually represent the number of people in a population who are affected by some event, such as a disease (e.g., Hess, Visschers, & Siegrist, 2011, who showed that the highly numerate focused more on finding a precise numerical estimate by counting the exact number of icons in a pictograph). It is important to know that if icons are presented randomly in the population pictograph, then it is hard to convey a meaningful representation of relative magnitude. In previous studies, fuzzy-trace theory predicts that ordered presentation of icons should be preferred over a scrambled presentation to communicate risk because a systematic pattern makes gist easier to extract (see Reyna, 2008, for a review).

McCaffery et al. (2012) used icons in pictographs to communicate risk of treatment to 120 adults with lower education. In this study, information about chance of survival from two treatments was presented in either pictographs (blocks or dots) or simple bar charts in a computer-based manipulation. Orientation of all graphs could be either horizontal or vertical. The denominator was always 1,000; however the numerator varied from small (100), medium (100 to 499), or large (500 to 999) sizes. In addition, the size of the difference also varied from small (2% to 17%), medium (18% to 33%), or large (34% to 49%). For each graph, subjects were asked to estimate the larger chance of survival (gist task) and the size of the difference (verbatim task). Reaction time and preferences for type of graph were also assessed. Accuracy in estimating the gist was high across all conditions, but verbatim estimation of size depended on the numerator size: Bar charts were less accurate for small numerators and more accurate for medium and large numerators than were pictographs. In line with this result, bar charts were generally processed slower for small numerators and faster for medium and large numerators than were pictographs. Overall, bar charts were preferred. Thus, efficient risk communication can result from user-friendly displays (see also Hawley et al., 2008).

Another common graphical illustration that can be helpful to communicate risk is a line graph. Whereas bar graphs communicate whether one treatment is better than another, line graphs can be helpful in communicating the differences over time (Lipkus & Hollands, 1999). The gist representation of a line graph is a monotonic trend, such as the effectiveness of a treatment over time, recurrence of a disease over time, or mortality and survival curves. People generally focus on the direction of the line (i.e., whether it is going up or down) rather than the numbers (Reyna & Brainerd, 1990). For example, Figure 6.4 shows differences between Drug A and Drug B in reducing pain from rheumatoid arthritis over a period of 10 months. Although Drug B initially reduces pain the most (i.e., line goes down in the initial months), the line graph displays that Drug A is superior in the long run (i.e., at

the end, Drug B pain relief is stable and Drug A pain relief goes farther down). The key to understand the message of a line graph is to note the change from the reference point, such as what happens after 7 months of taking medication: Drug A reduces more pain than Drug B. In other words, Drug A reduces pain more over time. A bar graph would effectively compare overall pain (i.e., relative gist) from both drugs, but seeing a trend in a series of bar graphs is harder than observing the slope of a line graph (e.g., Drug A pain is “going down”).

In another example, Brewer et al. (2012) investigated the effectiveness of representation-targeted risk communication techniques about breast cancer recurrence risk in 133 patients who were eligible for the Oncotype DX genomic test (Table 6.1). The test estimates 10-year risk of recurrence that varies along a continuum (though it can be roughly categorized as low, medium, and high) and helps patients decide whether to add adjuvant chemotherapy to endocrine therapy to prevent recurrence. Risk communication varied in complexity from a detailed standard report from a commercial test with (a) a simple explanation of risk, (b) the explanation and a simple graphic presenting risk of recurrence on a continuum (gist representation of risk), (c) both explanation and graphic followed by a description of the graphic and confidence interval reports, or (d) an additional format that involved an icon array. Patients were randomly assigned to receive one of the descriptions and were asked to estimate risk of 10-year recurrence (as low, medium, or high) followed by rating of their understanding and easiness of understanding of the material.

Results showed that subjects generated a greater number of errors when risk was communicated in the standard detailed report compared to other simpler formats. The gist-based format (risk continuum) generated the fewest errors in risk estimation and was rated among the most understandable and most liked format (Brewer et al., 2012). The result was consistent with fuzzy-trace theory prediction that simple meaningful presentation of risk (e.g., the risk continuum) enhanced understanding (Reyna, 2008; Reyna & Brainerd, 1990).

Because people usually have a hard time understanding numbers, and gist extraction does not require relying on exact numbers, risk communication has a lot to gain from meaningful graphical representation (Brewer et al., 2012; Fraenkel et al., 2012). Graphic representations can be a successful and user-friendly way to display risk information to patients (Garcia-Retamero & Cokely, 2011). According to fuzzy-trace theory, use of specific presentation formats plays an important role in efficiently communicating the meaning of risk. Thus, choosing a specific format requires having a message to be communicated in mind.

Disentangling Classes in Probability Judgment

In the preceding sections, we discussed how the use of the correct type of graphic facilitates the process of extracting the gist of risk because the relation between options is salient and people can extract meaning without encoding numbers (Reyna, 2008). Visual aids help decision makers to get the correct gist, and specific presentations also help reduce class inclusion confusion in judging conditional probabilities. Class inclusion confusion occurs when people think about probabilities or other nested or overlapping sets, such as the set of people with breast cancer and the set of people with the mutation that increases breast cancer (Reyna, 1991; Reyna & Brainerd, 1994; Reyna & Mills, 2007). Research on fuzzy-trace

theory has shown that understanding class inclusion is relevant for communicating risk because interference that produces errors in decision making is often due to nested or overlapping classes rather than due to lack of understanding of the concept of probability (i.e., that it is a ratio of frequencies; Reyna, 2004; Reyna et al., 2003, 2009).

When representing class inclusion information, such as positive predicted value of a test (i.e., the number of people with the disease who have a positive test result), a stacked bar graph, as mentioned earlier (Figure 6.2), can display one bar for each value and split conditions according to whether people actually have the disease or not. In this type of graph, the numerator and denominator are evident, helping to eliminate denominator neglect, which can bias patients (e.g., Schapira et al., 2004). However, other formats, such as the use of 2×2 tables, grids, Venn and Euler diagrams, icon arrays, or tagging can also portray class inclusion information in a clear and intuitive way. In the present section, we focus on explaining how these presentation methods can help to reduce interference and biases (e.g., base rate neglect, conjunction and disjunction fallacies) in risk communication by allowing decision makers to keep track of classes (Reyna, 1991, 2004, 2008; Wolfe, 1995; Wolfe & Reyna, 2010a, 2010b). Similar to the previous section, we will continue presenting our menu of formats that facilitate meaningful comprehension of risk supported by theory and evidence.

Fuzzy-trace theory encompasses effects of manipulating class inclusion confusion that is often a result of verbatim interference but originates in the confusion from ratios, such as probability. Because ratios involve classes that overlap (e.g., number of people with disease or number of people with a positive test result), confusion arises from identifying the denominator (e.g., number of people with disease overall or number of people with positive test result overall). According to this theory, risk communication strategies should focus on making the denominator clear (discretely) by disentangling the classes that overlap, which reduces errors (Wolfe, Fisher, and Reyna, in press; Reyna & Mills, 2007).

Disentangling classes to communicate the correct risk is not an easy task. Reyna and Lloyd (2006) demonstrated that even trained physicians show class inclusion errors. In this study, physicians (from various specialties, including cardiology) and students examined diagnostic judgments for nine patients (vignettes drawn from real patients; Table 6.2). For each of the patients, subjects estimated the probability that the patient had coronary artery disease (CAD), the imminent risk of myocardial infarction (MI), and the probability of either CAD or MI (or both). Even though specialists were better able than general practice physicians to discriminate between low- and high-risk patients when estimating probabilities, results showed that subjects at all levels of knowledge mistakenly estimated risk of CAD or MI (or both). According to fuzzy-trace theory, these judgments are a result of difficulties in keeping track of overlapping classes, such as the event class of having CAD but not being at risk of MI, being at risk of MI but not having CAD, both being at risk of MI and having CAD, and neither (Reyna, 1991; Reyna & Brainerd, 1994; Reyna & Lloyd, 2006).

Class inclusion confusions, disjunction fallacies, logical reasoning biases (e.g., syllogisms), and other errors of probability judgment can be reduced in health care contexts by, for

example, using 2×2 tables to facilitate communicate information involving joint probabilities (Reyna, 1991; Reyna & Brainerd, 2008). Diagnostic tests, for example, indicate whether a result was positive or negative, and the accuracy is expressed in terms of sensitivity (positive result when disease is present) and specificity (negative result when disease is not present). The key of the 2×2 table is to separate classes, such as the class of people who had breast cancer and a positive test result and the class of people without breast cancer who also had a positive test result. The first step would be identifying all possible combinations (i.e., cells of the table): (a) the patients with the disease who had a positive result, (b) the patients with the disease who had a negative result, (c) the patients without the disease who had a positive result, and (d) the patients without the disease who had a negative result. An example of a 2×2 table displaying this information from a breast cancer screening test is found in Figure 6.5.

Once separated, it is possible to understand overlapping and nested sets before finally recombining (assembled from the separate judgments) in specific ways to yield conjunction judgments, conditional probabilities, and other combinatorial judgments, such as how many people will have cancer among those who had a positive test result. When classes are separated, it is possible to “flip the denominators” more easily and also consider how many people will *not* have cancer among those who had a positive test result. Thus, a 2×2 table can be helpful in answering questions patients often confuse when information is not presented clearly, such as what a false alarm is if someone who does not have breast cancer tested positive in a screening mammography. Most patients show great worry after false positive results from a screening test. However, looking at the 2×2 table (Figure 6.5), we can easily see that only about half of the patients who tested positive have cancer (Salz, Richman, & Brewer, 2010). Thus, the table can help communicate that the screening result means only that the patient should do additional exams, so the woman should not be overly concerned that she has breast cancer or that she will develop breast cancer.

A 2×2 table was used in an intervention based on fuzzy-trace theory to teach about joint probability estimates in written and web-based tutorials (Wolfe & Reyna, 2010b). Wolfe and Reyna (2010b) focused on communicating relation among classes to improve gist-based (semantic) reasoning and diminishing fallacies (Table 6.2). Gist-based reasoning was improved by adding analogies that illustrated relationships between classes. Subjects read a brief description of a problem and were asked to estimate the probabilities of single and joint events. The authors used examples of overlapping sets (e.g., gynecologist–obstetrician), identical sets (e.g., chickenpox–varicella), mutually exclusive sets (e.g., hyperglycemia–hypoglycemia), and subsets (e.g., acute coronary syndromes–coronary artery disease) for probability estimates of single (e.g., A), conjunctive (e.g., A and B), and disjunctive (e.g., A or B) events.

Analogies and/or a diagram with explanation of how to use a 2×2 table were given before each problem. Gist-based performance from the group that received both an analogy and the 2×2 table was compared to (a) a group that received the analogy but no table, (b) a group that received no analogy but the 2×2 table, and (c) a group that received no analogy and no table. As a result, gist-based thinking (through analogies) was responsible for reducing conjunction and disjunction fallacies as well as increasing semantic coherence. After

learning how to interpret the 2×2 table (and identify estimates for each of the four classes in each cell of the table), those with the table committed fewer fallacies than those with no table. According to fuzzy-trace theory, the finding is a result of people improving gist-based (semantic) reasoning and no longer ignoring the denominator (Lloyd & Reyna, 2001, 2009; Lloyd, Reyna, & Whalen, 2001; Reyna, 2004, 2008; Reyna & Adam, 2003; Reyna, Lloyd, & Whalen, 2001).

Other visual displays that highlight the relationships among classes are Venn and Euler diagrams (Table 6.2). An example of a Venn diagram can be found in Figure 6.6, and an example of Euler diagram can be found in Figure 6.7. The Venn diagram displays a woman's risk of developing breast cancer at some point in her life and getting a positive or a negative result from screening. This diagram shows the same information shown in the 2×2 table from Figure 6.5 but represents the information in a specific way by visually overlapping the different categories, such as having a positive test result and having breast cancer (Figure 6.6). (Euler diagrams, such as the one in Figure 6.7, provide a visual set structure by distorting the shapes.) Whereas 2×2 tables discussed earlier are helpful in communicating multiple relations among probabilities and *flipping* the denominator when considering conditional probabilities (probability of A given B vs. probability of B given A for which numerators are the same but denominators differ), Venn diagrams can highlight one specific instance. Venn diagrams should be used when the information in the overlapping cases is what is meant to be communicated. Figure 6.6 shows how a Venn diagram could be used to communicate that a woman who is concerned about being diagnosed with breast cancer should get a screening because testing can detect presence of cancer. A 2×2 table is better at explaining information when one needs to consider denominators because it disentangles different classes from one another in a way that makes denominators clear.

According to fuzzy-trace theory (which relates mental representations of gist to additional assumptions accounting for confusion caused by overlapping classes), any format that disentangles classes should reduce class inclusion errors (e.g., losing track of denominators). To test multiple ways of disentangling classes and effectively presenting information about risk, Wolfe et al. (in press) used 2×2 tables, Euler diagrams, or frequencies (using poker chips). In this study, 100 subjects were randomly assigned to learn about joint probabilities in one of the four conditions (the fourth being a control with no visual aid). The task was similar to the one used by Wolfe and Reyna (2010b), in which subjects were asked to estimate probabilities of single (e.g., A), conjunctive (e.g., A and B), and disjunctive (e.g., A or B) events. Results showed that in comparison to the control group, learning about Euler diagrams and 2×2 tables improved semantic coherence and decreased inconsistency, although understanding some set relations were helped more by particular representations. These findings demonstrated that clarifying appropriate denominators reduce errors by affecting class inclusion reasoning (Wolfe et al., in press).

Although presenting probabilities (e.g., .01) in terms of frequencies (e.g., 1 in 100) often accomplishes this same separation of classes, frequencies are not inherently easier to manipulate than probabilities. As one example, Cuite, Weinstein, Emmons, and Colditz (2008) studied 16,133 people's performance on multiple computational tasks involving

health risks and found that performance was very similar for frequency (55% accurate) and probability (57% accurate).

Finally, another meaningful way to communicate health information regarding relative magnitude is the use of icon arrays and grids (Table 6.2). Two examples of icon arrays are shown in Figures 6.8 and 6.9. In these figures, the percentage of patients who develop severe side effects after taking a drug is shown in the black boxes. This design allows for visual representation of the risk of taking the medication that patients can understand quickly. Patients are able to compare the number of black boxes to the number of white boxes and easily appreciate the gist of the graphic without becoming bogged down in the details of the numbers.

Icon arrays can also be used to make the denominator clear, as shown in the difference in total icons between Figure 6.8 (out of 100 patients) and Figure 6.9 (out of 50 patients). Although both figures show that 7 patients develop side effects after taking the medication, it is important to distinguish that fewer patients were at risk in the sample in Figure 6.8 (7 out of 100 is a 7% risk) than in Figure 6.9 (7 out of 50 is a 14% risk), because the denominators are different. Often, people ignore the denominator, and when information about two drugs is presented separately, it is important to highlight (e.g., verbally) the denominator when communicating risk. When creating an icon array, all icons should be easily distinguished so that patients are able to discern the relative magnitude of the risks, even from a distance (e.g., making them salient, such as using black and white colors).

According to fuzzy-trace theory, grids that label classes distinctively also facilitate easily flipping the denominators to estimate risk. Lloyd and Reyna (2001) taught physicians to visually represent women with potential ischemic heart disease on a 10-by-10 grid with 100 squares (each square representing one woman). Once the grid was constructed, squares were completed with pretest information regarding the chances of ischemic heart attack and of coronary heart disease. Sensitivity and specificity were added by writing in plus or minus signs above each square. The grid accounted for all relevant classes, making it possible to visually estimate positive and negative predictive value (the probability of disease given a positive test result and the probability of no disease given a negative test result, respectively). The goal of the intervention was to represent each class discretely (patients with the disease and either a positive or a negative result, and patients without the disease and either a positive or a negative result). Because classes were represented discretely, diagnostic errors were reduced compared to risk estimation without the grid, as predicted by fuzzy-trace theory (Lloyd & Reyna, 2001).

Grids, diagrams, icons, and other decision aids that allow people to appreciate the qualitative gist (i.e., the meaningful relations or patterns) of information reduce reasoning and judgment errors considerably (e.g., Brainerd & Reyna, 1990; Lloyd & Reyna, 2001; Reyna, 1991; Wolfe et al., in press; Wolfe & Reyna, 2010a, 2010b). Success has been observed for reducing conjunction fallacies (overestimating conjunctive probability), disjunction fallacies (underestimating disjunctive probability), conditional probabilities (base rate neglect and *conversion* errors, such as mistaking the probability of having a gene given that one has cancer with the probability of having cancer given that one has the gene), and various kinds

of semantic incoherence. Hence, decision aids or information formatting that make key qualitative relations salient (e.g., disentangling classes) can undo many of the biases and illusions that characterize judgments of risks and probabilities (Reyna, 1991; Reyna & Mills, 2007; Wolfe and Reyna, 2010a).

Summary

In this section, we presented three frameworks of how to communicate risk information informed by human factors research relevant to health care. First, we discussed the fuzzy-trace theory prediction that the use of categorical gist is associated with efficient risk communication. The health care provider can communicate meaningful (gist) messages to the patient in order to facilitate better decision making. Next, we introduced graphical representations of risk, which aid understanding of specific numerical relationships. For example, stacked bar graphs can help avoid denominator neglect, and simple bar graphs can communicate relative difference between two magnitudes. Pie charts and icons can also convey relative magnitude, whereas line graphs are better at conveying change over time. Finally, we presented visual formats that disentangle classes and aid complex probability judgments. This included 2×2 tables, Venn diagrams, and Euler diagrams. Icon arrays also facilitate the understanding of relative risk and relative magnitude while making the denominator clear. As discussed in this section, graphical presentations can aid understanding of risk information for people regardless of numerical skill, but not all visual aids are helpful (Reyna, 2008). The gist of the intended message should determine what the most effective visual presentation should be.

CONCLUSIONS AND FUTURE DIRECTIONS: HUMAN FACTORS IN SUCCESSFULLY COMMUNICATING RISKS

In health care settings, effective communication of risk relies on the understanding of both the health care provider and the patient. The evidence informed by human factors of risk communication can aid understanding of how risk information can be better transmitted and how shared decision making between patients and health care providers can be improved. Many difficulties in the understanding of risk are due to a lack of numeracy, which can lead to inaccurate assessments of risk, but theory-based interventions and meaningful visual presentations can improve communication and lead to better-informed decisions.

In this chapter, we discussed relevant research and theory pertinent to how people understand health risk information through the perspectives of traditional dual-process theory and fuzzy-trace theory. This discussion focused on difficulties people have understanding numerical information. In particular, we showed that better mathematical skills are useful in preventing basic errors (e.g., confusion about place value) and that understanding the meanings behind percentages and ratios results in better (healthier) decisions. Then, we discussed the processes that determine how communication of risks can enhance (or degrade) health judgments and decisions given that people are often low in numeracy. We presented views from traditional approaches to risk communication (which emphasize telling dry facts and letting the decision maker connect the dots without being

directed toward a particular meaningful resolution) and fuzzy-trace theory (which emphasizes properly conveying the gist of the risk in a meaningful way).

Finally, we examined how communication can improve health decisions and introduced how meaningful (gist) representations of risk (e.g., categorical gist and line graphs when relaying information about change over time) can enhance understanding for all people, despite differences in numeracy. The recommendations are grounded in the empirical literature and based on empirically supported tenets of fuzzy-trace theory, which predicts that coherent decisions are made by understanding the meaning of numbers (gist-based processing) rather than just making accurate calculations (verbatim-based processing). The research we reviewed suggests that verbal and visual messages that highlight gist representations allow for better understanding of risk because such representations are more accessible in memory (i.e., less prone to interference) and generalize better to different situations. Further, we suggested specific graphic representations (e.g., 2×2 tables) that can better communicate health information to patients by representing different gist meanings and clarifying relations among classes of events (e.g., having breast cancer vs. having a genetic mutation), which can reduce common cognitive errors in decision making. Moreover, because meaning is at the core of how people process information (i.e., they have a fuzzy processing preference), communicating the right gist improves risk comprehension.

As we have discussed, how risk information is presented can greatly improve understanding of important health care messages, thus aiding in disease prevention and management options. Effective communication can help patients make informed decision about health risks, including choices between treatment options or whether to get a particular vaccine or not. This research also has many implications for both policy and health care. Policy makers could use the knowledge from the reviewed research to encourage better design and use of improved messaging and presentation formats in conveying risks (e.g., FDA warning labels or package inserts for drugs). Health care professionals can use meaningful (gist) representations of risk to further encourage healthy behaviors in varied aspects of life, including exercise, smoking, sexual behaviors, and flu vaccinations. In all of these cases, the communication of a meaningful message should encourage health-promoting actions, despite widespread lack of objective numeracy. The inclusion of facts and figures on posters or pamphlets should be designed with evidence from human factors research in mind, and these visual representations should be designed to communicate the gist of the message.

Because patients, health care providers, and the general public all can have difficulty understanding numbers, presentation formats that are compatible with the types of risks people are trying to communicate play a critical role in judging information and improving well-being. People attempting to communicate risk information should be trained to provide the gist of the intended message to their audience. We also suggest that health care providers should be trained to provide the gist of the risks of a decision to their patients. Even people with background knowledge or a general understanding of numbers may need help applying their knowledge and values to the particular situation they are in. Gist messages can help people determine what their best decision will be, whether they are making decisions about everyday health behaviors (e.g., exercising) or serious medical situations (e.g., treatment

options for cancer). The meaningful communication of risk should ultimately promote better life outcomes, but more research on outcomes is needed.

When applied correctly, research on human factors can help improve the decisions people make when considering health risks in all parts of their lives. As discussed in this chapter, implementing a fuzzy-trace theory–based intervention to communicate risk has been shown to substantially increase the proportion of subjects making informed choices about rheumatoid arthritis treatment (Fraenkel et al., 2012). Future research would benefit from the use of meaningful (gist) tools to influence health decisions in conditions that require high levels of self-management, such as insulin-dependent diabetes. This research is particularly important for young people low in objective numeracy, because adults with high objective numeracy have been found to better adhere to diabetes self-management (Cavanaugh et al., 2008). In the future, researchers should examine how gist, independent of objective numeracy, can improve ability to extract meaning of numbers and graphical representations and understand them in context. Understanding the gist allows people to go beyond the literal level (specific dosage) to the underlying cause of the nonadherence to medication (whatever the cause may be). The research in human factors that we reviewed suggests that intuitive (gist) representations enable informed and healthier decision making.

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Ratio of Healthy to Sick People after Treatment

Figure 6.1.

Example of stacked bar graph to communicate that absolute risk is roughly equal

Note: Stacked bar graphs showing absolute risk comparing the frequency of sick people and healthy people for two different treatments. Stacked bar graphs make absolute differences between two treatment types more evident (i.e., there is little difference) than a simple bar graph.

Figure 6.2.

Example of simple bar graph to communicate that ordinal gist (fewer sick for Treatment X vs. Y)

Note: Example of a simple bar graph showing the frequencies of sick patients for two treatment types. Bar graph makes simple relations (bigger or smaller number of sick patients) between the two treatments clearer than a stacked bar graph.

Chance of Fatal Side Effects

Figure 6.3.

Example of pie chart showing older groups experience more side effects (ordinal gist of which is most)

Note: A pie chart displaying the chance of fatal side effects for a treatment across age groups. Pie charts are good for explaining relative proportions. This pie chart shows the relative number of patients with side effects is much larger for patients 65 or older but also that the chance of side effects for patients 15 to 24 and 35 to 44 is relatively similar. A line graph may better communicate this information if the focus should be on the linear trend over time.

Figure 6.4.

Example of a line graph showing pain goes down for drug a over time (linear trend)

Note: A line graph displaying the long-term differences in pain from rheumatoid arthritis from two drugs. Line graphs are good to use when explaining changes over a period of time.

		Breast Cancer Diagnosis		
		Positive	Negative	Total
Actual Presence of Breast Cancer	Yes	332	88	420
	No	315	2765	3080
	Total	647	2853	3500

Figure 6.5.

Example of 2×2 table separating classes to reduce probability judgment fallacies

Note: A 2×2 table displaying the conditional probabilities of a woman's risk of developing breast cancer at some point during her life. The test results are for women 40 years of age and older. The statistics are extracted from the National Cancer Institute's website (National Cancer Institute, 2011). A 2×2 table can be used to reduce denominator neglect and other biases and to communicate multiple relations among probabilities at one time, clarifying relations among overlapping classes.

Figure 6.6.

Example of Venn diagram

Note: A Venn diagram clarifying a woman's risk of developing breast cancer throughout her lifetime as opposed to genetic risk for breast cancer. The information in this graph is based on statistics from the National Cancer Institute's website (National Cancer Institute, 2011). Venn diagrams are helpful when displaying overlapping classes, such as the presence of breast cancer in women with a positive genetic test result.

Figure 6.7.

Example of Euler diagram

Note: A Euler diagram clarifying a woman's risk of developing breast cancer throughout her lifetime as opposed to genetic risk for breast cancer. The information in this graph is based on statistics from the National Cancer Institute's website (National Cancer Institute, 2011). A Euler diagram visually displays the absolute size of the risks in overlapping cases, such as a large proportion of women with breast cancer who had a positive test result. Euler diagrams can also reduce denominator neglect.

Figure 6.8.

Example of an icon array with higher denominator

Note: An icon array communicating the relative risk of developing severe side effects in 7 out of 100 patients after taking a medication. Icon arrays can help visually convey relative magnitude of risk, in this case, the relatively small 7% risk of developing side effects.

Figure 6.9.

Example of an icon array with lower denominator

Note: An icon array communicating the relative risk of developing severe side effects in 7 out of 50 patients after taking a medication. Icon arrays can help make the denominator clear. The number of icons shows the number of patients who developed side effects (7 patients) but also highlights the denominator (50 patients, as opposed to 100), indicating a risk of 14% of developing side effects.

Table 6.1**Human Factors Recommendations for Visual Communication of Risks in Health Care**

Presentation Format	Message/Gist	Example	Illustrative Source
Simple bar graph	Gist-based relative magnitude judgment (<i>lower risk</i>) by comparing the heights of the bars	Number of patients with disease in two or more treatment options	Stone et al. (2003)
Stacked bar graph	Gist-based absolute magnitude judgment due to appropriate attention to denominators and numerators (avoid denominator neglect)	Number of patients with disease in two or more treatment options from the total number of patients	Stone et al. (1994)
Pie chart	Relative proportions	Number of patients with disease in two or more options	Fraenkel et al. (2012)
Line graph	Gist-based representation of global patterns of magnitude (monotonic trend) over time	Effectiveness of a drug over time; survival and mortality curves	Brewer et al. (2012)

Table 6.2

Human factors recommendations for disentangling classes when communicating risks in health care.

Presentation Format	Message/Gist	Example	Illustrative Source
Icon array	Relative magnitude and randomness (displaying icons in a systematic grouped fashion makes it easier to get the gist of relative magnitude, for example); other types of icon arrays can clarify conditional probabilities by disentangling nested classes, disambiguating denominators	Icons represent the number in a population affected by some event out of the total representative number of the population	Brewer et al. (2012)
2 × 2 table Venn (or Euler) diagram 100-square grid	Reduce processing interference from class inclusion by disentangling nested classes and making the denominator clear	Numbers in cells represent the number of people in a condition given the overall condition of which it is part	Wolfe & Reyna (2010b) Wolfe, Fisher, & Reyna (in press) Lloyd & Reyna (2001)