The Roles of Processing Difficulty and Numeracy in the Use of Numeric Risk Information

by

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DISSERTATION ABSTRACT

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One of the key challenges in risk communication is effectively conveying numeric information to the public. Research suggests that numeric information is often more complex and less likely to be used than narrative information, such as individual stories. This may be because numbers are more cognitively demanding, leading decision-makers to rely on easier-to-use narrative content. However, a study on the representativeness heuristic (judging probabilities based on resemblance) found that the use of information depends not on its type but on its difficulty and the cognitive resources available. Specifically, when cognitive resources are limited, people are more likely to use numeric information that is easier to process (shorter and presented before a long narrative) than they are to use more complex numeric information (longer and presented after a short narrative). However, when resources are ample, they are more likely to use more complex numeric information (longer and presented after a short narrative) than they are to use numeric information that is easier to process (shorter and presented before a long narrative).

The present two studies extended these ideas into risk assessment, focusing on numeracy instead of cognitive resources. It was hypothesized that participants paradoxically would be more sensitive to risk levels when numeric information was harder to process, with this effect being stronger among highly numerate individuals. In Study 1, the difficulty of information was manipulated by varying its length and order of presentation; in Study 2, it was manipulated by varying numeric precision and order of presentation. Results from Study 1 supported the hypothesis that participants would be more sensitive to risk levels when numeric information was harder to process (longer and presented after a short narrative) compared to when it was easier to process (shorter and presented before a long narrative). Interestingly, number preferences, rather than numeracy, emerged as a significant moderator in Study 1. However, the manipulation in Study 2 was unsuccessful, and the anticipated effects were not observed. Implications for enhancing risk communication strategies were subsequently discussed.

Keywords: risk communication, numeric information, narrative, processing difficulty, numeracy

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CHAPTER I INTRODUCTION

Risk communication involves exchanging risk information and influencing how people comprehend, perceive, and act on risks (Bostrom et al., 2018). An essential goal of risk communication is facilitating accurate judgment of risks (Cho & Friley, 2014), such as the probability of experiencing a side effect of a vaccine, the likelihood of a nuclear war, or the extent to which climate change may harm health.

Much of this information is expressed numerically. However, it can be challenging for risk communicators to make sense of such information to the public (Rakow et al., 2015; Betsch et al., 2011; National Academies of Sciences, 2017; Reyna et al., 2009). Numeric content can be challenging because numerals are abstract symbols, and the meanings of numbers vary in different contexts (Peters, 2012). Furthermore, scholars consider narratives easier to process because narratives are a fundamental form of human communication, given that humans are used to creating and sustaining shared beliefs, values, and norms through stories. For these reasons, risk communicators frequently combine narratives with numerical data, framing them as stories to explain complex issues (Cho & Friley, 2014; Fisher, 1984). In media coverage, for example, audiences are often given explicit likelihood assessments and accompanying narratives when reporting on hazards, such as the risk of severe COVID-19 infection, presenting a blend of probability data and personal stories.

A common concern about narratives, however, is that they can sway people from using the presented numeric information (Cho & Friley, 2014); an example is the phenomenon of base-rate neglect (e.g., Tversky & Kahneman, 1974; Kahneman & Tversky, 1973). For example, people asked to evaluate the likelihood of an individual being in a particular profession based on information about a base rate (i.e., probability) and a narrative (i.e., personality description) are more likely to assess the likelihood based on the narrative rather than the base rate, evincing considerable base-rate neglect. For example, people might evaluate a target individual as an engineer because his personality in the narrative resembles the engineer stereotype. However, they ignore the base rate—in this case, the fact that they were told the target person was drawn from a group consisting of many more lawyers than engineers—which should be considered in the likelihood estimate.

Relying on narratives to make judgements can lead to errors. For example, Dickson (1982) compared consumers' responses to narrative and statistical messages about refrigerator failure rates. It was found that narrative presentation produced an overestimation of the failure rate, whereas statistical presentation yielded a more accurate estimation of the rate. As a matter of fact, making better or more precise judgments and decisions often relies on using and understanding data (Peters, 2017). For example, in the context of risk communication, prior studies found that individuals are less likely to overestimate risk likelihood and more willing to take a prescribed medication when provided with numeric information than when given only non-numeric information (Myers et al., 2013; Peters, 2012; Peters et al., 2014; Trevena et al., 2006, 2013).

Individual differences in abilities like numeracy (numeric literacy) also are associated with the use of numeric and non-numeric information. For example, less numerate individuals are more likely to be insensitive to numerical risk information and to be sensitive to non-numeric information (e.g., narratives) in their judgments, whereas highly numerate individuals appear more sensitive to numbers than narratives (Dieckmann et al., 2009; Peters, 2012; Reyna et al., 2009). This differential use of information is consistent with dual-process theories of information processing—namely that intuitive or heuristic information is more likely used by people with limited cognitive resources, whereas deliberative or analytical information tends to be used by people with ample cognitive resources.

However, some researchers argue that it is the ease of information rather than the type of information (e.g., numeric vs. narrative), combined with cognitive resources, that determines information use. For example, Chun and Kruglanski (2006) challenged the assumption that numeric information is always less likely to be used than narratives. They conducted research within the classic base-rate neglect paradigm and manipulated the processing difficulty of both types of information by varying their length and presentation order. Their findings revealed that numeric information was more likely to be used when it was harder to process—specifically, when it was lengthy and presented after a short narrative, rather than when it was brief and preceded a longer narrative. The availability of cognitive resources moderated this effect. Individuals with limited cognitive resources tended to use numeric information when it was easier to process—shorter and presented before a lengthy narrative—whereas those with ample cognitive resources were more likely to use it when it was more difficult to process, i.e., longer and following a brief narrative. Although it was unclear whether the observed effects were due to numeric complexity, narrative complexity, or a combination of both, their findings highlighted the potential impact of manipulating information processing difficulty to influence its usage.

In this information-rich age, people face more choices and information than ever before. Making better or more precise judgments and decisions relies heavily on using and understanding data. Individuals with varying abilities may need different decision aids, especially for decisions that involve complex numbers. Consequently, a deeper understanding of how people with different abilities process risk information could significantly enhance the communication of risk to the public (Peters, 2008). The present study aims to extend Chun and Kruglanski's (2006) findings from occupational estimation to the domain of risk assessment. If, as they concluded, processing difficulty matters in information use rather than the type of information (numeric vs. narrative), then we should be able to influence the use of numeric risk information in making informed decisions by varying the information processing difficulty.

CHAPTER II LITERATURE REVIEW

Judgment Heuristics and Probability Neglect

According to dual-process theories of information processing, humans process information using two separate but interacting ways of thinking—one more affective and experiential, the other more thoughtful and deliberative (e.g., Epstein, 1994; Smith & Decoster, 2000; Reyna, 2004; Slovic et al., 2004; Kahneman, 2003; Petty & Cacioppo, 1986; Chaiken, 1987; Gawronski & Creighton, 2013). Processing in the affective mode is automatic, associative, and fast; it is thought to encode reality in images, metaphors, and narratives and to rely on experience and heuristic shortcuts. The deliberative mode is conscious, reason-based, and relatively slow. For instance, processing numeric information often demands cognitive effort in the deliberative mode (Epstein, 1994; Kahneman, 2003; Loewenstein et al., 2001; Sloman, 1996; Epstein & Pacini, 1999; Gawronski & Creighton, 2013).

When making judgments and decisions, humans tend not to do a complete cognitive analysis to determine optimal decisions; instead, they often rely on heuristics or cognitive shortcuts that quickly come to mind (e.g., Simon, 1947; Tversky & Kahneman, 1974; Kahneman, Slovic & Tversky; 1982; Kahneman, 2003). These heuristics include representativeness, availability, adjustment from an anchor, affect heuristic, and so on. Heuristics work quickly but also lead to systematic and predictable errors (Kahneman, 2003). Two types of heuristics relevant to this dissertation are introduced below.

Representativeness is often employed when people are asked to judge the likelihood that an object or event A belongs to class/ process B. For example, in the abovementioned base-rate neglect paradigm, if people are asked to guess an individual's profession based on a base rate and a narrative (personality description), they are more likely to assess based on the narrative, revealing considerable base rate neglect. In other words, people might evaluate a target individual as an engineer because his personality in the narrative resembles the engineer stereotype. At the same time, they ignore the base rate when told that the target person was drawn from a group consisting of more lawyers than engineers; the base rate, however, should be accounted for when estimating probability (e.g., Tversky & Kahneman, 1974; Kahneman & Tversky, 1973).

Affect, on the other hand, is an abstract feeling of "goodness" or "badness" about an object. It has been recognized as an essential component of human judgment and decision-making. Originating from risk perception research, the affect heuristic characterizes people's reliance on feelings about an object in determining how much risk is perceived. As the risk-as-feelings approach (Loewenstein, Weber, Hsee, & Welch, 2001; Slovic et al., 2007; Slovic et al., 2004) assumes, risk assessment is influenced not only by cognitions but also by immediate global affective reactions and specific emotions.

Building on this foundation, affect plays a pivotal role in shaping our perceptions of risks and benefits, ultimately driving our choices. Research suggests that affective responses to stimuli often precede and inform cognitive processes such as risk perception, benefit assessment, and behavioral intentions, making them more proximal in the judgment and decision-making process. As a result, the effect of manipulations, such as those in the current dissertation, may be stronger for affect than other assessed constructs. The "risk as feelings" hypothesis posits that these immediate emotional responses can dominate or even bypass cognitive evaluations, thereby exerting a significant influence on decisions. This primacy of affect underscores its critical role in the initial stages of judgment, suggesting that emotional responses may not only guide but also constrain subsequent rational analysis (Loewenstein et al., 2001, Slovic et al., 2004).

Furthermore, reliance on these immediate affective responses is quicker, easier, and more efficient when people navigate a complex, uncertain, and sometimes dangerous world; however, this approach may lead to judgmental bias, such as probability neglect. Sensitivity to the probability of a consequence decreases when an action or event's consequences evoke strong positive or negative affect. For example, the intense feelings associated with some threats (e.g., terrorism) may cause risk overestimation, potentially resulting in an overreaction (Sunstein, 2003; Hsee & Rottenstreich, 2004; Peters et al., 2012; Rottenstreich & Hsee, 2001).

Chun and Kruglanski (2006) used base rates and individuating information, drawing on materials adapted from studies on the representativeness heuristic within the base-rate neglect paradigm. In the present study on risk assessment, we instead employed materials incorporating numeric and narrative risk information, with the affect heuristic playing a role. As a result, a pilot test was conducted prior to the main studies to ensure that narratives of different lengths did not significantly differ in their effects on affect and risk perception toward a medication. Details of this pilot test are presented in later sections.

Narrative Bias

Unlike numeric information, which is mainly processed deliberately, narratives (also known as individuating information) describe a personally experienced event from a first- or third-person perspective and are often story-like and affect-rich (Betsch et al., 2011; Hinyard & Kreuter, 2007; Winterbottom et al., 2008). Narratives come in various forms. For instance, literary narratives might be expressed as novels or short stories, entertainment narratives as movies or TV series spanning multiple episodes, and research on health narratives often uses brief personal testimonials (Green & Appel, 2024).

The widespread presence of narrative and numeric information in daily life has sparked growing research interest in understanding its impact on individuals' judgments. Generally, narratives have inherent advantages over numbers or "dry data", as they are usually appealing, detailed, and easy to understand; they also can be highly emotional (e.g., Hibbard & Peters, 2003; Myers et al., 2013; Trevena et al., 2013; Berger, 1998; Betsch et al., 2012). In a classic example of the power of narratives, Borgida and Nisbett (1977) presented participants with one of three types of information: a statistical summary of course evaluations, testimonials from a few upper-level psychology students, or information about ten advanced psychology courses (a no-evaluation control condition). Then, students were asked in which course they would enroll. The researchers found that the vividness of individual experiences was a more powerful influence on choice than the non-vivid statistical data. In particular, participants who received only the face-to-face testimonials would enroll in more highly evaluated courses than those who received only statistical data, even though the statistical data were from a significantly larger group of participants and thus was more accurate and less biased.

The compelling power of narrative information raises concerns about narrative bias (e.g., Betsch et al., 2015). For instance, in Ubel et al. (2001), participants showed less sensitivity to numbers when written individual information was presented. Participants were asked to choose between two treatments for angina—balloon angioplasty and bypass surgery—based on two types of information: hypothetical statistical information about the percentage of angina patients who benefit from angioplasty and bypass surgery (50% and 75%, respectively) and written testimonials from hypothetical patients who benefited or did not benefit from the two treatments. The researchers altered the number and nature of testimonials participants were exposed to. They found that patient testimonials significantly influenced treatment choices even when statistical information about treatment success rates was constant. In particular, participants were more likely to choose bypass surgery in conditions offering three positive testimonials from patients who benefited from it and one negative testimonial from patients who did not, compared to conditions offering one positive and one negative testimonial.

Likewise, Betsch and colleagues (2010, 2011, 2013, 2015) conducted a series of studies to assess the perception of vaccine risk based on reading statistical and/or narrative information. Betsch et al. (2011) found that the more narratives reporting adverse events people read, the higher their perception of risk was, regardless of statistical information on adverse vaccine events. For example, in Study 1, conducted as a paper-and-pencil version of an online bulletin board, they tested the influence of the relative number of narratives reporting adverse events in the presence of statistical evidence. Seventy-two undergraduates were randomly assigned to one of three conditions (plus one control condition), with the relative number of narratives reporting adverse events as the independent variable. All participants were provided with constant statistical information (20%) from the World Health Organization (WHO) about the incidence of adverse events following vaccination. A visual presentation of statistics using icon arrays was employed to facilitate the comprehension of the presented statistic. In one condition, the relative number (i.e., ratio) of narratives reporting adverse events (2 out of 10) was consistent with the statistical information (20%); in two inconsistent conditions, the ratio was either lower (1 out of 10) or higher (4 out of 10) than the statistical probability. They found that reading narratives (vs. not reading narratives) increased the perception of the severity of adverse effects. Also, the relative number of narratives reporting adverse events significantly influenced perceived risk, even though all participants received the same statistical data (20%). The perceived risk was lower when the ratio of narratives suggested a lower incidence of adverse events compared to the statistics, than when both the narratives and statistics indicated the same incidence. Conversely, perceived risk was higher when the narratives implied an incidence greater than that suggested by the statistical data.

Overall, prior research suggests the power of narratives on risk perception, and the narrative's influence on probability neglect or narrative bias. Narratives vary in their purpose and content. Risk communicators need to be more cautious about using narratives when attempting to present unbiased information for informed decision making than when attempting to promote behavior change (Trevena et al., 2013).

Numeracy Research and Differential Use of Information

Processing numeric information is often thought to require more cognitive resources than processing narratives does. Individual differences in numeracy—the capability of processing and understanding basic probability and numerical concepts (e.g., Schwartz et al., 1997; Lipkus et al., 2001; Peters et al., 2006)—have been strongly associated with people's number use. Numeracy research suggests that not everyone can understand and use numbers. Individual differences in numeracy exist, and many people are "innumerate." Even highly educated individuals do not always comprehend numbers when making decisions (e.g., Lipkus et al., 2001; Peters, 2008; Peters et al., 2006; Reyna et al., 2009; Peters, 2020).

Beyond influencing number comprehension, numeracy influences the processing of numeric and non-numeric information. In particular, less numerate people are more likely to be insensitive to the numerical information provided and to use heuristic information instead. By contrast, more numerate people are more likely to use, and work well with the numbers provided (Peters et al., 2006; Peters, 2012, 2017; Reyna et al., 2009; Bruine De Bruin et al., 2015).

For instance, in Peters et al. (2006), participants were asked to draw a colored jelly bean from two bowls of colored and white jelly beans. The larger bowl contained 100 jelly beans, nine of which were colored and labeled as having “9% colored jelly beans,” while the smaller bowl contained ten jelly beans, one of which was colored, and was labeled as having “10% colored jelly beans.” The less numerate participants were significantly more likely to choose the larger bowl (subjectively more appealing but objectively worse) than the highly numerate participants. In another study relevant to risk assessment, they asked participants to assess the likelihood that a mental patient, “Mr. Jones,” would commit an act of violence. Participants based their decisions on a mental-patient scenario that they read in either a frequency (10 in 100) or a percentage (10%) format. Though the information they read was conceptually the same, the researchers found that the less numerate participants were more influenced by the numeric format than the highly numerate participants were. In particular, the highly numerate in both format conditions rated the likelihood of violence act as a medium risk. However, the less numerate participants gave a lower risk rating when they received the information as a percentage than when they received it as a frequency, presumably because the frequency format created more frightening images of violent patients than the percentage did. More negative feelings likely induced greater risk perceptions in response to the frequency format than the probability format (Slovic et al., 2004; Peters et al., 2006).

Moreover, when it comes to risk assessment involving both sources of information (narrative vs. numeric information), prior findings highlight differential use of information by people varying in numeracy. For example, in Dieckmann et al.’s (2009) Study 2, participants were asked to evaluate a terrorism risk based on risk forecasts, including both the numerical likelihood of the event (varying at levels: 1%, 5%, and 10%) and a narrative description of the evidence concerning the attack (randomly paired to the likelihood level), as well as a constant statement about the potential harm that would result if the attack were to occur. Participants were asked to rate their perceived likelihood of the attack after reading each forecast (0-100%), perceived usefulness of the forecast for decision-making, source credibility, and perception of the evidence described in each narrative (the overall credibility of the evidence in each narrative and how well the evidence in each narrative could be formed into a coherent story). The less numerate appeared to use the narrative evidence to a larger extent than the highly numerate (i.e., the more credible and coherent the evidence appeared, the more risk was perceived by the less numerate). The highly numerate showed this same effect to a smaller degree, and their risk perceptions also were sensitive to the explicit likelihood compared to the less numerate (i.e., the higher the provided numerical risk assessment appeared, the more risk was perceived by the highly numerate).

Such differential use of information by people varying in numeracy could also be found in studies on vaccine risk perceptions based on statistical and narrative information (e.g., Betsch et al., 2013, 2015; Bruine De Bruin et al., 2017). For instance, in Betsch et al.'s (2015) Study 2, participants (N = 464) responded to narratives reporting vaccine adverse events in a 2 (sequence of dependent variables: risk perception followed by subjective probability or vice versa) × 2 (sample size: 10 vs. 20 cases) × 3 (relative number of narratives reporting adverse events: 10% vs. 20% vs. 40%) between-subjects design plus four additional conditions. The statistical base-rate information was equal in all conditions (20%). The researchers then assessed risk perception, subjective probability, and objective numeracy, finding that highly numerate participants exhibited a weaker narrative bias compared to those with lower numeracy. In other words, the less numerate were more sensitive to the number of narratives reporting vaccine adverse events than the highly numerate, regardless of the statistical information presented.

In a similar vein, Bruine De Bruin et al. (2017) examined how participants varying in numeracy responded to anti-vaccine and pro-vaccine narratives. Participants (N = 1,113) were randomly assigned to an anti-vaccine or pro-vaccine narrative, as presented by a patient discussing a personal experience, a physician discussing a patient's experience, or a physician discussing the experiences of 50 patients. All participants additionally received the same statistical information from a publicly available pamphlet about vaccine benefits from the Centers for Disease Control and Prevention (CDC). Then, they were asked to indicate their probability of getting vaccinated and rate the informativeness of the narratives. The less numerate were more sensitive than the highly numerate to narrative information when making vaccine decisions. In particular, anti-vaccine narratives reduced the judged vaccination probabilities compared to pro-vaccine narratives. This effect was especially strong among participants with lower numeracy, who also perceived narratives as more informative than their counterparts.

The Role of Processing Difficulty

Typically, dual-process models imply that heuristic information will likely be favored by individuals with low processing resources. In contrast, deliberative information (e.g., statistical or logical contents, message arguments) will be used more when individuals have high processing resources. Prior numeracy research also highlights the variation in information use between numeric and non-numeric content among individuals with different levels of numeracy (e.g., Berger, 1998; Bruine De Bruin et al., 2015; Dieckmann et al., 2009; Trevena et al., 2006). However, and as noted earlier, some researchers have noted that it may not be the type of information that matters. Instead, the differential use of information may depend on information processing difficulty in combination with cognitive resources (e.g., Kruglanski & Thompson, 1999; Erb et al., 2003; Pierro et al., 2005).

For example, in dual-mode theories of persuasion, source information, unlike message argument information, is usually viewed as heuristic information (e.g., Chaiken, 1980; Petty &

Cacioppo, 1986). In Study 3 by Kruglanski and Thompson (1999), they tested the idea that increased processing difficulty of heuristic information would lead to greater reliance on it when participants had ample versus limited cognitive resources, based on their unimodal assumptions in the persuasion literature. To manipulate the processing difficulty of source information, they varied its length. Undergraduates at the University of Maryland (sample size was unknown) were exposed to a policy proposal requiring graduating seniors to pass a comprehensive exam in a 2 (source background: inexpert vs. expert) × 2 (distraction: no vs. yes) × 2 (source background length: short vs. long) experimental design. After receiving the source information, all participants were given the same one-page arguments in which the communicator argued in favor of the attitude topic (comprehensive exams). Orthogonal to the source information, they manipulated participants' cognitive load. Half the participants were presented at the outset with a nine-digit number and were asked to rehearse it to themselves as they went through the materials so as to be able to reproduce it later. No similar request was made to the remaining half of the participants. Also, to ensure that cognitive load would have an effect, all participants were run in a high-involvement condition from a prior study (the advocacy was said to involve a change in policy at participants' own university) to establish a sufficient baseline level of effortful processing. Then, they measured participants' attitudes toward comprehensive exams. They found a significant main effect of source expertise, such that attitudes were more favorable when the source was an expert than when he was not. The length of source information did not emerge as a main effect. However, a significant three-way interaction (expertise × distraction × length) emerged such that long source expertise information had a persuasive effect in the absence of cognitive load, mimicking message argument effects in prior persuasion research. Their study was replicated in Pierro et al.'s Study 1

(2005), confirming the effect of processing difficulty on information use via manipulating information length.

Of greater relevance to the present study, Chun and Kruglanski (2006) examined the impact of processing difficulty on the use of statistical information within the abovementioned base-rate neglect paradigm (Kahneman & Tversky, 1973). In Study 1, the researchers manipulated processing difficulty and base rates using a 2 (condition: replication, reversal) × 2 (base rate of engineers: 70%, 30%) between-subjects design. Ninety-two undergraduate students at the University of Maryland were randomly assigned to one of four conditions. In the replication condition, they replicated the classic base-rate neglect study by presenting brief base-rate information up front followed by lengthier individuating information. In the reversal condition, they reversed these relations by presenting brief individuating information first, followed by lengthier and more complex base-rate information. To make the statistics complex and lengthy, the overall base rate was decomposed into base rates of various subcategories. For example, rather than being told engineers comprised 70% of the population and lawyers comprised 30%, participants were told the population consisted of 14% electrical engineers, 6% chemical engineers, 9% divorce lawyers, 4% nuclear engineers, 10% civil engineers, 11% criminal lawyers, 12% sound engineers, 8% genetic engineers, 10% trade lawyers, and 16% mechanical engineers. All participants then estimated the likelihood of Dan being an engineer. Results revealed a significant interaction between condition and base rates. As shown in Table 1, base-rate neglect occurred in the replication condition, but when the narrative was brief and presented first and the statistics were longer and presented second, participants demonstrated considerable base-rate use, counter to findings in the base-rate neglect paradigm. They reasoned if participants were able to process the lengthy and late-appearing information (because the narrative was brief), they would tend to base their judgments on the later, more difficult-to-process information (although they could not determine whether the narrative was neglected but could identify whether the statistics were used more).

Table 1. Likelihood Estimation (Chances Out of 100) That the Target Is an Engineer as a Function of Condition and Base Rate (Chun & Kruglanski, 2006)

	Condition	
Engineer base rate	Replication	Reversal
70%	76.52	67.00
30%	72.69	44.35
Difference	3.83	22.65***

*** $p < .001$.

Then, the authors continued to examine if such base-rate use resulted from processing difficulty or use of a heuristic (in which the breakdown of the sample into its various subcategories somehow highlighted the relevance of the base rates to the judgmental task). In Study 2, they added a manipulation of cognitive load in which half of participants rehearsed a nine-digit number while reading the information. All participants then were asked to estimate the likelihood of Dan being an engineer. According to traditional findings with the representativeness heuristic, its use was expected to increase under cognitive load. A 2 (condition: replication, reversal) × 2 (base rate of engineers: 70%, 30%) × 2 (cognitive load: high, low) ANOVA was conducted. A significant main effect of the base rate showed that the likelihood of Dan being an engineer was judged as higher when the engineer base rate was high (vs. low). A significant main effect of the condition demonstrated that participants in the replication condition judged the likelihood of Dan being an engineer higher than participants in the reversal condition. Finally, the significant main effect of load indicated that the likelihood estimates of participants under high load were lower than those under low load.

Moreover, a three-way interaction between condition, base rates, and cognitive load was also significant, modifying the observed effects. In particular, the Study 1 results were replicated when participants were under low cognitive load but reversed when they were under high cognitive load (see Table 2).

Table 2. Likelihood Estimation (Chances Out of 100) That the Target is an Engineer as a Function of the Condition, Cognitive Load, and Base Rate (Chun & Kruglanski, 2006).

	Replication		Reversal	
Engineer base rate	High load	Low load	High load	Low load
70%	63.64	75.00	50.00	63.85
30%	43.00	63.33	45.38	35.38
Difference	20.64*	11.67	4.62	28.47***

* $p < .01$. *** $p < .001$.

Under low cognitive load, participants replicated the findings from Study 1 by relying more on base rates in the reversal condition, where the base rates were harder to process, compared to the replication condition, where they were easier to process. In contrast, under high cognitive load, participants relied more on base rates in the replication condition (easier to process) than in the reversal condition (harder to process). This challenges the traditional view that people rely more on heuristics when cognitive resources are limited. The authors argue that when individuals have sufficient cognitive resources, they can process complex, later-presented information, which overshadows simpler, earlier information. However, with limited cognitive resources, people focus on brief, upfront information to make their judgments.

Back to the question of whether the use of a subdivided base-rate resulted from processing difficulty or use of a heuristic (with heuristic processing, the breakdown of the base-rate into its various subcategories may have somehow highlighted the relevance of the subdivided base rates), the authors argued that if using the subdivided numeric information resulted from a heuristic, it should be more likely to be used by participants who had limited cognitive resources than participants who had more, based on prior findings in Dual Process Theory. However, in Study 2, the divided base rates were used only when there was no cognitive load, and participants had ample cognitive resources. Therefore, they excluded the possibility of heuristic use of complex subdivided base-rates and concluded that the relation between the processing difficulty of information and the cognitive resources determines the differential use of information.

Their findings have important implications for communicators: information with varying processing difficulty influences audiences differently based on their cognitive resources. Brief, upfront probabilities may be more effective when cognitive resources are limited, while complex, later-presented probabilities may work better with sufficient resources. Since risk communicators often use narratives alongside numerical data to clarify complex issues, testing these possibilities is essential. To the author's knowledge, no existing research has been conducted to test this hypothesis. Thus, the present study fills a gap in the literature.

With respect to processing numeric information, numeracy ability is a critical cognitive resource. Research in this area, however, has focused little on the length and order effects in processing numeric risk information in the presence of narrative evidence. Therefore, the present research aims to address this question by including numeracy instead of the cognitive load manipulation used in Chun and Kruglanski (2006). If processing difficulty matters in varied information use, then it may be possible to enhance the use of numeric risk information among people varying in numeracy by altering its difficulty. To the author's best knowledge, little research has been done on this issue. Therefore, the following hypotheses were proposed:

Hypothesis 1 (H1): Participants will be more sensitive to risk levels when numeric risk information is harder to process compared to when it is easier to process.

Hypothesis 2 (H2): H1 would be modified by numeracy such that the highly numerate would show stronger effects. The less numerate instead would be more likely to use easier-to-process numbers than harder-to-process numbers.

In Study 1, easier-to-process numbers were briefly presented before a long narrative, while harder-to-process numbers were complex and introduced after a brief narrative. Further details are provided in subsequent sections.

Beyond the length of numeric information, other factors may also contribute to processing difficulty. In particular, prior studies indicate that the precision level of numbers (e.g., 7% vs. 7.14%; the former one is less precise as numbers with fewer decimals or more trailing zeros are considered less precise (Pena-Marin & Yan, 2021) is another potential aspect of processing difficulty (Fassbender et al., 2014; Pena-Marin & Yan, 2021; Thomas et al., 2010). For instance, research suggests that fractions and decimals are more difficult than whole numbers. This is partly because whole numbers are the most frequently encountered in everyday language and the earliest experienced type of number (Iuculano & Butterworth, 2011; Wadhwa & Zhang, 2015, 2019). Indeed, in everyday communication, people are more likely to use simple numbers (e.g., this book is about \$10–\$12) than complex precise numbers (e.g., this book is about \$10.35–\$12.35) (Pollmann & Jansen, 1996; Wadhwa & Zhang, 2015). The processing fluency model posits that when a stimulus is encountered, a memory representation of its features and/or meaning is formed. This representation makes it easier to process the stimulus upon later exposures. Fluency is improved through incidental exposure and grows steadily with repeated encounters. Consequently, the frequent use and exposure to simple numbers boost their ease of processing (Janiszewski & Meyvis, 2001; Kettle & Häubl, 2010; Lee & Labroo, 2004). In other words, precise numbers with more decimals (e.g., 7.14%) are considered more demanding than imprecise numbers without decimals (e.g., 7%) (e.g., Jerez-Fernandez et al., 2014; Schindler & Yalch, 2006; Wadhwa & Zhang, 2015, 2019).

Moreover, the precision of numeric risks matters in risk perception and judgments. Research on fluency indicates that processing fluency, the subjective ease with which individuals process information about a target, serves as a metacognitive cue that can influence preferences and decision-making in various ways. The fluency amplification model further suggests that the subjective experience of fluency can enhance positive emotional reactions toward a positively perceived target and also intensify negative emotional reactions toward a negatively perceived target (Albrecht & Carbon, 2014; Alter & Oppenheimer, 2009; Carbon & Albrecht, 2016). Consistently, within a health risk context, Wadhwa & Zhang (2019) found that people indicated a higher intention to take a flu vaccine when exposed to a preventive message presenting flu-related numerical cues as round (e.g., 60.00%) versus precise numbers (e.g., 60.41%). In addition, exposure to round (vs. precise) numbers increased their negative affective reactions toward the flu risk, which mediated the impact of round versus precise numbers on the intention to take the vaccination.

However, to date, little attention has been paid to examining the processing difficulty of numbers, specifically in terms of precision, on risk perception in the presence of narratives. This was the focus of Study 2. Based on Chun and Kruglanski (2006), numeric risk information that is harder to process (i.e., precise and presented after a brief narrative) is expected to be used more by people with ample cognitive resources. In contrast, the easier numeric risk information (i.e., imprecise and presented before a long narrative) is expected to be used more by people with limited cognitive resources.

In sum, Study 2 continued to examine the hypotheses regarding the roles of information processing difficulty and numeracy in the use of numeric information. Easier-to-process numbers were imprecise presented before a long narrative, while harder-to-process numbers were precise and presented after a brief narrative. It was anticipated that participants would be more sensitive to risk levels when numeric risk information was precise and presented second, compared to when it was imprecise and presented first. Additionally, this effect was expected to be moderated by numeracy, with highly numerate individuals showing stronger effects, while less numerate individuals were more likely to rely on imprecise and earlier-presented information.

CHAPTER III METHODOLOGY

Method Overview

In each study, participants were randomly assigned to review an article that provided both numerical and narrative information about a medication, including a specific probability of side effects adapted from Peters et al. (2011). The processing difficulty of the numeric side effect information was manipulated by varying the complexity of both numeric and narrative content; the order of numerical information and narrative was also manipulated. Participants' sensitivity to numeric risk information then was assessed in the context of accompanying narratives. To capture key aspects of participants' attitudes and intentions toward the medication and provide a comprehensive assessment of their responses, the studies measured four key outcomes: affect, risk perception, benefit perception, and behavioral intention.

According to the risk-as-feelings approach, risk perception is influenced by both cognition and affect (or feelings). To account for this, a pilot test was conducted before the main studies to ensure that narratives of varying lengths did not significantly differ in inducing affect toward the medication without introducing confounding effects on risk perception. The study was approved by the University of Oregon Institutional Review Board and preregistered. For details, see Study 1 at https://osf.io/3jh97/?view_only=0fdbe722e19e445d9679e6f85ecf6b7d and Study 2 at https://osf.io/c985g/?view_only=9886ba108e6643da9e92d249c7f40644.

Power analysis

Using G*Power and assuming a small to medium effect size (f = .12) due to the lack of effect size data from previous studies, an alpha level of .05, and 80% power, numerator df = 1, number of groups = 4, an a priori power analysis for ANOVA indicated that at least 547 participants are needed for powering main effects and interactions. For ANCOVA, using a similar analysis with a small to medium effect size (f = .12), alpha = .05, power = .80, 1 numerator df, 4 groups, and 1 covariate, the required sample size also came out to 547 participants.

However, G*Power's estimates are often criticized for underestimating the sample size required for detecting interactions. Recent studies, such as Sommet et al. (2023), emphasize that detecting interactions, especially small effects, typically requires much larger sample sizes. Complex designs, like those involving three-way interactions, demand even greater statistical power to detect these effects reliably.

Ultimately, the final sample size determination was based on a combination of power analysis calculations, the size of the cleaned baseline cohorts, and the financial resources available. Given these constraints, the goal was to recruit as many participants as possible to detect the anticipated effects.

Participants

In Study 1, 751 participants were recruited from a cleaned CloudResearch baseline cohort (cohort N = 1503). In the baseline survey, participants had responded to several variables of interest, including numeracy, subjective numeracy, and demographics. The cleaned baseline cohort included participants who passed two attention checks, provided meaningful responses, did not use a calculator or search for answers, and had a U.S.-based IP address. To ensure reliability, participants were required to have a 99%-100% Human Intelligence Task (HIT) approval rating and have completed at least 500 HITs.

In Study 2, 1,000 participants were recruited from a cleaned Prolific baseline cohort of participants (cohort N = 1,460) who had responded to several variables of interest, including numeracy, subjective numeracy, and demographics. The cleaned baseline cohort was US-based, required English fluency, and excluded participants who failed all four attention checks or completed the survey in less than one-third of the median completion time (i.e. two participants were removed because they finished in under 5 minutes).

The surveys for Studies 1 and 2 included two attention checks: a first-grade level math question ("If John has 2 marmots and Matt has 3 marmots, how many marmots do John and Matt have together?") and a simple choice task ("What was the primary topic of the article you just saw? Please choose one: Education, Medication, Law, Agriculture, Immigration"). Participants who failed both attention checks were excluded from the analyses. Additionally, any participant who missed more than 5% of the responses was also excluded from the analyses.

Baseline Measures

Numeracy. In this dissertation, numeracy refers to objective numeracy, which was assessed using the Adaptive Numeric Understanding Measure (A-NUM). The A-NUM consists of 13 unique items and adapts by presenting different questions based on participants' performance. Participants were categorized into nine ability levels, ranging from 1 to 9 (Silverstein et al., 2023).

Subjective Numeracy Scale (SNS) (Fagerlin et al., 2007). Participants completed eight items, with four items assessing numeric self-efficacy and four items assessing number preferences, using 6-point scales ranging from 1 to 6. The overall score was calculated as the average of the eight items, and higher scores indicated greater subjective numeracy. (*Note: In Study 2, an additional item specifically assessing preferences between numeric and narrative formats in health decision-making was added to the scale. Consequently, scores in Study 2 were averaged across the nine items.*). This measure and its subscales were used for exploratory analysis.

Demographic. Participants' age, gender, race, education, and family income were collected (see Appendix for detailed items).

Key Outcome Measures

Affect. Participants' affective response to the medication was measured using a 5-point scale. They were asked, "How do you feel about ReliefMax?" with response options ranging from "Extremely negative" to "Extremely positive".

Risk Perception. Participants' perception of the risk associated with the medication was assessed using a 5-point scale adapted from Windschitl and Wells (1996). They responded to the question, "Based on what you read about ReliefMax, how risky do you think it is?" with options ranging from "Not at all risky" to "Very highly risky".

Benefit Perception. The perceived benefits of the medication were evaluated using a 5-point scale. Participants were asked, "How beneficial do you think ReliefMax is?" with response options ranging from "Not at all beneficial" to "Very highly beneficial".

Behavioral intention. Participants' intention to take the medication was measured using a 5-point scale. They answered the question, "How likely are you to take ReliefMax for headaches?" with options ranging from "Extremely unlikely" to "Extremely likely".

Other measures common to both studies

Numeric Processing Difficulty Manipulation Check. To assess the efficacy of the processing difficulty manipulation, participants rated the difficulty of processing the numeric data regarding the side effects of ReliefMax on a 5-point scale. They were presented with the statement: "You read an article about ReliefMax earlier. To what extent do you agree with this statement? It was difficult to read through and understand the numeric data regarding the side effects of

ReliefMax." Responses ranged from "Strongly disagree" to "Strongly agree", with higher scores indicating greater perceived numeric difficulty.

Data Evaluation. Participants evaluated the numeric risk information using a 6-point bipolar scale matrix. The following adjective pairs were used to assess their opinions: Boring – Interesting, Useless – Useful, Untrustworthy – Trustworthy, Confusing – Clear, Unconvincing – Convincing, and Biased – Accurate. An overall Data Evaluation index was created by averaging participants' responses across these six items. Higher scores reflected more positive evaluations of the numeric information.

Accuracy Motivation. Participants rated six items designed to assess their motivation to accurately process the numeric data on a 5-point scale ranged from "Strongly disagree" to "Strongly agree". The items included:

1) "I carefully evaluated the numeric data on ReliefMax side effects to ensure I made an accurate medication decision."

2) "I believe understanding numeric data accurately is crucial for making informed choices about ReliefMax."

3) "The reliability of numeric data on ReliefMax side effects was a primary concern for me."

4) "I relied more on intuition than numeric data when reading about ReliefMax side effects."

5) "Personal stories and testimonials significantly influenced my opinion about ReliefMax side effects."

6) "I found numeric data regarding ReliefMax side effects to be irrelevant or useless."

The last three items were reverse-coded, and an accuracy motivation index was created by averaging responses to all six items. Higher scores indicated a stronger motivation to process the numeric data accurately.

Pilot Test

A total of 150 participants were recruited through CloudResearch and randomly assigned to read narratives of varying lengths. Following their reading, participants were asked to respond to three questions (affect, risk perception, and benefit perception).

The instructional message provided to participants was as follows:

> “Imagine you frequently suffer from severe headaches that force you to miss work or school. Common headache medications do not work for you. Your doctor has given you an article about an alternative headache medicine called ReliefMax. The medication is generally effective, but some users may experience dizziness. Below, please read Sam's story about her experience with ReliefMax, and answer questions.”

On the next page, Sam’s story was presented as follows, with alternative versions provided in brackets:

> “I tried ReliefMax for headaches. Unexpectedly, I felt everything spinning uncontrollably. I felt as if my body wasn't mine, making it difficult for me to concentrate on the tasks at hand. My friends could not truly grasp how bad it made me feel. Although ReliefMax helped my headaches, the dizziness made me feel scared, isolated, and out of control.”

[“I tried ReliefMax for headaches. Everything spun, friends couldn't grasp my turmoil. It helped headaches but made me feel scared, isolated, and out of control.” Sam explained.]

Three t-tests were performed to assess whether there were significant differences in outcomes between the two conditions. Since the outcomes were not normally distributed, their logarithmic values were used for analysis. The results indicated no significant differences between the two narratives in terms of affect, $t(148) = 0.75$, $p = .45$, Cohen’s $d = .14$; risk perception, $t(148) = - 0.45$, $p = .65$, Cohen’s $d = -.07$; or benefit perception, $t(141)$ 1.93, $p = .06$, Cohen’s $d = .31$ Descriptive statistics (mean and standard deviation) are provided below in Table 3.

Table 3. Raw means and standard deviations for the three outcomes across conditions in the pilot test.

	Long Narrative (*N* = 77)	Short Narrative (*N* = 73)
Affect (higher numbers mean more positive affect)	1.87 (.78)	1.77 (.66)
Risk Perception	4.38 (.90)	4.44 (.88)
Benefit Perception	3.21(.92)	2.92 (.97)

Thus, the goal of the pilot test for the subsequent main studies has been achieved: narratives of varying lengths did not significantly differ in inducing affect toward the medication without introducing confounding effects on risk perception.

CHAPTER IV STUDY 1

Materials and Procedure

751 participants were recruited from the cleaned CloudResearch baseline cohort mentioned earlier. The invited participants first encountered an informed consent page, which indicated the details of the study, the researcher's contact information, and a statement of voluntary participation.

People who consented to participate were asked to imagine they suffered from headaches severe enough to cause them to miss work or school. Then, they were given information about a medication narrative with a fixed probability of side effects derived from Peters et al. (2011). Numeric side effect information was read as a percentage of patients experiencing dizziness after taking the medication.

In Study 1, the effect of processing difficulty, defined by numeric length and presentation order, was tested using a 2 (Numeric Processing Difficulty: easy vs. hard) × 2 (Risk Level: low vs. high) between-participants design. The narratives also varied in length between the easy and hard conditions (when numbers were easy and first, the narrative was longer and second; when numbers were harder and second, the narrative was shorter and first), similar to Chun and Kruglanski (2006). This approach deviated from the preregistered plan for Study 1, which had originally intended to hold narrative length constant across conditions. The decision was made to revert to the technique used in Chun and Kruglanski (2006) because it was deemed more likely to reveal an effect, providing a sound starting point for the study.

Risk level was manipulated as low (2%) versus high (12%). In the easy numeric condition, the risk was presented briefly (e.g., 12%) before a longer narrative. In contrast, in the hard numeric condition, the risk information was made more complex by detailing risk levels in levels that vary no more than 2% from the average, and was presented after a brief narrative. Therefore, participants were randomly assigned to one of four experimental conditions, as outlined below (Table 4):

Table 4. Four experimental conditions in Study 1.

Easy Low	In recent clinical trials, approximately 2% of ReliefMax users experienced dizziness, which ranged from barely noticeable to very severe. Sam shared the following: "I tried ReliefMax for headaches. Unexpectedly, I felt everything spinning uncontrollably. I felt as if my body wasn't mine, making it difficult for me to concentrate on the tasks at hand. My friends could not truly grasp how bad it made me feel. Although ReliefMax helped my headaches, the dizziness made me feel scared, isolated, and out of control."
Easy High	In recent clinical trials, approximately 12% of ReliefMax users experienced dizziness, which ranged from barely noticeable to very severe. Sam shared the following: "I tried ReliefMax for headaches. Unexpectedly, I felt everything spinning uncontrollably. I felt as if my body wasn't mine, making it difficult for me to concentrate on the tasks at hand. My friends could not truly grasp how bad it made me feel. Although ReliefMax helped my headaches, the dizziness made me feel scared, isolated, and out of control."
Hard low	"I tried ReliefMax for headaches. Everything spun, friends couldn't grasp my turmoil. It helped headaches but made me feel scared, isolated, and out of control," Sam shared.

	In recent clinical trials, the level of dizziness experienced by ReliefMax users varied: 0.2% reported it as barely noticeable, 0.2% as very mild, 0.3% as mild, 0.3% as somewhat moderate, 0.3% as moderate, 0.3% as moderately severe, 0.2% as quite severe, 0.1% as severe, and 0.1% as very severe.
Hard high	"I tried ReliefMax for headaches. Everything spun, friends couldn't grasp my turmoil. It helped headaches but made me feel scared, isolated, and out of control," Sam shared. In recent clinical trials, the level of dizziness experienced by ReliefMax users varied: 0.7% reported it as barely noticeable, 1.1% as very mild, 1.5% as mild, 2% as somewhat moderate, 2.2% as moderate, 2.3% as moderately severe, 1.6% as quite severe, 0.3% as severe, and 0.3% as very severe.

Measures

The measures introduced in the methodology Chapter III were implemented, including a manipulation check, four key outcomes (Affect, Risk Perception, Benefit Perception, and Behavioral Intention), Data Evaluation (Cronbach's α = .89), and Accuracy Motivation (Cronbach's α = .64). In addition, an open-ended question was included asking participants to list at least three different thoughts or feelings they had during the task, "As best you can, please list at least three different thoughts or feelings you had during the task." All study materials have been preregistered and can be accessed at https://osf.io/3jh97/?view_only=0fdbe722e19e445d9679e6f85ecf6b7d. Detailed measurements can be found in the Appendix.

Data analysis strategy

RStudio was used for data cleaning and all statistical analyses. Participants who failed two attention checks or missed more than 5% of responses were excluded from the dataset. A manipulation check was performed, and the assumptions for Multivariate Analysis of Variance (MANOVA), Analysis of Variance (ANOVA), and regression were examined and met.

A MANOVA was conducted to test the effect of factors on combined outcomes for H1. This approach is particularly advantageous when dealing with multiple correlated outcomes, as it controls the overall Type I error rate (false positives) more effectively than running separate ANOVAs on each outcome individually (Huberty & Morris, 1989; Stevens, 2009; Tabachnick et al., 2019). Upon finding a significant multivariate effect, follow-up individual ANOVAs were performed to identify which specific outcomes contributed to the observed effect.

For testing Hypothesis 2, which examined the moderating effect of numeracy on H1, MANCOVAs and ANCOVAs were employed. Additionally, MANCOVAs and ANCOVAs were conducted in exploratory analyses replacing numeracy with other potential moderators of interest. To decompose interactions to compare effects at high vs. low ability, values at ± 1 SD from the mean were used in inferential analysis.

Results

Data cleaning and demographics

After data cleaning, one participant was removed due to failing both attention checks. Of the 750 participants after data cleaning, the average age was 45.40 years (*SD* = 12.65). Women comprised 43.07% of the sample. The racial composition was predominantly White (non-

Hispanic) at 78.8%, followed by Black (7.5%), Asian (7.5%), Hispanic (2.9%), Native American (0.1%), Middle Eastern (0.3%), Multiple/Mixed (2.4%), and Other (0.5%).

Regarding education, nearly half of the participants (44.4%) were 4-year college graduates, followed by those with a high school diploma or GED (24%), a 2-year college or technical degree (14.7%), a Master's degree (14.1%), and a PhD or other professional degree (JD, MD, etc.) (2.8%). The most frequently reported income levels were \$40,000 - \$49,999 and \$30,000 - \$39,999, with 10.7% and 9.3% of participants, respectively.

Condition effects across demographics (i.e., age, gender, race, education, family income) and baseline abilities were examined and did not reveal significant differences across conditions (see Table 5). Additionally, descriptive statistics about key outcomes are provided in Table 6, and correlations between variables are presented in Table 7.

Table 5. No Significant Differences in Demographics and Baseline Abilities Across Conditions in Study 1.

	EasyLow (N=200)	EasyHigh (N=181)	HardLow (N=204)	HardHigh (N=165)	Test Statistic p-value
Age	45.37 (*SD* = 12.40)	44.88 (*SD* = 13.06)	45.72 (*SD* = 12.91)	45.61 (*SD* = 12.23)	$F(3, 746) = .16$, $p = .92$
Gender					$\chi^2\,(12) = 11.43$, $p = .49$
Woman	83	79	88	73	
Man	114	101	114	88	
Transgender	1	0	1	0	
Non-binary/non-conforming	1	1	0	0	
Other (optional description)	0	0	0	0	
Prefer not to respond	1	0	1	4	
Race					$\chi^2\,(21) = 20.41$, $p = .50$
White (non-Hispanic)	149	147	161	134	
Black	13	17	14	12	
Hispanic	8	6	5	3	
Asian	19	8	16	13	
Native American	0	0	1	0	
Middle Eastern	2	0	0	0	
Multiple/Mixed	7	3	5	3	
Other	2	0	2	0	
Education					$\chi^2\,(12) = 6.14$, $p = .91$
High school diploma or GED	51	47	46	36	
2-year college or technical degree	33	26	32	19	
4-year college graduate	86	76	92	79	
Master's degree	27	27	28	24	
PhD or other professional degrees (JD, MD, etc.)	3	5	6	7	

Income					χ^2 (39) = 35.75, p = .62
Less than $10,000	7	5	9	4	
$10,000 - $19,999	11	14	13	11	
$20,000 - $29,999	20	15	14	17	
$30,000 - $39,999	22	13	21	14	
$40,000 - $49,999	23	18	28	11	
$50,000 - $59,999	16	26	16	15	
$60,000 - $69,999	17	17	13	21	
$70,000 - $79,999	21	19	15	9	
$80,000 - $89,999	14	9	18	9	
$90,000 - $99,999	11	9	12	12	
$100,000 -$119,999	14	12	15	12	
$120,000 - $149,999	7	10	16	15	
$150,000 or more	16	14	14	15	
NA	1	0	0	0	
Numeracy (range = 1 to 9)	4.92 (SD = 1.48)	4.90 (SD = 1.38)	4.95 (SD = 1.44)	4.96 (SD = 1.39)	$F(3, 746) = .08$, $p = .97$
Subjective Numeracy (range = 1.5 to 6)	4.79 (SD = .81)	4.85 (SD = .88)	4.85 (SD = .80)	4.90 (SD = .82)	$F(3, 746) = .61$, $p = .61$

Table 6. Descriptive statistics about key outcomes in Study 1.

Variables	n	Mean	SD	Min	Max
Affect	750	2.87	1.09	1	5
Risk perception	750	2.69	0.86	1	5
Benefit perception	750	3.22	0.93	1	5
Behavioral intention	750	2.86	1.36	1	5

Table 7. Correlations between variables in Study 1.

	Processing Difficulty	Risk Level	Affect	Risk Perception	Benefit Perception	Behavioral Intention	Data Evaluation	Accuracy Motivation	Numeracy	Subjective Numeracy Scale	Numeric Self-efficacy	Number Pre-ferences
Processing Difficulty	-											
RiskLevel	-.03	-										
Affect	.09 *	-.13 ***	-									
Risk Perception	-.15 ***	.13 ***	-.64 ***	-								
Benefit Perception	.08 *	-.13 ***	.71 ***	-.57 ***	-							
Behavioral Pntention	.03	-.15 ***	.82 ***	-.61 ***	.72 ***	-						
Data Evaluation	-.02	.05	.19 ***	-.12 ***	.23 ***	.2 ***	-					
Accuracy Motivation	.15 ***	-.08 *	.37 ***	-.39 ***	.33 ***	.37 ***	.36 ***	-				
Numeracy	.02	0	.16 ***	-.18 ***	.14 ***	.14 ***	.13 ***	.23 ***	-			
Subjective Numeracy Scale	.04	.03	.07	-.02	.07 *	.03	.14 ***	.22 ***	.44 ***	-		
Numeric Self-efficacy	.03	.03	.06	-.01	.04	.01	.09 *	.14 ***	.43 ***	.89 ***	-	
Number Preferences	.03	.02	.05	-.02	.09 *	.05	.16 ***	.25 ***	.3 ***	.81 ***	.46 ***	-

Note: In the study, two manipulations were coded respectively as 'Processing Difficulty' and 'Risk level';
*** p < .001, ** p < .01, * p < .05

Manipulation Check

On a 5-point Likert scale, participants were asked, "To what extent do you agree with this statement? It is difficult to read through and understand the numeric data regarding the side effects of ReliefMax." An independent samples t-test was conducted to compare manipulation check scores between the easy and hard conditions. The manipulation was effective, as evidenced by a significant difference in scores between the easy (shorter and upfront; M = 1.73, SD = 0.95) and hard (longer and later; M = 2.10, SD = 1.16) processing difficulty conditions; $t(710) = -4.84$, $p < .001$.

Hypotheses Testing

H1 (that participants will be more sensitive to risk levels when numeric risk information is harder to process compared to when it is easier to process).

The MANOVA results revealed significant effects of Processing Difficulty (Pillai's Trace = .03, $F(4, 743) = 6.20$, $p < .001$, $\eta_p^2 = .01$), Risk Level (Pillai's Trace = .03, $F(4, 743) = 4.80$, $p < .001$, $\eta_p^2 = .02$), and their interaction (Pillai's Trace = .02, $F(4, 743) = 2.90$, $p = .02$, $\eta_p^2 = .003$) on the combined outcomes. To foreshadow the more detailed results that follow, according to the univariate ANOVA results from the MANOVA, Processing Difficulty had a significant effect on affect ($p = .02$), risk perception ($p < .001$), and benefit perception ($p = .02$), but not on behavioral intention ($p = .44$). Risk Level significantly influenced all four outcomes ($p < .001$ for each). Finally, the interaction between Processing Difficulty and Risk Level was significant only for affect ($p = .01$) and not for risk perception ($p = .58$), benefit perception ($p = .16$), or behavioral intention ($p = .33$).

Given the significant effects of factors in MANOVA results, individual Type III ANOVAs were performed for each outcome to identify specific effects.

1) Affect

The effect of Processing Difficulty on affect was significant, $F(1, 746) = 4.47$, $p = .03$, $\eta_p^2 = .006$. Participants in the easy conditions ($M = 2.78$, $SE = .06$) reported less positive affect to the medication compared to those in the hard conditions ($M = 2.94$, $SE = .06$). The effect of Risk Level on affect was significant, $F(1, 746) = 13.50$, $p < .001$, $\eta_p^2 = .02$. Participants in the low conditions ($M = 3.01$, $SE = .05$) reported more positive affect to the medication compared to those in the high conditions ($M = 2.72$, $SE = .06$). Notably, the interaction between Processing Difficulty and Risk Level was significant, $F(1, 746) = 6.73$, $p = .01$, $\eta_p^2 = .009$. Post hoc pairwise comparisons revealed that under the hard processing condition, participants' affect toward the medication was significantly more sensitive to the risk levels (See Table 8). Specifically, they reported less positive feelings to the 12% high-risk condition than in the 2% low-risk condition but especially in the hard condition (mean difference was larger in the hard condition).

Table 8. Estimated Marginal Means and SEs of Affect Predicted by Processing Difficulty and Risk Level in Study 1.

	Processing Difficulty	**Risk Level**	**Affect**
	Easy	Low	2.82 (.08)
		High	2.73 (.08)
Difference			.09
	Hard	Low	3.19 (.08)
		High	2.70 (.08)
Difference			.49***

*** p < .001, ** p < .01, * p < .05

2) Risk Perception

The effect of Processing Difficulty on risk perception was significant, $F(1, 746) = 16.00$, $p < .001$, $\eta_p^2 = .02$. Participants in the easy conditions ($M = 2.82$, $SE = .04$) reported higher risk perception of the medication compared to those in the hard conditions ($M = 2.57$, $SE = .04$). The effect of Risk Level on risk perception also was significant, $F(1, 746) = 12.73$, $p < .001$, $\eta_p^2 = .02$. Participants in the low-risk conditions ($M = 2.59$, $SE = .04$) reported lower risk perception of the medication compared to those in high-risk conditions ($M = 2.81$, $SE = .05$). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 746) = .31$, $p = .58$, $\eta_p^2 = .000$.

3) Benefit Perception

The effect of Processing Difficulty on benefit perception was significant, $F(1, 746) = 4.17$, $p = .04$, $\eta_p^2 = .006$. Participants in the easy conditions ($M = 3.14$, $SE = .05$) reported lower benefit perception of the medication compared to those in the hard conditions ($M = 3.28$, $SE = .05$). The effect of Risk Level on benefit perception was significant, $F(1, 746) = 12.45$, $p < .001$, $\eta_p^2 = .02$. Participants in the low-risk conditions ($M = 3.33$, $SE = .05$) reported higher benefit perception of the medication compared to those in high-risk conditions ($M = 3.09$, $SE = .05$). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 746) = 1.95$, $p = .16$, $\eta_p^2 = .003$.

4) Behavioral intention

The effect of Processing Difficulty on behavioral intention was not significant, $F(1, 746) = .33$, $p = .57$, $\eta_p^2 = .000$. In contrast, the effect of Risk Level on behavioral intention was significant, $F(1, 746) = 17.49$, $p < .001$, $\eta_p^2 = .02$. Participants in the low-risk conditions ($M = 3.05$, $SE = .07$) reported higher behavioral intention to use the medication compared to those in high-risk conditions (M = 2.64, SE = .07). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 746) = .94$, $p = .33$, $\eta_p^2 = .003$.

For exploratory purposes, the means across conditions were examined. Although the interactions between Processing Difficulty and Risk Level for risk perception, benefit perception, and behavioral intention were not statistically significant, the mean differences across conditions provided directional support for H1. Specifically, risk perception exhibited directionally greater sensitivity to risk levels under hard conditions compared to easy conditions ($M_{\text{HardHigh}} - M_{\text{HardLow}}$ = .26 vs $M_{\text{EasyHigh}} - M_{\text{EasyLow}}$ = .19). Similarly, benefit perception showed directionally higher sensitivity to risk levels under hard conditions compared to easy conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}}$ = .33 vs $M_{\text{EasyLow}} - M_{\text{EasyHigh}}$ = .14). Finally, behavioral intention showed directionally higher sensitivity to risk levels under hard conditions compared to easy conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}}$ = .51 vs $M_{\text{EasyLow}} - M_{\text{EasyHigh}}$ = .32). See Figure 1 for an illustration of the interaction between processing difficulty and risk level in relation to individual outcomes.

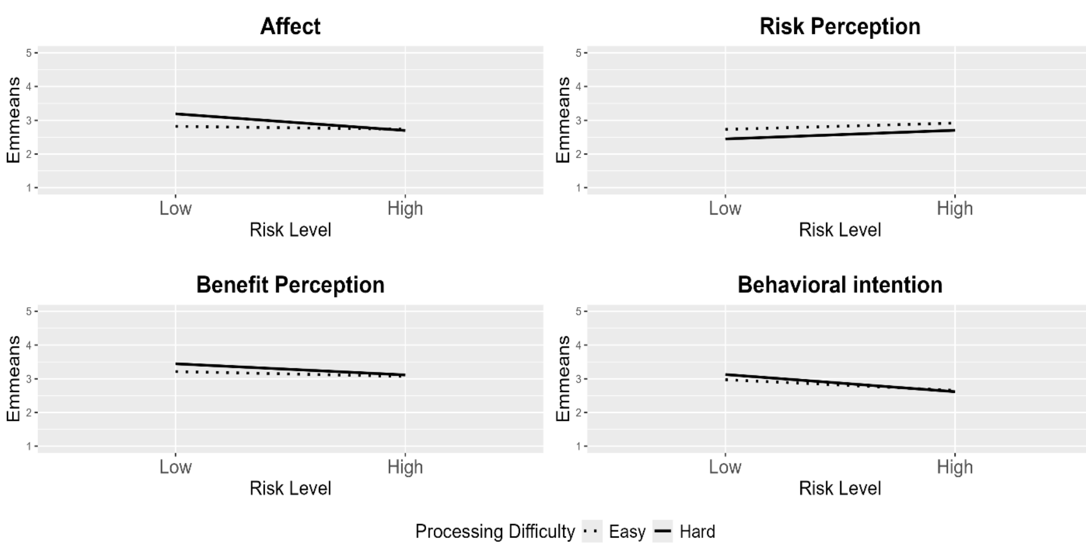

Figure 1. Increased sensitivity to risk levels in the hard numeric conditions compared to the easy numeric conditions for the four outcome variables. Note: Significance of the interaction was observed only for Affect.

H2 (that H1 would be modified by numeracy such that the highly numerate would show stronger effects of using numbers when it's harder than easier. The less numerate instead would be more likely to use easier-to-process numbers than harder-to-process numbers).

A MANCOVA was conducted to evaluate the effects of processing difficulty, risk level, numeracy, and their interactions on the combined outcomes (affect, risk perception, benefit perception, and behavioral intention). The analysis indicated that none of the predictors or their interactions had a statistically significant effect on the combined dependent variables. Individual ANCOVAs were not conducted due to the lack of significant effects in the MANOVA. However, for exploratory purposes, the raw means and standard deviations of the outcomes were calculated for each condition. To further analyze interactions by comparing means at high versus low ability levels, numeracy was categorized into "High" (n = 86) and "Low" groups (n = 136). "High" numeracy was defined as numeracy values greater than or equal to the mean plus one standard deviation, while "Low" numeracy included values less than or equal to the mean minus one standard deviation. Cases falling within one standard deviation of the mean were excluded from the analysis. The descriptive statistics are presented in Table 9. The expectation based on H2 was that the mean difference between risk levels was expected to be larger in the hard condition than in the easy condition for highly numerate participants, whereas for low-numerate participants, the mean difference was expected to be larger in the easy condition than in the hard condition.

Table 9. Raw Means and standard deviations of key outcomes across conditions in Study 1.

	Numeracy	Processing Difficulty	Risk Level	n	Affect	Risk perception	Benefit perception	Behavioral intention
	Low	Easy	Low	38	2.79 (1.19)	2.97 (.94)	3.08 (1.12)	2.82 (1.35)
		Easy	High	30	2.43 (1.17)	3.33 (.96)	2.83 (.99)	2.37 (1.22)
Difference					.36	-.36	.25	.45
		Hard	Low	39	2.77 (.99)	2.69 (.80)	3.23 (.87)	2.85 (1.29)
		Hard	High	29	2.31 (1.04)	2.86 (.92)	2.86 (.92)	2.31 (1.34)
Difference					.46	-.17	.37	.54
	High	Easy	Low	28	3.25 (1.00)	2.29 (.81)	3.57 (1.00)	3.79 (1.29)
		Easy	High	21	2.57 (.98)	3.05 (.80)	2.95 (.67)	2.24 (1.14)
Difference					.68	-.76	.62	1.55
		Hard	Low	21	3.57 (.81)	2.14 (.48)	3.90 (.83)	3.52 (1.21)
		Hard	High	16	3.19 (.91)	2.56 (.81)	3.19 (.75)	3.00 (1.32)
Difference					.38	-.42	.71	.52

As shown in Table 9, low-numerate participants in the easy condition demonstrated greater sensitivity to risk perception compared to those in the hard condition, directionally supporting H2. However, they showed weaker sensitivity to affect, benefit perception, and behavioral intention in the easy condition than in the hard condition, which does not align with H2.

In contrast, highly numerate participants in the hard condition exhibited stronger sensitivity to benefit perception compared to those in the easy condition, supporting H2. However, these individuals showed weaker sensitivity to affect, risk perception, and behavioral intention in the hard condition than in the easy condition, which does not support H2.

Exploratory analysis

A MANCOVA was conducted to assess the effects of Processing Difficulty and Risk Level on the four combined outcomes, with Subjective Numeracy Scale (SNS) (Cronbach's α = .86), replacing numeracy as a covariate. Notably, a significant three-way interaction was found, Pillai's Trace = .01, $F(4, 739) = 2.38$, $p = 0.04997$. However, no significant three-way interaction between Processing Difficulty, Risk Level, and Subjective Numeracy emerged in the univariate ANOVA results from the MANOVA.

Subsequently, two MANCOVAs were performed to examine the effects of Processing Difficulty and Risk Level on the four combined outcomes, using subsets of SNS. Namely, in these models, Numeric Self-efficacy (NS) (Cronbach's α = .90) and Number Preferences (NP) (Cronbach's α = .79) were employed as covariates in place of numeracy. The first model, with numeric self-efficacy as a covariate, did not reveal any significant effects.

However, the model with number preferences as a covariate produced several significant effects. Specifically, the Processing Difficulty was significant, Pillai's Trace = .01, $F(4, 739) = 2.75$, $p = .03$. The interaction between Processing Difficulty and Risk Level was significant, Pillai's Trace = .02, $F(4, 739) = 3.56$, $p = .01$. The interaction between Processing Difficulty and Number Preferences was also significant, Pillai's Trace = .02, $F(4, 739) = 3.61$, $p = .01$. Most notably, the three-way interaction among Processing Difficulty, Risk Level, and Number Preferences was significant, Pillai's Trace = .02, $F(4, 739) = 3.85$, $p < .01$.

According to the univariate ANCOVA results from the MANCOVA, Processing Difficulty had a significant effect on affect ($p = .01$), risk perception ($p < .001$), and benefit perception ($p = .02$), but not on behavioral intention ($p = .44$). Risk Level significantly affected all four outcomes ($p < .001$ for each). The interaction between Processing Difficulty and Risk Level was significant only for affect ($p = .01$) and not for risk perception ($p = .57$), benefit perception ($p = .16$), or behavioral intention ($p = .33$). The interaction between Processing Difficulty and Number Preferences was significant only for affect ($p < .01$) and not for risk perception ($p = .09$), benefit perception ($p = .28$), or behavioral intention ($p = .29$). The interaction between Risk Level and Number Preferences was not significant for any of the outcomes. Notably, the three-way interaction between Processing Difficulty, Risk Level, and Number Preferences was significant for both benefit perception ($p = .01$) and behavioral intention ($p = .049$). However, it was not significant for affect ($p = .67$) or risk perception ($p = .99$).

In light of the significant effects found in MANOVA results, individual Type III ANCOVAs were conducted for each outcome, using Number Preferences as a covariate, to identify specific effects.

1) Affect

The model revealed a significant main effect of Processing Difficulty on affect, $F(1, 742) = 6.39$, $p = .01$, $\eta_p^2 = .009$. Participants in the easy conditions ($M = 2.78$, $SE = .06$) reported less positive affect toward the medication compared to those in the hard conditions (*M* = 2.94, *SE* = .06).

Additionally, the interaction between Processing Difficulty and Number Preferences was significant, $F(1, 742) = 8.45$, $p < .01$, $\eta_p^2 = .01$. Among participants with low scores for Number Preferences, those in the easy conditions (*M* = 2.83, *SE* = .08) reported more positive affect toward the medication than those in the hard conditions (*M* = 2.76, *SE* = .08). In contrast, among participants with high scores for Number Preferences, those in the easy conditions (*M* = 2.72, *SE* = .08) reported less positive affect than those in the hard conditions (*M* = 3.11, *SE* = .08). The three-way interaction was not significant.

2) Risk perception

The model did not reveal any significant effects.

3) Benefit perception

The effect of Processing Difficulty on benefit perception was not significant, $F(1, 742) = .57$, $p = .45$, $\eta_p^2 = .000$. The effect of Risk Level on benefit perception was not significant, $F(1, 742) = .08$, $p = .77$, $\eta_p^2 = .000$. However, the effect of Number Preferences on benefit perception was significant, $F(1, 742) = 7.36$, $p = .01$, $\eta_p^2 = .010$. A significant interaction was also found between Processing Difficulty and Risk Level, $F(1, 742) = 7.65$, $p = .01$, $\eta_p^2 = .01$. In the easy conditions, low-risk conditions (*M* = 3.22, *SE* = .06) led to higher benefit perception compared to high risk (*M* = 3.07, *SE* = .07), while in the hard conditions, low-risk conditions (*M* = 3.45, *SE* = .06) resulted in higher benefit perception than high-risk conditions (*M* = 3.10, *SE* = .07). Participants in the easy conditions demonstrated weaker sensitivity to risk levels ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .15$) compared to those in the hard conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .35$).

Most notably, a significant three-way interaction was found between Processing Difficulty, Risk Level, and Number Preferences, $F(1, 742) = 6.59$, $p = .01$, $\eta_p^2 = .009$. Post hoc pairwise comparisons revealed that participants with low scores for Number Preferences in the hard conditions exhibited the greatest sensitivity to risk levels ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .49$, $p = .01$), whereas those in the easy conditions showed the least sensitivity ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = -.04$, $p = 1.00$). Conversely, participants with high scores for Number Preferences were more sensitive to risk levels in the easy conditions ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .34$, $p = .17$) compared to the hard conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .19$, $p = .84$). See Table 10 for details.

Table 10. Estimated Marginal Means and SEs of Benefit Perception Predicted by Processing Difficulty, Risk Level and Number Preferences in Study 1.

	Number Preferences	**Processing Difficulty**	**Risk Level**	**Benefit perception**
	Low	Easy	Low	3.07 (.09)
		Easy	High	3.11 (.09)
Difference				.04
	Low	Hard	Low	3.39 (.09)
		Hard	High	2.90 (.10)
Difference				.49*
	High	Easy	Low	3.37 (.10)
		Easy	High	3.03 (.09)
Difference				.34
	High	Hard	Low	3.50 (.09)
		Hard	High	3.31 (.10)
Difference				.19

*** p < .001, ** p < .01, * p < .05

4) Behavioral intention

The effect of Processing Difficulty on behavioral intention was not significant, $F(1, 742) = .87$, $p = .35$, $\eta_p^2 = .001$. The effect of Risk Level on benefit perception was not significant, $F(1, 742) = .10$, $p = .75$, $\eta_p^2 = .000$. The effect of Number Preferences on benefit perception was not significant, $F(1, 742) = 2.38$, $p = .12$, $\eta_p^2 = .003$.

The interaction between Processing Difficulty and Risk Level was significant, $F(1, 742) = 4.41$, $p = .04$, $\eta_p^2 = .006$. In the easy conditions, low-risk conditions ($M = 2.98$, $SE = .10$) resulted in higher behavioral intention compared to high-risk conditions ($M = 2.66$, $SE = .10$), while in the hard conditions, low-risk conditions ($M = 3.13$, $SE = .09$) similarly led to higher behavioral intention than high-risk conditions ($M = 2.61$, $SE = .10$). Notably, participants in the easy conditions demonstrated weaker sensitivity to risk levels ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .32$) compared to those in the hard conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .52$).

The interaction between Processing Difficulty and Number Preferences was not significant, $F(1, 742) = 1.05$, $p = .31$, $\eta_p^2 = .001$. The interaction between Risk Level and Number Preferences was also not significant, $F(1, 742) = 1.07$, $p = .30$, $\eta_p^2 = .001$.

Most notably, the three-way interaction among Processing Difficulty, Risk Level, and Number Preferences was significant, $F(1, 742) = 3.88$, $p = .049$, $\eta_p^2 = .005$. Post hoc pairwise comparisons indicated that participants with low scores for Number Preferences in the hard conditions exhibited greater sensitivity to risk levels ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .61$, $p = .05$) compared to those in the easy conditions, who showed the least sensitivity ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .03$, $p = 1.00$). Participants with higher scores for Number Preferences demonstrated more sensitivity to risk levels in the easy conditions ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .62$, $p = .04$) compared to the hard conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .43$, $p = .37$). See Table 11 for further details.

Table 11. Estimated marginal means and SEs of behavioral intention predicted by Processing Difficulty, Risk Level and Number Preferences in Study 1.

	Number Preferences	Processing Difficulty	Risk Level	Behavioral Intention
	Low	Easy	Low	2.81 (.13)
		Easy	High	2.78 (.14)
Difference				.03
		Hard	Low	3.05 (.14)
		Hard	High	2.44 (.15)
Difference				.61
	High	Easy	Low	3.16 (.14)
		Easy	High	2.54 (.14)
Difference				.62*
		Hard	Low	3.21 (.13)
		Hard	High	2.78 (.14)
Difference				.43

*** $p < .001$, ** $p < .01$, * $p < .05$

To explore the mechanism of using numbers in the presence of narratives, participants' motivation to use numbers in the presence of narratives, as well as their engagement with the provided numbers, was suspected to influence the relationship between factors and outcomes. However, individual MANOVAs using the accuracy motivation index as a moderator revealed no significant three-way interaction, Pillai's Trace = .00, $F(4, 739) = .83$, $p = .51$. Similarly, with the Data Evaluation index as a moderator, the three-way interaction was not significant, Pillai's Trace = .01, $F(4, 739) = .94$, $p = .44$. Additionally, the effects of the factors on Data Evaluation were explored, but no significant effects were identified.

The primary goal of analyzing thought listings was to investigate the effects of experimental conditions on number sensitivity. Two independent human coders, with a high agreement rate of over 92%, coded comments as 1 if they mentioned probability information (e.g., “%”, “percent”, “chance”, “high/low”) and 0 otherwise. Similarly, they were coded as 1 for any mention of Arabic numerals (e.g., “2”, “2%”, “12”) and 0 otherwise. Based on H1, the effects of processing difficulty and risk levels on number sensitivity (i.e., mentioning probability information and/or Arabic numerals) were expected, with participants in the hard condition predicted to show greater number sensitivity than those in the easy condition. Two logistic regressions were conducted with either type of mention as the dependent variable, using processing difficulty, risk level, and their interaction as predictors. No significant effects on number sensitivity were found.

However, numeracy demonstrated a significant effect when included in the model regarding mention of Arabic numerals, $\chi^2(1) = 5.72$, $p = .02$. Individuals with higher numeracy were more likely to mention Arabic numerals in their thought listings compared to those with lower numeracy.

To refine Study 2, comments were coded for skepticism toward the experimental materials (1 = skepticism, 0 = no skepticism). A logistic regression indicated that risk level was marginally significant, $\chi^2(1) = 3.23$, $p = .07$. The predicted probability of skepticism was higher in the low-risk conditions (*PP* = .11, *SE* = .02) compared to the high-risk conditions (*PP* = .06, *SE* = .01).

Thematic analysis identified four categories of skepticism: Dramatic story (*n* = 12); Need more information (e.g., why Sam experienced dizziness) (*n* = 5); Doubt percentages (e.g., believe they are fake or inaccurate) (*n* = 9); Need more information to make a decision (e.g., cost, ingredients, more testimonies, why the doctor offered this message) (*n* = 31).

Notably, twelve participants perceived Sam’s story as exaggerated or overly dramatic. Some of their responses included:

"This person seems a little dramatic. A 12% chance seems pretty manageable. I'm not entirely inclined to believe this would affect me the same way. I wonder what the positives of using this could be."

"I thought the chance of side effects was very low (2%). The review seemed somewhat ridiculous."

Of these 12 participants, eight were in low-risk conditions (three in easy mode, five in hard mode), and four were in high-risk conditions (one in easy mode, three in hard mode). This pattern aligns with the statistical results, indicating that participants in the low-risk conditions displayed greater skepticism compared to those in the high-risk conditions.

Therefore, to address skepticism arising from the perceived contradiction between the narrative and the numeric risk level, the risk levels for Study 2 were adjusted from "Low 2% vs. High 12%" to "Low 8% vs. High 19%." This change preserved a meaningful distinction between low and high-risk conditions while reducing potential skepticism.

Discussion

In testing H1, the significant main effect of Processing Difficulty across key outcomes suggests that participants experienced less positive affect, higher risk perception, and lower benefit perception in the easy condition, where brief statistics were presented before a long narrative, compared to the hard condition, where subdivided statistics followed a short narrative. Notably, there were no significant differences in these measures between the two narrative lengths in the pilot test. Moreover, the direction of the means in both conditions was opposite to what was observed in the pilot, suggesting that participants' perceptions of the statistics may have influenced the results.

A possible explanation might relate to skepticism arising from the perceived contradiction between the narrative and the numeric risk level. In the easy condition, after encountering the brief statistics, participants likely had enough cognitive resources to fully process the subsequent long narrative. However, they may have experienced expectation violation when the emotional tone of the narrative didn't align with the earlier statistics, creating cognitive dissonance and leading to less positive affect, higher risk perception, and lower benefit perception. In the hard condition, a similar mismatch may have occurred: the short narrative might have seemed less favorable when presented alone, but after processing the subdivided statistics, participants may have perceived the percentages as smaller and less threatening, which reassured them, resulting in increased positive affect, lower risk perception, and higher benefit perception.

Of particular interest, the significant interaction effect between Processing Difficulty and Risk levels supported H1, revealing that sensitivity to numeric risk levels was significantly stronger in the hard conditions compared to the easy conditions. Specifically, participants in the hard conditions demonstrated greater sensitivity to risk levels in their affect toward the medication than those in the easy conditions. Results for affect may have been stronger than for the other three outcome variables because affective responses to stimuli often precede and inform cognitive processes such as risk perception, benefit assessment, and behavioral intentions (Loewenstein et al., 2001, Slovic et al., 2004). Thus, the extension of Chun and Kruglanski's main finding into risk perceptions was partially successful.

However, no significant evidence was found to support H2, which hypothesized that objective numeracy would moderate the effect outlined in H1. It is possible that the study did not have sufficient power to detect such a three-way interaction, particularly given the sample size as well as the subtlety and complexity of the effects in question.

Exploratory analysis revealed significant three-way interactions among Processing Difficulty, Risk Level, and Number Preferences on both benefit perception and behavioral intention. Specifically, participants with low Number Preferences scores in the hard condition showed greater sensitivity to risk levels than in the easy condition, whereas those with high Number Preferences scores in the easy condition showed greater sensitivity to risk levels than in the hard condition.

CHAPTER V STUDY 2

Materials and Procedure

1000 participants were recruited from a cleaned Prolific baseline cohort (cohort N = 1,460). As in Study 1, the invited participants first encountered an informed consent page, which indicated the details of the study, the researcher's contact information, and a statement of voluntary participation.

People who consented to participate were asked to imagine they suffered from headaches severe enough to cause them to miss work or school. Then, they were given information about a medication narrative with a fixed probability of side effects derived from Peters et al. (2011). Numeric side effect information was read as a percentage of patients experiencing dizziness after taking the medication.

In study 2, the effect of processing difficulty defined by the numeric precision and presenting order. Participants responded to a medication narrative in a 2 (Numeric processing difficulty: imprecise vs. precise) × 2 (risk level: low vs. high) between-participants design. The same narratives, which varied in length in Study 1, were used in Study 2.

Risk level was manipulated as indicated at the end of Study 1: low (8%) vs. high (19%). Hard risk was defined by making the number more precise by including decimals (e.g., 8.41%) and presenting it after a short narrative; easy risk was operationalized by presenting them as a round number (e.g., 8%) and before a long narrative. Thus, participants were randomly assigned to one of four conditions as shown in Table 12 below:

Table 12. Four experimental conditions in Study 2.

Easy Low	In recent clinical trials, approximately 8% of ReliefMax users experienced dizziness, which ranged from barely noticeable to very severe. Sam shared the following: "I tried ReliefMax for headaches. Unexpectedly, I felt everything spinning uncontrollably. I felt as if my body wasn't mine, making it difficult for me to concentrate on the tasks at hand. My friends could not truly grasp how bad it made me feel. Although ReliefMax helped my headaches, the dizziness made me feel scared, isolated, and out of control."
Easy High	In recent clinical trials, approximately 19% of ReliefMax users experienced dizziness, which ranged from barely noticeable to very severe. Sam shared the following: "I tried ReliefMax for headaches. Unexpectedly, I felt everything spinning uncontrollably. I felt as if my body wasn't mine, making it difficult for me to concentrate on the tasks at hand. My friends could not truly grasp how bad it made me feel. Although ReliefMax helped my headaches, the dizziness made me feel scared, isolated, and out of control."
Hard low	"I tried ReliefMax for headaches. Everything spun, friends couldn't grasp my turmoil. It helped headaches but made me feel scared, isolated, and out of control," Sam shared. In recent clinical trials, approximately 8.41% of ReliefMax users experienced dizziness, which ranged from barely noticeable to very severe.

Hard high	"I tried ReliefMax for headaches. Everything spun, friends couldn't grasp my turmoil. It helped headaches but made me feel scared, isolated, and out of control," Sam shared. In recent clinical trials, approximately 19.41% of ReliefMax users experienced dizziness, which ranged from barely noticeable to very severe.

Measures

The measures introduced in the methodology chapter III were implemented, including a manipulation check, four key outcomes (Affect, Risk Perception, Benefit Perception, and Behavioral Intention), Data Evaluation (Cronbach's $\alpha = .88$), and Accuracy Motivation measurements (Cronbach's $\alpha = .62$). In addition, to enhance our understanding of participants' sensitivity to numbers provided, an open-ended question was included asking participants to recall the numeric information from the materials, "In the article you just read, what percentage of ReliefMax users experienced dizziness? Please try your best to recall the percentage." Responses were coded as correct (=1) if they fall within ±5% of the correct answer; responses outside this range were considered incorrect and scored as 0. All study materials have been preregistered and can be accessed at https://osf.io/c985g/?view_only=9886ba108e6643da9e92d249c7f40644. Additionally, refer to the Appendix for detailed measurement items.

Data analysis strategy

As in Study 1, RStudio was used for data cleaning and all statistical analyses. The data cleaning criteria included excluding participants who failed two attention checks or missed more than 5% of responses. A t-test was conducted for the manipulation check. The assumptions for

MANOVA, ANOVA, and regression were examined and met. MANOVAs and ANOVAs were used to test Hypothesis 1, while MANCOVAs and ANCOVAs were employed for Hypothesis 2. Additionally, MANCOVAs and ANCOVAs were performed in exploratory analyses. To decompose interactions and compare effects at high versus low ability, values at ±1 SD from the mean were used for inferential analysis.

Results

Sample

No participant was removed during data cleaning. Of the 1000 participants, the average age was 48.80 years (*SD* = 15.44). Women comprised 50% of the sample. Most participants identified as White (75.4%), followed by Black (9.4%), Asian (5.1%), Hispanic (3.5%), Multiple/Mixed (6.1%), Middle Eastern (0.1%) and Other (0.4%).

Regarding education, 35.4% of participants held a 4-year college degree, followed by 29.4% with a high school diploma or GED, 18.3% with a 2-year college or technical degree, 12.8% with a Master's degree, 3.5% with a PhD or other professional degree (JD, MD, etc.), and 0.6% with less than a high school diploma or GED. The most frequently reported income levels were $30,000 - $39,999 and $50,000 - $59,999, with 10.3% and 10.1% of participants, respectively.

Condition effects across demographics (i.e., age, gender, race, education, family income), numeracy and subjective numeracy were examined and did not reveal significant differences across conditions (see Table 13). Additionally, descriptive statistics about key outcomes are provided in Table 14, and correlations between variables are presented in Table 15.

Table 13. No Significant Differences in Demographics and Baseline Abilities Across Conditions in Study 2.

	EasyLow (N=245)	EasyHigh (N=242)	HardLow (N=260)	HardHigh (N=253)	Test Statistic p-value
Age	50.13 (*SD* = 14.89)	48.37 (*SD* = 16.08)	49.13 (*SD* = 15.08)	47.60 (*SD* = 15.69)	$F(3, 996) = 1.22$, $p = .30$
Gender					$\chi^2\ (15) = 7.47$, $p = .94$
Woman	128	123	129	120	
Man	112	114	129	131	
Transgender	1	1	1	0	
Non-binary/non-conforming	2	2	1	2	
Other (optional description)	1	1	0	0	
Prefer not to respond	1	1	0	0	
Race					$\chi^2\ (18) = 16.04$, $p = .59$
White (non-Hispanic)	186	179	199	190	
Black	22	22	24	26	
Hispanic	7	8	10	10	
Asian	16	17	8	10	
Native American	0	0	0	0	
Middle Eastern	1	0	0	0	
Multiple/Mixed	12	16	16	17	
Other	1	0	3	0	
Education					$\chi^2\ (15) = 15.92$, $p = .39$
Less than high school diploma or GED	1	1	1	3	
High school diploma or GED	72	73	82	67	
2-year college or technical degree	50	45	42	46	
4-year college graduate	74	92	98	90	

Master's degree	42	24	27	35	
PhD or other professional degrees (JD, MD, etc.)	6	7	10	12	
Income					χ^2 (36) = 39.85, *p* = .30
Less than $10,000	10	9	7	11	
$10,000 - $19,999	10	18	15	17	
$20,000 - $29,999	19	22	26	26	
$30,000 - $39,999	27	28	25	23	
$40,000 - $49,999	23	13	20	24	
$50,000 - $59,999	23	34	23	21	
$60,000 - $69,999	21	19	24	22	
$70,000 - $79,999	8	18	13	22	
$80,000 - $89,999	17	8	13	13	
$90,000 - $99,999	15	17	18	18	
$100,000 -$119,999	19	18	20	9	
$120,000 - $149,999	31	17	30	16	
$150,000 or more	22	21	26	31	
Numeracy (range = 1 to 9)	4.82 (*SD* = 1.35)	4.66 (*SD* = 1.48)	4.80 (*SD* = 1.51)	4.75 (*SD* = 1.60)	*F*(3, 996) = .53, *p* = .66
Subjective Numeracy (range = 1.6 to 6)	4.61 (*SD* = .80)	4.47 (*SD* = .88)	4.49 (*SD* = .85)	4.51 (*SD* = .89)	*F*(3, 996) = 1.36, *p* = .25

Table 14. Descriptive statistics about key outcomes in Study 2.

Variables	**n**	**Mean**	**SD**	**Min**	**Max**
Affect	1000	2.57	1.02	1	5
Risk perception	1000	3.11	0.86	1	5
Benefit perception	1000	2.96	0.85	1	5
Behavioral intention	1000	2.51	1.30	1	5

Table 15. Correlations between variables in Study 2.

	Processing Difficulty	Risk Level	Affect	Risk Perception	Benefit Perception	Behavioral Intention	Data Evaluation	Accuracy Motivation	Numeracy	Subjective Numeracy Scale	Numeric Self-efficacy	Number Pre-ferences
Processing Difficulty	-											
RiskLevel	0	-										
Affect	.1 **	-.13 ***	-									
Risk Perception	-.02	.18 ***	-.58 ***	-								
Benefit Perception	.03	-.11 ***	.66 ***	-.53 ***	-							
Behavioral Pntention	.07 *	-.14 ***	.77 ***	-.55 ***	.69 ***	-						
Data Evaluation	-.04	.05	.16 ***	-.16 ***	.27 ***	.22 ***	-					
Accuracy Motivation	.08 **	0	.2 ***	-.24 ***	.22 ***	.22 ***	.36 ***	-				
Numeracy	.01	-.03	.02	-.12 ***	.07 *	.07 *	.08 *	.13 ***	-			
Subjective Numeracy Scale	-.03	-.04	-.01	-.01	.01	-.02	.13 ***	.18 ***	.43 ***	-		
Numeric Self-efficacy	-.04	-.03	0	0	0	-.01	.08 *	.13 ***	.46 ***	.89 ***	-	
Number Preferences	.01	-.06	.01	-.05	.03	-.01	.14 ***	.22 ***	.32 ***	.85 ***	.56 ***	-

*** p < 0.001, ** p < 0.01, * p < 0.05

Manipulation Check

As in Study 1, participants were asked to rate their agreement with the statement, "It is difficult to read through and understand the numeric data regarding the side effects of ReliefMax," using a 5-point Likert scale. An independent samples t-test was conducted to compare manipulation check scores between the easy and hard conditions. The scores in the easy conditions (M = 1.45, SD = .82) were almost identical to those in the hard conditions (M = 1.49, SD = .79); this difference was not statistically significant, $t(990) = -.74$, $p = .46$.

Although the manipulation check was not successful, hypothesis tests were conducted nonetheless.

Hypotheses Testing

H1 (that participants will be more sensitive to risk levels when numeric risk information is harder to process compared to when it is easier to process).

The MANOVA revealed significant main effects for Processing Difficulty (Pillai's Trace = .01, $F(4, 993) = 3.5$, $p = .01$, $\eta_p^2 = .005$) and Risk Level (Pillai's Trace = .04, $F(4, 993) = 9.4$, $p < .001$, $\eta_p^2 = .02$) on the combined outcomes. However, their interaction was not significant (Pillai's Trace = .002, $F(4, 993) = 0.4$, $p = .78$, $\eta_p^2 = .001$). According to the univariate ANOVA results from the MANOVA, Processing Difficulty had a significant effect on affect ($p = .002$) and behavioral intention ($p = .03$), but not on risk perception ($p = .58$) and benefit perception ($p = .41$). Risk Level significantly influenced all four outcomes ($p < .001$ for each). Finally, the interaction between Processing Difficulty and Risk Level was not significant for all four outcomes.

Subsequently, individual Type III ANOVAs were performed for each outcome.

1) Affect

The effect of Processing Difficulty on affect was significant, $F(1, 996) = 9.96$, $p = .00$, $\eta_p^2 = .01$. Participants in the easy conditions ($M = 2.47$, $SE = .05$) reported less positive affect to the medication compared to those in the hard conditions ($M = 2.67$, $SE = .04$). Similarly, the effect of Risk Level on affect was significant, $F(1, 996) = 16.17$, $p < .001$, $\eta_p^2 = .02$. Participants in the low-risk conditions ($M = 2.70$, $SE = .05$) reported more positive affect to the medication compared to those in the high-risk conditions ($M = 2.44$, $SE = .05$). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 996) = .92$, $p = .34$, $\eta_p^2 = .001$. Since the interaction was not significant, post hoc pairwise comparisons were not conducted. Instead, the raw means across conditions were explored to identify patterns that might be helpful for future studies. In the easy conditions ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .32$), participants showed directionally stronger sensitivity to risk levels compared to those in the hard conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .20$), the opposite of the hypothesized effect. Descriptive statistics of affect across conditions are shown in table 16.

Table 16. Descriptive statistics of affect across conditions in Study 2.

	EasyLow	EasyHigh	HardLow	HardHigh
Mean	2.63	2.31	2.77	2.57
SD	1.05	0.95	1.03	1.02

2) Risk Perception

The effect of Processing Difficulty on risk perception was not significant, $F(1, 996) =.30$, $p = .58$, $\eta_p^2 = .000$. In contrast, the effect of Risk Level on risk perception was significant, $F(1, 996) = 33.94$, $p < .001$, $\eta_p^2 = .03$. Participants in the low-risk conditions ($M = 2.96$, $SE = .04$) reported lower risk perception of the medication compared to those in high-risk conditions ($M = 3.27$, $SE = .04$). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 996) = 1.08$, $p = .30$, $\eta_p^2 = .001$. Exploratory means across conditions revealed that, in the easy conditions (M_{EasyHigh} - M_{EasyLow} = .36), participants showed directionally stronger sensitivity to risk levels compared to those in the hard conditions (M_{HardHigh} - M_{HardLow} = .26), again the opposite of the hypothesized effect. Descriptive statistics of risk perception across conditions are shown in table 17.

Table 17. Descriptive statistics of risk perception across conditions in Study 2.

	EasyLow	EasyHigh	HardLow	HardHigh
Mean	2.95	3.31	2.97	3.23
SD	0.9	0.82	0.87	0.8

3) Benefit Perception

The effect of Processing Difficulty on benefit perception was not significant, $F(1, 996)$ = .68, p = .41, η_p^2 = .001. In contrast, the effect of Risk Level on benefit perception was significant, $F(1, 996)$ = 11.38, p < .001, η_p^2 = .01. Participants in the low-risk conditions (M = 3.05, SE = .04) reported higher benefit perception of the medication compared to those in high-risk conditions (M = 2.87, SE = .04). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 996)$ = .64, p = .42, η_p^2 = .001. Exploratory means across conditions revealed that, in the easy conditions (M_{EasyLow} – M_{EasyHigh} = .22), participants showed directionally stronger sensitivity to risk levels compared to those in the hard conditions (M_{HardLow} – M_{HardHigh} = .14), the opposite of the hypothesized effect. Descriptive statistics of benefit perception across conditions are shown in table 18.

Table 18. Descriptive statistics of benefit perception across conditions in Study 2.

	EasyLow	EasyHigh	HardLow	HardHigh
Mean	3.05	2.83	3.05	2.91
SD	0.90	0.83	0.85	0.79

4) Behavioral intention

The effect of Processing Difficulty on behavioral intention was significant, $F(1, 996) = 4.59$, $p = .03$, $\eta_p^2 = .005$. Participants in the easy conditions ($M = 2.42$, $SE = .06$) reported lower intention to use the medication compared to those in hard conditions ($M = 2.59$, $SE = .06$). Additionally, the effect of Risk Level on behavioral intention was significant, $F(1, 996) = 21.34$, $p < .001$, $\eta_p^2 = .02$. Participants in the low-risk conditions ($M = 2.69$, $SE = .06$) reported greater intention to use the medication compared to those in high-risk conditions ($M = 2.32$, $SE = .06$). However, the interaction between Processing Difficulty and Risk Level was not significant, $F(1, 996) = .17$, $p = .68$, $\eta_p^2 = .000$. Exploratory means across conditions revealed that, in the easy conditions ($M_{\text{EasyLow}} - M_{\text{EasyHigh}} = .41$), participants showed directionally stronger sensitivity to risk levels compared to those in the hard conditions ($M_{\text{HardLow}} - M_{\text{HardHigh}} = .35$). Descriptive statistics of behavioral intention across conditions are shown in table 19.

Table 19. Descriptive statistics of behavioral intention across conditions in Study 2.

	EasyLow	EasyHigh	HardLow	HardHigh
Mean	2.62	2.21	2.77	2.42
SD	1.3	1.22	1.31	1.31

2. H2 (that H1 would be modified by numeracy such that the highly numerate would show stronger effects of using numbers when it's harder than easier. The less numerate instead would be more likely to use easier-to-process numbers than harder-to-process numbers).

A MANCOVA was conducted to evaluate the effects of processing difficulty, risk level, numeracy, and their interactions on the combined dependent variables (affect, risk perception, benefit perception, and behavioral intention). The analysis indicated that none of the factors or their interactions had a statistically significant effect on the combined dependent variables. For exploratory purposes, the raw means and standard deviations of the dependent variables were calculated for each condition. To further analyze interactions by comparing means at high versus low ability levels, numeracy was categorized into “High” and “Low” groups. “High” numeracy was defined as numeracy values greater than or equal to the mean plus one standard deviation, while “Low” numeracy included values less than or equal to the mean minus one standard deviation. Cases falling within one standard deviation of the mean were excluded from the analysis. The descriptive statistics are presented in Table 20. The expectation based on H2 was that the mean difference between risk levels was expected to be larger in the hard condition than in the easy condition for highly numerate participants, whereas for low-numerate participants, the mean difference was expected to be larger in the easy condition than in the hard condition.

Table 20. Raw mean and standard deviation of key outcomes across conditions in Study 2.

	Numeracy	Processing Difficulty	Risk Level	Affect	Risk perception	Benefit perception	Behavioral intention
	Low	Easy	Low	2.21 (.86)	3.40 (.85)	2.79 (.91)	2.06 (1.09)
		Easy	High	2.55 (.99)	3.22 (.86)	2.98 (.98)	2.33 (1.33)
Difference				-0.34	0.18	-0.19	-0.27
		Hard	Low	2.66 (1)	3.21 (.93)	2.89 (.80)	2.60 (1.31)
		Hard	High	2.73 (1.09)	3.33 (.91)	2.88 (.85)	2.50 (1.36)
Difference				-0.07	-0.12	0.01	0.10
	High	Easy	Low	2.68 (1.06)	3.05 (.71)	2.95 (.85)	2.74 (1.28)
		Easy	High	2.25 (.93)	3.44 (.81)	2.94 (.57)	2.50 (1.15)
Difference				0.43	-0.39	0.01	0.24
		Hard	Low	2.96 (1.11)	2.78 (.95)	3.30 (.93)	2.96 (1.49)
		Hard	High	2.66 (1.04)	3.17 (.66)	2.97 (.87)	2.72 (1.39)
Difference				0.30	0.39	0.33	0.24

In addition, several MANCOVA tests were conducted to assess the effects of Processing Difficulty and Risk Level on four key outcomes, using different moderators—namely, Subjective Numeracy Scale, Numeric Self-efficacy, Number Preferences, Accuracy Motivation, and Data Evaluation—in place of numeracy. No significant moderating effects were found.

Further, a logistic regression analysis was performed to assess the impact of Processing Difficulty and Risk Level on the binary outcome of number recall ($M = 0.82$, $SD = 0.38$). The analysis revealed only a significant main effect of Processing Difficulty, $\chi 2$ (1) = 4.16, $p = .04$. Participants in the easy conditions ($M = 1.37$, $SE = .11$) had lower recall accuracy for numeric information compared to those in the hard condition ($M = 1.70$, $SE = .12$). No significant effects of the factors or their interactions were found, except for a main effect of numeracy when it was included in the model as a covariate. Similar results were observed in models where either the Accuracy Motivation index or the Data Evaluation index was included as a covariate.

Discussion

The manipulation of processing difficulty in Study 2 was not successful. This might be because the precise numbers used in the hard condition weren't actually difficult enough to process.

For exploratory purposes, hypothesis tests for H1 and H2 were conducted. No evidence supported H1; however, the mean patterns indicated that participants in the easy conditions exhibited greater sensitivity to risk levels compared to those in the hard conditions, the opposite of the expected pattern.

Additionally, no evidence was found to support H2 (that objective numeracy would moderate the effect outlined in H1). Exploratory mean patterns across conditions showed that, for lower-numeracy individuals, the easy conditions exhibited directionally greater sensitivity across all key outcomes (affect, risk perception, benefit perception, and behavioral intention) compared to the hard conditions. In contrast, for highly numerate individuals, directional results suggested that the easy conditions demonstrated stronger sensitivity to affect but weaker sensitivity to benefit perception, whereas sensitivity to risk perception and behavioral intention remained consistent across conditions. Nonetheless, no significant results emerged with numeracy.

Exploratory analyses revealed a significant effect of Processing Difficulty on number recall accuracy, with participants in the easy condition demonstrating lower accuracy in recalling numeric information compared to those in the hard condition, which supported H1 that participants would be more sensitive to risk levels when numeric risk information is harder to process compared to when it is easier to process.

No significant moderating effects were detected from other variables, including the Subjective Numeracy Scale, Numeric Self-Efficacy, Number Preferences, Accuracy Motivation, and Data Evaluation. Consequently, the Subjective Numeracy Scale, Numeric Self-Efficacy, Accuracy Motivation, and Data Evaluation will not be discussed further in the manuscript due to their lack of significant effects in exploratory analyses across both Study 1 and Study 2.

CHAPTER VI GENERAL DISCUSSION

The present dissertation extended the findings of Chun and Kruglanski (2006) into the context of risk communication and focused on numeracy as a means to assess the availability of cognitive resources for processing risk statistics. To confirm that the observed condition effects were the result of our manipulations, a comprehensive analysis of demographic and baseline ability differences across conditions for the two studies was conducted and ruled out the possibility that the observed condition effects were related to demographic and baseline ability variations across conditions.

Consistent with H1, Study 1 participants were more sensitive to risk levels when numeric risk information was harder to process (lengthy and presented after a short narrative) compared to when it was easier to process (brief and presented before a long narrative). Specifically, under the hard conditions compared to the easy conditions, participants' affect toward the medication demonstrated significantly higher sensitivity to risk levels. Although the interactions between Processing Difficulty and Risk Level for risk perception, benefit perception, and behavioral intention were not statistically significant, the mean values across conditions for each outcome supported H1 directionally. These results suggest that participants used the numeric risk information more when it was harder to process rather than when it was easier. A possible explanation is that the brief narrative in the hard condition left participants with enough capacity to process the later-presented statistics. Due to the recency effect, where more recent information tends to be better remembered and more influential (e.g., Glanzer & Ctrmrz, 1966; Murdock et al., 1962), judgments were primarily based on this later information, overshadowing earlier details. Conversely, in the easy condition, brief statistics preserved sufficient cognitive capacity to process the subsequent narrative, with a similar recency effect influencing judgments.

However, no significant evidence was found in Study 1 to support H2, which proposed that objective numeracy would moderate the effect outlined in H1. It is possible that the study did not have sufficient power to detect such an three-way interaction, particularly given the sample size as well as subtlety and complexity of the effects in question.

To explore and deepen our understanding of how participants use numeric risk information, multiple individual MANOVAs were conducted to examine the moderating effects of Subjective Numeracy and its subscales (i.e., Numeric Self-Efficacy and Number Preferences) as substitutes for objective numeracy in the relationship between study factors and outcomes. These analyses revealed significant three-way interactions among Processing Difficulty, Risk Level, and Number Preferences on both benefit perception and behavioral intention. Specifically, participants with low Number Preferences scores in the hard condition showed greater sensitivity to risk levels than in the easy condition, while those with high Number Preferences scores in the easy condition showed greater sensitivity to risk levels than in the hard condition.

One possible explanation is that individuals with lower preferences for numbers may have fully processed the narrative upfront in the hard numeric condition, intense feelings triggered by the narrative (e.g., angry, shocked, curious, etc.) might help them process the subsequent complex numeric information more effectively, resulting in greater sensitivity to risk levels. As noted in the affect heuristic literature, affect or emotions play critical roles in judgments of risk and benefits (e.g., Loewenstein, Weber, Hsee, & Welch, 2001; Slovic et al., 2007; Slovic et al., 2004; Finucane et al., 2000). Peters, Lipkus and Diefenbach further identified four functions of affect. For instance, affect can function as a spotlight, guiding our attention toward certain information, and as a motivator of information processing (Peters, Lipkus, et al., 2006). Thus, for individuals with low preferences for numbers, intense emotional reactions to the narrative may have guided their cognitive focus toward the source of their feelings (i.e., the side effects of the medication) and motivated them to engage more deeply with the complex numeric data related to these side effects that followed, resulting in stronger sensitivity to risk levels. In contrast, when participants with low Number Preferences encountered the statistics upfront in the easy condition, they may have disregarded the numeric information and relied more heavily on the later, lengthier narrative, resulting in weaker sensitivity to risk levels. This aligns with findings from classical base-rate neglect studies (e.g., Tversky & Kahneman, 1974; Kahneman & Tversky, 1973), where individuals often ignore statistical information in favor of narratives.

On the other hand, individuals with a higher preference for numbers tended to fully process the numbers when presented with risk numbers followed by more challenging narratives, as in the easy condition. This allows them to use numeric data more effectively, resulting in stronger sensitivity to risk levels. This finding is consistent with prior numeracy research (e.g., Peters et al., 2006; Peters, 2012, 2017; Reyna et al., 2009; Bruine De Bruin et al., 2015), which suggests that highly numerate individuals are less influenced by narratives. In line with this, Numeracy and Number Preferences were positively correlated in Study 1 ($r = .3$, $p < .001$), supporting the idea that individuals with a stronger preference for numbers were more likely to process risk information thoroughly, without being swayed by subsequent narratives in the easy condition. However, in the hard condition, these individuals may become disengaged when presented with a narrative upfront, leading to reduced cognitive effort in processing the later numeric data, and thus, weaker sensitivity to risk levels.

The manipulation of processing difficulty in Study 2 was not successful. However, exploratory analyses detected a significant effect of Processing Difficulty on number recall accuracy. Participants in the easy condition had lower accuracy in recalling numeric information compared to those in the hard condition, possibly consistent with H1 that participants would be more sensitive to risk levels when numeric risk information is harder to process compared to when it is easier to process.

Implications of the Findings

The findings from the dissertation have several important implications for risk communication, particularly when numeric information is involved:

Impact of Processing Difficulty: The nonintuitive results from Study 1 indicate that processing difficulty significantly influences participants' sensitivity to risk levels. When numeric information is more difficult to process—due to its length and being presented after an easier narrative—participants become more sensitive to risk levels, likely because the brief narrative in the hard condition preserves enough cognitive capacity to focus on later-presented statistics, resulting in the recency effect, where more recent information is better remembered and more influential, leading judgments to be based on this later information and overshadowing earlier details, whereas in the easy condition, brief statistics similarly preserve capacity for the subsequent narrative, influencing judgments in a comparable manner. This implies that the complexity and presentation order of numeric data, in the context of accompanying narratives, can substantially impact how individuals perceive risk.

Moderating Effect of Number Preferences: The exploratory findings that Number Preferences moderates the relationship between processing difficulty, risk level and benefit perception or behavioral intention indicate that individuals' preference in handling numeric information influences how they perceive and react to risks. This underscores the importance of considering number preferences in risk communication strategies, as it may dictate how different segments of the population respond to the same information.

In conclusion, communicators must first identify the goals of their communication and determine the specific information that their audience needs to achieve those goals. Once identified, they should apply evidence-based strategies to effectively convey the message (Peters et al., 2017; Schwabish, 2021). When the goal is to facilitate informed decision-making through the use of numeric risk information, the findings of this dissertation suggest that tailoring the complexity and presentation of numeric information is crucial. Additionally, these strategies should be carefully designed with consideration for the audience's number preferences to ensure the numeric risk message is acted upon effectively.

CHAPTER VII LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that should be acknowledged. First, the statistical power to detect significant effects was constrained by limited monetary resources, which restricted the sample size and would have diminished the study's ability to identify smaller effects. Sommet et al. (2023) highlights the challenges of interpreting interactions in complex factorial designs, noting that achieving adequate statistical power often requires sample sizes that are impractically large under typical resource constraints. Future research could benefit from increased funding, enabling more extensive sampling and, in turn, greater statistical power to detect nuanced effects.

Second, the manipulation of processing difficulty in Study 2 was not successful, as evidenced by the manipulation check's lack of differentiation between the easy and hard conditions. Precise numbers with more decimals are often perceived as more demanding than imprecise numbers without decimals (e.g., Jerez-Fernandez et al., 2014; Schindler & Yalch, 2006; Wadhwa & Zhang, 2015, 2019); however, few studies have empirically examined this. A pilot test could have helped refine this manipulation, ensuring that the intended differences in processing difficulty were effectively established. Future research should consider conducting pilot tests to validate experimental manipulations before proceeding with full-scale studies.

Third, the study combined the processing difficulty of numeric information with narrative complexity, following the approach of Chun and Kruglanski (2006). Although the narratives across conditions were pilot tested to ensure consistent response levels on the outcomes, this design still posed challenges for interpreting the results. Future research should address these challenges by independently manipulating numeric and narrative complexities. This approach would provide clearer insights into how each type of processing difficulty uniquely influences decision-making and perception when both types of information are present. Moreover, the presenting order and information complexity were intentionally combined to replicate the approach used by Chun and Kruglanski (2006). However, future research should separate these factors to better examine the recency effect in making risk judgments discussed earlier.

APPENDIX MEASUREMENT

Manipulation check

Please rate each of the following statements on a scale of 1 to 7 (1 = Strongly Disagree, 7= Strongly Agree).

It was difficult to fully process the numeric data provided by the doctor.

Affect

Based on what you read about ReliefMax, please describe how you feel about ReliefMax:

1) Extremely negative

2) Somewhat negative

3) Neutral

4) Somewhat positive

5) Extremely positive

Risk Perception

Based on what you read about ReliefMax, how risky do you think it is?

1) Not at all risky

2) Low risk

3) Moderately risky

4) Highly risky

5) Very highly risky

Benefit Perception

How beneficial do you think ReliefMax is?

1) Not at all beneficial

2) Low benefit

3) Moderately beneficial

4) Highly beneficial

5) Very highly beneficial

Behavioral intention

How likely are you to take ReliefMax for headaches?

1) Extremely unlikely

2) Somewhat unlikely

3) Neither likely nor unlikely

4) Somewhat likely

5) Extremely likely

Thought listing question in Study 1

Please list at least three different thoughts you had during the task.

Accuracy Motivation

Use a 7-point Likert scale: 1 (Strongly Disagree) to 7 (Strongly Agree).

During this task,

1. I carefully evaluated the statistics on ReliefMax side-effects to ensure I make an accurate medication decision.

2. I believe understanding statistics accurately is crucial for making informed choices about ReliefMax side-effects.

3. The reliability of statistics on ReliefMax side-effects was a primary concern for me.

4. I relied more on intuition than statistics when reading about ReliefMax side-effects.

5. Personal stories and testimonials significantly influenced my opinion about ReliefMax side-effects.

6. I found statistics on ReliefMax side-effects to be irrelevant or useless.

Data Evaluation

Please share your opinions on the numeric data regarding the side effects of ReliefMax.

Use a bipolar-style matrix table assessing the following items (extremely, somewhat, slightly, slightly, somewhat, extremely):

1. Interesting – Boring

2. Useful – Useless

3. Trustworthy – Untrustworthy

4. Confusing – Clear

5. Convincing – Unconvincing

6. Biased – Accurate

Demographic Variables and Baseline Abilities

age

Please provide your current age (in years) in the box provided. Use whole numbers only.

Education (as measured in the baseline survey for Study 1)

Please indicate the highest degree you have completed.

1) High school diploma or GED

2) 2-year college or technical degree

3) 4-year college graduate

4) Master's degree

5) PhD or other professional degrees (JD, MD, etc.)

Education (as measured in the baseline survey for Study 2)

Please indicate the highest degree you have completed.

1) Less than high school diploma or GED

2) High school diploma or GED

3) 2-year college or technical degree

4) 4-year college graduate

5) Master's degree

6) PhD or other professional degrees (JD, MD, etc.)

Gender

Which of the following do you identify as?

1) Woman

2) Man

3) Transgender

4) Non-binary/non-conforming

5) Other (optional description)

6) Prefer not to respond

Race (as measured in the baseline survey for Study 1)

Which of the following options best describes your racial identification?

1) White (non-Hispanic)

2) Black

3) Hispanic

4) Asian

5) Native American

6) Middle Eastern

7) Multiple/Mixed

8) Other (please describe below)

Race (as measured in the baseline survey for Study 2)

Which of the following options best describes your racial identification? Select all that apply.

1) White (non-Hispanic)

2) Black

3) Hispanic

4) Asian

5) Native American

6) Middle Eastern

7) Multiple/Mixed

8) Other ________

Family Income

Last year (2022), which of the following best captures your family income, before taxes?

1) Less than $10,000

2) $10,000 - $19,999

3) $20,000 - $29,999

4) $30,000 - $39,999

5) $40,000 - $49,999

6) $50,000 - $59,999

7) $60,000 - $69,999

8) $70,000 - $79,999

9) $80,000 - $89,999

10) $90,000 - $99,999

11) $100,000 -$119,999

12) $120,000 - $149,999

13) $150,000 or more

Numeracy (Silverstein et al., 2023)

In this dissertation, numeracy refers to objective numeracy. This ability was assessed using Adaptive Numeric Understanding Measure (A-NUM). The A-NUM consists of 13 unique items and will present different questions depending on the participant's performance on the assessment. Participants were categorized into nine ability levels (range: 1-9).

Subjective Numeracy Scale (Fagerlin et al., 2007)

1. How good are you at working with fractions? (1- Not at all good, 6 - Extremely good)
2. How good are you at working with percentages? (1- Not at all good, 6 - Extremely good)
3. How good are you at calculating a 15% tip? (1- Not at all good, 6 - Extremely good)
4. How good are you at figuring out how much a shirt will cost if it’s 25% off? (1- Not at all good, 6 - Extremely good)
5. When reading the newspaper, how helpful do you find tables and graphs that are parts of a story? (1- Not at all helpful, 6 - Extremely helpful)
6. When people tell you the chance of something happening, do you prefer they use words (“it rarely happens”) or numbers (“there’s a 1% chance”)? (1- Always prefer words, 6 - Always prefer numbers)
7. When you hear a weather forecast, do you prefer predictions using percentages (“there will be a 20% chance of rain today”) or predictions using only words (“there is a small chance of rain today”)? (1- Always prefer words, 6 - Always prefer percentages)
8. How often do you find numerical information to be useful? (1- Never, 6 - Very often)

(An additional item was added to the scale in Study 2: When making health decisions, how often do you find that personal stories and testimonials significantly influence your opinion? (1- Never, 6 - Very often)

Numeric risk probability recall (measured exclusively in Study 2), adapted from Shoots-Reinhard et al. (2020).

Participants were asked, “In the article you just read, what percentage of ReliefMax users experienced dizziness? Please try your best to recall the percentage.”

Codebook for Thought Listings Analysis in Study 1

Coding Category	Example Thought listings	Coding Instructions
Probability related info was mentioned in any form (e.g., %, percent, chance, high/low, 1 in 50)	“This person seems a little dramatic. 12% seems pretty manageable as a number, I'm not entirely inclined to believe this would effect me the same. I wonder what the positives for using this could be.” “I thought about the risk and reward. Even though there was a low chance of the side effect, it was severe enough to make me look for an alternative. The possible dizziness seemed worse than about any headache I could imagine.”	Code “1” in the “Probability_info” column if applicable; otherwise, code “0”
Arabic integer related to a percentage was specifically used	“It sounds very unpleasant to be that dizzy. 2% is pretty low. The benefits probably outweigh the 2% risk.”	Code “1” in the “Arabic_ integer” column if applicable; otherwise, code “0”
Skepticism regarding the materials provided	“This person seems a little dramatic. 12% seems pretty manageable as a number, I'm not entirely inclined to believe this would	Code “1” in the “Skepticism” column if

for the study that may hinder engagement in various forms, including doubts about the study, the brand name, the narrative, the data, the doctor, or the actual existence of the medication.	effect me the same. I wonder what the positives for using this could be.” “I had doubts as to the reliability of the drug. The user's results using the drug were telling for me. There needs to be more information as to actual use and poor responses. Did the doctor receive any compensation for recommending the drug to a patient?” “What ingredients in the medicine caused dizziness. I am skeptical of the product because of the claims. The product does work for migraines even though it has side effects.” “The instances of dizziness (2%) seemed low. These side effects seem mild. I can't understand why the person leaving the review was being so dramatic.” “I thought that calling it an "alternative" medicine was a mistake, because alternative usually means that it is fake and does nothing. I felt mildly bored. I felt generally neutral.” “I wondered what alternative medicine actually meant. Is this FDA approved? Is it homeopathic, what is in it?” “I'm confused why the scenario only focused on the negatives of ReliefMax when only 2% of users suffered negative symptoms. I also don't understand why a doctor is giving me an article instead of making their own recommendations about whether or not to use the drug. There is no mention of why conventional medicines don't relieve headaches but the alternative drug is effective, which is difficult to believe.”	applicable; otherwise, code “0”

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