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INDIVIDUAL DIFFERENCES AND RISK PERCEPTION: NUMERACY PREDICTS DIFFERENCES IN GENERAL AND SPECIFIC RISK PERCEPTIONS

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MADHURI RAMASUBRAMANIAN
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INDIVIDUAL DIFFERENCES AND RISK PERCEPTION: NUMERACY PREDICTS DIFFERENCES IN GENERAL AND SPECIFIC RISK PERCEPTIONS

A THESIS APPROVED FOR THE
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BY THE COMMITTEE CONSISTING OF

Dr. Edward T. Cokely, Chair

Dr. Robert Terry

Dr. Adam Feltz

Dr. Rocio Garcia-Retamero

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Abstract

People's risk perceptions are often related to attitudes and decisions with significant social and economic consequences (e.g., Fischhoff, 2009; Slovic, 1987). In recent years, a growing body of research has demonstrated that *personal* risk perceptions (e.g., How much risk does HIV pose for you, personally?) tend to be associated with individual differences in numeracy and risk literacy (e.g., the ability to evaluate and understand risk; Cokely et al. 2012; 2018). However, research on the relations between these skills and *societal* risk perceptions has remained largely unexplored (e.g., How much risk does HIV pose for human health, safety and prosperity?). To address this, I conducted a series of studies. In Study 1, a diverse sample of 17,000+ participants from over 100 countries evaluated five emerging risks for society (e.g., hacking, UAVs). Analyses revealed that numeracy robustly predicted risk perceptions, such that higher numeracy was related to lower risk perceptions, partially mediated by decision quality. In Study 2, participants evaluated various aspects of 39 risks along with numeracy and decision quality. Analyses indicated that numeracy was again related to lower societal risk perceptions both in general and emerging risk categories (e.g., weather, cybersecurity, terrorism). Finally, results from a preliminary study with a sample of 500 U.S. residents collected during the early stages of COVID-19 infections are also presented (e.g., late March 2020; <1,200 reported US patient deaths). This study provided a novel test of a short form assessment of broad societal risk perceptions in general, which were found to mediate the relationship between numeracy and COVID-19 risk perceptions. Taken together, results suggest that perceptions about specific emerging risks to society often reflect differences in more comprehensive attitudes about all risks to society in general, which in turn may reflect differences in general decision making skills (e.g., numeracy and risk literacy).

Keywords: Risk Perceptions, Numeracy, Risk Literacy, COVID-19

INDIVIDUAL DIFFERENCES AND RISK PERCEPTION: NUMERACY PREDICTS DIFFERENCES IN GENERAL AND SPECIFIC RISK PERCEPTIONS

Chapter 1: Risk Perceptions

Between 1980 and 2000, over 400,000 people in the United States died due to HIV/AIDS. One potential reason for these fatalities was attributed to 'HIV complacency' (i.e., minimizing the threat of HIV/AIDS; Valdiserri, 2004). This complacency led to decreased support related to HIV prevention activities (e.g., community awareness, medical interventions, or policy implementation). In 1993, after peak incidence of HIV cases had been recorded, the CDC established new testing guidelines and screening procedures (CDC, 1993). In these ways and others, risk perceptions (i.e., "intuitive risk judgements"), may often shape behaviors and policies on a societal level (Fischhoff, 2009; Slovic, 1987). However, not all individuals perceive risks the same. The growing literature suggests that risk perceptions can be distorted when they are studied through 'one size fits all' lens (see Bader, 2008; Lee et al., 2015; Liao et al., 2011). Individual differences in risk perceptions can influence subsequent behaviors that affect individuals and societies (e.g., voluntary actions, voting intentions etc.; Connor et al., 1999; Peacock et al., 2004). While some of the more commonly studied individual differences include socio-economic status and demographics, relatively less research has investigated the role of more *general cognitive skills*, such as numeracy and risk literacy (e.g., the ability to evaluate and understand risk in the service of informed decision making; see RiskLiteracy.org). Are numeracy and risk literacy related to differences in emerging risk perceptions?

Measuring Risk Perceptions

There are two common types of risk perceptions: personal and societal. When many people imagine risk perceptions, they think about the risk to themselves, personally. As seen in Figure 1, this factor can be subdivided into *General Personal Risk Perceptions* (e.g., How scary is the world to you?) and *Specific Personal Risk Perceptions* (e.g., How risky is HIV specifically?). One measurement method for *personal* risk perceptions is Domain Specific Risk Taking Scale (DOSPERT), which assess risk attitudes. This type of measurement is sensitive to individual differences, often useful for risk communications, and there have been many recent advances in how to measure other individual differences and factors (Botzen & Bergh, 2012; Brewer et al., 2004). Although extensive research has investigated these types of risk perceptions, relatively less research has focused on individual differences in *societal* risk perceptions (both general and specific) which can have many valuable implications. Thus, the focus of the present study is on societal risk perceptions, both general (e.g., to what extent are general risks known to science) and specific (e.g., How risky is HIV for health and human welfare?), and the influence of individual differences on the perceptions of these societal risks.

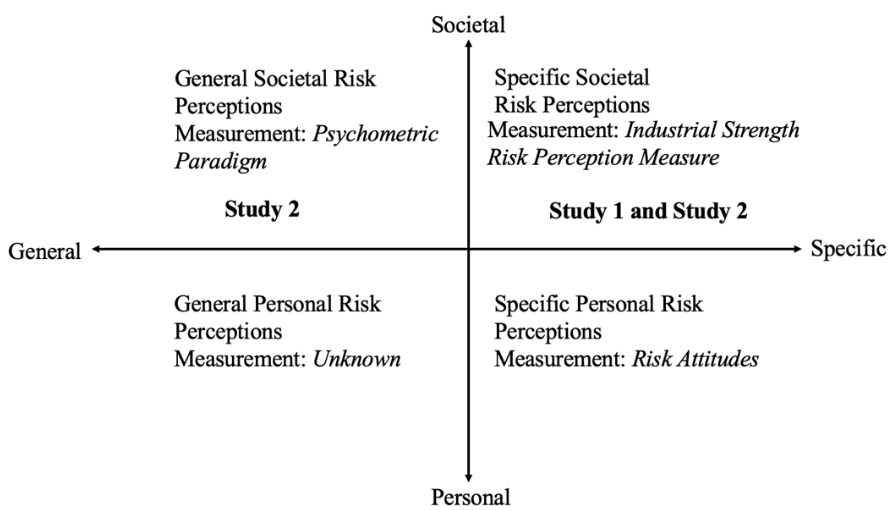

Figure 1. Orientations of Risk Perceptions

Societal Risk Perceptions

In the last four decades, a large body of research has investigated risk perceptions, and developed some standard approaches with respect to societal risks (e.g., For health and human welfare, how dangerous is HIV?). An initial, now standard approach is roughly characterized in Figure 1, *general societal risk perceptions*. This approach was rooted in a "revealed preferences" method used by Starr (1969). Starr conducted a cost-benefit analysis of economic losses and gains using archival data (i.e., revealed preferences) and used this as a method of estimating society's views towards risks. Despite many advantages of the revealed preferences approach, Fischhoff and colleagues (1978) noted that this approach failed to appreciate non-market valuations of public goods. In order to provide a broader view of risk perceptions and situating it in the field of psychology, Fischhoff and colleagues (1978) developed the psychometric paradigm, which has become a leading standard in psychological research. This paradigm focused on "expressed preferences," (i.e., elicited public opinions of risks and benefits). Fischhoff et al. (1978) studied 30 technologies and activities on nine characteristics: severity of consequences, voluntariness, immediacy of effect, knowledge about risk to the exposed and to science, dread risk, control over risk, newness and catastrophic risk. Using factor analysis, these nine dimensions were distilled to two major factors that influence people's risk perceptions: *dread* and *unknown*. For example, nuclear power plants were deemed to be a 'safe technology' using *revealed preferences*, however, *expressed preferences* indicated that people perceived it to be highly unknown and highly dreaded. These expressed preferences influenced perceptions of siting nuclear waste repositories (e.g., issues with Yucca Mountain). The psychometric paradigm further leveraged measurement theory to study differences in risk perceptions across groups of people and time (see Fox-Glassman & Weber, 2016). Ironically, although the psychometric paradigm focuses on societal risks, individual differences have not played a central role in this measurement tradition. In recent years, more methods of assessing risk perceptions have emerged. One of the frequently used scales to measure *specific societal risk perceptions* is the

Industrial Strength Risk Perception Measure developed by Kahan, (2017). This scale asks participants one question about how much risk an activity poses to human health, welfare and prosperity. While this research has given attention to individual differences, most of the focus has been on values and cultural cognition, rather than the role of more general cognitive skills. The current study utilizes both these general and specific measures of societal risk perceptions in order to test relations with individual differences.

Risk Perception and Individual Differences

While the measurement of risk perceptions has evolved over the decades, an area which lacks research is that between individual differences and risk perceptions. The study by Fischhoff et al., (1978), made prescriptions based on aggregated data to describe general tendencies, not individual differences. For example, one oft cited finding was that nuclear power was perceived as highly dreaded and unknown for society. However, there are some individual differences that can influence perceptions of risks for society. According to Slovic (1987), experts perceive risks very differently from the lay public (i.e., experts' risk perceptions align more with fatalities related to the risk). More recent work suggests the same; individual differences can often be useful in relation to risk perceptions. Specifically, Siegrist, Keller and Kiers (2002) conducted a 3-way Principal Component Analysis and found that participants are a considerable source of variance in risk perceptions. Similarly, Marris et al. (1998), analyzed risk perceptions at both the individual and aggregated level and found that individuals varied in risk perceptions for the same risk, and that data at the aggregated level did not translate to the individual level ratings. Furthermore, recent research investigating the relationship between self-report risk perceptions and other individual differences found that of six candidate correlates studied (age, sex, household income, years of education, fluid intelligence and crystallized intelligence) only age and sex showed robust associations with general risk preferences (Frey et al., 2020). The evidence indicates that individual differences may often be related to perceptions of risk. In particular, the current study focuses on the role of numeracy and risk literacy.

Numeracy, Risk Literacy and Decision Quality

Over the last two decades, increasing research has shown that numeracy (i.e., one's ability to reason with numbers, especially in real-world contexts) is often related to risky decision making. In 1997, a three item numeracy test developed by Schwartz, Woloshin, Black and Welch (1997) found that participants who scored well on this test tended to have better disease risk interpretations. More recently, Cokely et al., (2012) developed the Berlin Numeracy Test (BNT), a 4-item adaptive test, which demonstrated that numeracy often tends to be the strongest single predictor of decision quality, in college educated samples. Repeated testing of the BNT in other countries has validated this relationship. Consistent with Skilled Decision Theory, evidence suggests that numeracy predicts decision quality because numeracy involves dealing with probabilistic information under uncertainty as well as metacognitive processes which are reflective of real world decision processes (Cokely & Kelley, 2009; Cokely et al., 2018, Reyna et al., 2004; 2008). Furthermore, numerate people are also less likely to be influenced by nonnumeric information such as affective states, indicating that higher numeracy is associated with affective calibration (Peters, 2012). Across domains (health, weather, and finance), numeracy and decision making quality are linked (Allan et al., 2017; Petrova et al., 2016). Together, this suggests that numeracy may be a domain general skill.

Numeracy and Risk Perceptions

Recent evidence suggests that numeracy may play an important role in how people process, understand and perceive risks, particularly for themselves. In a study by Keller and

Siegrist (2009), participants were asked to evaluate medical risk scenarios pertaining to Down's syndrome and colon cancer in three formats. The results supported the hypothesis that participants with higher numeracy were better able to evaluate risk information, especially for low-risk scenarios, although high risk scenarios led people to consistently overestimate risks. Other studies that have investigated numeracy and risk perceptions have found varied results (Chen & Yang, 2015; Hess et al., 2011; Siegrist et al., 2006; Vogel et al., 2016) However, a study by Malo (2011) observed that numeracy significantly predicted cancer risk perceptions among people with previous cancer related diagnoses, which implies that experience with risks could significantly interact with numeracy. While these studies have focused on the relationship between numeracy and personal risk perceptions, there is less research on how this relationship might generalize to societal risk perceptions. Interestingly, research thus far suggests that the picture may be complex. Recently, a study by Ramasubramanian et al., (2019) observed that numeracy and societal weather risk perceptions were significantly correlated. However, when a structural equation model was conducted on the data, the relationship became non-significant (i.e., the effect of numeracy was indirect). Similarly, a recent study Fox – Glassman and Weber (2016) did not find any relationship between numeracy and risk perceptions (information from personal communication). However, the latter study had a sample size of 83 participants which could indicate that the relationship could not be obtained due to low power. Therefore, does numeracy predict *societal specific* risk perceptions? To what extent does risk literacy mediate the effect of numeracy on risk perceptions?

Current Studies

The current studies aimed to provide a stronger test of whether or not numeracy may often be related to some specific emerging societal risk perceptions (referred as ***specific risk perceptions*** for the rest of this study) as measured by Kahan's Industrial Strength Risk Perception Measure (2017). In Study 1, I tested the hypothesis that numeracy would be related to specific societal risks, by assessing risks that are new, emerging and evolving. This study involved a diverse sample of 20,000 participants from 98 countries. Relations between numeracy, risk perceptions, and decision quality were assessed using a structural equation modeling approach.

Study 2 was designed to extend and replicate Study 1. I started first by estimating *domain general* risk perceptions (referred as ***general risk perceptions*** for the rest of this study), using a high fidelity measurement paradigm developed by Fischhoff et al., (1978). Study 2 included 39 risks, (30 risks from the original 1978 study, and nine new, emerging and evolving risks were added). Thus, I attempted to replicate and extend the factor analysis from the original study (dread and unknown) for both the original and new risks. After I estimated indicators of general risk perceptions, I then analyzed the relationships between numeracy and risk literacy, perceptions of general and specific risks using a series of structural equation models, through direct and indirect paths. General discussion will focus on implications for risk perception measurement advances, as well as future research.

Chapter 2: Study 1

Participants and Procedure

In Study 1, the goal was to investigate the relationship between numeracy, decision quality and risk perceptions in a broad sample, focusing on specific and emerging risks. There were 17,886 participants in this study, obtained from a larger dataset of over 20,000 responses. Data was cleaned to remove people who spent less than three minutes on the survey as well as any responses that were partially or fully incomplete. Participants were readers of the British Broadcasting Corporation's online forum (BBC.com). The majority of the participants were male

(72%), and the reported age range of the participants were between 18-99 years old. Data were collected from over 100 countries in this survey. Participants completed the survey via Qualtrics. After informed consent they were asked to first complete the numeracy and decision quality assessments followed by risk perceptions[1]. Demographics were completed at the end and the average time to complete the survey was 10-15 minutes. All ethical standards as outlined by the IRB were followed.

Measures

Industrial Strength Risk Perception Measure. Developed by Kahan et al. (2017), the industrial strength risk perception measure consists of one item: "How much risk do the following pose for human health, safety and prosperity?". The scale ranged from 0 (No Risk at All) to 10 (Extremely High Risk). Participants were asked to rate five robust risks that were chosen based on previous analyses of risk perception data (Ramasubramanian et al., 2019). These risks were used as indicators of *specific and evolving* risk perceptions. The risks asked were: Drought, Hacking, Sexually Transmitted Diseases (STDs), Unmanned Aerial Vehicles (UAVs), and Terror Attacks. Risks were also chosen based on how salient they are in society today. For instance, damages associated with each drought event costs the United States $9.5 billion (NCEI, 2017). Hacking and UAVs represented new and emerging technological risks, while STDs and Terror Attacks were chosen to indicate uncontrollable, involuntary risks.

Berlin Numeracy Test. Numeracy was measured using the Berlin Numeracy Test (see RiskLiteracy.org). Following best-practice recommendations, I used the BNT-S form, which includes three items taken from Schwartz et al., (1997), and provides increased sensitivity among

[1] The study also included more measures of cognitive skills which are beyond the scope of this thesis and therefore are not discussed in the current study.

less skilled and less educated individuals (e.g., non-college graduates, older-adults). An example item is, *"Imagine we are throwing a five-sided die 50 times... out of 50 throws what proportion will result in an odd number?"*

Risk Literacy and Decision Quality. Risk literacy was assessed via a battery of questions that have been shown to exhibit good psychometric properties (Allan, 2018). Since this survey was supposed to be brief, four questions of *general risk-taking behavior* (e.g., lotteries, ratio bias intertemporal choice) were included (Table 1). Per best-practice guidelines, the correct answer is that which accords with expected value theory (Frederick, 2005). The composite of these scores was used to assess participants risk literacy and decision quality.

Table 1. Decision Quality Outcomes.

Item	**Question**
Intertemporal Choice	Which option do you prefer? £3400 this month £3800 next month
Gain Framed Lottery	Which option do you prefer? £100 for sure 60% chance of £250
Loss Framed Lottery	Which option do you prefer? 75% chance to lose £200 £100 surely lose
Ratio Bias	With the new drug BENOFRENO, the risk of death from a heart attack may be reduced for people with high cholesterol. A study of 900 people with high cholesterol showed that 80 of the 800 people who have not taken the drug died after a heart attack, compared with 16 of the 100 people who did take the drug. How beneficial was the Benofreno? *1 (Not Beneficial) -7 (Very Beneficial)*

Results and Analyses

Numeracy and decision quality were significantly related to all the risks (except drought; as seen in Table 2). To test relationships between numeracy, risk literacy and risk perceptions, a structural modeling approach was used, and a latent trait of risk perceptions was estimated. First, a confirmatory factor analysis was tested with all five risk perceptions loading on a latent variable (i.e., a unidimensional latent trait). The model had good fit ($\chi^2(4) = 244.53$, CFI = .98, TLI = .96, RMSEA = .06). Therefore, in subsequent analyses, the one factor model of risk perceptions was used. Figure 2 illustrates relationships between numeracy, risk literacy and risk perceptions, wherein risk literacy partially mediated the relationship between numeracy and risk perceptions, indicating that numeracy influenced risk perceptions both directly and indirectly. The model had adequate fit: $\chi^2(12) = 972.95$, CFI = .95, TLI = .92, RMSEA = .07 (0.06 – 0.07), SRMR = 0.04.

Table 2. Correlations Between Variables (Study 1)

		1	2	3	4	5	6	7	8	9
Individual Differences										
1	Numeracy	1.0								
2	Decision quality	.32**	1.0							
Demographics										
3	Age	-.10**	-.03**	1.0						
4	Gender	.11**	.11**	.06**	1.0					
Risk Perceptions										
5	UAV	-.16**	-.18**	-.13**	-.16**	1.0				
6	Terror Attacks	-.17**	-.22**	-.18**	-.15**	.48**	1.0			
7	Drought	.03**	.01	-.14**	-.13**	.24**	.32**	1.0		
8	Hacking	-.13**	-.13**	-.14**	-.16**	.42**	.41**	.29**	1.0	
9	STDs	-.14**	-.12**	-.15**	-.14**	.28**	.37**	.28**	.32**	1.0

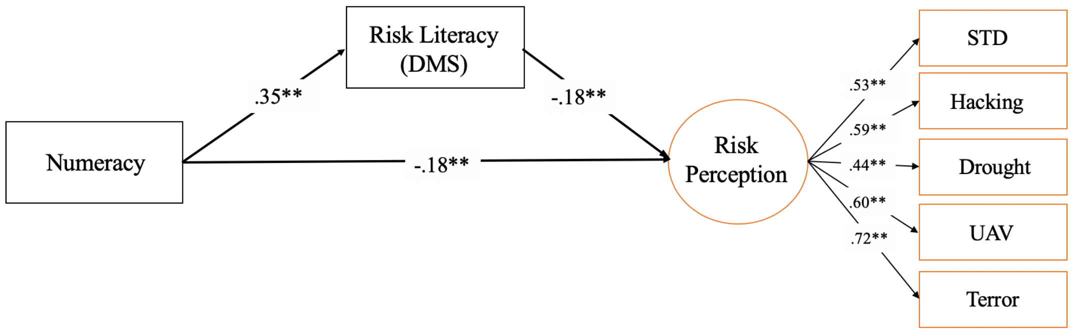

Figure 2. Model 1 – Structural Equation Model.

Previous research has further suggested that risk perceptions are influenced by demographics such as age and gender (Frey et al., 2020; Flynn et al., 1994). Therefore, I tested a similar model as Figure 2, including demographics. Age and gender emerged as consistent predictors of both risk perceptions, as well as numeracy, as displayed in Figure 3. This model also had good fit: $\chi^2(22) = 1137.97$, CFI = .95, TLI = .92, RMSEA = .05 (0.05 – 0.06), SRMR = 0.03.[2]

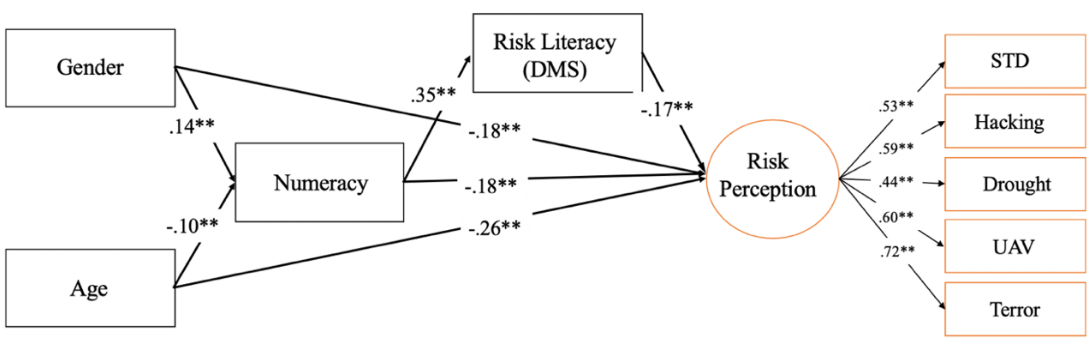

Figure 3. Model 2 – Structural Equation Model (with Demographics).

Taken together, these analyses indicate that emerging specific societal risk perceptions may generally vary systematically due to some individual differences, including numeracy, risk

[2] For all models: *p <. 05, **p<.01. Non-significant coefficients have no asterisks.

literacy, age and gender. Moderating relationships were also analyzed; however, they were not significant, and were removed from the model.

Study 1 Discussion

Using a large sample of diverse participants, and focusing on a few specific, emerging risks, Study 1 tested the relationships between numeracy, risk literacy and risk perceptions. Numeracy emerged as a direct and indirect predictor of emerging risk perceptions, indicating that people with higher numeracy may generally tend to have lower specific risk perceptions. Similarly, the models indicated that people with higher decision quality (risk literacy) tend to have lower specific risk perceptions. Theoretically, results suggest that decision quality and risk literacy may in general mediate the relationship between numeracy and specific risk perceptions. In accord with established findings (Slovic, 1987) more informed participants and experts generally have lower risk perceptions, which may reflect their ability to read risks appropriately. Research has demonstrated that more numerate individuals are better able to understand and evaluate risk information in the service of decision making (Cokely et al., 2012; 2018). Similarly, the current models suggest that individuals who are more numerate and have the skill to make decisions in accord with the risk information, also tend to be less afraid of specific risks. This might also indicate that people with higher numeracy are better at synthesizing information related to these specific risks and adjusting their perceptions accordingly.

Demographic variables were also examined in relation to numeracy and risk perceptions. Consistent with previous research, males and younger individuals tended to have higher numeracy (Cokely et al., 2012). Similarly, gender and age were significantly related to risk perceptions, such that males had lower risk perceptions on average (Flynn et al., 1994). However, in the current study, age and risk perceptions were negatively related, indicating that older adults had lower perceived risk than their younger counterparts. Some previous research on age and risk perceptions is mixed (Wachinger et al., 2013), such that the direction of the relationship can vary across different hazards. Another study by Kellens et al. (2011) indicates that risk perceptions may increase with age, while other studies have found no relationship (Plapp & Werner, 2006; Siegrist & Gutscher, 2006). Recent research has also indicated that older individuals may have better emotional self-regulation, which then can aid them in feeling lower negative emotions overall (Eberhardt, Bruine de Bruin & Strough, 2019).

This study provides initial evidence that numeracy and risk literacy may often be related to differences in perceptions of specific emerging risks, independent of certain demographics. However, while the latent trait of risk perceptions assessed in this study were emerging risks, they were not strictly *domain specific* (i.e., the five risks belonged to different domains). These results further encourage exploration of the underlying mechanisms in the relationships between numeracy and emerging risk perceptions. Since numeracy is a domain general skill, it is reasonable to think that the relationship between numeracy and specific emerging risk perceptions might in part be explained by *general* evaluations of risk (general risk perceptions).To test this hypothesis, I conducted another study to replicate the relations seen here, with a larger number of strictly domain specific risks including more indicators of domain general risk perceptions, in accord with the high fidelity measurement standards established by Fischhoff et al., (1978).

Chapter 3: Study 2

Study 2a

Study 2 focused on two objectives, which are divided into two sections for ease of explication. In Study 2a I attempted to replicate and extend the seminal research for assessing risk perceptions proposed by Fischhoff et al., (1978), using the factor analytic approach that was used in the original study (dread versus unknown). In Study 2b I first distilled indicators of general risk perceptions. I then tested the relationship between individual differences and specific risk perceptions and included general risk perceptions in these analyses. Using a broader range of specific risks, the goal was to test a structural model of the underlying relations between numeracy, risk literacy and risk perceptions when both general and specific risks were present.

Participants and Procedure

There were 250 participants in this study. Participants were students at the University of Oklahoma, recruited through the SONA. Over half the respondents were female (56%), and the age range of the participants were generally between 18-22 years old. The data came from an online portion of a larger study that involved data collection both online in the lab. Participants were asked to first complete numeracy assessments, followed by risk perception measures and ended with demographics. The online survey took about 90 minutes on average to complete, and participants were asked to complete it in one sitting. Participants signed up for the study as part of required course credit. All ethical standards as outlined by the IRB were followed.

Measures

Berlin Numeracy Test. In this study, numeracy was measured using the Berlin Numeracy Test (see RiskLiteracy.org). Following best-practice recommendations, I used the BNT- S form, which includes three items taken from Schwartz et al., (1997), and provides increased sensitivity among less skilled and less educated individuals.

Risk Literacy. Risk Literacy was assessed using a composite of the Adult Decision Making Competence Scale and a battery of more ecological decision making items. Due to time constraints, abbreviated versions of these scales were used. From the ADMC, five subscales were represented: Resistance to Framing, Applying Decision Rules, Consistency in Risk Perceptions, Resistance to Sunk Costs, and Path Independence (Bruine de Bruin, Parker & Fischhoff, 2007). The ecological decision making battery included lotteries, intertemporal choice, medical decisions, and financial decisions (see Allan, 2018; Brunswik, 1955; Dhami, Hertwig & Hoffrage, 2007; Ghazal et al., 2014). The standardized proportional composite of the five components of the ADMC and the four components of an ecological decision battery were combined to make one composite score of general decision quality.

Risk Perceptions

Industrial Strength Risk Perception Measure. Developed by Kahan et al. (2017), this measure consists of one item: "How much risk do the following pose for human health, safety and prosperity?". The scale ranged from 0 (No Risk at All) to 7 (Extremely High Risk). Participants were asked to rate 39 (30 existing risks and 9 emerging) prevalent risks consisting of technology, activity, weather, health and cybersecurity risks. The risks asked are presented in the table below.

Table 3. 30 Risks Asked in Fischhoff et al., (1978)

Risks		
Commercial Aviation	Prescription Antibiotics	Skiing
Contraceptives	Railroads	Fire Fighting
Electric Power	Spray Cans	Large Construction
Food Coloring	Vaccinations	Motorcycles
Food Preservatives	X-Rays	Mountain Climbing
High School and College Football	Bicycles	Railroads
Swimming	Smoking	Police Work
Hunting	Alcoholic Beverages	Surgery
Home Appliances	Handguns	Pesticides
General Aviation	Motor Vehicles	Nuclear Power

Table 4. Domain Specific Risks.

Weather	Cybersecurity	Health/Safety
Tornados	Phishing	Heart Attacks
Hurricanes	Identity Theft	HIV
Severe Weather	Hacking	Terrorism

In addition to these 30 risks, nine new and emerging risks were added to the list of 30 risks used by Fischhoff and colleagues (1978) in their original study. These were split into 3 domains: health and safety, weather and cybersecurity (Table 4). For instance, over the last few years, extreme weather events have resulted in tremendous damages both economically (i.e., $4.3 billion on average per flooding event; NOAA, 2019) and socially (100 deaths in the wake of Hurricane Harvey; Blake & Zelinksy, 2018). Similarly, a relatively new substantial threat that individuals face today are risks related to cybersecurity, particularly for those active on social media platforms. As for the health and safety domain, these three risks represent evolving or emerging threats that are vivid and highly salient. Taken together, this sample of new and evolving risks were selected because they are often high priority issues for risk communication researchers.

Nine Dimensions of Risk. In their 1978 study, Fischhoff and colleagues developed nine characteristics of risks that were asked for each risk. These were used in the current study. The table below presents the questions and scale labels.

Table 5. Description of the Nine Dimensions of Risk Asked in the Current Study.

Dimensions	Description
Voluntariness of risk	Do people get into these risky situations voluntarily? **(1 = voluntary; 7 = involuntary.)**
Immediacy of effect	To what extent is the risk of death immediate-or is death likely to occur at some later time? **(1 = immediate; 7 = delayed.)**
Knowledge about risk	To what extent are the risks known precisely by the persons who are exposed to those risks? **(1 = known precisely; 7 = not known.)**
Knowledge about risk	To what extent are the risks known to science? **(1 = known precisely; 7 = not known.)**
Control over risk	If you are exposed to the risk of each activity or technology, to what extent can you, by personal skill or diligence, avoid death while engaging in the activity? **(1 = uncontrollable; 7 = controllable.)**
Newness	Are these risks new, novel ones or old, familiar ones? **(1 =new; 7 = old.)**
Chronic-catastrophic	Is this a risk that kills people one at a time (chronic risk) or a risk that kills large numbers of people at once (catastrophic risk)? **(1 =chronic; 7 = catastrophic.)**
Common-dread	Is this a risk that people have learned to live with and can think about reasonably calmly, or is it one that people have great dread for-on the level of a gut reaction? **(1 = common; 7 = dread.)**
Severity of consequences	When the risk from the activity is realized in the form of a mishap or illness, how likely is it that the consequence will be fatal? **(1 = certain not to be fatal; 7 =certain to be fatal.).**

Study 2a: Understanding the Factor Structure of Original Risks

First, I started by replicating the factor analysis from Fischhoff et al (1978). In the original study, the factor analysis was conducted by calculating an average score for each risk on each characteristic across all the participants, generating a 30x9 matrix. An Exploratory Factor Analysis (EFA) revealed two orthogonal factors: dread and unknown. The dread factor consisted of severity of consequences, and to a lesser extent, catastrophic risks, and high dread risks. The unknown factor consisted of risks known to persons exposed, known to science, as well as risks that are new, voluntary, immediate and controllable. The cumulative variance explained by these factors were 80%, with the unknown factor explaining 59% of the variance, and 21% of the variance explained by the dread factor. In a recent replication of this study (Table 6), conducted by Fox Glassman & Weber (2016), the two factor solution was obtained with relatively similar loadings, however, the cumulative variance explained by these two factors were 84%, with the unknown and dread factor explaining 47% and 37% respectively. A plausible reason for the increase in the dread factor could be the impact of mass media and its impacts on risk perceptions nowadays compared to 1978 (Fox – Glassman & Weber, 2016).

In the current study, a factor analysis of the original 30 risks as proposed by Fischhoff and colleagues (1978) was conducted. The factor loadings are depicted in Table 6. There are a few differences to note. In this study, the unknown factor consisted of risks known to persons, known to science, new and controllable, and the dread factor consisted of severity of consequences, dread, catastrophic, immediate and voluntary. The unknown factor explains 38% of the variance, and the dread factor explains 31% of the variance in this analysis. In an effort to plot the risks on a two dimensional space similar to Fischhoff and colleagues (1978), the current study used z scores for both the unknown and dread factors (Figure 4). Figure 4 provides an illustration of the positions of the risks on the dread and unknown dimensions. Overall, most of the risks seem to evoke less dread today except for handguns and nuclear power. Similarly, most risks are perceived as less unknown, with the exception of smoking and alcohol. A reason for smoking to be perceived as more unknown today could have to do with the increased consumption of e-cigarettes and activities such as vaping. Similarly, a potential reason for alcohol consumption to be perceived as more unknown might be related to experiences faced by the undergraduate sample present in this study. The figure also provides some key comparisons between risk perceptions today and in the original study (approximate coordinates used from original data). As observed, some risks have stayed the same (pesticides, skiing, motorcycles, and food coloring). However, a few risk perceptions have changed. While nuclear power is perceived as less unknown, it still remains as dreaded as forty years ago. Perceptions of risks such as alcohol, smoking and football have become more unknown, but are more stable on the dread dimension across both studies. Taken together, the results suggest that consistent with the original study and the earlier replication (Fox-Glassman & Weber, 2016), the present analyses provide a conceptual replication of the findings with appropriate sensitivity.

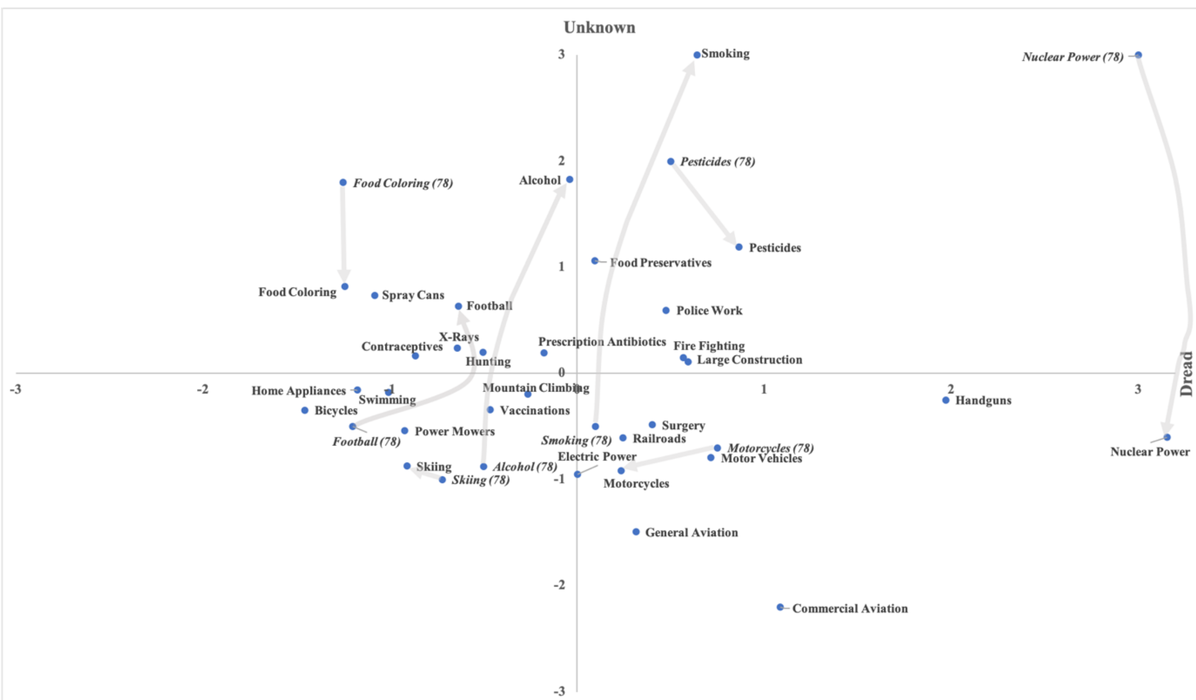

Figure 4. Positions of 30 Risks on the Two Factor Space (Dread v. Unknown)

Table 6. Factor Loadings of the Nine Characteristics with Original 30 Risks

Scale	Voluntary	Immediacy	Known (Exposed)	Known (Science)	Controllable	New	Catastrophic	Dread	Severity	Proportion of Variance
Fischhoff et al. (1978)										
Unknown	0.89	0.70	0.88	0.88	-0.83	-0.87	0.62	0.67	0.11	0.59
Dread	0.03	-0.45	-0.39	-0.28	-0.24	0.14	0.55	0.60	0.91	0.21
Fox-Glassman & Weber (2016)										
Unknown	0.64	0.83	0.98	0.85	-0.34	-0.88	-0.18	-0.20	-0.70	0.47
Dread	0.65	-0.18	0.03	-0.10	0.88	-0.31	0.85	0.90	0.67	0.37
Current Study										
Unknown	0.59	0.37	0.92	0.50	-0.62	-0.80	0.20	0.13	0.32	0.31
Dread	0.61	-0.46		0.46	-0.35	0.28	0.85	0.92	0.94	0.38

Where Do the New Risks Fit?

Here, to characterize the new risks, I began with a large factor analysis including the nine new risks. Another factor analysis was conducted, this time including the new risks (39x9 matrix). An orthogonal two factor solution was obtained, with similar factor loadings on both the dread and unknown factors. The dread factor explained 42% of the variance and the unknown factor explained 26% (summarized in Table 7). Figure 5, which depicts all 39 risks plotted as a function of their dread and unknown z-scores (new risks are designated by red dots). From this figure, it is evident that eight of the nine new risks are in the quadrant that represents high dread and high unknown consistent with the hypothesis that the selected nine risks were suitable indicators of emerging and evolving characteristics of these risks.

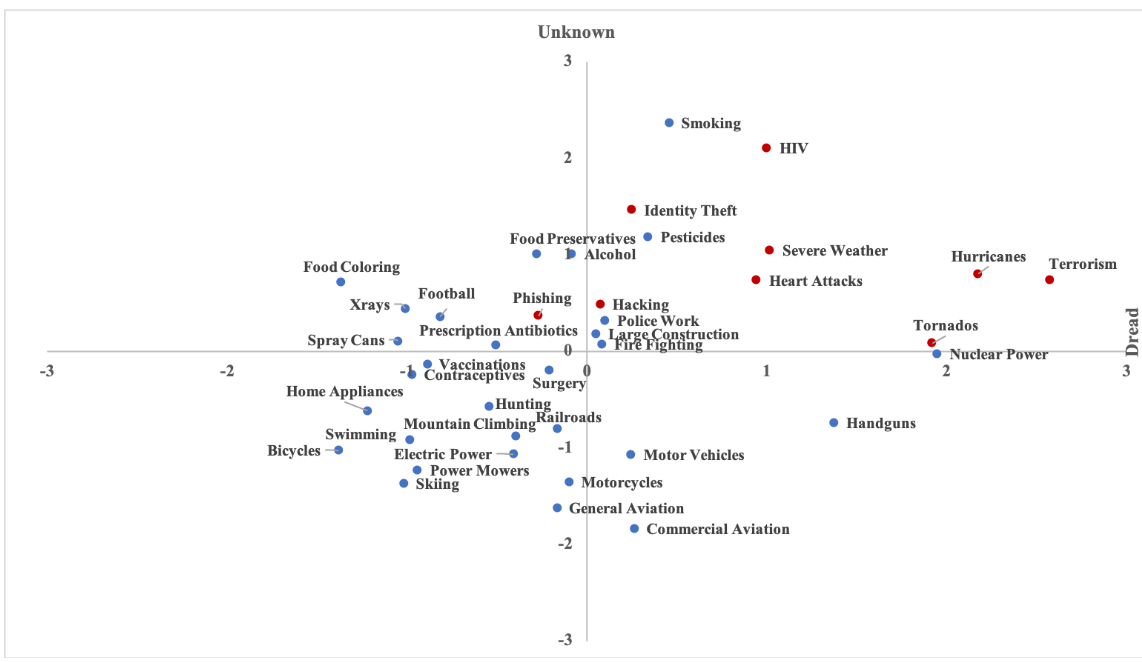

Figure 5. Positions of 39 Risks on the Two Factor Space (Dread v. Unknown)

Table 7. Factor Loadings of the Nine Characteristics with 39 Risks

	Voluntary	Immediacy	Known (Exposed)	Known (Science)	Controllable	New	Catastrophic	Dread	Severity	Proportion of Variance
Unknown	0.28	0.50	0.97	0.57	-0.23	-0.71			-0.38	0.26
Dread	0.80	-0.33	0.16	0.38	-0.68	0.30	0.90	0.94	0.78	0.42

Study 2b: General Risk Perceptions

The associations between numeracy, general and specific risk perceptions were examined. First, risk ratings for each of the risks on each of the nine dimensions were standardized using z-scores. Then, based on the factor analysis in Table 7, each risk was assigned an unknown score and a dread score, calculated as the sum of individual z-scores pertaining to each factor. For instance, if we consider how people perceive the risk of smoking, it was measured using 10 scales (9 belonging to Fischhoff's risk perception measurement, seen in Table 5, and one using Kahan's Industrial Strength Risk Perception Measure). Z-scores for the nine risk characteristics developed by Fischhoff (1978) were generated. Of these, z-scores pertaining to the immediacy, newness, known to persons and known to science of smoking risk perceptions were added to generate a composite "Unknown" score, based on the factor analysis in Table 7. Similarly, z-scores pertaining to voluntariness, controllability, dread, catastrophic and Severity of consequences were added to generate a composite "Dread" score (Table 7). These scores were generated for all 39 risks, following which the unknown and dread scores were added across all risks to yield one unknown composite score and one dread composite score to represent *general risk perceptions* aggregated across all 39 risks. Therefore, each participant had one composite dread and one composite unknown score. Finally, z-scores of the dread and unknown composite scores for each participant were generated, in order to compare dread and unknown risk perceptions (general) to numeracy and specific risk perceptions.

Predicting Risk Perceptions: A Structural Equation Modeling Approach

Following our analytical plan, similar to Study 1, I started by testing a model of the new, specific risk perceptions represented as latent trait from the three domains. Structural models were constructed to test whether numeracy was related to each of the latent traits of risk perceptions, controlling for the influence of general risk perceptions and decision quality factors. For each model, at least three candidate structures were tested, based on theory. Results present the models that were above the threshold according to standard fit statistics. A similar model to Figure 2 was hypothesized, such that risk literacy partially mediated the relationship between numeracy and risk perceptions. However, specific relationships between numeracy, risk literacy and general risk perceptions were determined in an iterative process considering three candidate models. The models for the three domains of risk perceptions are presented below.

Weather. The fit for this model was good: $\chi^2(9) = 22.18$, CFI = .97 TLI = .94, RMSEA = .07 (0.03– 0.11), SRMR = 0.05, seen in Figure 6. An interesting relationship was observed between unknown risk perceptions and weather risks such that individuals who perceived general risks to be more unknown tended to have lower weather risk perceptions.

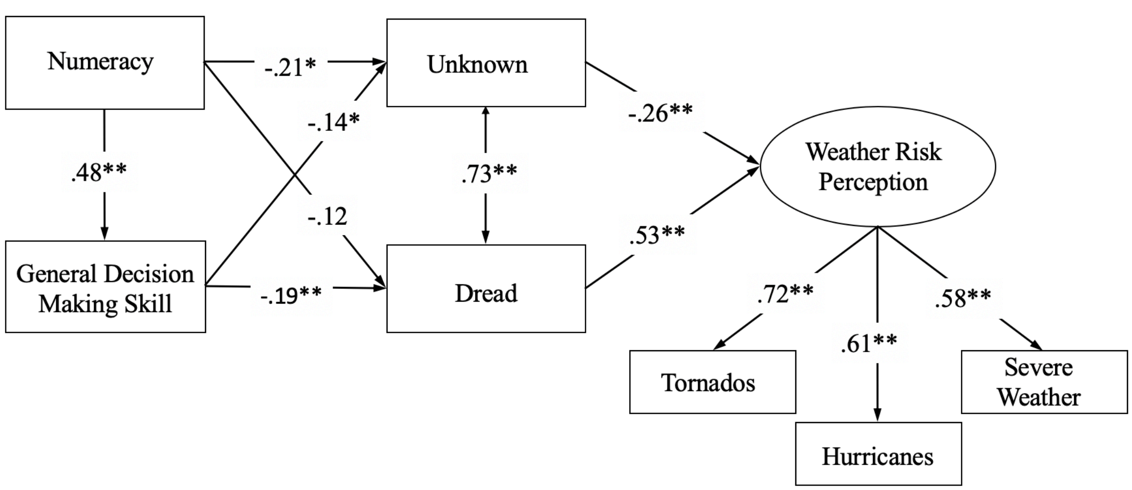

Figure 6. Structural Equation Model for Weather Risk Perception.

Cybersecurity. A similar model was specified as Figure 6, for the cybersecurity domain (Figure 7). The fit for this model was very good: $\chi^2(9) = 8.39$, CFI = 1.00, TLI = 1.00, RMSEA = .00 (0.00– 0.07), SRMR = 0.03.

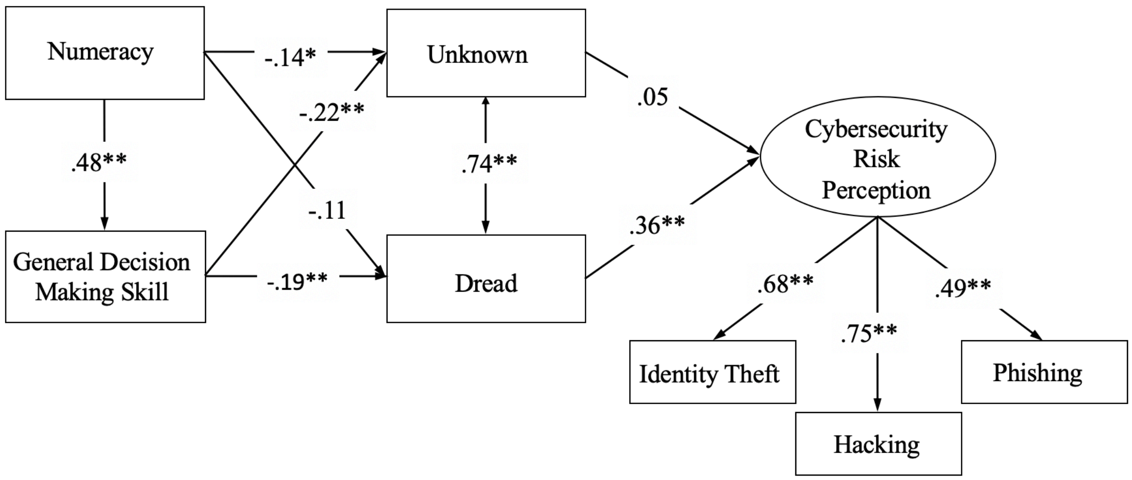

Figure 7. Structural Equation Model for Cybersecurity Risk Perception.

Health and Safety. A similar model was specified as Figures 6 and 7 for the health and safety domain. The fit for this model was very good: $\chi^2(9) = 16.18$, CFI = .98, TLI = .97, RMSEA = .05 (0.00– 0.09), SRMR = 0.05.

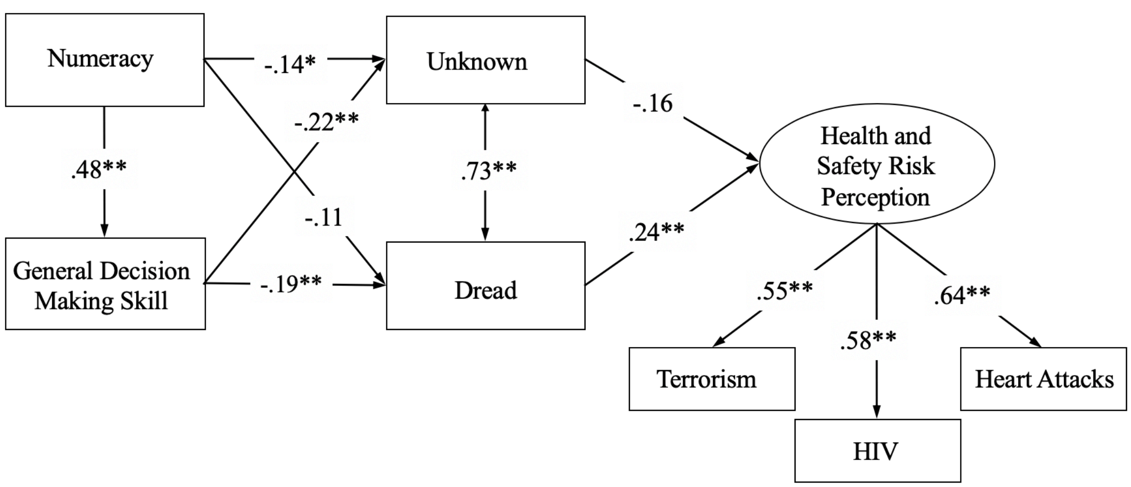

Figure 8. Structural Equation Model for Health and Safety Risk Perception.

Table 8. Correlations Between Variables (Study 2)

		1	2	3	4	5	6	7	8	9	10	11	12	13
Individual Differences														
1	Numeracy	1.0												
2	Decision Quality	.48**	1.0											
Domain General Risk Perceptions														
3	Dread	-.19**	-.28**	1.0										
4	Unknown	-.22**	-.24**	.75**	1.0									
Domain Specific Risk Perceptions														
5	Tornados	.02	-.03	.17**	.05	1.0								
6	Hurricanes	-.09	.02	.18**	.05	.45**	1.0							
7	Severe Weather	-.05	-.14*	.20**	.23**	.43**	.31**	1.0						
8	Heart Attacks	-.01	-.04	.17**	.08	.40**	.35**	.31**	1.0					
9	Terrorism	-.15*	-.17**	.08	.03	.29**	.30**	.22**	.34**	1.0				
10	HIV	-.15*	-.13*	.12**	.05	.31**	.31**	.24**	.33**	.34**	1.0			
11	Phishing	-.01	.07	.10	.04	.14*	.20**	.06	.14*	.05	.10	1.0		
12	Hacking	-.04	.01	.21**	.23**	.22**	.33**	.21**	.08	.18**	.26**	.35**	1.0	
13	Identity Theft	-.09	.01	.14*	.12	.23**	.29**	.18**	.14**	.18**	.29**	.33**	.50**	1.0

Study 2b Discussion

As seen in Figures 6, 7 and 8, similar to Study 1, numeracy and risk literacy tend to explain specific risk perceptions, but are mediated by general risk perceptions. For unknown risk perceptions, numeracy had an influence via direct and indirect paths, indicating that numeracy still explained some unique variance of the extent to which general risks were perceived as unknown. These relationships were negative, indicating that higher numeracy and risk literacy were associated with lower unknown risk perceptions (i.e., risks were perceived to be more known). Numeracy had an indirect influence on dread risk perceptions. The relationship was negative, showing that higher levels of risk literacy were associated with lower dread risk perceptions, suggesting that people better able to understand risks and read risk information tended to be more affectively calibrated (Peters et al., 2012).

As part of the candidate models, direct paths from numeracy, decision making skill and general risk perceptions were tested. The effect of numeracy and risk literacy on specific risk perceptions was largely indirect via general risk perceptions, particularly dread. This might be due to most risks being quite well known to the sample. From Figure 5, only few risks were perceived as highly unknown, while more risks were highly dreaded. Demographics such as age, gender and race failed to significantly predict general or specific risk perceptions. A potential reason for this is the homogenous sample collected from University of Oklahoma's SONA system.

Is Numeracy only Indirectly Related to Specific Risk Perceptions?

Examination of the first order correlations indicated that of the nine risks, numeracy was not correlated with seven. Two notable exceptions that did correlate with numeracy were HIV, and Terrorism (Table 8). When structural equation models were conducted for these risks independently, a direct effect from numeracy to specific risk perceptions is observed. Figures 9 and 10 illustrate Structural Equation Models for HIV and terrorism respectively. Additionally, HIV and terrorism were perceived as highly unknown and highly dreaded respectively, in our college sample (Figure 5). Therefore, a potential explanation for this relationship may be that numeracy predicts emerging risks that seem to be especially salient (extremely scary, or extremely unknown).

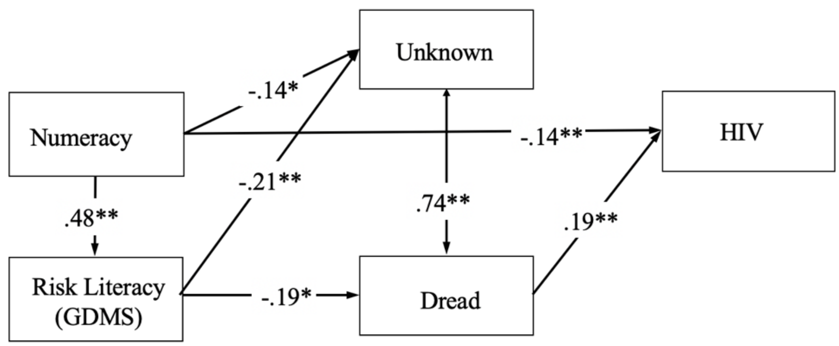

Figure 9. Structural Equation Model for HIV Risk Perceptions

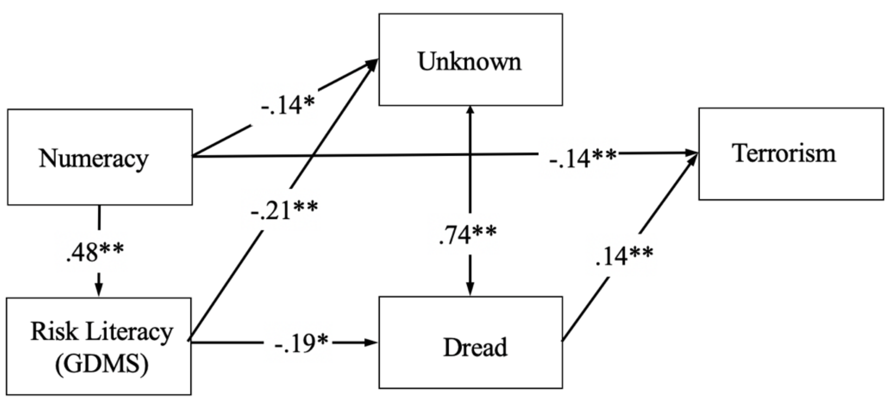

Figure 10. Structural Equation Model for Terrorism Risk Perceptions

The fit statistics for HIV were good: $\chi^2(1) = 1.07$, CFI = 1.00, TLI = .99, RMSEA = .01 (0.00– 0.18), SRMR = 0.01. Similarly, the fit statistics for terrorism was also above threshold:

The fit for this model was adequate: $\chi^2(1) = 3.02$, CFI = .99, TLI = .93, RMSEA = .09 (0.00–0.22), SRMR = 0.02.

Given the current analyses, results suggest that numeracy may generally predict specific risk perceptions because of general risk perceptions, however, evidence from Figures 9 and 10 indicates that numeracy may be uniquely related to specific fields of interest (HIV and Terrorism).

Chapter 4: General Discussion

The goal of this series of studies was to test whether individual differences in numeracy and risk literacy may often be related to differences in emerging risk perceptions that are often useful for policy decisions. In Study 1, using a very large and diverse sample, I observed that numeracy did indeed predict risk perceptions (such as terrorism and STDs). Moreover, the structural model suggests, in accord with Skilled Decision Theory, that in part the relationship between numeracy and specific risk perceptions, may reflect specific skills related to decision quality (e.g., one's ability to evaluate and understand risks in decision making). In Study 2, I once again tested this hypothesis using a higher fidelity approach in accord with the leading standard. This allowed me to not only model a larger sample of specific risks but also to test my hypothesis across three conceptual categories (weather, health/safety and cybersecurity). Study 2b demonstrated that numeracy sometimes predicts specific risks directly (HIV and Terrorism), however results suggest that the relationship between numeracy and specific risk perceptions may more generally be mediated by general risk perceptions. In theory, if individual differences do systematically relate to risk perceptions, they can have implications for policy decisions, anticipating public responses to new and emerging risks, as well as the effective communication of these risks. So, how much do individual differences matter?

How Much Do Individual Differences Matter?

The results from Study 1 and Study 2 illustrate that general risk perceptions may often follow from individual differences in abilities and skills. To explore the role of individual differences in these perceptions, I turn to generalizability theory.

Generalizability theory is a statistical method that is used for characterizing the reliability (or dependability) of sources of measurement Cronbach, Gleser, Nanda, & Rajaratnam, 1972; see also Brennan, 2001; Shavelson & Webb, 1991). This theory has its roots in Classical Test Theory, however, it deviates from the Classical Test Theory in that G Theory considers both systematic and unsystematic sources of error variation and disentangles them simultaneously. Typically, every application of G Theory involves a unit of measurement, usually called 'Persons' that are generalizable to a population. The other component in a G Theory, is a facet, (i.e., a source of measurement error), such as items from a test. There are many designs that the G Theory can be applied to. A one facet universe indicates that apart from the persons, only one facet is being investigated for measurement error (i.e., items; pxi). Similarly, a two facet universe consists of persons, items, and occasions (pxixo). G Theory can also be utilized in nested designs. if items are subsumed within occasions, the design would be two facet nested design (p x (i:o)). The notation for a one facet crossed design is notated as: $X_{pi} = \mu + \nu_p + \nu_i + \nu_{pi}$. Here, μ is the grand mean and the ν's are referred to as effects, or components, in the language of G-theory (Brennan, 2001). In particular, ν_p and ν_i are the main effects and ν_{pi} is the interaction effect. This interaction effect is sometimes denoted as $\nu_{pi,e}$ to express that it is confounded with unmeasured or unsystematic variability (Shavelson & Webb, 1991). G studies are used to estimate the variance of the measurements, which is decomposed into the variance of the components. This information allows the researcher to identify the sources contributing the greatest variability to the measurements.

In order to assess how much variance in risk perceptions are due to individual differences, the current study used a G Theory Framework. The design employed was a one facet universe design, where persons and items are assessed. In this analysis, the items are the 39 risks that were assessed, and this was conducted for each of the ten measurements of risk perceptions asked in the study. The variance components are presented below.

Table 9. One Facet G Theory Variance Components Estimates.

Dimensions of Risk	**Characteristics of Risk**	**Variance Components**			
		Person	Item	Person*Item	Dependability
Unknown	Known to Science	32.7%	2.1%	65.2%	.95
	Known to Persons	20.9%	4.6%	74.5%	.91
	Newness	20.8%	12%	67.2%	.92
	Immediacy	11.3%	14.3%	74.4%	.85
Dread	Dread	20.6%	14.5%	64.9%	.92
	Catastrophic	12.9%	24.4%	62.7%	.89
	Severity of Consequences	13.1%	18.9%	68%	.88
	Voluntary	11.2%	15.3%	73.5%	.85
	Controllability	12.4%	6%	81.6%	.85
	ISRPM	13.9%	33.4%	52.7%	.91

Based on the results from Table 6, analyses suggest that both the persons and the items contribute unique variance in the risk perception ratings. These measurement scales appear to have a high degree of reliability or dependability However, a notable exception are the item variance components for both known to persons and known to science, which are both lower than 5%. According to G-Theory, this would indicate that most of the variance in risk perception ratings for these dimensions of risks, may be attributed to individual differences in persons. On the other hand, when we consider rating risks according to how catastrophic they are, almost 25% of the variance is from the item, while only 13% is from persons. This indicates that there are some individual differences that play a role here, but most of the variance is due to the items, i.e., there were differences in which risks were rated low or high catastrophic.

These findings reaffirm that individual differences are often an integral part of risk perceptions even when participants are asked to rate risks across different dimensions. Further, it is interesting to note that variance components of the dimensions belonging to the unknown factor have more variability on the person level, indicating that unknown risk perceptions are explained to larger extent by individual or person differences than item differences. The sources of variance in the dimensions belonging to the dread factor, however, are less stable in their person and item level variance across different scales of measurement, with catastrophic and controllable having a larger percentage of the variance on the person or individual level. Taken together, the analyses suggest that finer grained assessment in both persons and items may often provide a more accurate understanding of the underlying psychology in risk perceptions, as demonstrated in the current set of studies.

Why Does Numeracy Predict Risk Perceptions?

The findings seen in Study 1 and 2 are consistent with a number of theories. According to fuzzy trace theory, information is encoded into memory in two forms: verbatim and gist representation. People tend to use the gist representation of information to make decisions in the short and long term (i.e., fuzzy trace; Reyna, 2008). For example, one study shows that in accord with theory, fuzzy trace theory representations had an influence on decisions relating to vaccinations (Reyna, 2012).

Similarly, Skilled Decision Theory posits that numeracy tends to predict decision making skill, through a cascade of heuristic deliberative, confidence and affective processes (see also Slovic & Peters, 2006). For example, numerate individuals tend to have a better metacognitive understanding of themselves, have a representative understanding of the problem, and use adaptive heuristics to make decisions in accord with their goals and values (Cokely et al., 2018). As such, more risk literate individuals are better able to interpret information, akin to the mechanisms that allow experts to make good decisions based on detailed, complex, nuanced representations. In Study 2, using a broader range of emerging, specific risks, the models attempt to replicate and extend the findings observed in Study 1, and include a higher fidelity measurement (i.e., general risk perceptions). The relationship in all three models (Figures 6, 7 and 8) suggest that higher risk literacy is associated with lower unknown risk perceptions (individuals believe that risks are known to science and known to persons). Similarly, the relationship between dread and risk literacy suggests that persons with higher risk literacy tend to view risks as lower dread (e.g., less catastrophic, fatal, more controllable and voluntary). Study 2 also observed that societal specific risk perceptions are driven in large part by general dread risk perceptions. This finding is consistent with previous research where risk perceptions are often shaped by affect (e.g., feelings of dread, fear and anxiety; Slovic & Peters, 2006; Slovic et al., 2007; Lowenstein et al., 2001). Thus, one potential reason why numerate people tend to have different risk perceptions is because they may generally have a more precise and consistent understanding of the risks.

These results may have implications for designing effective risk communications or tailoring interventions that aim to improve skills like numeracy or risk literacy for vulnerable individuals. A substantive amount of research has documented the efficacy of using visual aids in order to communicate risk information to low numerate people (provided they are graph literate; see Garcia-Retamero & Cokely, 2011; Garcia-Retamero & Galesic, 2010; Zikmund-Fisher et al., 2014). Presenting visual risk information related to new and emerging risks might bridge the gap between risk perceptions of low numerate and high numerate individuals. Future research can focus on replicating the models presented in these studies with more new, diverse and emerging risks. Additionally, it would be valuable for stakeholders such as policy makers, scientists and media to develop more robust and effective ways to communicate risks to manage societal specific risk perceptions and potentially save lives.

Predicting New, Evolving and Emerging Risks

This thesis has further clarified a gap that has existed across measurement traditions (general and specific risk perceptions), with a lack of research focusing on the role of individual differences in perceptions of emerging specific risks (see Figure 1). The studies presented above demonstrate that numeracy and risk literacy are robust predictors of (general) risk perceptions across both the studies. Further, perceptions of new and emerging risks are often influenced by perceptions of general and existing risks. These results may be valuable because they empower risk perception researchers to identify vulnerable populations (low numerate and risk literate) where risk perceptions can be impacted (high dread, high unknown), which could subsequently impact protective behaviors. For instance, people who perceive extremely high risks generally might have more feelings of dread or anxiety that can lead to maladaptive behaviors (e.g., driving away from a tornado when they should shelter in place; Jauernic & Broeke, 2015). Similarly, on the other end, having extremely high risk perceptions might influence individual investment in mitigation procedures that may be unnecessary (e.g., increased rates of unwarranted screening; Peters et al., 2006). Conversely, extremely low risk perceptions may impact other protective behaviors (e.g., not buying flood insurance when located on a floodplain, see Blake and Zelinsky, 2018).

To further illustrate, another example that is especially salient is the ongoing COVID-19 pandemic. Based on the results from studies 1 and 2, it would be intuitive to conclude that societal specific risk perceptions of a new and emerging risk like COVID-19 might be shaped by general perceptions of existing risks and may also be related to factors such as numeracy and risk literacy. As some preliminary evidence, I analyzed some data from an online study conducted in the first week of April 2020, a few weeks after the COVID-19 pandemic spread to all 50 states in the United States. 400 participants were recruited on Amazon's Mechanical Turk to complete a 15-minute study using a small battery of risks from this study, as well as some robust indicators of unknown and dread, selected based on an analysis of Study 2. Although this is only a preliminary analysis, the results below replicate the models seen in Study 2 and have good fit: $\chi^2(2) = 4.26$, CFI = .99, TLI = .95, RMSEA = .06 (0.00 – 0.13), SRMR = 0.03.

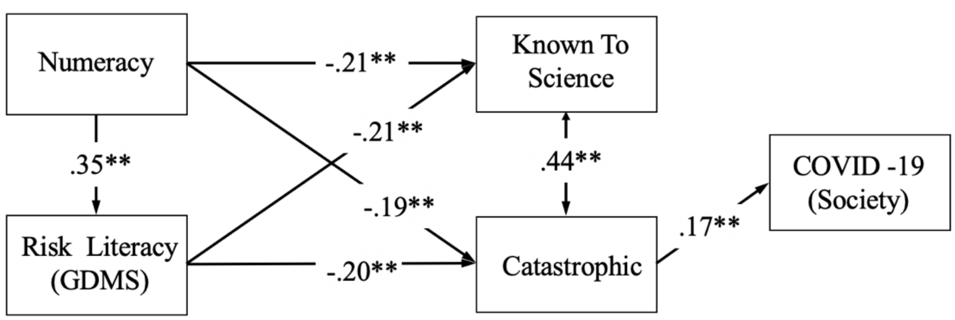

Figure 11. Structural Equation Model for COVID-19 Risk Perceptions.

This analysis provides more evidence in the robust relations between numeracy, specific and general risk perceptions. From these results, numeracy and risk literacy do explain differences in new, novel, emerging risks, generally mediated by general risk perceptions. In the present scenario, this study has some important implications for understanding the perceptions of risk related to COVID-19. Results from this study could be used to design effective risk communications to bridge gaps between high and low numerate people. Another avenue for future research can include measuring these risk perceptions across different times and identifying when the public perceives COVID-19 as more or less risky and how this can influence decisions relating to protective behavior (i.e., a behavioral radar).

This study also paves the way for more research on other diverse individual differences. For instance, potential research can more heavily focus on what other individual differences matter in general and specific risk perceptions (values, emotional and social intelligence, and resilience to name a few), as well as how an individual's *decision making profile* can impact risk perceptions of new, emerging and specific risks. One such individual difference that can have manifold implications in risk perceptions is that of expert consensus (i.e., to what extent individuals' beliefs align with expert recommendations; Barke & Jenkins-Smith, 1993). Given the high degree of individual variance in the known to science and known to persons measurement, I speculate that it is likely that expert consensus might mediate relationships between numeracy, general and specific risk perceptions.

Limitations

As with all studies, there are some limitations to this study. First, both studies were conducted online and thus employed convenience samples. Study 1 was completed by subscribers to an online magazine while Study 2 was completed by undergraduate students looking to gain course credit. It should be noted though, that Study 1 included an extremely diverse sample, with no restrictions on age, race and gender. In Study 2, there is a restriction of range in Study 2, regarding age, race and education. Constraints with the sample aside, Study 2 used a wider range of stimuli to replicate robust relationships found in Study 1. Similarly, while the structural models presented in Study 2 can be generalized to the college sample, future research should focus on replicating these models with diverse populations. Finally, both studies were correlational and exploratory, no experimental manipulation was imposed. Therefore, while I present structural equation models, these models were often iterative (i.e., different paths were tested in accord with previous research). Future research should focus on developing new measures risk perceptions, and sampling from more representative and diverse populations. Together, this will pave the way for research on the role of risk communications on risk perceptions.

Conclusions

The present studies sought to examine the relationship between individual differences and specific risk perceptions. Results suggest that key individual differences (numeracy and risk literacy) may be robust predictors of perceptions of new, emerging and evolving specific risks, which are often mediated by general risk perceptions. Taken together, these studies suggest that individual difference measures including brief general risk perception scales may be useful tools for predicting *who* is most vulnerable to having extreme risk perceptions and under what circumstances (increased dread, more unknown). Given that the number of risks in our world seems to be growing, and the hazards to cope with are increasing, research in the field of risk perceptions can support the development of technologies and interventions to anticipate future risks and effectively communicate information. Together this will support informed decision making and empower disadvantaged populations.

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