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ORIGINAL ARTICLE

Risk Information Seeking and Processing Model: A Meta-Analysis

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This study relies on state-of-the-art meta-analytical techniques to assess overall effects of the Risk Information Seeking and Processing (RISP) model. The results support the utility of the RISP model in predicting risk information seeking and systematic processing. However, the model demonstrated limited explanatory power for heuristic processing. A reduced model composed of only 2 variables—current knowledge and informational subjective norms—accounted for a substantial proportion of variance in the outcome variables. This more parsimonious explanation of information seeking and systematic processing might extend the utility of the RISP model to other communication settings not related to risk. Theoretical boundaries of the RISP model and implications for future research are discussed.

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Over the past 4 decades, risk communication research has emerged as a subfield of communication as evidenced by the large number of scholarly works published in mainstream journals in the discipline (Rimal, 2001; Trumbo, 2002). At the center of this subfield is research that examines how individuals deal with risk information to aid their decision-making processes (McComas, 2006). Grounded in information seeking research from multiple disciplines (Afifi & Weiner, 2004; Case, 2002), risk information seeking research tailors to the unique nature of risk, which recognizes that information is crucial when individuals feel threatened by a potential harm, yet uncertain about the most effective recourse. In particular, risk-information-seeking research examines the impact of risk perceptions on the way in which individuals seek and manage risk information. One of the most comprehensive models that aim to disentangle the social, psychological, and communicative factors that drive risk information seeking is the Risk Information Seeking and Processing Model (RISP) (Griffin, Dunwoody, & Neuwirth, 1999).

Since its original development, the RISP model has guided over a dozen empirical studies in a variety of risk communication settings (see e.g., Griffin et al., 2008; Yang, Kahlor, & Li, 2013). In addition, the key relationships evinced in the RISP model

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have influenced scores of other studies in health and risk communication (Johnson, 2005; Trumbo, 2002). Griffin and colleagues built the model largely based on social psychology theoretical models such as the Heuristic-Systematic Model (HSM) (Eagly & Chaiken, 1993) and the theory of planned behavior (TPB) (Ajzen, 1991). Risk perceptions research (Johnson & Tversky, 1983) and media theories (Kosicki & McLeod, 1990) also informed the design of the model. The model was originally proposed to pinpoint the cognitive and sociopsychological variables that account for individuals' information seeking and processing related to a specific environmental or health hazard, such as eating contaminated fish from the Great Lakes (Griffin, Neuwirth, Dunwoody, & Giese, 2004) or participating in a cancer clinical trial (Yang et al., 2010a, 2010b). More recent research by Kahlor and colleagues expanded the RISP model to examine its applicability in explaining general health information seeking with results indicating that the model could account for up to 64% of the variance in information seeking intentions (Hovick, Kahlor, & Liang, in press; Kahlor, 2010).

In reviewing the empirical research based on the RISP model, Griffin, Dunwoody, and Yang (2012) recently synthesized key findings from studies that examined one or more key concepts from the model and offered a comprehensive overview of the model's theoretical development. Although these authors offered an incisive summary of the research to date, a more systematic meta-analysis is necessary to identify patterns among research findings and sources of disagreement among these studies. Meta-analysis promises to provide precise estimates among key study factors and an overall account of the model's predictive validity across various study contexts. Thus, this study relies on state-of-the-art meta-analytic procedures to directly compare results from 15 published articles (based on 13 studies) that examine the key propositions of the RISP model. Below, we first offer a brief theoretical review of the model and its development over the past 15 years. Readers who are interested in a more detailed overview of the model components and history are referred to Griffin et al. (2012).

Theoretical overview

The RISP model offers a framework to depict the key factors that predispose individuals to seek and process relevant risk information in a more systematic or thoughtful manner. More thoughtful information processing, as proposed, would engender greater compliance with the recommendations communicated in risk messages, regardless of message format. The RISP model suggests that active seeking and systematic processing of risk information are primarily motivated by one's psychological need for information sufficiency (termed as *information insufficiency* hereafter). This idea is largely adopted from the HSM's sufficiency principle—"people will exert whatever effort is required to attain a 'sufficient' degree of confidence that they have satisfactorily accomplished their processing goals" (Eagly & Chaiken, 1993, p. 330). According to Trumbo (2002), the RISP model forms effective links between the questions of where people get information about a particular topic and how they deal with this information.

Communication research on information seeking originated from the classic uses-and-gratifications literature that emphasized a dichotomy between active and passive seeking based on effort and intensity (Chaffee, 1986). Given an increasing number of information providers that are different from the mass media, however, recent research also accounts for individuals' active choosing or avoiding of information (Brashers, Goldsmith, & Hsieh, 2002). The RISP model incorporates this dimension of multichannel information seeking and states that *information insufficiency* motivates information seeking that varies in breadth and depth (Griffin et al., 1999). For example, past research has employed the RISP model to examine information seeking through various channels (Yang et al., 2011). Past research has also applied the RISP model to examine information avoidance when individuals choose to maintain a degree of information insufficiency because their uncertainty appraisal suggests that getting more information about a risk is not desirable (Yang & Kahlor, 2013; Yang et al., 2011).

To conceptualize information processing, the RISP model adopts the HSM's notion of heuristic and systematic processing. In particular, heuristic processing is termed as a more superficial processing mode that relies less on cognitive resources and mental effort. Systematic processing, by comparison, is a more analytical and in-depth mode of information processing. These two concepts resemble the central route and peripheral route as proposed in the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986), however, the HSM asserts that even persuasion through heuristic processing is based on simple decision rules or cues that are associated with message validity. The ELM, on the other hand, specifies motives that could produce attitude change without generating active elaboration about the specific issue (Chaiken & Stangor, 1987). Consistent with the HSM's assumptions, the RISP model's focus on how information is integrated to affect beliefs and attitudes renders it applicable not only to persuasion settings but also to other situations in which people "gain new information about attitude objects or ruminate about information they already possess" (Eagly & Chaiken, 1993, p. 257).

In addition to the accuracy motivation that accounts for *information insufficiency* (Eagly & Chaiken, 1993), defense and impression motivation also likely trigger information seeking and processing. Defense motivation is one's desire to form and hold beliefs that are consistent with his or her material interests and fundamental values. Defense motivation is distinct from accuracy motivation, which is reserved to measure the validity of one's beliefs in relation to existing facts. Impression motivation refers to one's desire to express attitudes that help an individual meet his or her immediate social goals, such as getting along with others (Chen & Chaiken, 1999). Chaiken, Liberman, and Eagly (1989) proposed that both defense motivation and impression motivation could lead to either heuristic or systematic processing, depending on the social contexts in which they function. For instance, when defense-motivated individuals receive information from an authority figure that is in line

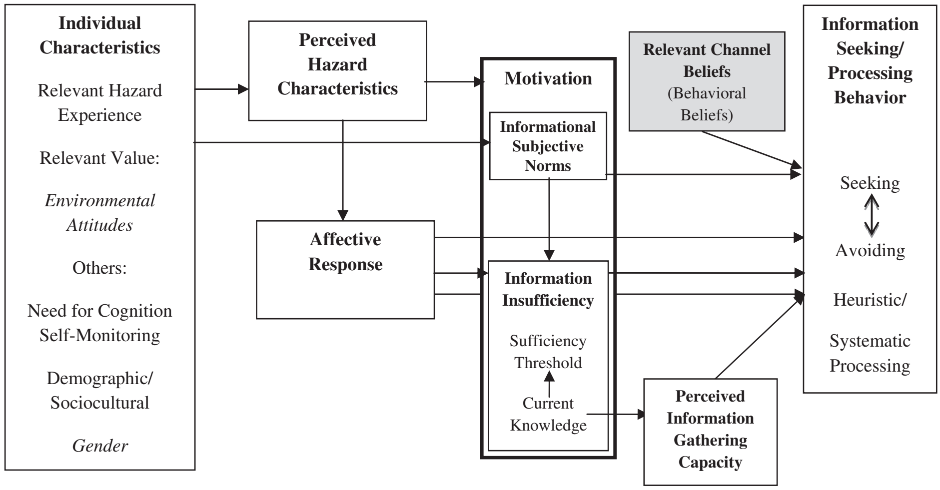

Figure 1 Risk information seeking and processing model (Griffin et al., 2012).

with their position, they may adopt heuristics such as "expertise and specialized knowledge are always trustworthy." However, when the same defense-motivated individuals receive a similar message from a less-valued source, they may engage in further deliberation to reinforce their own belief. Similarly, even though following a simple decision rule such as "go with the consensus" sounds heuristic in nature, the desire to identify the consensus and reach conformity might generate more active information seeking and more effortful information processing.

The RISP model alludes to defense motivation and impression motivation through concepts such as *informational subjective norms* (*ISN*) and *relevant channel beliefs* (*RCB*). Informed by the TPB's subjective norm concept, the RISP model has traditionally depicted *ISN* as individuals' inclination to respond to social pressures or expectations that they should acquire sufficient information to deal with a risky situation. The reasoning is that individuals under greater normative influence from those who are important to them will be more likely to engage in information seeking and processing. This component of the RISP model takes into account potential influence from the surroundings in which communication behaviors occur. Thus, different from other information seeking models that are purely based on individuals' internal calculations (Afifi & Weiner, 2004; Johnson & Meischke, 1993), the RISP model has leeway to assess the impact of sociocultural factors on individuals' motivations. Recent development has identified both direct and indirect influence from *ISN* on information seeking and processing (Griffin et al., 2008; Kahlor, 2010). Thus, Griffin et al. (2012) formally restated the positioning of *ISN* in the RISP model as a direct motivator for information seeking and processing, along with *information insufficiency* (Figure 1).

Even though the conceptualization and measurement strategies associated with *RCB* are still under refinement, overall, this component describes whether or not individuals believe that a particular information channel could provide useful information, while at the same, is unbiased and trustworthy. These notions mainly reflect the findings from communication research that individuals' habitual information processing strategies are influenced by their perceived images of the media (Kosicki & McLeod, 1990). Informed by Chaffee's (1986) cost–benefit analysis approach to explain information channel selection, Griffin et al. (2005) offered a more detailed account for this component, focusing on the perception whether a particular information channel contains information that is most relevant to individuals' processing task. This cost–benefit analysis also involves another component of the RISP model—*perceived information gathering capacity* (*PIGC*), which will be described in more detail next. Because of the concern with reliability issues and the fact that in this day and age, information seeking rarely involves just one specific information channel, later RISP research has evolved to use the TPB's behavioral beliefs concept to assess beliefs that people associate with information seeking activities (Kahlor, 2007, 2010). Thus, due to the lack of consistency in conceptualization and operationalization of *RCB*, the current analysis does not include this component as a key variable of interest.

Similar to other dual-process theories, the RISP model recognizes that in addition to motivation, *capacity* also plays an important role in determining information seeking and processing. That is, at any level of motivation, people still need to weigh the various information options available to them and choose the information channel that is most accessible to them. Thus, people with higher *PIGC* will perceive more behavioral control related to information seeking and processing. As mentioned earlier, this component represents certain *perceived costs* associated with information seeking and processing activities. For instance, individuals with lower capacity will find it more challenging to select a reliable information source and to identify the information that is most valuable to aid their risk-related decisions. The time and energy involved in gathering and processing the relevant information represent potential costs involved. Even though the RISP model originally proposed that *PIGC* would be positively related to information seeking and systematic processing and negatively related to heuristic processing, empirical research has shown mixed evidence (Kahlor, 2007; Yang, 2012). When the RISP model was first proposed, traditional mass media were still the dominant information sources for most individuals. As we enter an information-saturated society, with the availability of the Internet, there are fewer and fewer barriers to information acquisition. Thus, the costs associated with information seeking and processing might be much lower, which means that *PIGC* might play a more marginal role in the model.

While *RCB* and *PIGC* exert moderating influence in the model, antecedents to *information insufficiency* include individuals' cognitive evaluations of and affective responses to a particular risk. Griffin et al. (1999) proposed that given the negative valence of risk perception, *affective responses* associated with these perceptions are likely negative in nature. However, in their subsequent theorization, Griffin et al. (2008) recognized that positive affective responses such as hope could also constitute emotions engendered from a risky situation. Social psychologists have long argued that both hope and anxiety could originate from an appraisal that is based on an uncertain outcome (Ortony & Clore, 1981), whereas empirical evidence has shown that emotions characterized by an uncertain appraisal could promote systematic processing (Tiedens & Linton, 2001). Since uncertainty is an indisputable part of risk perception, it is reasonable to assume that emotions of a positive valence could also play a role in the RISP model. To date, *worry* has been the single affective response that is most consistently researched in different RISP studies. Therefore, the current meta-analysis will focus on *worry* as representing the *affective response* component of the model.

The cognitive evaluation of risk, formally termed as *perceived hazard characteristics* (PHC), involves several distinct dimensions. Up until now, Griffin et al. (2004) offered the most comprehensive description for this construct. Besides the broadly used measures of risk judgment based on subjective evaluation of the probability and severity of potential harm, two more relevant variables were included: personal control and institutional trust. Personal control deals with people's belief that they could do something to protect themselves or others. In contrast, institutional trust depicts one's willingness to rely on experts or authorities for protection (Siegrist, Cvetkovich, & Roth, 2000). Later, causal attribution was integrated as part of PHC (Griffin et al., 2008), largely due to data indicating that different attribution styles shape risk perception in different ways (Kahlor, Dunwoody, & Griffin, 2002). Different RISP studies have explored different dimensions of PHC. However, risk judgment (perceived likelihood × severity) is the most consistent dimension that studies have incorporated. Thus, the current meta-analysis will focus on *risk judgment* as representing the PHC component of the RISP model.

Lastly, demographic variables, past experience, political philosophy, and other sociocultural factors contribute to within-audience variations in terms of information need and information acquisition styles. Past research has found that women, minorities, those who are younger, and those who have had previous experience generally report slightly greater *informational insufficiency* (Griffin et al., 2004). Education level has also been associated with current knowledge and *PIGC* (ter Huurne, Griffin, & Gutteling, 2009). Overall, however, these variables have accounted for a comparatively miniscule amount of variance in the dependent variables compared to other RISP factors.

To summarize, this meta-analysis will focus on the key variables of the RISP model—*information insufficiency* (assessed as the gap between *current knowledge* and *sufficiency threshold*), *ISN*, *risk judgment* (assessed as the product term of *perceived likelihood* and *severity*), *worry*, and *PIGC*. The overall goal is to contrast and compare findings from various empirical studies to determine the overall explanatory power of the RISP model. In addition, the RISP model has been criticized for its lack of parsimony (Braun & Niederdeppe, 2012) and thus, a secondary goal of this study is to identify a more parsimonious version of the model by highlighting the combination of key variables that account for the largest proportion of the variance in information seeking, systematic processing, and heuristic processing. To address this secondary aim, analyses will test a reduced model with only the key motives of information seeking and processing (*information insufficiency* and *ISN*) to see whether these two most central concepts of the model perform consistently across the different studies (Figure 1). Theoretically, if the reduced model offers comparable explanatory power to the full model, future research could concentrate on these two variables, which will make the RISP model much more testable and viable in other communication settings.

In summary, this study advances Griffin et al.'s (2012) review in at least three important ways. First, the current study advances understanding of the RISP model by quantifying and estimating the magnitude of the overall model effects. Second, the current study relies on state-of-the-art meta-analytic techniques that allow model testing whereas the majority of meta-analyses test bivariate relationships within a give model (e.g., Feeley, Moon, Kozey, & Slowe, 2010). Third, the current analysis seeks to examine the viability of a reduced RISP model and in so doing attempts to identify more parsimonious explanations of information seeking and processing. An important consideration in the current study is the reliance on overall variance explained to estimate overall model effects. As the goal of this meta-analysis is to gauge the explanatory power of the RISP model, our interest is in the magnitude of the overall effects, understanding that some bivariate relations within the model may be positive or negative in terms of direction.

Method

Data collection

In an effort to retrieve relevant studies, two methods of data collection were employed. First, all articles included in Griffin et al.'s (2012) theoretical overview were reviewed. Second, the *cited reference search* procedure was used through the *Social Sciences Citation Index* database, specifying Griffin et al.'s (1999) seminal publication as the cited work. Since 1999, a total of 97 articles have cited the RISP model. However, as reflected in Griffin et al. (2012), a much smaller subset of these articles actually tested the RISP model in its entirety.

Inclusion criteria were established to guide review of studies for model comparisons and vet which comparisons to incorporate in meta-analytic procedures. Specifically, studies had to include the six key components of the RISP model mentioned above. Of the entire pool of identified studies, 81 were excluded because they did not directly test the RISP model; three additional studies were excluded due to a lack of inclusion of critical variables, even though these studies sought to test the overall model (Clarke & McComas, 2012; Hovick, Freimuth, Johnson-Turbes, & Chervin, 2011; Johnson, 2005). Specifically, Hovick et al. (2011) did not include *ISN* and *PIGC*, Johnson (2005) did not include *ISN*, and Clarke and McComas (2012) assessed *information insufficiency* with a perceived insufficiency scale, rather than the two-item measure traditionally used in RISP studies. For the 15 articles included in the final analysis, e-mail contact was made to first authors to request the original datasets and all but one author complied and submitted full datasets. For several reasons the original datasets are required for the current analysis, but the most important need is the correlation matrices examining (attenuated) relations among pairs of model variables. The one missing dataset was from a multicountry comparative study, and the dataset from the United States part of the study was included (ter Huurne et al., 2009). For studies with multiwave panel designs (for instance, Griffin, Neuwirth, Giese, & Dunwoody, 2002), only data from the first wave were included for more direct model comparisons. Table 1 shows the list of studies included in the final analysis. All 13 studies included information seeking as the outcome variable, while eight included systematic processing and heuristic processing as the outcome variables.

Data preparation

Several study variables displayed low-reliability coefficients when multiple indicators were used to assess key variables (i.e., information seeking, systematic processing, heuristic processing, *PIGC*). When reliability scores were below .60, attempts were made to improve reliability (e.g., removal of items). When a conventionally acceptable reliability level was not achieved, a decision was made to select a single item that was used consistently across different studies. For all single-item measures, analyses assumed a .60 reliability to account for measurement error (Hunter & Schmidt, 1990).

For the final data file, basic study characteristics were recorded as study moderators due to their potential to account for significant differences observed across different research contexts and methods. We chose these moderators either because they are routine moderators to be included in meta-analysis (e.g., data collection year, research method, demographics, sample type) or for theoretical reasons to see whether the specific types of risks examined in these studies would affect the results (Lipsey & Wilson, 2001). Twelve potential moderators were examined: (a) data collection year, (b) survey method (1 = Random Digit Dialing [RDD] surveys, 2 = other), (c) sample (1 = national sample, 2 = undergraduate sample), (d) risk type (1 = health risks, 2 = environmental risks), (e) risk distance (1 = close, 2 = far), (f) age (mean), (g) sex (percent of female), (h) ethnicity (percent of White respondents or Han Chinese respondents), (i) education (adjusted mean), (j) current knowledge (adjusted mean), (k) sufficiency threshold (adjusted mean), and (l) *ISN* (adjusted mean). Adjusted means were calculated as the difference between actual means and the midpoint of the scales. For instance, for education with a mean score of 5.22 on a 1–8 scale, the adjusted mean was .72. The first and third authors coded all studies based on these moderators and achieved perfect reliability.

Effect sizes

The effect size for this study was the adjusted variance explained ($\widetilde{R}_i^2$) estimated for each dataset. Specifically, for each model a correlation matrix was computed with an equal number of covariates (i.e., predictors) for each dataset. All correlations were

Table 1 Studies Included in This Meta-Analysis

Study ID	*N*	Risk	Survey Method	Articles
1	634	Eating fish from the Great Lakes	RDD adult residents of Milwaukee and Cleveland	(1) Griffin et al. (2002)
2	252	Drinking tap water drawn from the Great Lakes	RDD adult residents of Milwaukee and Cleveland	(2) Kahlor, Dunwoody, Griffin, Neuwirth, and Giese (2003) (3) Griffin et al. (2004) (4) Kahlor, Dunwoody, Griffin, and Neuwirth (2006)
3	303	Flooding of the Menomonee River watershed	RDD adult residents of Milwaukee	(5) Griffin et al. (2008)
4	456	Eco-health of the Menomonee River and Oak Creek watersheds	RDD adult residents of Milwaukee	
5	828	Global warming	Online national research panel	(6) Kahlor (2007)
6	296	Industrial risks	Mail random sample of adult residents in Milwaukee[a]	(7) ter Huurne et al. (2009)
7	804	Health risks	Online national research panel	(8) Kahlor (2010)
8	500	Cancer clinical trials	RDD adult members of the Leukemia & Lymphoma Society	(9) Yang et al. (2010a)
9	500	Cancer clinical trials	RDD national representative sample	(10) Yang et al. (2010b) (11) Yang et al. (2011)
10	371	H1N1 vaccine	Online convenience sample of undergraduates	(12) Yang (2012)
11	736	Climate change	Online convenience sample of undergraduates in United States	(13) Yang and Kahlor (2013) (14) Yang et al. (2013)
12	645	Climate change	Online convenience sample of undergraduates in China	
13	1,007	Health risks	Online purposive sample of national research panel	(15) Hovick, Kahlor, & Liang (JOHC)

[a]Data from the Netherlands sample were not available.

corrected for attenuation and then estimated the explanatory power of the model as R_i^2 (see Appendix for details). Finally, each R_i^2 was adjusted by the number of covariates and then its variance (which is needed for the current meta-analysis) was computed. All the technical details related to the computation of our effect sizes are explained in the Appendix.

Analyses

The analyses were based on current meta-analytical techniques. The original methods were proposed by Hedges and Olkin (1985) and also described in Cooper, Hedges, and Valentine (2009). The current analyses adopted random-effects or mixed models. Random-effect models were used for both the full model and the reduced model. The weights under random-effects were computed as $w_i^* = 1/\left(v_i + S^2\right)$, where the between-sample uncertainty (S^2) for k effects was estimated using restricted maximum likelihood estimator. When adopting mixed-effects models, both predictor variables and additional between-studies uncertainty in the effect variances were incorporated. To assess the explanatory power of the moderators that contribute to explained variability among the effects, a measure of variance explained denoted as R^2_{Meta} was used (Aloe, Becker, & Pigott, 2010; Borenstein, Hedges, Higgins, & Rothstein, 2009). All computations were conducted in R (R Core Team, 2012), using the metafor package (Viechtbauer, 2010). Categorical and regression analyses were conducted to examine differences due to study moderators. For continuous and categorical analyses, the results reported were based on mixed-effects models estimating a common between-study variance. Weighted mean effects, standard errors, and Q statistics are presented within each analysis.

Independence of effects is an essential assumption of most standard analyses in meta-analysis (see Becker, 2000). For each of the reported analyses, each data set contributed to only one data point (i.e., effect size). Thus, the assumption of independence was not violated.

Publication bias

Publication bias occurs on the assumption that statistically significant results are more likely to be published than nonsignificant results. When publication bias (Rothstein, Sutton, & Borenstein, 2005) exists, meta-analysis results may not represent the population of interest and overestimate a given relationship. Publication bias was formally accessed via Egger's regression test (Egger, Davey Smith, Schneider, & Minder, 1997), which tested for the linear association between the effect size and its standard error. In the absence of publication bias, the data should look as a funnel when effect sizes are plotted against their standard errors. The results indicated that there were not statistically significant asymmetries for information seeking ($z = -0.81, p = .42$) and systematic processing ($z = 0.15, p = .88$). However, statistical significance was found for heuristic processing ($z = 2.84$, $p < .05$). This raises some concern about the possibility of publication bias for the heuristic processing outcome. Thus, the results for this outcome should be interpreted with caution.

Results

Results are presented in three sections with each section organized around each outcome variable in the model (i.e., information seeking, systematic processing, and heuristic processing). Within each section, the overall results are detailed for the full and reduced models.[1] Categorical and continuous moderator analyses for the reduced models for the three sets of outcome variables are also reported where significant findings were identified.[2]

Information seeking

For the full model, the estimated adjusted variance explained ($\widetilde{R}_i^2$) for information seeking ranged from .10 to .72 with a median of .52 and the distribution was slightly negatively skewed. The overall weighted average estimated effect size under the random-effects model was .51 ($SE = .06$, $z = 9.17$, $p < .05$), with a 95% *CI* from .40 to .62. Thus, on average, 51% of the variance in information seeking was explained by the full RISP model factors. The homogeneity test, $Q_T\ (12) = 826.44$, $p < .05$, $I^2 = 98.46\%$, $\tau^2 = .04$, indicated that the effects did not all arise from the same population. Next, we described the reduced model for the same outcome.

For the reduced model, the estimated adjusted variance accounted for information seeking ranged from .10 to .66 with a median of .37 and the distribution was also slightly negatively skewed. The overall weighted average estimated effect size, for the reduced model, under the random-effects model was .40 ($SE = .05$, $z = 7.93$, $p < .05$), with a 95% *CI* from .30 to .50. By comparison to the full model, the reduced model accounted for 11% less variance in information seeking. The homogeneity test, $Q_T\ (12) = 671.55$, $p < .05$, $I^2 = 97.70\%$, $\tau^2 = .03$, indicated a significant amount of variance across different studies. Next, we present moderator analyses for the reduced model to examine potential sources of variability.

Moderator analyses

While the primary purpose of this manuscript was to conduct a meta-analysis of the datasets regarding the variance accounted for in outcome variables by key RISP components, several moderators of interest were examined to determine their potential impact on the effect sizes (i.e., adjusted variance explained). For these analyses, the weighted mean effects, standard errors, and *Q* statistics are presented in Table 2.

Survey method. A categorical analysis was conducted to compare the effect of survey method in the magnitude of the effect size. The analysis showed a higher mean variance explained for surveys not based on RDD surveys. Under the mixed model, the between-factor level difference was statistically significant, $Q_B\ (1) = 9.6$, $p < .05$, $R^2_{\text{Meta}} = .43$. However, significant variation was found among RDD surveys, Q_R $(5) = 88.33$, $p < .05$, and non-RDD surveys, $Q_R\ (6) = 162.39$, $p < .05$. Under this analysis, the mean effect for RDD surveys was .27 ($SE = .06$, $p < .05$) and the mean effect for non-RDD surveys was .51 ($SE = .05$, $p < .05$). Thus, the model better predicts information seeking when study methods rely upon data collection methods other than RDD surveys.

Table 2 Overall Results for Full and Reduced Models and Moderator Analyses for Reduced Models

	Seeking			Systematic Processing			Heuristic Processing		
Categories	k	Mean (SE)	$Q_{Residual}$	k	Mean (SE)	$Q_{Residual}$	k	Mean (SE)	$Q_{Residual}$
Overall									
Full model	13	.51* (.056)	826.44*	8	.32* (.090)	1169.52*	8	.14* (.050)	193.62*
Reduced model	13	.40* (.051)	671.55*	8	.24* (.072)	473.60*	8	.06* (.019)	46.76*
	Seeking			Categorical Moderators			Heuristic Processing		
Categories	k	Mean (SE)	$Q_{Residual}$	k	Mean (SE)	$Q_{Residual}$	k	Mean (SE)	$Q_{Residual}$
Method	**Q_B (1) = 9.6, $p < .05$**			Q_B (1) = 2.27, $p = .13$			Q_B (1) = 3.05, $p = .08$		
RDD survey	6	.27* (.058)	88.33*	6	.18* (.076)	140.69*	6	.05 (.018)	30.83*
Non-RDD survey	7	.51* (.053)	162.39*	2	.41* (.131)	98.91*	2	.12* (.037)	0.33
	Seeking			Continuous Moderators			Heuristic Processing		
Categories	k	Mean (SE)	$Q_{Residual}$	k	Mean (SE)	$Q_{Residual}$	k	Mean (SE)	$Q_{Residual}$
Sufficiency threshold	**Q_M (1) = 5.84, $p < .05$**			**Q_M (1) = 23.37, $p < .05$**			Q_M (1) = 2.93, $p = .09$		
Slope	13	−.11* (.045)	448.85*	8	−.18* (.037)	54.78*	8	−.03 (.017)	24.04*
ISN	Q_M (1) = 0.17, $p = .68$			Q_M (1) = 1.16, $p = .28$			**Q_M (1) = 6.64, $p < .05$**		
Slope	13	−.02 (.055)	670.35*	3	−.08 (.075)	262.53*	8	−.04* (.014)	30.69*

Note: The degree of freedom for $Q_{Residual}$ are $k - 1$; k = number of effects. Significant between-factor level differences are shown in bold.
*$p < .05$.

Sufficiency threshold. The model test was statistically significant under the mixed model, Q_B (1) = 5.84, $p < .05$, $R^2_{Meta} = .30$, indicating that this moderator explained differences among the effects. After accounting for variability in the mixed-effects models, there was still significant variability among the effects, Q_R (11) = 448.85, $p < .05$. Thus, sufficiency threshold was significantly related to the size of the effect under the mixed-effects model ($b = -.11$, $SE = .05$, $p < .05$), indicating that sufficiency threshold is inversely related to the variance explained.

ISN. ISN was not instrumental in explaining any differences among the effects under the fixed-effect or mixed-effects models, Q_M (1) = 0.17, $p = .68$.

Systematic processing

For the full model, the estimated adjusted variance explained for systematic processing ranged from .03 to .78 with a median of .34 and the distribution was positively skewed. The overall weighted average estimated effect size under the random-effects model was .32 ($SE = .09$, $z = 3.61$, $p < .05$), with a 95% *CI* from .15 to .50. Thus, almost one third of the variance in systematic processing was explained by the full model. The homogeneity test, Q_T $(7) = 1169.52$, $p < .05$, $I^2 = 98.97\%$, $\tau^2 = .06$, indicated that the effects did not all arise from the same population.

For the reduced model, the estimated adjusted variance explained ranged from .02 to .65 with a median of .22 and the distribution was also slightly positively skewed. The overall weighted average estimated effect size, for the reduced model, under the random-effects model was .24 ($SE = .07$, $z = 3.34$, $p < .05$), with a 95% *CI* from .10 to .38. The homogeneity test, Q_T $(7) = 473.60$, $p < .05$, $I^2 = 98.24\%$, $\tau^2 = .0398$, indicated a large amount of heterogeneity.

Moderator analyses

In this section we report the results of both categorical and continuous moderator analyses. Again, the weighted mean effects, standard errors, and *Q* statistics are presented in Table 2.

Survey method. Once again, the analysis showed a higher mean variance explained for non-RDD surveys than RDD surveys. The initial variability that this model explained was reduced under the mixed model and the between-factor level difference was not statistically significant, Q_B $(1) = 2.27$, $p = .13$.

Sufficiency threshold. This model was statistically significant under the mixed model, Q_B $(1) = 23.37$, $p < .05$, $R^2_{\text{Meta}} = .78$, indicating that this moderator did explain differences among the effects. However, there was still significant variability among the effects, Q_R $(6) = 54.78$ $p < .05$. Thus, sufficiency threshold did relate significantly to the size of the effect under the mixed-effects model ($b = -.18$, $SE = .04$, $p < .05$), indicating that this variable is inversely related to the effect size (i.e., variance explained).

ISN. An initial fixed-effects test indicates a relationship between *ISN* and the size of the effects. However, the difference between the effects disappeared when the additional unexplained variation was incorporated into the analysis, Q_M $(1) = 1.16$, $p = .28$. Thus, *ISN* did not relate significantly to the size of the effect under the mixed-effects model ($b = -.08$, $SE = .08$, $p = .28$).

Heuristic processing

For the full model, the estimated adjusted variance explained for heuristic processing ranged from .01 to .38 with a median of .10 and the distribution was positively skewed. The overall weighted average estimated effect size under the random-effects model was .14 ($SE = .05$, $z = 2.77$, $p < .05$), with a 95% *CI* from .04 to .23. The homogeneity test, Q_T $(7) = 193.62$, $p < .05$, $I^2 = 97.91\%$, $\tau^2 = .0188$, indicated that the effects did not all arise from the same population.

For the reduced model, the estimated adjusted variance explained ranged from .01 to .15 with a median of .06 and the distribution was also slightly positively skewed. The overall weighted average estimated effect size, for the reduced model, under the random-effects model was .06 ($SE = .02$, $z = 3.41$, $p < .05$), with a 95% *CI* from

.03 to .10. The homogeneity test, Q_T (7) = 46.76, $p < .05$, $I^2 = 88.51\%$, $\tau^2 = .0023$, indicated a large amount of heterogeneity. Thus, the effects did not all arise from the same population.

Moderator analyses

For these analyses, the weighted mean effects, standard errors, and Q statistics are presented in Table 2.

Survey method. A categorical analysis showed a higher mean variance explained for non-RDD surveys than RDD surveys. However, under the mixed model, the between-factor level difference was not statistically significant, Q_B (1) = 3.05, $p = .08$. There was significant variation among RDD survey effects, Q_R (5) = 30.83, $p < .05$, but not for non-RDD survey effects, Q_R (1) = 0.33, $p = .57$. Under this analysis, the mean of the RDD survey effect was .05 ($SE = .02$, $p < .05$) and the mean of the non-RDD survey effect was .12 ($SE = .04$, $p < .05$).

Sufficiency threshold. The initial variability that this model explained disappeared when the additional unexplained variation was incorporated into the mixed model analysis, Q_M (1) = 2.93, $p = .09$. Thus, sufficiency threshold did not relate significantly to the size of the effect under the mixed-effects model ($b = -.03$, $SE = .02$, $p = .09$).

ISN. This moderator was statistically significant under the mixed model, Q_B (1) = 6.64, $p < .05$, $R^2_{\text{Meta}} = .52$, indicating that this moderator did explain differences among the effects. However, there was still significant variability among the effects, Q_R (6) = 30.69 $p < .05$. Thus, *ISN* did relate significantly to the size of the effect under the mixed-effects model ($b = -.04$, $SE = .01$, $p < .05$), indicating that *ISN* is inversely related to the effect size (i.e., variance explained).

To summarize, the overall model accounted for up to 72% of the variance in information seeking, 78% of the variance in systematic processing, and 38% of the variance in heuristic processing. The reduced model with only two variables (*current knowledge* and *ISN*) accounted for up to 66% of the variance in information seeking, 65% of the variance in systematic processing, and 15% of the variance in heuristic processing. Based on the mean effect sizes (Table 2), the reduced model accounted for 78% of the variability in the full model for information seeking and 75% of the variability in the full model for systematic processing.

However, we also found more variability than expected by chance across the studies. For models with information seeking as the outcome variable, survey method accounted for significant variability, with non-RDD surveys showing a higher explanatory power (51%). Sufficiency threshold also accounted for 30% of the variability among the effect, suggesting that the reduced model accounted for more variance in information seeking when respondents' sufficiency threshold (perceived need for risk information) was lower. For models with systematic processing as the outcome variable, sufficiency threshold accounted for 78% of the variability in effect sizes for the reduced model, indicating that the reduced model accounted for more variance in systematic processing when respondents' sufficiency threshold was lower. Lastly, for models with heuristic processing as the outcome variable, both survey method and *ISN* significantly moderated the effect sizes across different studies. In particular, non-RDD surveys showed a higher explanatory power (12%), while the reduced model accounted for more variance in heuristic processing when respondents reported less social expectations that they should know something about the risk (lower *ISN*).

Discussion

This meta-analysis synthesized research findings from 15 published articles (13 studies) that tested the RISP model in its entirety. Due to a lack of consistency in conceptualization and operationalization of the *RCB* component, this variable was not included in the analysis. Otherwise, all other model components were intact (see Figure 1). Overall, the RISP model exemplified excellent explanatory power in analyses with information seeking and systematic processing as the outcome variables. A key finding was the discovery that current knowledge and *ISN* accounted for a large proportion of the variance in these variables. This result should not be too surprising given that information insufficiency and *ISN* represent the key motives behind information seeking and processing, occupying the central part of the model. However, this more parsimonious explanation of information seeking and systematic processing extends the utility of the reduced model to other communication settings not related to risk because current knowledge and *ISN* are not specifically tied to risk issues. Nonetheless, a more efficacious way to test the full model is also warranted in future research. For instance, a more reliable and internally consistent set of multi-item indices that assess key variables might allow researchers to test the full model with structural equation modeling.

An unexpected finding was the influence that current knowledge, rather than information sufficiency threshold, consistently exerted on the outcome variables. Several interpretations for this finding are possible here. First, compared to assessing how much we know about a particular risk, it is more challenging to estimate how much information is required for us to deal adequately with a potential risk, as the latter estimation is less intuitive. Thus, using current knowledge and information sufficiency threshold to assess *information insufficiency* may not be the most ideal strategy. Aside from this issue, moderator analysis shows that information sufficiency threshold had a *negative impact* on overall effect sizes. As individuals require more information to satisfy their processing goals, the amount of variance accounted for in information seeking and systematic processing decreases. Thus, the model is less effective in explaining information seeking and systematic processing when survey respondents are less familiar with the risk. Addressing theoretical boundary, this finding indicates that the RISP model is more applicable to research that examines risks that are relatively familiar or personally relevant to the respondents. For instance, risks related to food consumption (Griffin et al., 2004) and health threat (Hovick et al., in press) seem more appropriate topics. Researchers should take this into account when considering the RISP model as the theoretical guide for their studies. That said, predictors of information seeking and processing, such as information insufficiency and *ISN*, could offer insight for the design of risk messages or risk communication campaigns when the objective is to elevate perceived relevance of the risk among target audiences. Thus, the RISP model still offers much practical value as a theoretical framework.

Compared to the explanatory power afforded by the models for information seeking and systematic processing, the model explained significantly less variance in heuristic processing. Two explanations could account for this observation. First, the HSM clearly states that heuristic processing is the default mode of information processing unless individuals are motivated to spend more time and effort to process information systematically. Thus, we can interpret heuristic processing as a less deliberate mechanism that involves fewer cognitive resources and less rational thinking. In contrast, the RISP model pinpoints intricate processes that link cognitive evaluation of potential risks and information sufficiency, affective responses to risks, psychological reactions to social influence, and communicative factors such as capacity to gather information and assessment of information sources. All these variables are based on an individual's *thorough elaboration* of the risk information (i.e., systematic processing). Therefore, there seems to be a mismatch in theorization of the RISP model and conceptualization of heuristic processing. Second, among the three outcome variables, heuristic processing achieved the lowest reliability across the studies. In six out of the eight studies analyzed, the reliability was lower than .60. Although the correlations between key variables and heuristic processing were attenuated due to measurement error, this is a cause for concern regarding scale construction for heuristic processing. Future research should focus more on information seeking and systematic processing when applying the RISP model. At the least, measurement strategy for information processing, especially heuristic processing, needs further improvement, which is a sentiment echoed by other researchers (e.g., Schemer, Matthes, & Wirth, 2008).

The small effect that *ISN* had on the heuristic processing models also deserves some attention. In particular, the reduced model accounted for more variance in heuristic processing when respondents reported lower perceived social expectations that they should know something about the risk. Stated differently, current knowledge and *ISN* accounted for more variance in heuristic processing when *ISN* was lower. To explain this curious finding, perhaps when survey respondents perceived less social pressure to stay on top of information about an issue, they were more likely to rely on an existing general knowledge structure to make a quick judgment or to go with the general consensus on how to cope with the risk. In those circumstances, it makes sense that other parts of the RISP model, such as risk perceptions and information gathering capacity, play a minor role in influencing heuristic processing.

Among the 12 moderators included in these analyses, only three exerted significant impacts on the effect sizes. Admittedly, many of these moderators were examined on an exploratory basis. In addition to the influence of information sufficiency threshold and *ISN* discussed above, another interesting finding lies in the contrast of

RDD surveys when compared to other data collection methods. Among the studies analyzed, RDD surveys recruited respondents based on probability sampling from either a specific geographic area or a nationally representative sample, while non-RDD surveys relied primarily on convenience sampling of online research panels or undergraduates. This finding alerts us that studies based on nonprobability surveys and convenience samples might have amplified effect sizes, which might have over exaggerated the explanatory power of the RISP model. Alternatively, in those studies, individuals who are predisposed to seek information about a risk and think about it systematically might be more inclined to participate in the research. Regardless, future research should strive to use more probability sampling technique and large national samples to provide a more precise estimate of the model.

While identifying the meaningful patterns observed through this meta-analysis, it is also important to point out limitations in the current study. First, in order to obtain full correlation matrices with all the key variables of interest, we could not include all the empirical studies that have examined the RISP model. The final sample size was relatively small for our analysis. It should be noted, however, that the current analysis of 13 studies required a substantial amount of coordination related to obtaining the datasets, reanalyzing data, and overall model testing. Second, there is still a minor cause for concern due to measurement error, as on several occasions, it was necessary to account for measurement error attenuation due to the use of single-item measures or the use of multiple-item measures with unacceptable reliabilities. For single-item measures, we relied on a reliability estimate at .60 (Hunter & Schmidt, 1990). This conservative estimate of reliability score might have reduced the explanatory power of certain components of the RISP model. For instance, 6 of the 13 studies with information seeking as the dependent variable used a single item to measure *ISN*, while the other seven studies that included multiple items achieved reliability scores ranging from .71 to .93. Also, a decision was made to include only *worry* to represent the affective response component, as it is the single negative emotion that was consistently assessed in all 13 studies. However, the majority of RISP studies have relied on multiple specific emotions to assess affective response, with reliability scores ranging from .68 to .92. (Hovick et al., in press; ter Huurne et al., 2009; Yang et al., 2013). Therefore, the impact of affective response on information seeking and processing might have been underrepresented in our analysis.

In summary, this meta-analysis relied on state-of-the-art meta-analytical techniques to assess overall effects of the RISP model. The results support the utility of the RISP model in predicting risk information seeking and systematic processing. The reduced model, which accounted for a substantial proportion of the variance in the outcome variables, was composed of only two key variables, current knowledge and *ISN*. Compared to variables such as perceived hazard characteristics and affective responses to risks, current knowledge and *ISN* are not specifically related to risk contexts. Thus, this more parsimonious explanation of information seeking and systematic processing might extend the utility of the reduced model to other communication settings not related to risk. Future research on information seeking and processing should also take into account individuals' existing knowledge about an issue and their perceived social expectations regarding how informed they should be about the issue. When applying the RISP model to risk contexts, care should be exercised to assure that the research subjects have a heightened sensitivity and perceived relevancy to the risk.

Notes

1 The reduced model with *current knowledge* and *ISN* accounted for equal amount of variance in the dependent variables as the reduced model with the three factors of *current knowledge*, *sufficiency threshold*, and *ISN* as independent factors. Thus, results from the two-factor model are reported hereafter for the reduced model as it is more parsimonious.

2 Only the moderators that are significantly related to one of the three outcome variables are reported.

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Appendix

In this meta-analysis, the effect size of interest is the adjusted variance explained. We consider three different outcome variables (i.e., information seeking, systematic processing, and heuristic processing) and for each outcome variable we consider a full and a reduced model. Specifically, for each outcome variable, the full models included the variables *risk perceptions*, *worry*, *ISN*, *knowledge*, *threshold*, and *PIGC*, and for the reduced models only the variables *ISN* and *knowledge* were in the model. Next, we outlined the steps used to obtain the explanatory power of each study with the same number of covariates.

The Pearson product–moment correlations (r_{ij}) between the variables of interest (i.e., information seeking/systematic processing/heuristic processing, risk perceptions, worry, *ISN*, knowledge, threshold, and *PIGC*) were estimated from each data set. Then the reliability information from each variable was used to correct the correlations for attenuation (Hunter & Schmidt, 1990). Specifically, $r = r_{ij}/\sqrt{r_{ii}}\sqrt{r_{jj}}$, where r is the unattenuated correlation, r_{ij} is the correlation between variable i and variable j, r_{ii}, and r_{jj} are the reliabilities associated with variables i and variable j, respectively. Then we described the treatment of each correlation matrix.

Let the unattenuated intercorrelation matrix for each independent study be denoted as **R**. Thus, matrix **R** can be partitioned into (Cooley & Lohnes, 1971):

$$\mathbf{R} = \left|\begin{array}{cccccc|c} 1 & r_{12} & r_{13} & \cdots & r_{1,p-1} & & r_{1p} \\ r_{21} & 1 & r_{23} & \cdots & r_{2,p-1} & & r_{2p} \\ r_{31} & \mathrm{r} & 1 & \cdots & r_{3,p-1} & & r_{3p} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ r_{p-1,1} & r_{p-1,2} & r_{p-1,3} & \cdots & 1 & & r_{p-1,p} \\ \hline r_{p1} & r_{p2} & r_{p3} & \cdots & r_{p,p-1} & & 1 \end{array}\right| = \left|\begin{array}{c|c} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \hline \mathbf{R}_{21} & 1 \end{array}\right|$$

where $\mathbf{R}_{11}$ is the matrix of intercorrelations among the predictors, and $\mathbf{R_{21}} = \mathbf{R_{12}^T}$ is the column of vectors of the predictors with the dependent variable. Thus, we obtained the vector **b**, the standardized slope vector, as

$$\mathbf{b} = \mathbf{R}_{11}^{-1}\mathbf{R}_{12}.$$

Then, the squared multiple correlation, or R^2, was computed as the vector of the product of **b** and the correlations of the predictors with the dependent variable as

$$R^2 = \mathbf{b}^{\mathrm{T}}\mathbf{R}_{12}.$$

Then, each R_i^2 (the total variance explained for each study) was adjusted as (Wherry, 1931)

$$\widetilde{R}_i^2 = 1 - \left(1 - R_i^2\right)\left(\frac{N_i - 1}{N_i - p - 1}\right),$$

where N_i is the sample size for data set ith, and p is the number of covariate (i.e., predictors) which is equal among studies. The variance of $\widetilde{R}_i^2$ was estimated as (see Olkin & Finn, 1995, p. 161)

$$var\left(\widetilde{R}_i^2\right) = \frac{4\widetilde{R}_i^2\left(1 - \widetilde{R}_i^2\right)^2\left(N_i - p + 1\right)^2}{\left(N_i^2 - 1\right)\left(N_i + 3\right)}.$$

The same procedure was repeated for each data to obtain both full and reduced models.