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The Influence of Environmental Hazard Maps on Risk Beliefs, Emotion, and Health-related Behavioral Intentions

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Abstract

To test a theoretical explanation of how attributes of mapped environmental health hazards influence health-related behavioral intentions and how beliefs and emotion mediate the influences of attributes, 24 maps were developed that varied by four attributes of a residential drinking water hazard: level, proximity, prevalence, and density. In a factorial design, student participants (*N*=446) answered questions for a subset of maps. Hazard level and proximity had the largest influences on intentions to test water and mitigate exposure. Belief in the problem's seriousness mediated attributes' influence on intention to test drinking water, and perceived susceptibility mediated the influence of attributes on intention to mitigate risk. Maps with carefully illustrated attributes of hazards may promote appropriate health-related risk beliefs, intentions, and behavior.

Keywords

environmental health; risk communication; visual communication; health promotion; hazard proximity; visual perception

Maps are useful for sharing information with health professionals and community members because viewers can see the locations and spatial relationships of depicted information (Choi, Afzul, & Sattler, 2006; Riner, Cunningham, & Johnson, 2004; Severtson & Burt, 2012). Common goals of environmental health communication are to increase awareness about the presence and magnitude of environmental hazards and to promote health and prevent disease. An example of the latter goal is reflected in the Environmental Public Health Tracking Program's mission (Center for Disease Control, 2006) to generate information, including maps, to "drive actions to improve the health of communities" (p. 3). Despite increasing use of hazard maps, there is scant evidence on whether or how maps influence lay people's environmental health risk beliefs or related behaviors (Bostrom, Anselin, & Farris, 2008).

The substudy reported here is an initial test of a framework developed in earlier work and described below. A substudy addresses different research questions but uses some or all of the participants from the parent study (National Institute of Health, 2004). The purpose of this substudy was to measure the influences of four attributes of mapped hazards (hereafter, attributes) on people's health-related behavioral intentions (hereafter, intentions) and assess the roles of risk beliefs and emotion in mediating these influences.

Integrated Representational and Behavioral Framework

Maps and other images are composed of multiple features such as color and shape (Wolfe, 2005). The usefulness of maps for communicating information is influenced by the viewer's

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interpretation of map features (Caley, 2004; Slocum, McMaster, Kessler, & Howard, 2009). In an earlier study, map features shaped the meaning that lay people derived from environmental hazard maps (Severtson & Vatovec, 2012). To represent these findings, theoretical concepts from the fields of visual cognition, semiotics, learning and memory, and health behavior were used to create the Integrated Representational and Behavioral Framework (hereafter called the framework, Figure 1), which can guide theory-based research on how images influence health-related behavior and predictors of behavior (Severtson & Vatovec, 2012).

Visual representations and information processing

People derive meaning from what they see. For a visual representation (an image), visual cognition involves how seeing an image is related to the meaning derived (cognitive representation) from what is seen. This process is explained by "top-down" and "bottom-up" information processing. Deliberate top-down processing is consciously directed by the viewer, as when one assesses hazards near one's home. Conversely, unconscious bottom-up processing occurs due to the neurological link between the eyes and cognitive processing areas in the brain (Healey, 2007; Johnson et al., 2006; Pinker, 1990). Bottom-up processing explains how people can comprehend what they see without conscious effort. Given the challenges of measuring top-down and bottom-up information processing, (Melloni, van Leeuwen, Alink, & Müller, 2012; Wulff, 2007) these processes are rarely measured and were not measured in this substudy.

Pinker (1990) proposed that four basic factors explain what people see: unit of perception, magnitude, Gestalt laws, and coordinate system. Unit of perception is conceptualized as the unit at which information is displayed (Severtson & Vatovec, 2012). People tend to notice extremes in the magnitude of visual features (Pinker, 1990). Gestalt laws of visual perception describe how proximity, similarity, and continuity foster perception of recognizable objects and patterns from visual stimuli. The universally understood coordinate system for maps is latitude and longitude (Severtson & Vatovec, 2012). These four factors also explain derived meaning, as vision is tightly integrated with cognition (Tversky, 2005).

Properties of visual features can support comprehension. Preattentive features are comprehended via bottom-up processing (Healey, 2007; Wolfe, 2005). Cleveland and McGill (1984, 1985) proposed ten such preattentive features that support accurate bottom-up comprehension; three of these features – length, area, and position on a scale (e.g., a ruler) – are relevant to the substudy. Pinker's (1990) factors pertain to preattentive features (Severtson & Vatovec, 2012); for example, length, area, and position on a scale convey magnitude.

Semiotic properties of features also support comprehension. Semiotics is the study of signs including icons and symbols; both support cognition by standing for a thing or idea. An icon conveys meaning by resembling or imitating a thing or idea (e.g., airplane icon to convey airport), while the meaning of a symbol must be learned (Chandler, 2002). Chandler (2002) observed that maps can iconically represent the geospatial relationships among mapped landmarks. The commonly understood meaning of stoplight color symbols, learned via socio-cultural conventions, explains why participants in the initial study described green and blue as meaning safe, yellow as caution, and red as warning (Severtson & Vatovec, 2012). Map features are better comprehended when a legend is not needed to explain their meaning (Robinson, Sale, Morrison, & Muehrcke, 1984), hence the value of iconic features and commonly understood symbols.

Cognitive and emotional representations, intentions, and health-related behavior

The meaning derived from hazard maps is conceptualized as the cognitive representation, which is comprised of risk beliefs. A body of evidence from the Common Sense Model (Leventhal, Brissette, & Leventhal, 2003) and Precaution Adoption Process Model (Weinstein, 1988) indicates established predictors of health-related behavior (hereafter, behavior). These theories illustrate that identifying a risk (identity) has a key role in motivating behavior and is comprised of specific and global risk beliefs. In the framework, specific risk beliefs include perceived (a) susceptibility to a hazard, (b) severity of associated consequences, and (c) locational social comparison of one's own location-based risk compared to the location-based risk of others "residing" on the map (Severtson & Burt, 2012). Specific risk beliefs explain global risk beliefs, such as whether the hazard is perceived as a serious problem. Global risk beliefs explain intentions, which predict behavior (Weinstein, 1988). Risk information also influences the emotional representation of risk, which is linked to the cognitive representation and is linked through intention to behavior (Leventhal, et al., 2003). Notably, "maps allow viewers to identify location-based risk" (Severtson & Vatovec, 2012).

Behavioral intentions predict behavior (Ajzen & Fishbein, 1980; Weinstein, 1988). A meta-analysis showed a mean correlation of .53 between intentions and behavior ($N = 82{,}105$); intentions explained 28% of the variance in behavior (Sheeran, 2002). In response to environmental hazard information, appropriate behaviors include monitoring to identify the presence of a hazard and mitigating to decrease exposure to, or the presence of, a hazard. Monitoring includes laboratory testing, such as testing for drinking water contaminants. Mitigation includes actions to reduce exposure, such as filtering tap water.

Personal characteristics

Personal characteristics also influence response to risk information. Females tend to have stronger risk beliefs and intentions to mitigate risk (Slovic, 1999). Numeracy, defined as "the ability to comprehend, use, and attach meaning to numbers," also influences risk beliefs and decisions (Nelson, Reyna, Fagerlin, Lipkus, & Peters, 2008, p. 262). Prior beliefs and experiences (MacEachren, 1995; Verdi & Kulhavy, 2002) and personal relevance (Hegarty, Canham, & Fabrikant, 2010; Swienty, Reichenbacher, Reppermund, & Zihl, 2008) substantially influence the meaning derived from maps.

The framework was developed to guide research on the influence of features of visual representations on cognitive and emotional representations that, in turn, influence intentions that predict behavior. In this framework, cognitive and emotional representations are mediators of the influence of visual features on intentions and behavior, and personal characteristics may moderate the influence of visual features.

Role of Maps in Risk Beliefs, Intentions, and Behavior

Only three studies of maps and people's risk beliefs, intentions, and behavior were located in the literature (none included emotion), denoting scant research on this topic. An interactive map about hurricane risk generated stronger perceived susceptibility to hurricanes and intentions to evacuate than a brochure (Collins, 1998). Investigators who studied volcano risk maps found that 2 of 45 participants changed their risk beliefs after viewing the maps (Haynes, Barclay, & Pidgeon, 2007). In another study, investigators found participants used neighborhood maps to increase physical activity by planning walking routes (McNeill & Emmons, 2012). These studies suggest maps can influence risk beliefs, intentions, and behavior, but little systematic and theory-based research has been conducted on this topic.

This substudy was informed by an initial qualitative study (Severtson & Vatovec, 2012) that was conducted to discover what people saw and the meaning of what they saw as they viewed maps depicting a fictitious drinking water hazard in private residential wells. One type of study map used dots to depict well water hazards. Personal relevance led to a top-down interest in hazards near participants' perceived home location on the map. Gestalt properties of continuity and proximity potentially led participants to notice (bottom-up) dot patterns such as clusters of hazards. Participants' perceived proximity to large mapped hazards had a primary influence on the strength of their risk beliefs derived from study maps. Results suggested four bottom-up or semiotic influences (embodied in four attributes) on risk beliefs: preattentive length (proximity), magnitude (hazard level, prevalence), symbolic risk colors (hazard level), and Gestalt Laws (recognizable patterns) (Severtson & Vatovec, 2012). Furthermore, the spatial arrangement of the dots resembled (iconically) the distribution of the "on the ground" hazard data. Participants perceived their proximity to dots as resembling their "on the ground" proximity to hazard.

The purpose of the parent study of the substudy was to quantify the map influences noted in the initial study (Severtson & Vatovec, 2012) for the same drinking water hazard and four attributes of the mapped hazard: proximity, hazard level, prevalence, and patterns (Severtson & Burt, 2012). A mathematical model was developed to quantify the combined influence of these attributes. This proximity-based hazard model generated a numeric estimate of hazard *(PBH)* for a participant's map location based on surrounding visualized hazards.

In the parent study, 24 maps were designed to test *PBH* against the four underlying attributes. Of nine risk belief and emotion variables, perceived susceptibility was most correlated with attributes and *PBH*. Attributes and *PBH* explained similar amounts of variance in susceptibility. Of the attributes, hazard level and proximity had the largest influences on susceptibility (Severtson & Burt, 2012).

Aims and Research Questions of Present Study

Unanalyzed data from the parent study were used to address the substudy aims. Substudy aims were to measure the influences of attributes of mapped hazards on dependent variables of risk beliefs, emotion, and intentions and the roles of risk beliefs and emotion in mediating these influences. Attributes were expected to exert different amounts of influence on each dependent variable. Beliefs and emotion were expected to mediate different amounts of influence between attributes and intentions. Research questions (RQ) were:

RQ1 What were the influences of attributes on risk beliefs, emotion, and intentions?

RQ2 What were the influences of risk beliefs and emotion on intentions?

RQ3 What were the mediating roles of risk beliefs and emotion in indirectly transmitting the influences of attributes on intentions?

RQ4 How much variance in dependent variables was explained by the map attributes versus the mediating variables in the model?

Methods

Study Design and Experimental Maps

This substudy was an analysis of participants' survey responses to 24 maps from the parent study that used dots as the unit of perception for the mapped hazard. Dots depicted water test results for a fictitious drinking water hazard called rhynium to allow experimental manipulation on maps. Rhynium was described as a naturally occurring contaminant that was recently found to cause cancer. The map legend depicted five ordinal hazard levels (ranges of test results in parts per billion (ppb), see Figure 2). Modified stoplight colors were used to symbolize hazard levels.

The parent study used a full factorial 2 × 2 design to create 16 attribute-defined map subsets resulting in 24 experimentally designed maps (see Severtson & Burt, 2012 for details). Parent study maps varied by four attributes: proximity, hazard level, prevalence, and patterns. The proximity attribute was measured as (a) categorized distance from the assigned "you live here" map location to mapped hazard (Figure 2), or (b) assigned location inside or outside of a hazard pattern (a cluster). Figure 3 illustrates how dots were arranged to operationalize attributes.

In the substudy, the 24 maps were classified as (a) 16 distance-only maps (b) 4 cluster location-only maps and (c) 4 maps that were both distance and cluster location maps (see examples in Figure 3). For the subgroup of 20 distance maps, attributes were hazard level, distance, and prevalence (incomplete factorial 3 × 3 × 3 design). Distance maps depicted hazard only with blue and dark red dots (lowest and highest hazard levels in the legend) symbolizing safe and unsafe test results based on the drinking water standard of 10 ppb. Hazard levels for the 20 distance maps were 1 = all blue dots, 2 = mixed dots, and 3 = all red dots. Distance from assigned location to mapped hazard was: 1 = far, 2 = medium, and 3 = near. Prevalence of the hazard was operationalized as 1, 2, or 8 dots.

For the subgroup of 8 cluster location maps, attributes were hazard level, cluster location, and cluster density (full factorial 2 × 2 × 2 design). Hazard levels were 2 = mixed dots and 3 = all red dots. Cluster location inside or outside of a hazard pattern was: 1 = outside and 2 = inside. Dots in the cluster were loose (cluster density = 1) and tight (cluster density = 2).

Maps were organized into four blocks with six maps in each. Blocks included a similar mix of distance and cluster location maps. Within each block, the six maps were arranged to accentuate the contrast from one map to the next. (All blocks are shown in Severtson & Burt, 2012, and http://research.son.wisc.edu/wellstudy/MapBlockss.pdf.)

Survey Measures

Variables with proposed mediating roles were: (a) three specific beliefs (susceptibility, severity, locational social comparison); (b) one global belief (serious problem); and (c) one emotion (distress). Intention variables were monitor intentions (intentions to test water) and mitigate intentions (intentions to drink less unfiltered well water than assigned pre-map use of "main source of drinking water"). Response scales for each variable are shown in Table 1.

The four survey versions, one for each block of six maps, were identical except for the map block. In survey booklets (4 versions), survey items measuring variables of beliefs, emotion, and intentions accompanied each of the six maps; when the page was turned, they viewed a different map. Participants were instructed to answer survey items based on an assigned map location (Figures 2 and 3).

Self-reported age and race/ethnicity were collected to describe the study sample. Personal characteristics (covariates) were numeracy, gender, current water use, and prior residence (Table 1). Participants' current water use (drinking water) and dominant type of prior residence (rural-urban) were used to control for personal experiences that may have influenced intentions.

Numeracy was the sum of responses to the subjective numeracy scale (Zikmund-Fisher, Smith, Ubel, & Fagerlin, 2007). The numeracy scale was modified by deleting items 5 and 7 from the 8-item scale (Fagerlin et al., 2007). Item 6 was reworded into two items (prefer words, prefer numbers) with a 5-point response scale from *Never* to *Always*. Participants therefore rated seven items: their ability to use numbers (four items) and their preferences for words or numbers (three items). Cronbach's alpha for the revised scale was .82 for this substudy and also .82 for the original 8-item scale (Fagerlin et al., 2007).

Sample and Procedure

The University Institutional Review Board approved the study as minimum risk. Undergraduate students (1,045) in three courses (psychology, sociology, nursing) were verbally invited to participate; 750 students picked up surveys (versions ordered 1–4, repeatedly within each pile) as they left their classrooms. This approximated random assignment to one of the survey versions. Of invited students, 43% (N=446) returned completed surveys; see details in Severtson and Burt (2012). The median age of the sample was 19 years (range 17 – 44 years), and 28% were males. Self-reported race was 92% white, 5% Asian, and 3% as other or another race. Each survey included both types of maps (distance and cluster location), so personal characteristics were the same across distance and cluster location map subgroups.

Because most undergraduate students at this university lived in the city of Madison, most participants' residences were supplied by municipal water. In contrast, all residents in the township (Springdale) depicted on study maps had residences with private wells. Based on 2010 data (US Census Bureau, 2012), the adult population in Springdale was older (median age 40) and had a larger proportion of males (51%).

Analysis

All variables met criteria for normality (Tabachnick & Fidell, 2001). Separate path models were developed for distance maps and cluster location maps. Attributes were specified as independent variables in these path models (Figures 4, 5). Attributes embodied visual cognition concepts depicted in the framework and appear on the left of the path models. Dependent variables were specific and global risk beliefs, emotion, and intentions. The order of variables in the path models reflected the order depicted in the framework.

Path analysis effectively assesses chains of influence that explain how independent variables indirectly influence outcomes through mediating variables. Path models are used to understand, but not to formally test, mediation (Brown, 1997). To facilitate assessing indirect effects and comparing results across the two path models, (a) path models were specified to include all unidirectional paths leading from variables in each tier of the model to all variables in subsequent tiers and (b) non-significant paths were not deleted. No correlated errors were specified within mediating tiers. Gender was specified a priori to load on severity, numeracy on susceptibility, and current water use and prior residence on both intentions.

Models were analyzed using Mplus version 5.1 with maximum likelihood estimation. The following were estimated: direct effects from one variable to another; total indirect effects from each attribute to the global belief, emotion, and intentions; and total effects (sum of direct and indirect effects). Total indirect effects through each mediating variable were summed to estimate general magnitude. Model fit (see captions of Figures 4 and 5) was acceptable based on Hu and Bentler's (1999) guideline of ≤ 0.08 for the standardized root mean residual (SRMR), but not for the ≥ .95 comparative fit index (CFI) guideline. Kline (1998) adopted Cohen's (1988) recommendations for describing general effect sizes for social science research with absolute values of standardized path coefficients less than .10 as "small," around .30 as "medium," and greater than .50 as "large." These recommendations were applied to describe the general magnitudes of direct, indirect, and total effects.

Because each participant viewed six maps, the analysis used the Mplus CLUSTER command to account for non-independence of observations (Muthen & Muthen, 2007 – 2011). Covariance matrixes for path models are at http://research.son.wisc.edu/wellstudy/CovarienceMatrix.pdf.

To assess explained variance in dependent variables originating from only the attributes compared to the additional variance contributed by the mediators, path models were also estimated with attributes as the only predictors of dependent variables. The difference in the percentage of variance explained by only the attributes and the variance explained by attributes with preceding mediating variables was calculated to identify the percentage of variance contributed by the mediating variables.

For coefficients with similar standard errors, non-overlapping 84% confidence intervals (CIs) are generally aligned with a $p < .05$ test of significance (Payton, Greenstone, & Schenker, 2003). Therefore, the 90% CIs calculated using Mplus provide conservative support for statements about the magnitude of difference between total effects.

Results

All study variables with means and standard deviations, numeric codes for attributes, and response scales for the survey items are shown in Table 1. Paired sample *t*-tests indicated that for both types of maps participants had stronger intentions to monitor risk than to mitigate risk: (a) for distance maps, the mean difference (*SD*) = −1.10 (1.16), $t = -44.65$, *df*(2220), $p < .001$; (b) for cluster location maps, the mean difference (*SD*) = −0.75 (1.02), $t = -22.05$, *df*(886), $p < .001$. Distance maps showed large direct effects of hazard level on susceptibility, of susceptibility on the global belief of serious problem, and of distance on locational social comparison (Figure 4). Cluster location maps showed large direct effects of cluster location on susceptibility and locational social comparison (Figure 5). Gender had medium effects on severity; all other covariate effects were null or small (see captions for Figures 4 and 5).

RQ1. Influence of Map Attributes on Risk Beliefs, Emotion, and Intentions

Total effects—For distance maps, hazard level and distance had medium to large total effects (.280 – .567, Table 2) on all dependent variables except perceived severity. For cluster location maps, a similar pattern was found but with small to large total effects of hazard level and cluster location (.123 – .522) on all dependent variables except perceived severity. Hazard prevalence and cluster density had small total effects on dependent variables (absolute values .019 – .119).

For distance maps, hazard level had a larger total effect than distance on all variables except locational social comparison and perceived severity (see CIs in Table 2). For cluster location maps, cluster location had a larger total effect than hazard level on all variables except susceptibility and perceived severity (see CIs). For distance maps, hazard level had the largest total effects on intentions (Tables 2 and 3). For cluster location maps, cluster location had the largest total effects on intentions. For both map subsets, the smallest total effects were on perceived severity.

Interactions—Interactions between hazard level and each type of proximity (distance, cluster location) were analyzed because these interactions had substantial influences on susceptibility in the parent study (Severtson & Burt, 2012). Hazard level by distance interactions had significant direct effects on: susceptibility = 1.06, locational social comparison = .87, severity = .26, and emotion = −.23 (standardized coefficients). Hazard level by cluster location interactions had significant direct effects on: susceptibility (.31) and

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mitigate intentions (−.36). To further examine these interaction effects, models were estimated for each hazard level. The total effects of attributes on intentions for low, mixed, and high hazard levels are shown in Table 2.

Distance had no effects on either intention for maps with low hazard levels. Cluster location had a larger influence on intention to mitigate for maps with high hazard levels compared to those with mixed hazard levels. For distance maps, means for intentions to monitor and mitigate at each hazard level (with standard deviations in parentheses) were: low hazard= 2.79 (1.34) to monitor and 1.45 (0.88) to mitigate, medium hazard = 4.18 (1.04) to monitor and 2.99 (1.29) to mitigate, high hazard = 4.41 (0.90) to monitor and 3.45 (1.29) to mitigate. Results for cluster location maps were: medium hazard = 4.49 (0.81) to monitor and 3.58 (1.24) to mitigate, high hazard = 4.66 (0.66) to monitor and 4.07 (1.07) to mitigate.

Total indirect effects—Table 3 shows total effects, total indirect effects, and direct effects of attributes on intentions, and percentages of total indirect effects relative to total effects. Percentages were ≥ 80% for hazard level and proximity attributes (distance and cluster location) on both intentions, and for prevalence on mitigating intentions. Percentages were < 80% for prevalence (73%) and density (61%) on monitoring intentions and for density (71%) on mitigating intentions.

RQ2. Influence of Risk Beliefs and Emotion on Intentions

Both models showed that the global belief of problem seriousness had medium to large total effects on monitoring intentions (.444 – .461), and susceptibility had medium to large total effects on mitigating intentions (.403 – .495; Table 4). Total effects for other beliefs and emotion ranged from .054 – .365.

RQ3. Indirect Effects through Mediating Variables

The largest total indirect effects on monitoring intentions were through the global belief of problem seriousness (distance maps sum = .467, cluster location maps sum = .374, see Table 4). The largest total indirect effects on mitigating intentions were through susceptibility (distance maps sum = .555, cluster location maps sum = .444). (The total effects of a mediator can be smaller than the sum of indirect effects transmitted through the mediator due to the negative direction of some effects within the model.)

Figures 4 and 5 illustrate the primary chains of influence (bolder paths) from attributes through mediating variables to intentions. Stronger chains originated from hazard level and the proximity variables (distance and cluster location). Susceptibility had larger direct effects on mitigating intentions (distance maps = .27, cluster location maps = .21) than on monitoring intentions (distance maps = .07, cluster location = ns). Locational social comparison, emotion, and severity had small or very small indirect effects (sums ranging from .025 – .163) on intentions (Table 4). There were no primary chains of influence through these variables.

Percentages of indirect effects on intentions (relative to the total effects) at or over 45% were through beliefs and emotion for (Table 4): (a) susceptibility (from hazard level, distance, cluster location), (b) the global belief of problem seriousness (from hazard level, cluster location), and (c) locational social comparison (from distance, cluster location). For variables with percentages of indirect effects less than 45%, percentages for severity were smaller (1.7% –11.4%) compared to other variables (6.5% – 39.9%).

RQ4. Percentage of Explained Variance

Path models of effects of only attributes explained a larger percentage of variance in dependent variables for distance maps than for cluster location maps (see Table 5), and effects were larger for mitigating intentions than monitoring intentions. For distance maps, variance in dependent variables explained by only attributes was more than 50%. For cluster location maps, variance in dependent variables explained by only attributes was more than 50% for the global belief of problem seriousness and for mitigating intentions.

Discussion

Results provide initial support for the relationships depicted in the framework (Severtson & Vatovec, 2012). Overall, substudy results suggest that maps can influence health-related beliefs, emotions, and intentions, which in turn may influence behavior. A public health goal of risk communication is to promote monitoring for the presence and level of household hazards. For hazards such as drinking water contaminants or radon, monitoring is a key step because appropriate mitigation depends on laboratory test results (some homes in a hazard area may have “acceptable” levels of a contaminant). As such, results showing greater intentions to test water than to mitigate potential exposure are encouraging and confirm previous findings that maps of drinking water hazards promote intentions to test water (Severtson & Vatovec, 2012).

Model fit was acceptable based on the standardized root mean residual (SRMR) but not based on the comparative fit index (CFI). Hu and Bentler (1998) warned against strict adherence to fit indices guidelines, and others have cautioned that theory rather that fit indices should guide modeling decisions to avoid rejecting adequate models (Type I error) (Marsh, Hau, & Wen, 2004). As such, substudy path models were considered adequate for this initial test of the framework in which path models were specified to assess and compare total and indirect effects rather than to assess model fit.

Map Attributes’ Influence on Beliefs, Emotion, and Intentions

Theoretical properties of visual representations (magnitude; Gestalt laws; and preattentive, iconic and symbolic features) (Figure 1) were embodied in the attributes of mapped hazards and may explain why hazard level and proximity had the largest total effects on intentions. Visual features used to communicate the meaning of hazard level were preattentive position on a scale and color symbols. In addition, non-visual information in the legend included numeric ranges of test results and a numeric safety standard.

Test results compared to safety standards influence risk beliefs (Weinstein & Sandman, 1992). Hazard levels on study maps were the lowest and highest positions on the legend scale, which may preattentively (bottom-up) convey magnitude (Cleveland & McGill, 1984, 1985) independent of the numeric values (Severtson & Myers, 2012). Using conventional stoplight color symbols to convey hazard levels may facilitate comprehension of magnitude and associated safety because the meaning is readily available from memory (Severtson & Burt, 2012; Young & Wogalter, 1990). Symbolic risk colors may have influenced beliefs and emotion beyond the numeric and preattentive meaning of hazard level displayed in the legend. Comprehension of proximity may be explained by bottom-up processing of preattentive distance to dots and the iconic resemblance of mapped dots to “on the ground” proximity to hazard. Icons that embody preattentive features may support comprehension via bottom-up processes and resemblance (Severtson & Myers, 2012).

As described above, numeric test results, safety standards, color symbols, the iconic resemblance of spatial relationships, and bottom-up processing of distance and preattentive position on the scaled legend all may have had roles in conveying the magnitude and the meaning of hazard levels and proximity. These properties of the map information along with top-down interest in near and large hazards driven by personal relevance may explain why hazard level and proximity had the largest influences on dependent variables.

Proximity only influenced dependent variables for maps with elevated risk. Participants located within either hazard cluster (mixed or all red) may have felt threatened because they were surrounded by elevated hazard, thus attenuating the influence of hazard level relative to cluster location. These results are supported by findings from the qualitative study that showed participants paid more attention to nearer and larger hazards and often commented on the warning meaning of red (Severtson & Vatovec, 2012).

Cluster location maps had only two levels of location compared to three for distance maps. Perception of clustered dots, however, may explain the stronger influence of cluster location than distance. The close proximity of clustered dots indicates they are related, a Gestalt Law concept (Pinker, 1990). MacEachren (1995) proposed two characteristics that explain why patterns may be perceived as a figure against a background: contour (a discernible edge) and surroundedness (surrounded patterns perceived as a unit). On study maps, dot clusters were surrounded by white space; the tight clusters had well-defined edges, thus enhancing perception of cluster patterns. Interpreting clusters as a hazard area could increase perceived risk beyond that of living near many hazards. Using red to symbolize unsafe hazard levels may have intensified this effect.

Prevalence had considerable variance (1, 2, or 8 dots) but had only small positive total effects on intentions. Visual complexity (more dots) may result in less focused attention (Florence & Geiselman, 1986; Yantis, 2005), thereby diminishing the influence of prevalence on outcomes. In addition, the dominant impact of cluster location appeared to overshadow the influence of cluster density.

Direct and Indirect Influences of Beliefs and Emotion on Intentions

Mediators (variables in the cognitive and emotional representations) explain the mechanisms by which attributes influence intentions. Perceived susceptibility and the global belief of problem seriousness had the largest mediating roles, locational social comparison and emotion were smaller influences, and the effect of perceived severity was small or insignificant. The primary chains of influence depicted in Figures 4 and 5 were through susceptibility and the global belief of problem seriousness.

Perceived susceptibility (belief in the likelihood of having contaminated drinking water) had the largest total effects on intentions to mitigate exposure. The total effects were roughly split between direct and indirect effects. Hazard level, proximity attributes, and interactions between these had the largest influences on perceived susceptibility, illustrating that nearness to unsafe hazards increases perceived susceptibility and supporting Weinstein's (1988) claim that identifying personal susceptibility to a threat is crucial for motivating behavior to decrease risk, in this case by mitigating exposure.

Seriousness of the problem had the largest effect on monitoring intentions, supporting Weinstein's claim that global beliefs are strong predictors of behavior (Weinstein, 1988; Weinstein & Sandman, 1992). The influences of proximity attributes on monitoring intentions did not vary for high and mixed hazard levels. Beliefs and intentions may be strong for drinking water hazards whether the hazard is medium or high because people rate drinking water safety as highly important (Center for Disease Control, 2000). If people see an unsafe hazard on a community-level map, they may believe it poses a serious drinking water problem and want to monitor for the hazard's presence.

Other chains of influence linking attributes to intentions had one or more weak links. The very small or null effects of attributes on severity were expected because mapped attributes did not convey information about the severity of health consequences. The large effects of distance and cluster location on locational social comparison support the proposition that spatial risk information will influence how people compare their own risk to that of others on the map (Severtson & Burt, 2012). The weak link between locational social comparison and problem seriousness, however, attenuated the chain of influence to intentions. Distress was not part of an influential chain due to the generally weak influences of attributes on distress and of distress on intentions. Previous research shows people with a private well have generally mild emotional responses to information about well test results, even when the test results are for their own drinking water (Severtson, Baumann, & Brown, 2008).

The only personal characteristic with a substantial influence was gender, a finding supported by evidence that women are more risk averse than men (Slovic, 1999). Numeracy effects may have been null because images can address numeracy barriers (Nelson, et al., 2008). In another map study, numeracy influenced comprehension of numeric values in the legend, but had no effect on comprehension of incremental risk levels that were visually represented on the map (Severtson & Myers, Advance online publication).

Mediating variables are established predictors of health-related behavioral intentions, and specific beliefs are established predictors of global beliefs (Weinstein, 1988; Weinstein & Sandman, 1992). For distance maps, “only attributes” explained more or similar variance in the global belief of problem seriousness, emotion, and intentions than the additional variance contributed by mediators. For cluster location maps, “only attributes” explained more or similar variance in the global belief and mitigating intentions. These results further highlight the substantive role of mapped hazard attributes in shaping cognitive and emotional representations and intentions.

Limitations

The artificiality of study maps (manipulated dots, fictitious substance, assigned map location), the limited relevance of drinking water from a private well for university students, most of whom used municipal water, and the potential influence of earlier maps on the beliefs derived from later maps limit generalizability of results. Cluster location maps had less variance than distance maps in hazard level and proximity, so results are not directly comparable. Other limitations include the lack of a control group receiving non-mapped risk information, use of single-item variables lacking error terms, and not measuring or controlling for prior beliefs and emotions about drinking water hazards. Finally, only one facet of emotion was measured.

Implications for Research

More research is needed to test the value of the framework for explaining the mechanisms by which maps influence behavioral intentions to address environmental hazards. Future studies should move to establish external validity of the framework by using samples that represent the target population, maps of actual hazards, and participants’ actual perceived map locations. All of these may increase personal relevance, which shapes the meaning derived from maps. External validity also would be enhanced by testing maps depicting different drinking water contaminants and, eventually, different environmental hazards. Future studies should include measures of behavioral responses to mapped hazards.

Internal validity would be enhanced by measuring prior beliefs that influence what people see and derived meaning. Using a non-map control condition (e.g., an alphanumeric table to convey the map information) would result in a more rigorous assessment of whether and

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how maps influence beliefs and intentions. Using structural equation modeling with latent variables would enhance measuring proposed influences. Studies are also needed to measure the influences of map features. Features of interest include symbolic risk colors compared to non-symbolic colors for representing hazard level and the potential moderating influence of map scale to assess whether attributes have a stronger influence on beliefs and intentions for maps depicting a local geographic area compared to a larger region.

The framework can be used to study how map features depicting the locations, prevalence, and levels of a variety of health-related determinants (e.g., health and social services, social support, sources of healthy food) influence health-related beliefs, intentions, and behavior. Such studies can include the role of proximity in shaping these outcomes. The framework may be useful for researchers of health communication because images can improve meaningful comprehension and address literacy barriers (Ancker, Senathirajah, Kukafka, & Starren, 2006; Johnson, et al., 2006; Nelson, Hesse, & Croyle, 2009) in a variety of applications, such as patient or community health education or the use of graphics to convey electronic health record data. To understand how maps and other images can be used to foster appropriate cognitions and health-related behavior, a body of evidence will be needed to understand the theory-based visual concepts that generalize to various types of applications and the subpopulations and contexts that modify how visual concepts operate.

Implications for Practice

Results suggest environmental hazard maps have the potential to influence monitoring and mitigation behavior for environmental hazards. The influence of maps on monitoring intentions is promising because identifying the presence of a hazard is often the first step in taking appropriate actions to mitigate a hazard. Given the strong influences of hazard level and proximity, choosing how to depict these attributes could influence how maps are interpreted and used for decisions. Health professionals also can use maps to support risk assessment and community-level interventions by illustrating the juxtaposition of at risk populations, determinants of risk, and locations where services can be provided (Choi, et al., 2006; Riner, et al., 2004). Examples of using maps to develop community interventions are provided by Gesler et al. (2004) for a diabetes prevention program and Caley (2004) for an intervention to reduce rates of low birthweight.

Maps can facilitate communicating with and gathering input from various community stakeholders by sharing and eliciting input on location-based information and where services can be located (Caley, Shiode, & Shelton, 2008; Meyer et al., 2011). Results from this substudy support the claim that well-designed images, including maps, can be effective communication tools for improving the meaningful comprehension of health-related information (Nelson, et al., 2009).

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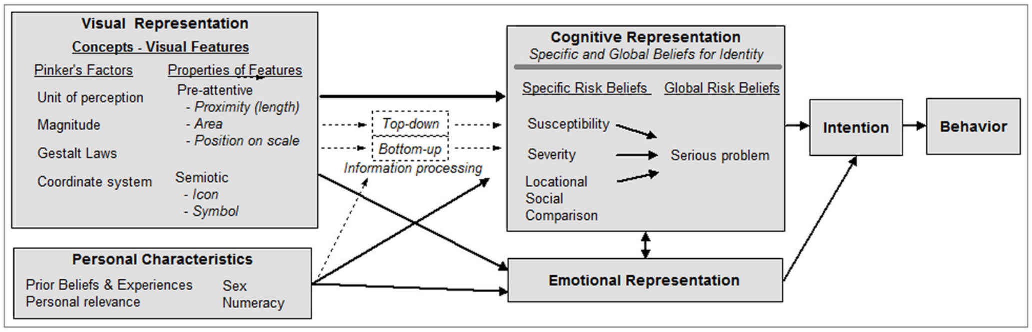

Figure 1.

The Integrated Representational and Behavioral Framework (the framework) with minor revisions from the original version (Severtson & Vatovec, 2012) to illustrate the theoretical concepts used in this study. Pinker'sFactors are proposed to explain what people see from the visual stimuli detected by the retina. Properties of features are proposed to explain the meaning (beliefs and emotion) derived from what is seen. Top-down and bottom-up information processing were not measured in this study thus depicted with dotted lines. Top-down and bottom-up information processing are important concepts that explain how images influence cognitive and emotional representations. Information processing is influenced by personal characteristics of the viewer.

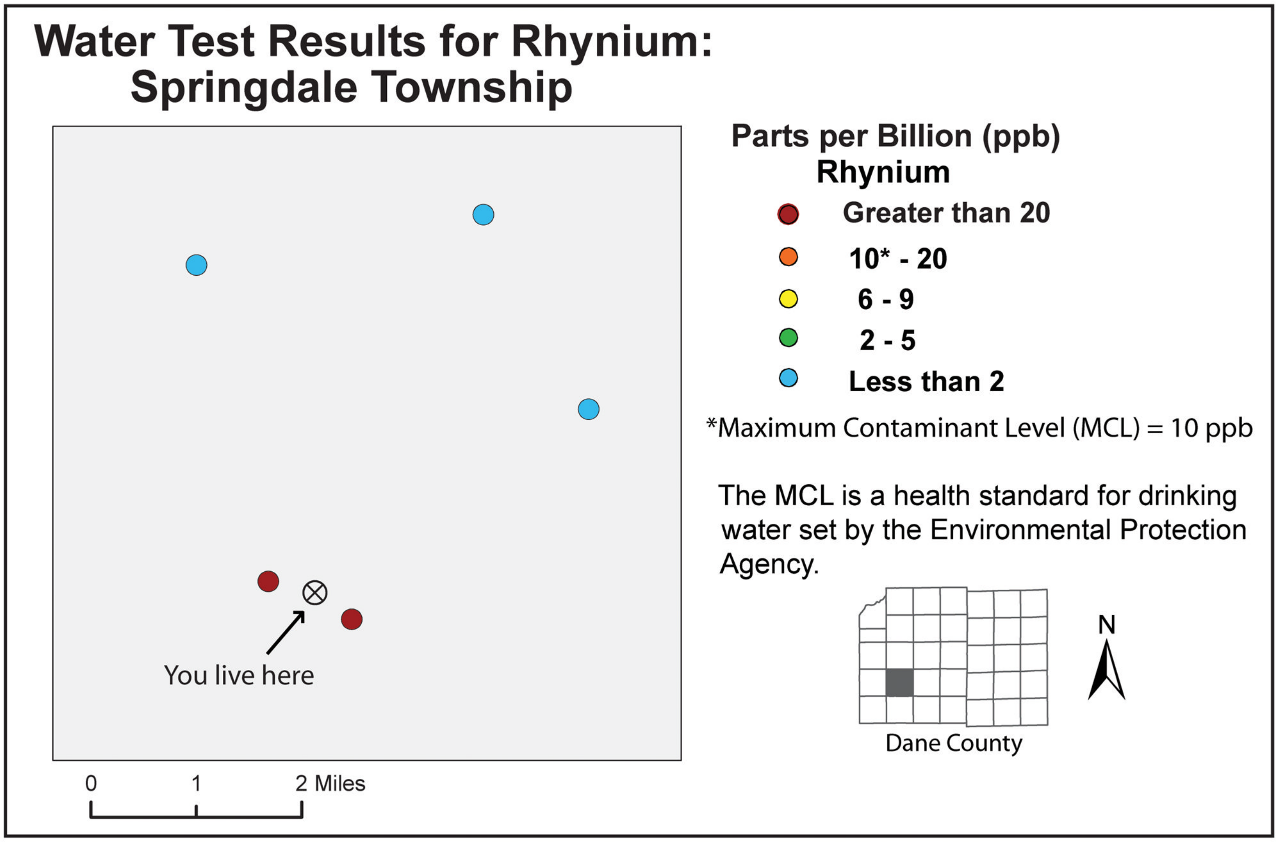

Figure 2.
This is one of the 24 study maps. Dot colors in the legend (bottom to top) are blue, green, yellow, red, and dark red. Study maps depicted only blue and dark red dots. Onthis black and white map, blue appears light gray and dark red appears dark gray. The maximum contaminant level (MCL) is a term for drinking water standard (U.S. Environmental Protection Agency, 2004). Dots inthe lower half of the map were arranged to measure attributes. Participants were instructedto answer survey items based on their assigned map location. This is an example of a distance map.

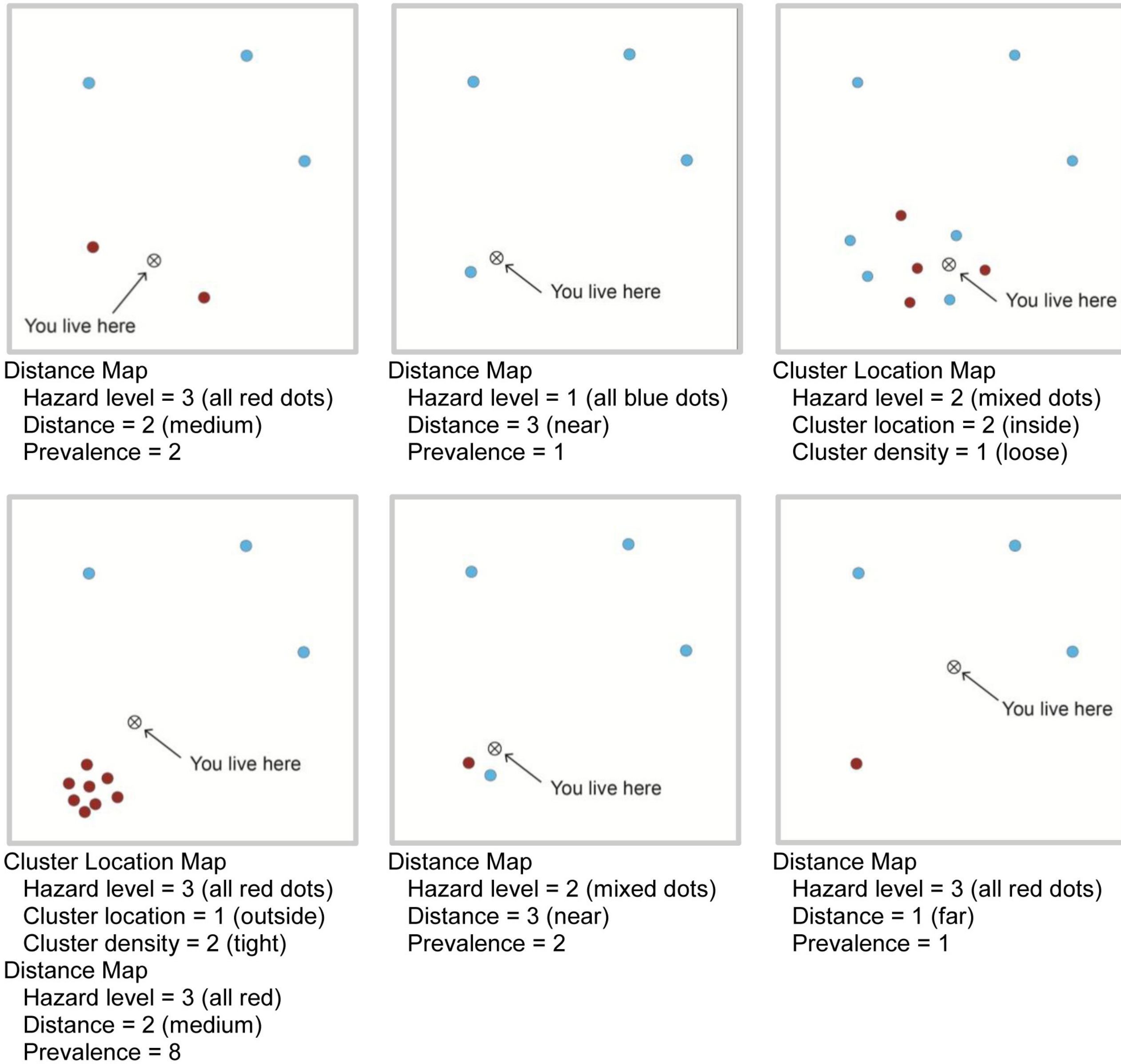

Figure 3.

Six of the 24 experimental maps with numeric codes for attribute measures. Dots in the lower half of the map were arranged to measure attributes.When printed in black and white, the blue dots appear gray and the dark red dots appear dark gray. All maps organized by block are available at http://research.son.wisc.edu/wellstudy/MapBlocks.pdf.

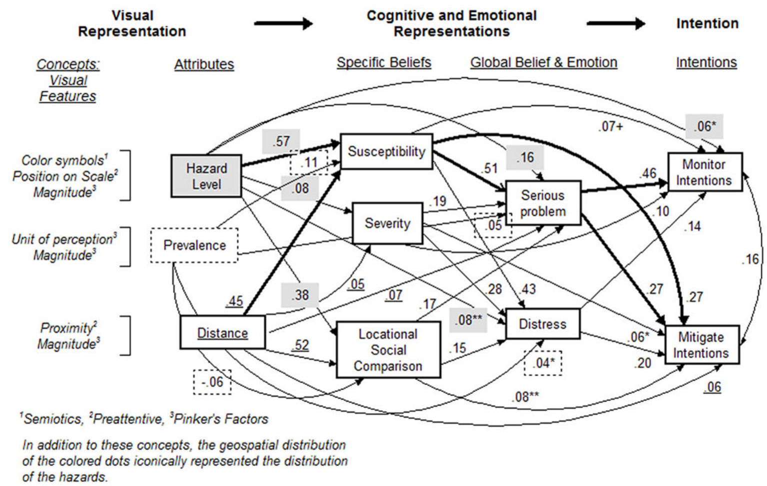

Figure 4.

Path model with distance map attributes and standardized path coefficients. Labels at the top (bolded in row one and underlined in row two) illustrate how the path modelis aligned with The Framework. Visual cognition concepts on the left illustrate theoretical concepts embodied in each attribute. Symbols facilitate matching path coefficients from attributes to variables (hazard level = shading; prevalence = dotted outline; distance = underline). Primary mediating paths from attributes through beliefs to intentions are bolded. All path coefficients significant at $p < .001$ unless otherwise noted: $+p < .10$, $*p < .05$, $**p < .01$. Non-significant (ns) coefficients are not depicted in the path model. ATable showing all standardized path coefficients is available at http://research.son.wisc.edu/wellstudy/PathCoefficients.pdf.

Path Model Fit Indices are: SRMR = .061 and CFI= .896. Standardized loadings for covariates are: sex on severity = .37, numeracy on susceptibility = .02ns, current water use on mitigate= +.04, prior residence on mitigate = +.05 current water use on monitor = 0, prior residence on monitor= −.04ns.

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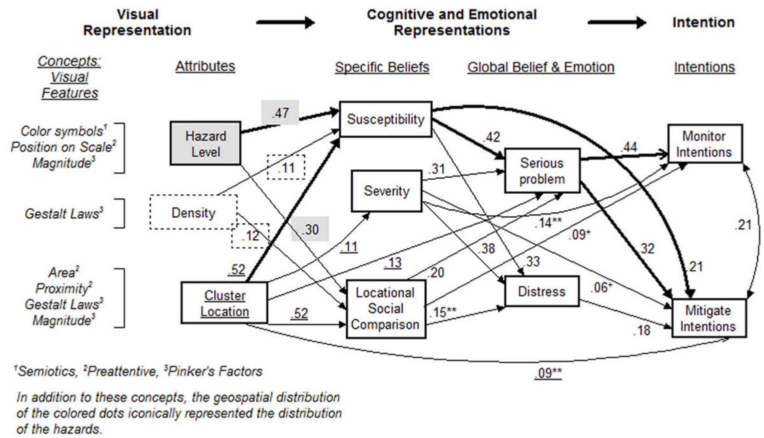

Figure 5.
Path model with cluster map attributes and standardized path coefficients. Labels at the top (bolded in row one and underlined in row two) illustrate how the path modelis aligned with The Framework. Visual cognition concepts on the left illustrate theoretical concepts embodied in each attribute. Symbols facilitate matching path coefficients from attributes to variables (hazard level = shading; prevalence = dotted outline; distance = underline). Primary mediating paths from attributes through beliefs tointentions are bolded. All path coefficients significant at $p < .001$ unless otherwise noted: $+p < .10$, $*p < .05$, $**p < .01$. Non-significant (ns) coefficients are not depicted in the path model. ATable showing all standardized path coefficients is available at http://research.son.wisc.edu/wellstudy/PathCoefficients.pdf.

Path Model Fit Indices are: SRMR = .062 and CFI= .886. Standardized loadings for covariates are: sex on severity =.34, numeracy on susceptibility = −.01ns, current water use on mitigate= .03ns, prior residence on mitigate = .01ns; current water use on monitor = 0, prior residence on monitor= −.03ns.

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Table 1

Model Variables: Means and Standard Deviations (N = 446)

Variables	Description of Measure	RS[b]	Distance: 20 maps 2230[a] obs.		Cluster Location: 8 maps 892[a] obs.	
			Mean	*SD*	Mean	*SD*
Hazard level	*Low level* (all blue), *mixed levels* (even mix of blue and dark red), *high level* (all dark red)	1,2,3	2.4	0.7	2.5	0.5
Proximity - Distance	*Far* (2.5 miles, 3 map cm), *medium* (1.25 miles, 1.5 map cm), *near* (0.5 miles, 0.6 map cm)	1,2,3	2.4	0.9		
Prevalence	1, 2, 8 dots	1,2,8	4.2	3.2		
Proximity - Cluster location	*Outside*, *inside*	1,2			0.5	0.5
Cluster density	*Loose, tight*	1,2			0.5	0.5
Subjective Numeracy Scale[c]	7 items (arithmetic average), 5 and 6 point scales	1 – 6 1 – 5	4.6	0.6	4.6	0.6
Gender	*Male* = 0, *female* = 1	0, 1	0.7	0.5	0.7	0.4
Water use	Current drinking water use *(no treatment, filtered, bottled)*; coded as *untreated; treated*	0,1	0.6	0.5	0.6	0.5
Prior residence	Dominant residential experience on ordinal scale *(rural, small town, suburban, urban)*	1 – 4	2.7	0.9	2.7	0.9
Susceptibility	% chance of rhynium over drinking water standard on11-point scale	0–100	57.1	27.3	71.1	20.7
Severity	Rhynium-related health problems are serious. *(SA-SD)*[d]	1 – 6	5.2	0.9	5.3	0.8
Locational social comparison	My risk compared to others in the township *(much less – much more)*	1 – 7	5.1	1.5	5.5	1.2
Serious problem	Rhynium is a serious problem for my well *(SA-SD)*[d]	1 – 6	4.4	1.4	5.0	1.0
Distress	I feel distressed about rhynium risk *(SA-SD)*[d]	1 – 6	4.0	1.5	4.5	1.3
Monitor intentions	Intentions to have water tested for rhynium (*definitely not test, definitely will test*)	1 – 5	4.2	1.1	4.6	0.7
Mitigate intentions	Intentions to drink less untreated water compared to assigned use of all of the time *(as usual – stop drinking)*	1 – 5	3.2	1.4	3.8	1.2

[a] 446 students × 5 distance maps = 2230 observations; 446 students × 2 cluster maps = 892 observations

[b] RS = numeric codes for attribute measures and response scale for survey items (personal characteristics and dependent variables)

[c] Revised from 8-item scale (Zikmund-Fisher, Smith, Ubel, & Fagerlin, 2007)

[d] *SA-SD* = Strongly Agree – Strongly Disagree

Table 2

Total Standardized Effects (with 90% Confidence Intervals) of Attributes on Beliefs, Emotion, and Intentions

	Attributes of Distance Maps			Attributes of Cluster Location Maps		
Dependent Variables	**Hazard Level**	**Distance**	**Prevalence**	**Hazard Level**	**Cluster Location**	**Cluster Density**
Susceptibility	.567 [.544, .591]	.448 [.424, .472]	.106 [.083, .129]	.469 [.429, .509]	.522 [.491, .553]	.112 [.066, .158]
Locational social comparison	.382 [.353, .410]	.515 [.489, .542]	−.064 [−.090, −.037]	.300 [.249, .350]	.515 [.481, .548]	.119 [.068, .171]
Severity	.079 [.041, .117]	.054 [.028, .080]	.019§ [−.012, .049]	.068§ [−.004, .140]	.111 [.085, .138]	.029§ [−.043, .102]
Serious problem	.525 [.497, .553]	.388 [.360, .417]	.100 [.073, .127]	.266 [.213, .318]	.484 [.446, .522]	.092** [.034, .149]
Distress	.400 [.369, .432]	.280 [.252, .309]	.079 [.051, .107]	.179 [.111, .248]	.312 [.280, .345]	.110** [.042, .178]
Monitor intentions	.413 [.378, .448]	.300 [.267, .333]	.089 [.059, .119]	.123 [.064, .182]	.302 [.260, .343]	.087* [.027, .148]
Mitigate intentions	.444 [.417, .470]	.384 [.357, .410]	.078 [.051, .105]	.224 [.164, .285]	.452 [.418, .486]	.115** [.052, .178]
Analysis by Hazard Level[a]						
Intentions: Hazard Level 3						
Monitor intentions		.391 [.336, .446]	.005§ [−.057, .066]		.298 [.221, .374]	.061§ [−.021, .143]
Mitigate intentions		.516 [.469, .564]	.034§ [−.017, .085]		.532 [.482, .582]	.108* [.022, .193]
Intentions: Hazard Level 2						
Monitor intentions		.448 [.356, .541]	.135** [.058, .211]		.311 [.264, .358]	.106* [.018, .193]
Mitigate intentions		.426 [.338, .514]	.106* [.034, .178]		.407 [.361, .454]	.125* [.029, .220]
Intentions: Hazard Level 1						
Monitor intentions		−.027§ [−.120, .067]				
Mitigate intentions		.039§ [−.058, .137]				

Notes: Significant at $p < .001$ unless otherwise noted;

* $p < .05$,

** $p < .01$,

§ = non-significant.

[a] Results from analysis to follow up on interaction effects between hazard level and proximity variables. Path models were analyzed for each hazard level.

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Table 3

Standardized Effects and Percentage of Indirect Effects of Attributes on Monitor and Mitigate Intentions for Two Path Models

		Effects: Distance Maps				Effects: Cluster Location Maps			
Intentions	**Attributes**	**Total Effects**	**Total Indirect Effects**	**Direct Effects**	**% Indirect[a] Effects**	**Total Effects**	**Total Indirect Effects**	**Direct Effects**	**% Indirect[a] Effects**
Monitor	Hazard level	.413	.357	.056[*]	86%	.123	.132	−.009[§]	107%
	Distance or CL[b]	.300	.269	.031[§]	90%	.302	.256	.046[§]	85%
	Prevalence or CD[b]	.089	.065	.024[§]	73%	.087[*]	.053[*]	.034[§]	61%
Mitigate	Hazard level	.444	.410	.034[§]	92%	.224	.240	−.016[§]	107%
	Distance or CL[b]	.384	.327	.057	85%	.452	.362	.090[**]	80%
	Prevalence or CD[b]	.078	.067	.011[§]	86%	.115[**]	.082	.033[§]	71%

Notes: All path coefficients significant at $p < .001$ unless otherwise noted,

[*] $p < .05$,

[**] $p < .01$,

[§] = non-significant.

[a] Percentages indicate the proportion of total attribute influences on intentions that were indirectly mediated through beliefs and emotions (total indirect effects ÷ total effects × 100).

[b] Attributes for cluster location maps were: CL = cluster location and CD = cluster density. Attributes for distance maps were distance and prevalence.

Table 4

Total Effects of Beliefs and Emotion on Intentions, Total Indirect Effects of Attributes on Intentions through Beliefs and Emotion, and Percentage of Total Indirect Effects Relative to Total Effects

		Distance Maps								Cluster Maps								
		Total Effects[a]	Total Indirect Effects of Attributes through Beliefs and Emotion[b]							Total Effects[a]	Total Indirect Effects of Attributes through Beliefs and Emotion[b]							
Intention	Predictor	Beliefs Emotion	HL[c]	%	Dst[c]	%	Prv[c]	%	Sum[d]	Beliefs Emotion	HL[c]	%	CL[c]	%	Den[c]	%	Sum[d]
Monitor	Susceptibility	.365	.207	*56.7*	.164	*44.9*	.039	*10.7*	.410	.143	.067*	*46.9*	.075*	*52.4*	.016*	*11.2*	.158
	Locational SC[c]	.124	.047	*37.9*	.064	*51.6*	−.008**	*6.5*	.103	.175	.052**	*29.7*	.090	*51.4*	.021**	*12.0*	.163
	Severity	.230	.018**	*7.8*	.012**	*5.2*	.004§	*1.7*	.034	.299	.020§	*6.7*	.033	*11.0*	.009§	*3.0*	.062
	Serious prob[c]	.461	.242	*52.5*	.179	*38.8*	.046	*10.0*	.467	.444	.118	*26.6*	.215	*48.4*	.041**	*9.2*	.374
	Distress	.143	.057	*39.9*	.040	*28.0*	.011**	*8.4*	.108	.054	.010§	*18.5*	.017§	*31.5*	.006§	*11.1*	.033
Mitigate	Susceptibility	.495	.281	*57.9*	.222	*44.8*	.052	*10.5*	.555	.403	.189	*46.9*	.210	*52.1*	.045	*11.2*	.444
	Locational SC[c]	.155	.059	*38.1*	.080	*51.6*	−.010**	*−6.5*	.139	.157	.047**	*29.9*	.081	*51.6*	.019*	*12.1*	.147
	Severity	.166	.013**	*7.8*	.009**	*5.4*	.003§	*1.8*	.025	.229	.016§	*7.0*	.026	*11.4*	.007§	*3.1*	.049
	Serious prob[c]	.267	.140	*52.4*	.104	*39.0*	.027	*10.1*	.271	.319	.085	*26.6*	.155	*48.6*	.029*	*9.4*	.270
	Distress	.197	.079	*40.1*	.055	*27.9*	.016	*8.1*	.150	.177	.032*	*18.1*	.055**	*31.1*	.019+	*10.7*	.106

Notes: Significant at $p < .001$ unless otherwise noted:

+ $p < .10$,

* $p < .05$,

** $p < .01$,

§ = non-significant. *P*-values are not available for the sum of indirect effects.

[a] Total effects of each belief and emotion on intentions (monitor and mitigate).

[b] Total indirect effects of attributes through each belief and emotion on intentions (monitor and mitigate).

[c] CL = cluster location, Den = density, Dst = distance, HL = hazard level, Prv = prevalence, prob = problem, SC = social comparison

[d] Sum of indirect effects through this mediator; calculated by hand so no *p*-values. The total effects of a mediator can be smaller than the total indirect effects transmitted through the mediator due to negative relationships within the model.

Table 5

Variance (R^2) and Percentage of Variance in Dependent Variables Explained by Attributes Alone and Attributes with Preceding Mediating Variables

Mediating Variables and Intentions		Distance Maps: Only Attributes (OA)	Distance Maps: Attributes With Preceding Mediating Variables (PMV)	Cluster Location Maps: Only Attributes (OA)	Cluster Location Maps: Attributes With Preceding Mediating Variables (PMV)
Specific Beliefs	R^2 Susceptibility	.53		.51	
	R^2 Severity	.04*		.04**	
	R^2 Locational social comparison	.44		.37	
Global Belief (serious problem)	R^2	.42	.61	.31	.52
	R^2 percentage OA[a]		68.9%		59.2%
	R^2 percentage PMV[b]		31.1%		40.8%
Emotion (distress)	R^2	.23	.42	.13	.35
	R^2 percentage OA		54.3%		37.8%
	R^2 percentage PMV[b]		45.7%		62.2%
Monitor Intention	R^2	.25	.49	.11	.33
	R^2 percentage OA		51.0%		33.4%
	R^2 percentage PMV[b]		49.0%		66.6%
Mitigate Intention	R^2	.32	.56	.24	.49
	R^2 percentage OA		57.0%		50.1%
	R^2 percentage PMV[b]		43.0%		49.9%

Note: Explained variance significant at $p < .001$ unless noted as follows:

* $p < .05$,

** $p < .01$.

[a] R^2 percentage OA = (R^2 of OA ÷ R^2 attributes with PMV) × 100

[b] R^2 percentage contributed by PMV = 100% minus R^2 percentage OA