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The Theory-based Influence of Map Features on Risk Beliefs: Self-reports of What is Seen and Understood for Maps Depicting an Environmental Health Hazard

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Abstract

Theory-based research is needed to understand how maps of environmental health risk information influence risk beliefs and protective behavior. Using theoretical concepts from multiple fields of study including visual cognition, semiotics, health behavior, and learning and memory supports a comprehensive assessment of this influence. We report results from thirteen cognitive interviews that provide theory-based insights into how visual features influenced what participants saw and the meaning of what they saw as they viewed three formats of water test results for private wells (choropleth map, dot map, and a table). The unit of perception, color, proximity to hazards, geographic distribution, and visual salience had substantial influences on what participants saw and their resulting risk beliefs. These influences are explained by theoretical factors that shape what is seen, properties of features that shape cognition (pre-attentive, symbolic, visual salience), information processing (top-down and bottom-up), and the strength of concrete compared to abstract information. Personal relevance guided top-down attention to proximal and larger hazards that shaped stronger risk beliefs. Meaning was more local for small perceptual units and global for large units. Three aspects of color were important: pre-attentive "incremental risk" meaning of sequential shading, symbolic safety meaning of stoplight colors, and visual salience that drew attention. The lack of imagery, geographic information, and color diminished interest in table information. Numeracy and prior beliefs influenced comprehension for some participants. Results guided the creation of an integrated conceptual framework for application to future studies. Ethics should guide the selection of map features that support appropriate communication goals.

Keywords

risk communication; visual communication; visual cognition; environmental health; health behavior; hazard proximity

Despite wide use, few studies examine how people understand maps depicting environmental health risks. To address this gap, we conducted a theory-based qualitative study. Our primary purpose was to examine how features of risk maps influenced verbal self-reports of what people saw and derived meaning as they viewed three formats (dot map, ¹ choropleth map,¹ table) depicting water test results for private wells.

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Theories from multiple disciplines are needed to explain how visual features influence what is seen and meaning derived from what is seen. Visual cognition theories explain how vision is seamlessly integrated with cognition. Semiotics explains how visual symbols convey meaning. Health behavior theories explain how concrete and abstract risk information shapes internal cognitive representations that shape protective behavior. Fuzzy trace theory (learning and memory) explains why people prefer to understand and apply the global gist of information rather than specific details. This literature suggests how visual features of risk maps may influence meaningful comprehension and protective behavior.

Theoretical Concepts: Visual Cognition

Visual cognition theory

What do people see when they look at a map, and how does the "seen" shape comprehension? MacEachren (1995) claimed "representation is an act of knowledge construction," but cautioned that derived knowledge may differ from the intended meaning. He cited Pinker (1990) to describe how external visual representations (e.g. maps) influence internal cognitive representations through four integrated processes: (1) images provide visual stimuli detected by the retina, (2) from these stimuli, the brain perceives "what is seen", (3) meaning derived from the "seen" is shaped by cognitive processes, and (4) prior knowledge influences what is seen and derived meaning. Thus, human variability in vision, cognitive capacity, and prior knowledge explains discrepancies between intended and imparted meaning of a visual representation. These processes explain how meaning is derived from maps.

Factors that influence what is seen

How are visual stimuli perceived as a coherent image? Pinker (1990) proposed four primary factors (spatial location, Gestalt Laws, magnitude, coordinate system) that explain "what is seen". We are neurologically equipped to perceive our surroundings. As such, spatial *location* is a key factor and defined by units of perception. In this study, perceptual units of risk were discrete data points (Figure 1) or statistical information across townships (Figure 2). Gestalt Laws describe how attributes of proximity, similarity, and continuity integrate features such as lines and color into a coherent entity (Wertheimer, 1938). Magnitude includes quantifiable dimensions, e.g., length or incremental color gradations. The spatial location of perceptual units is represented within a coordinate system represented by latitude and longitude on maps. These factors suggest what people "see" in a map.

Cognitive processes that give meaning to what is seen

Top-down and bottom-up processes explain how visual information is consciously and unconsciously understood. User-defined goals direct top-down processing, e.g. to answer questions. Bottom-up processing occurs because our visual system is neurologically connected to cognition areas in the brain such that "seeing" is literally linked with "knowing"² and enhances comprehension by freeing short-term memory for other processing needs (Pinker, 1990). Cleveland and McGill (1984) proposed ten "pre-attentive" visual features (processed bottom-up) of statistical graphics and ranked these by estimated accuracy of comprehension as: (1) position on a common scale, (2) positions on nonaligned scales, (3) length, direction, angle, (4) area, (5) volume, curvature, and (6) shading, color saturation. These features may enhance meaningful map comprehension.

¹Dot maps depict the distribution of a phenomenon using small symbols. Choropleth maps depict statistical information across areal enumeration units such as a county (Slocum, 2005). ²For example, seeing two marks on a linear scale results in knowledge about the magnitude of their relationship.

Attention influences cognition

Cognition is strongly shaped by *attention*. A user-defined goal directs top-down attention to some visual features over others. *Visual salience* drives bottom-up attention and is "the distinct subjective perceptual quality which makes some items in the world stand out from their neighbors and immediately grab our attention" (Itti, 2007), e.g. color, position, texture, or motion. Hegarty, Canham, and Fabrikant (2010) found top-down attention directed eye fixations on maps, but strategic use of visual salience improved task performance. Their research illustrates how top-down and bottom-up processes influence map use and cognition, and suggests *personal relevance* drives top-down attention.

Semiotics

Semiotics, the study of signs, has a socio-cultural perspective that complements the private psycho-representational perspective described earlier (MacEachren, 1995). Visual symbols, a type of sign, stand for a thing or idea (DeLoach, 1995). Map symbols range from abstract to iconic (represent real-world counterparts) and are better understood when less abstract (Robinson, Sale, Morrison, & Muehrcke, 1984). Some symbols use culturally-derived meaning (MacEachren). Easily recognized symbols decrease short-term memory load and increase comprehension because meaning is readily accessible from long-term memory. Preattentive and symbolic features of study maps are described below.

Pre-attentive and Symbolic Map Features

Color symbols—Color is a common map symbol, e.g. blue iconically conveys water bodies. Stoplight colors of green for safe, yellow for caution, and red for danger symbolize risk levels via cultural norms (Griffith & Leonard, 1997). Symbolic risk colors may enhance meaningful comprehension, but could prompt unwarranted alarm if misused.

Color gradations to convey magnitude—Color gradations pre-attentively convey magnitude. Brewer (2006) used this feature to develop color schemes for maps. *Sequential schemes* illustrate incremental magnitude using incrementally darker gradations of a single color (e.g. Figure 2). *Diverging schemes* depict incremental increase and decrease using two or more colors with incremental gradations above and below a midpoint - appropriate for data with meaningful midpoints such as safety standards. Sequential and diverging schemes facilitate pre-attentive perception of trends across an area. *Spectral schemes* use different colors - appropriate for nominal or categorical data. A modified *spectral diverging risk color scheme* uses typical risk colors (red, orange, yellow, green, blue) with lightness gradations to show risk above and below a midpoint (e.g. Figure 1).

Symbolizing uncertain data—Data certainty can vary by location. Brewer (2006) recommends illustrating sparse (uncertain) data on choropleth maps with a hatching pattern.

Proximity to hazards—Maps illustrate the spatial distribution of information. On maps, this is conveyed by pre-attentive features (e.g. distance, direction) and by the universal map *coordinate system* of latitude and longitude. For maps, spatial distribution has geographic meaning missing from other images. Proximity is a key component of relevance for geospatial information (Swienty, Reichenbacher, Reppermund, & Zihl, 2008). Personal relevance will likely motivate individuals to assess (top-down) the distribution of risk relative to perceived map location. In addition, seeing proximity to mapped hazards may pre-attentively influence risk beliefs. We found no published studies that examined hazard proximity for maps. However, "on the ground" hazard proximity is often related to stronger perceived risk (Brody, Highfield, & Alston, 2004; Lindell & Hwang, 2008) consistent with the proposition that nearness to hazard increases risk.³

Theoretical Concepts: Risks Beliefs and Protective Behavior

Cognitive representations

MacEachren (1995) summarized how maps (an external representation) shape internal knowledge-based cognitive representations. Despite the importance of knowledge, perceptions and beliefs are better predictors of decisions and actions (National Cancer Institute, 2005). Leventhal's Common Sense Model of Self-regulation conceptualizes *lay* knowledge and beliefs about health threats as cognitive representations (Leventhal, Brissette, & Leventhal, 2003) and illustrates cognitive and emotional processes that shape cognitive and emotional representations of health threats that shape behavior. This dual processing system is related to top-down and bottom-up processes driven respectively by abstract and concrete sensory-experiential information. Concrete information influences beliefs and behavior more than abstract information. The common sense model is aligned with visual cognition theory by specifying the substantial role of concrete sensory information in shaping cognitive representations. It differs by emphasizing belief-based rather than knowledge-based cognitive representations and by including emotional representations and behavioral outcomes. Cognitive representations of health threats are comprised of beliefs characterized by five dimensions: *identity. cause. timeline*. consequences, and control.⁴ Identity, how a person recognizes and labels a threat, is a core dimension (Leventhal, et al., 2003). Maps allow viewers to *identify* location-based risks.

Beliefs that identify risk

Weinstein (1988) asserts people must *identify* a risk's existence and believe they are susceptible before taking protective action. Perceived risk is predicted by specific risk beliefs of perceived susceptibility and severity of health consequences (Weinstein, 1988, 1993); although *global beliefs* are more predictive of behavior. Weinstein (1988) noted "perhaps the driving force behind the adoption of precautions is not some algebraic function of likelihood [susceptibility] and severity, but a more global appraisal of the hazard suggested by such ill-defined terms as seriousness, threat, concern and danger" (p. 372).

Meaningful and enduring gist

This proclivity for global beliefs and their role in shaping action is embodied in fuzzy trace theory (Reyna & Brainerd, 1995a). Fuzzy trace research shows that people seek to derive global gist from information, rather than precise (verbatim) details and prefer making gistbased decisions. Verbatim memory tends to fade, while meaningful gist is incorporated into enduring representations (Brainerd & Reyna, 2004). Positive or negative valence, e.g. assessed goodness or badness of a phenomenon, is an emotional component of gist and gistbased decision-making (Rivers, Reyna, & Mills, 2008). Risk beliefs have a negative valence. Maps allow viewers to identify location-based susceptibility to risks based on perceived proximity. As such, maps may influence both specific and global (gist-like) risk beliefs.

Prior knowledge and beliefs

Information in long-term memory supports cognition and shapes perception. Indeed, MacEachren (1995) observed "we often seem only able to see what we know to look for" (p. 182). Prior knowledge substantially influences learning from images (Cook, 2006) and maps (Verdi & Kulhavy, 2002). Visual features have a stronger influence when prior knowledge is

³Sometimes proximity is related to weaker perceived risk, perhaps because familiar hazards are perceived as less dangerous or because polluting industries provide economic benefits (Heath, Seshadri, & Lee, 1998). ⁴These dimensions explained beliefs related to contaminated drinking water from a private well (Severtson, Baumann, & Brown,

^{2008).} Beliefs that identified water safety were key influences on protective behavior (Severtson, Baumann, & Brown, 2006).

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Research Questions

Research questions included:⁵ (1) How does format influence what people see and derived meaning? (2) How does derived meaning vary based on hazard amount (conveyed by map color), hazard proximity, and data uncertainty? (3) What are discrepancies between intended and derived meaning across formats and potential causes of discrepancies? (4) How do prior knowledge and beliefs influence derived beliefs? and (5) What formats are preferred and why? This study is the qualitative arm of a mixed methods study (in progress) designed to examine the impact of map features on beliefs and behavioral intensions.

METHODS

Study materials

We developed three information formats (dot map, choropleth map, table; Figures 1-2 and Table 1, color maps at www.research.son.wisc.edu/JoHC/Figures 1 2), to convey water test results for private wells across labeled townships⁶ within Dane County, Wisconsin. Maps typified those provided in well testing programs. The table was an alphanumeric control. We used actual nitrate well tests, but labeled as fictitious, "rhynium" to decrease bias from prior beliefs about known contaminants (Carlo et al. 1992) and allow experimental manipulation of mapped hazards. Dots, the *unit of perception* on the dot map (Figure 1), represented the location of test results using a modified spectral diverging risk color scheme. Dot colors symbolized the safety meaning of rhynium test results for ranges over (red, dark red) and under (blue, green, yellow) the maximum contaminant level (MCL).⁷ Townships were the unit of perception on the choropleth map (Figure 2), hereafter called township map. A red sequential color scheme depicted increasing percentages of well tests exceeding the MCL. A sequential non-risk color map used purple. Words and numbers were the unit of perception for the table (Table 1) of alphabetized township names and number and percentages of test results exceeding the MCL. Uncertain data (< 7 tests per township as in agency maps) was depicted: (1) using hatching over a white background⁸ and defined as *insufficient data* for the township map, (2) labeled as *insufficient data* in the table's percent column, and (3) showing sparse or no dots within a township for the dot map.

Study design and participants

We used cognitive interviews⁹ (Beatty & Willis, 2007; Willis, 2005) to assess what people saw and understood as they viewed formats. Cognitive interviews require few rounds (3–4); each with a small sample (5–10 participants). Saturation (no new discovered content) determines number of rounds (Willis, 2005). Three rounds were conducted among adults

⁵We also assessed (1) how map titles supported comprehension, (2) how formats influenced intentions to test water, and (3) participant comments that reflected other common sense model dimensions. Results related to these objectives are posted at https://research.son.wisc.edu/wellstudy/JoHC2012.pdf.
⁶A township is a geographic surveyor's unit measuring six by six miles square. Towns are a local form of government that usually

⁶A township is a geographic surveyor's unit measuring six by six miles square. Towns are a local form of government that usually have the same dimensions as their corresponding township (Wisconsin Towns Association, 2009).

⁷The maximum contaminant level (MCL), commonly referred to as a drinking water standard, is the highest permissible level of contaminant in drinking water deemed suitable for human consumption. MCLs are enforced for public water supplies, (U.S. Environmental Protection Agency, 2010a) but not private wells. (U.S. Environmental Protection Agency, 2010b)

⁸Brewer (2006) recommends using hatching patterns over color on choropleth maps to designate uncertainty when information is based on a small sample. Our pre-study development of maps found people did not notice hatching, so the background color was removed to make it more conspicuous. ⁹Cognitive "think aloud" interviews have a long history as a method to discover cognitive processes as people engage in a task

²Cognitive "think aloud" interviews have a long history as a method to discover cognitive processes as people engage in a task (Ericsson & Simon, 1993). Cognitive interviewing has evolved to include questions about meaning and comprehension (Beatty and Willis (1997).

who currently or previously had a private well for residential drinking water. For round one, we recruited five participants via e-mail to 229 graduate nursing students. For round two, we recruited three participants via email to 40 town residents. For round three, we recruited five participants via telephone to four individuals recommended by an agency professional. Of 13 participants, 4 were male, 2 had prior well experience (students), and 11 were current well users. We made three minor format revisions between rounds.¹⁰

Procedure

Face-to-face cognitive interviews used general and targeted open-ended and "think aloud" questions. Questions assessed three of four processes (what was seen, meaning, prior knowledge) that explain visual cognition (Pinker, 1990). Since pre-trial dot maps answered township map questions, format order was dot map, township map, and table. First, prior knowledge and beliefs about groundwater and well water were assessed. Next, the interviewer described rhynium as a fictitious naturally occurring carcinogenic contaminant with a recently assigned MCL of 10 parts per billion.¹¹ General questions assessed what participants saw and derived meaning. Following this, targeted questions assessed the meaning of hazard proximity. To assess hazard proximity, participants pointed to and described meaning for their home's location. Participants evaluated three other locations with different hazard amounts and "insufficient data." After assessing formats, participants selected their preference and explained their choice.

Analysis

We used directed content analysis to analyze transcribed data using Nvivo (QSR International, 1997). Codes were created to categorize what was seen, meaning, discrepancies between intended and derived meaning, and instances when prior beliefs shaped meaning. We coded the interview progression to identify responses from earlier general and later specific questions. Inter-rater reliability (90%) between two researchers' codes for five interviews denoted good reliability (Topf, 1986).

RESULTS AND DISCUSSION

Results are summarized and discussed with occasional references to Table 2 by column (C) and row (R) numbers which categorizes some results and illustrative quotes.

Features that Influenced What was Seen and Derived Meaning

Unit of perception, color, hazard proximity, geographic distribution, and visual salience had the most substantial influences on the cognitive representation. The frequency of unprompted comments about these features and plausible theoretical support for mechanisms that explain what is seen and derived meaning support this conclusion.

Unit of Perception—Unit of perception shaped what participants saw: red townships, colored dots, and columns of township names and data (Table 2, R1). The integration between seeing and meaning suggests why the township map was interpreted as indicating "a problem" for much of the county, the dot map as providing the amount and location of well test results, and the table as providing the number of MCL exceedances for each

¹⁰After round 1, we adjusted (unsuccessfully) the dark red dot to look less brown. After round 2, we deleted the term *percent* from the township map title to ease comprehension and changed the term *drinking water standard* to *MCL* for all formats. We provided the purple township map (following the red map) to five round 1 and 2 participants as time allowed. ¹¹This information approximates that of arsenic, a drinking water contaminant of groundwater and well water. Participants were

¹¹This information approximates that of arsenic, a drinking water contaminant of groundwater and well water. Participants were asked to pretend rhynium was real.

township. The tight integration between *seeing* and *meaning* was especially evident among those who claimed to "*see areas where it is unsafe*" on the township map or "*seeing wells*" on the dot map rather than requested visual features. Unit of perception also shaped participants' questions, e.g. why some areas had more *problems* than others (township map) or *fewer well tests* than others (dot map) (C2-R4). Alignment of unit and question suggests the pervasive influence of perceptual unit on participants' attempts to understand formats.

For maps, spatial distribution included concrete geographic meaning lacking in the table, a shortfall noted by many participants (Table 2, C3-R5, 2nd quote). Geographic distribution of perceptual units influenced observed geographic trends (R3): county-level trends and causal explanations were seen and inferred for the township map ("*watershed*", C1-R3) and local-level trends on the dot map ("*crevice*", C2-R3). *Gestalt Laws* of *similarity, proximity*, and *continuity* appeared to lead participants to see map trends, e.g. a northwest to southeast risk trend on the township map due to a continuous swath of similarly shaded proximal townships. For the table, one participant saw a numerical trend that townships with more sampling had higher exceedance rates; perhaps prompted by seeing two digits for both columns. Findings suggest perceptual units have a dominant influence on what people see and the meaning of what is seen.

Color and visual salience—Frequent comments suggest color was often noticed (Table 2, R1); consistent with Healey's (1993) description of color as a pre-attentive feature. Several said color decreased the time and need to read supporting text. Color conveyed intended meaning by three mechanisms. First, participants derived conventional symbolic meaning from risk colors (red meant warning, yellow - caution, blue and green - safe). One described dot colors as "hot to cold gradient". Many said red meant "danger", "alert", or "warning" and one said, "I think red is really bad." Second, pre-attentive township map gradations conveyed increasing hazard magnitude. Third, visually salient colors drew attention - red and yellow were "attention getting." Participants wanted colors for unsafe information to get their attention and match risk color conventions. None thought purple was an appropriate risk color. One said red and purple had the same meaning, but several others commented purple was benign, while red meant warning or a problem "on purple it's not so clear, it doesn't have the bad connotation." Some described dark red dots as brownish and less conspicuous and therefore a poor color for highest test results. Another commented, "For yellow I'd want a color that doesn't stand out so much because on here [taps legend] yellow is safe."

Dot and township map results suggest symbolic meaning of color interacts with size of perceptual unit and visual salience to influence risk beliefs. The symbolic risk meaning of *"attention getting"* red conveyed a stronger and more *"urgent"* warning message for township than dot maps. Large units of red may explain why township maps *"screamed warning"* or were *"high alert"*. The small perceptual unit, complexity, less bold contrast, less color, and far less warning color may have attenuated the warning message for the dot map; described as *"less urgent"* than the township map (Table 2, C2-R2).

Viewers said the dot map was *"busy"* and would require more time to process than the township map (Table 2, C2-R2), as supported by research showing attention is more distributed and less focused for complex displays of many similar objects (Yantis, 2005), and leads to longer search times (Florence & Geiselman, 1986). Top-down processing may have directed attention to dots because participants wanted to see the amount and location of test results (C2-R2). Bottom-up attention to areas with many dots is explained by Pinker's (1990) proposition that extremes in magnitude are more noticeable. Attention to red and yellow dots may have occurred due to top-down attention to personally relevant larger risks and bottom-up attention to visually salient colors.

Lack of color and imagery led many to observe the table was *"just data"*, less interesting, and showed a less serious problem than maps (Table 2, C3-R2); perhaps because it lacked visual salience. Described meaning was often a verbatim repetition of table information thus more likely to fade over time compared to gist (Brainerd & Reyna, 2004).

Features that shaped overall gist—Perceptual unit, color, geographic distribution, and visual salience appeared to shape the gist of each format: (1) township map conveyed an urgent message of problem areas across the county, (2) dot map conveyed a complex message of many wells many of which were safe, and (3) table conveyed less interesting data showing the percent of wells exceeding the safety standard. Township and dot maps prompted county-level gist, but the table "*means to me that I'm focusing on [township where I live].*"

Perceived hazard proximity—Prior to targeted proximity questions, most directed attention to their perceived location, *"Where I live, so my eyes go right there."* consistent with Hegarty et.al.'s (2010) finding that personal relevance directs attention. Most appeared to use labeled townships and sometimes borders and corners to estimate home location. Although locational accuracy was not assessed, a companion study suggested township labels guided participants to the correct township, but borders and corners did not (Severtson, In review).

Living among or near larger hazards resulted in stronger risk beliefs, perhaps from top-down attention to personally relevant proximal hazards and bottom-up pre-attentive awareness of proximity to hazard. No evidence indicated participants consciously estimated distance to hazards; however, comments showed nearness prompted stronger risk beliefs. Pre-attentive processing of map distance would explain seemingly automatic comprehension of proximity - supported by Pinker's factors (1990) that explain what is seen (magnitude of distance in a two dimensional coordinate system) and Cleveland and McGill's (1984) proposal that length (distance) is accurately understood. A follow-up study tested a model that calculates proximity-based hazard for any given map location and employed a randomized trial to assess the estimate's influence on risk beliefs (Severtson & Burt, Early View).

Unit of perception (key factor) moderated interpretations of proximity. For the dot map, risk beliefs were primarily influenced by dots near participants' estimated home location. "I have a problem with rhynium in a very proximal area to where I live because two of the three wells did exceed and the one that didn't is on the border of exceeding." For the township map, hazard proximity was defined by the color of one's township and nearby townships: "I'd live pretty close to lower percents so I'd feel a little more comfortable". For the table, risk was interpreted at one's township level. Proximity had almost no role because participants could not see proximal hazards based on location, "Here I am next to Montrose, that's alphabetical order. I don't even know where that is... it doesn't give me as much context as I'd like." Gestalt Laws (key factor) supported seeing trends that moderated proximity's influence for several; e.g. being in the path of a more distant line of dots; "Patterns and stuff, but not necessarily distance. It's the trends."

Global risk beliefs—Across formats, participants talked about risk in global terms such as "*a problem,*""*a concern,*" or "*bad.*" Susceptibility was sometimes implied when participants used global risk terms - consistent with claims that global risk beliefs include a component of susceptibility (Weinstein & Sandman, 1992). Severity was sometimes implied, "*why [was testing] being done – what were the concerns?*" Although not depicted, severity of health consequences may have identified carcinogenic rhynium's importance. The predominant use of global terms is explained by the fuzzy trace theory proposition that people prefer to understand and apply gist at the simplest level, even when actual understanding is more

specific (Reyna & Brainerd, 1995b). The township map prompted the most global beliefs, perhaps because it displayed summary information across larger perceptual units. Even though the table also provided summary information for townships, the alphanumeric format was less meaningful, and typically understood verbatim at a township level. For the dot map, beliefs were primarily shaped by proximal wells although some derived a global understanding that rhynium could occur anywhere on the map – supported by findings that dot map viewers either focus on detailed patterns or see global trends (McCleary, 1975).

Emotion and Valenced Beliefs—Stated emotions were generally absent or weak, e.g., "*concern*", although two used the stronger term "*worry*". Emotion was embodied in varying degrees of negative valence; e.g. "*problem*,", "*bad*,", "*warning*". Beliefs had stronger negative valence for maps compared to the table, for the township compared to dot map, and for map locations near rather than far from high risks. The risk meaning of color on both maps (compared to the table) and the large amount of risky red on township maps (compared to dot maps) appeared to prompt meaning with stronger negative valence for the township map (e.g., "*warning*", "*urgent*", "*emergency*"). One even said, "*the red is very scary*." Color's impact on valence is plausible because even non-risk color evokes emotions (Valdez & Mehrabian, 1994). We only examined the impact of non-risk color for five participants; comments from two indicated red prompted beliefs with a stronger negative valence than did purple (see <u>Color and visual salience</u>).

Intended and Imparted Meaning

The dot map and table were most accurately understood - perhaps because the dots concretely conveyed actual data and the table was understood at a verbatim level. The Gestalt Law of similarity conveyed dots had the same meaning, readily interpreted by all as wells. Although the township map promoted the most global gist-like beliefs, it generated the largest discrepancy between intended and imparted meaning. Initially, seven participants did not understand the township map's rate exceedance information, and five were still confused at interview's end. Numeracy¹² apparently contribute to this gap with four of these five stating they did not like working with numbers. Despite these barriers, all but one got the gist – darker red areas had a larger problem than lighter areas (Table 2, C1-R2). The ease of understanding the symbolic warning meaning of red and pre-attentive processing of sequential shades to mean risk magnitude appeared to promote comprehension of the global message, even for those who did not understand rate exceedances. This conclusion is supported by claims the legend wasn't needed to understand the basic meaning of red gradations (C1-R2). However, for those who accurately understood rate exceedances, the legend provided the best support. Results suggest carefully selected pre-attentive and symbolic features can foster accurate gist even when details are poorly understood.

Meaning of uncertainty—The discrepancy between the intended and imparted meaning of data uncertainty, symbolized by abstract hatching, was also greatest for the township map. Numeracy did not appear to have a clear role in this discrepancy. Many were not sure what *insufficient data* meant. Variability in explanations (Table 2, C1-R4) suggests neither the label nor hatching symbol were effective. Data uncertainty was better understood when participants could see the concrete visual distribution of test results on dot maps (C2-R4); perhaps supported by bottom-up processing.

¹²Numeracy, the ability to understand basic probability and mathematical concepts, influences the comprehension of risk information (Nelson, Reyna, Fagerlin, Lipkus, & Peters, 2008).

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Prior Knowledge and Beliefs

Four types of prior groundwater beliefs influenced what people saw and derived meaning; all included a geographic component. Some believed groundwater moves: "*It's hard to put a boundary on something like groundwater which can be here but end up over here.*" This belief shaped how participants noticed and interpreted trends and attenuated the influence of perceived proximity to local risks. Beliefs that agriculture is a source of contamination shaped expectations for geographic areas showing more or less contamination - even though we described rhynium as a naturally occurring substance. Beliefs about residential distribution shaped participants' interpretations of data uncertainty to mean either a lack of wells or of testing. Finally, some related knowledge of well depth to beliefs of good water that was protected from contamination. Although not provided on study maps, well depth influences water quality and safety.

Our most striking example for the effect of prior beliefs on meaning did not concern groundwater. The recent purchase of a dishwasher led one participant to believe contaminant levels should exceed drinking water standards since efficient appliances exceed energy use standards. Her prior beliefs of standards impeded understanding the strong visual message on the township map that worked so well for others - consistent with the claim that prior knowledge decreases the influence of visual features (Cook, 2006). To address this confusion, we changed *"drinking water standard"* to *"maximum contaminant level"* because it implies an upper limit. However, two of five subsequent participants expressed confusion about the replacement. Both terms are commonly used in information provided to private well owners suggesting the need for more straightforward terminology. Johnson (2008) also found some people are confused by the "exceeds standard" term and tested alternative phrases.

Format Preferences

About half preferred the dot map because it concretely illustrated the amount and location of test results across the county (Table 2, C2-R5). Participants liked seeing the actual geographic distribution rather than results summarized by *"artificial"* township boundaries, although some thought the dot map was too detailed. Three preferred the township map because it provided county-level summary information (C1-R5). Others thought the percent exceedance information was too confusing. The importance of geographic information was highlighted by many who said a main drawback of the table was not being able to see (thus understand) the geographic distribution of test results "in context" and inhibited their ability to "see" proximity to hazards. However, three preferred the table because it was straightforward; they could find and read results for their township (C3-R5). Six participants wanted more than one format because each provided unique insights.

Integrated Representational and Behavioral Framework

Based on these findings, we integrated theory-based concepts into a framework (Figure 3) to illustrate how visual representations shape protective behavior via cognitive and emotional representations within a context of user characteristics. Some concepts complement others, e.g. *magnitude* is a component of *pre-attentive* features such as color shading and proximity. For maps, visual features influence viewers' abilities to approximate home or community locations and to see personally relevant proximal risk. Concepts related to information processing that shape how *seeing* informs derived *meaning* are challenging to measure, thus denoted in gray text within a gray arrow.¹³ We propose specific and global beliefs,

 $^{^{13}}$ Seeing is tightly integrated with meaning - distinguishing between these remains a challenge to the field of visual cognition (Tversky, 2005). Representing "what is seen" in the model is a reminder that this step occurs, whether or not it is measured.

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especially personally relevant beliefs at a household or personal level, are related to protective behavior.¹⁴ Dotted lines represent verbatim details to reflect proposed waning influence over time. Image features may also influence emotions and emotional valence embodied in the representation.

Conclusions and Implications

Conclusions—Findings are significant because they suggest theoretical mechanisms that explain how image features shape what people see and how the seen shapes derived meaning. The unit of perception, color, hazard proximity, geographic distribution, and visual salience had substantial impacts on what participants saw and believed. Potential explanations for these influences include: theoretical factors that shape what is seen, properties of features that shape cognition (pre-attentive, symbolic, visual salience), information processing (top-down and bottom-up), and the strength of concrete compared to abstract information. The geographic distribution of perceptual units shaped what people saw on maps: problem areas on township maps and locations and amounts of well test results on dot maps. Perceptual units shaped verbatim meaning derived from the table as percent of township wells exceeding the MCL. Color conveyed the meaning of mapped hazards – embodied in global risk beliefs with a negative valence. Three aspects of color were important: pre-attentive "incremental risk" meaning of sequential shading, symbolic safety meaning of stoplight colors, and visual salience that drew attention. Color had a stronger influence on the negative valence of beliefs for larger units. Meaning was more local for small units and global for large perceptual units. The lack of imagery, geographic information, and color diminished interest in table information.

Personal relevance appeared to guide top-down attention to proximal and larger hazards that shaped stronger risk beliefs. Numeracy appeared to impede comprehension of rate exceedances on the township map for some individuals, but nearly all understood the gist due to the pre-attentive and symbolic meaning of red shading. This suggests carefully selected pre-attentive and symbolic features can foster accurate gist even when details are not understood. Detailed beliefs were more accurate for the dot than township map because the detailed meaning of dot information was visually concrete but rate information was not. However, beliefs for the township map were more gist-like, perhaps because it provided summary information. An individual's prior beliefs influenced interpretations of hazard information, and varied by participant.

Limitations—Cognitive interviewing is not intended to produce generalizable results, but rather to provide insights into thought processes and derived meaning as people engage in a task (Beatty & Willis, 2007). The interview likely prompted more deliberate information processing than typical map use. We could only speculate whether comments reflected seeing or meaning and bottom-up or top-down processing. Although ordered to minimize the influence of prior formats, comprehension of the dot map and table was likely influenced by earlier formats. Demographics were not assessed so the sample cannot be compared to the county population. Motivation to participate in the study may have resulted in a biased sample.

Implications for research—The *Integrated Representational and Behavioral Framework* provides guidance for variables and relationships of interest. Experimental and longitudinal quantitative research is needed to measure the differential effects of map features on protective behavior, the mediating roles of specific and global risk beliefs and emotion, how

 $^{^{14}}$ We acknowledge that specific beliefs underlie rather than cause global beliefs. Denoting specific as causing global beliefs supports an analysis of this relationship and the unique role of each belief in mediating the relationship between features and behavior.

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these operate within a context of user characteristics, and the development of gist over time. Assessing effects of perceptual unit, color symbols, hazard proximity, and numeracy are of particular interest. Work is needed to distinguish the effects of personal relevance and visual salience. Interviews in combination with eye-tracking, recommended by Wulff (2007), may facilitate assessing visual attention as participants describe meaning. The type of risk may impact derived meaning, thus studies of other risk maps are warranted.

Implications for practice—Creating maps to communicate risk presents ethical challenges because the message is easily manipulated by the choice of map features. Substantial differences in meaning derived from dot and township maps illustrate the importance of choosing the perceptual unit for displaying data. Using symbolic risk colors to convey risk information when health standards or benchmarks are lacking may convey an inappropriate risk message. Risk colors prompted stronger beliefs when visual units were large, thus map creators need to consider how features work together to convey appropriate risk messages. Choosing features that facilitate map orientation (e.g. roads) is important because the accuracy of perceived map location may influence perceived risk. Several views of the same information may support comprehension better than a single format. Maps and information should be pre-tested on target audience members with varied prior beliefs to assess how text, visual features, and the legend support comprehension. Guidance for mapping risk information is available from other sources.¹⁵

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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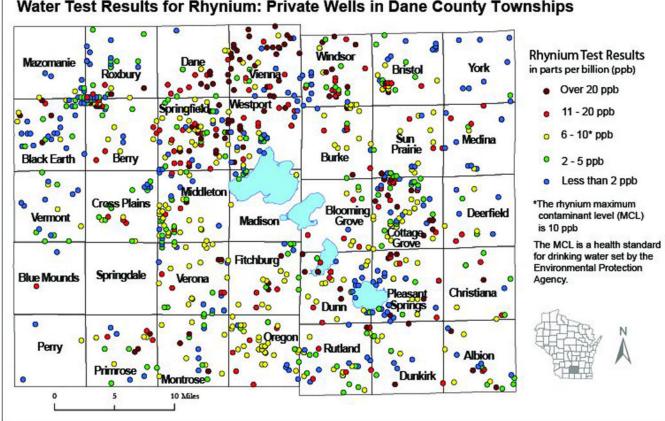
References

- Anselin L. How (Not) to Lie with Spatial Statistics. American Journal of Preventive Medicine. 2006; 30 Supplement 1(2):S3–S6. [PubMed: 16458788]
- Beatty PC, Willis GB. Research Synthesis: The Practice of Cognitive Interviewing. Public Opinion Quarterly. 2007; 71(2):287–311.
- Bell BS, Hoskins Richard, Pickle Linda, Wartenberg Daniel. Current practices in spatial analysis of cancer data: mapping health statistics to inform policymakers and the public. International Journal of Health Geographics. 2006; 5(1):49. [PubMed: 17092353]
- Brainerd CJ, Reyna VF. Fuzzy-trace theory and memory development. Developmental Review. 2004; 24(4):396–439.
- Brewer CA. Basic mapping principles for visualizing cancer data using geographic information systems (GIS). American Journal of Preventive Medicine. 2006; 30 Supplement 1(2):S25–S36. [PubMed: 16458787]
- Brody SD, Highfield W, Alston L. Does location matter?: Measuring environmental perceptions of creeks in two San Antonio watersheds. Environment and Behavior. 2004; 36(2):229–250.

¹⁵For example see: Anselin (2006), Bell, Hoskins, Pickle and Wartenberg (2006), Brewer (2006), Monmonier and Johnson (1997), Monmonier (1996), and Slocum (2005).

- Carlo GL, Lee NL, Sund KG, Pettygrove SD. The interplay of science, values, and experiences among scientists asked to evaluate the hazards of dioxin, radon, and environmental tobacco smoke. Risk Analysis. 1992; 12:37–43. [PubMed: 1574616]
- Cleveland WS, McGill R. Graphical perception: Theory, experimentation, and application to the development of graphical methods. Journal of the American Statistical Association. 1984; 79(387): 531–554.
- Cook MP. Visual representations in science education: The influence of prior knowledge and cognitive load theory on instructional design. Science Education. 2006; 90(6):1073–1091.
- DeLoache JS. Early understanding and use of symbols: The model model. Current Directions in Psychological Science. 1995; 4(4):109–113.
- Ericsson, KA.; Simon, HA. Protocol analysis: Verbal reports as data. 2nd ed.. Cambridge, MA: MIT Press; 1993.
- Florence D, Geiselman R. Human performance evaluation of alternative graphic display symbologies. Perceptual and Motor Skills. 1986; 63:399–406.
- Griffith LJ, Leonard SD. Association of colors with warning signal words. International Journal of Industrial Ergonomics. 1997; 20:317–325.
- Healey CG. Perception in Visualization. 2007 from http://www.csc.ncsu.edu/faculty/healey/PP/ index.html.
- Heath, Robert L.; Seshadri, Shaila; Lee, Jaesub. Risk communication: A two-community analyasis of proximity, dread, trust, involvement, uncertainty, openness/accessibility, and knowledge on support/opposition toward chemical companies. Journal of Public Relations Research. 1998; 10(1): 35–56.
- Hegarty M, Canham MS, Fabrikant SI. Thinking about the weather: How display salience and knowledge affect performance in a graphic inference task. Journal of Experimental Psychology: Learning, Memory, and Cognition. 2010; 36(1):37–53.
- Itti L. Visual salience. Scholarpedia. 2007 (1/16/2010). from http://www.scholarpedia.org/article/ Visual_salience.
- Johnson B. Public views on drinking water standards as risk indicators. Risk Analysis. 2008; 28(6): 1515–1530. [PubMed: 18793283]
- Leventhal, H.; Brissette, I.; Leventhal, E. The common-sense model of self-regulation of health and illness. In: Cameron, LD.; Leventhal, H., editors. The self-regulation of health and illness behavior. London: Routledge; 2003. p. 42-65.
- Lindell MK, Hwang SN. Households' perceived personal risk and responses in a multihazard environment. Risk Analysis. 2008; 28(2):539–556. [PubMed: 18419668]
- MacEachren, AM. How maps are imbued with meaning. In: Paperback, editor. How maps work: Representation, visualization, and design. New York: The Guilford Press; 1995. p. 213-215.
- McCleary, GF. In pursuit of the map user; Paper presented at the Auto-Carto II; Washington DC. 1975 Sep 21–25.
- Monmonier, M. How to lie with maps. 2nd ed.. Chicago: University of Chicago Press; 1996.
- Monmonier M, Johnson BB. Design guide for environmental maps. 1997 from http://tinyurl.com/ 6k2gq2k.
- National Cancer Institute. Theory at a glance: A guide for health promotion practice. 2nd. Edition. Washington D.C.: National Institutes of Health; 2005.
- Nelson W, Reyna VF, Fagerlin A, Lipkus I, Peters E. Clinical implications of numeracy: Theory and practice. Annals of Behavioral Medicine. 2008; 35:261–274. [PubMed: 18677452]
- Pinker, S. A theory of graph comprehension. In: Freedle, R., editor. Artificial intelligence and the future of testing. Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers; 1990. p. 73-126.
- QSR International. NVivo 8: QSR International. 2007
- Reyna VF, Brainerd CJ. Fuzzy-trace theory: An interim synthesis. Learning and Individual Differences. 1995a; 7(1):1–75.
- Reyna VF, Brainerd CJ. Fuzzy-trace theory: Some foundational issues. Learning and Individual Differences. 1995b; 7(2):145–162.

- Rivers SE, Reyna VF, Mills B. Risk Taking Under the Influence: A Fuzzy-Trace Theory of Emotion in Adolescence. Developmental Review. 2008; 8(1):107–144. [PubMed: 19255597]
- Robinson, AH.; Sale, RD.; Morrison, JL.; Muehrcke, PC. Elements of Cartography. New York: Wiley; 1984.
- Severtson DJ. Predictors of locational map accuracy: Implications for designing maps that communicate environmental risk. (in review).
- Severtson DJ, Baumann LC, Brown RL. Applying a health behavior theory to explore the influence of information and experience on arsenic risk representations, policy beliefs, and protective behavior. Risk Analysis. 2006; 26(2):356–372.
- Severtson DJ, Baumann LC, Brown RL. Applying the common sense model to understand representations of arsenic contaminated well water. Journal of Health Communication. 2008; 13(6):523–554. [PubMed: 18726810]
- Severtson DJ, Burt JE. The influence of mapped hazards on risk beliefs: A proximity-based modeling approach. Risk Analysis. 2011 Early View Online.
- Slocum, TA. Thematic cartography and geographic visualization. 3rd ed. Prentice Hall; 2009. Choropleth mapping; p. 250-270.
- Swienty O, Reichenbacher T, Reppermund S, Zihl J. The role of relevance and cognition in attentionguiding geovisualisation. Cartographic Journal, The. 2008; 45:227–238.
- Topf M. Three estimates of interrater reliability for nominal data. Nursing Research. 1986; 35:253–255. [PubMed: 3636827]
- Tversky, B. Visuospatial reasoning. In: Holyoak, KJ.; Morrison, RG., editors. The Cambridge handbook of thinking and reasoning. New York: Cambridge University Press; 2005. p. 209-240.
- U.S. Environmental Protection Agency. [Retrieved 7/22/2010] Ground water & drinking water. 2010a. from http://www.epa.gov/safewater/index.html
- U.S. Environmental Protection Agency. [Retrieved 7/22/2010] Private drinking water wells. 2010b. from http://www.epa.gov/safewater/privatewells/index2.html
- Valdez P, Mehrabian A. Effects of color on emotions. Journal of Experimental Psychology: General. 1994; 123(4):394–409. [PubMed: 7996122]
- Verdi MP, Kulhavy RW. Learning with maps and text: An overview. Educational Psychology Review. 2002; Vol. 14:27–46.
- Weinstein ND. The precaution adoption process. Health Psychology. 1988; 7:355–386. [PubMed: 3049068]
- Weinstein ND. Testing four competing theories of health-protective behavior. Health Psychology. 1993; 12(4):324–333. [PubMed: 8404807]
- Weinstein ND, Sandman PM. Predicting homeowners' mitigation responses to radon test data. Journal of Social Issues. 1992; 48(4):63–83.
- Wertheimer, M. Laws of organization in perceptual form. In: Ellis, WD., editor. A source book of Gestalt psychology. London: Routledge; 1938.
- Willis, GB. Cognitive interviewing: A tool for improving questionnaire design. Thousand Oaks, CA: Sage Publications; 2005.
- Wisconsin Towns Association. About towns. 2009 from http://www.wisctowns.com/about_towns.
- Yantis S. How visual salience wins the battle for awareness. Nature Neuroscience. 2005; 8(8):975– 977.



Water Test Results for Rhynium: Private Wells in Dane County Townships

Figure 1. Dot Map

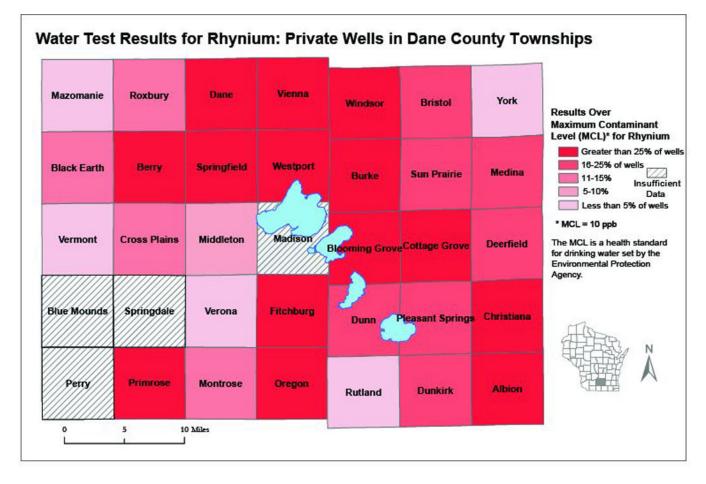
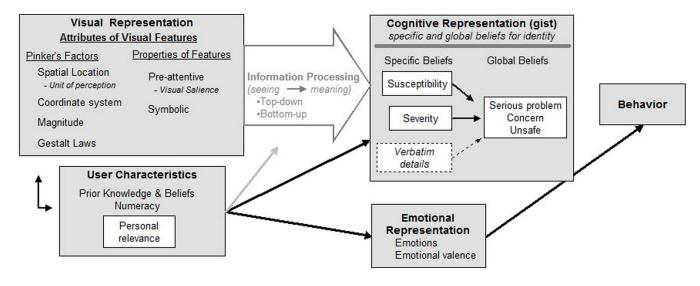


Figure 2. Township map: A choropleth map (shades of light red to red)

Severtson and Vatovec



Integrated Representational and Behavioral Framework

Table 1

Water Test Results for Rhynium: Private wells in Dane Country Townships

Albion6 of 2227%Berry10 of 3132%Black Earth5 of 3514%Blooming Grove4 of 1233%Blue Mounds1 of 2Insufficient dataBristol6 of 2722%Barke5 of 1827%Christiana3 of 1033%Cottage Grove22 of 7330%Coross plains2 of 2010%Dane15 of 2463%Deerfield2 of 1217%Dunkirk3 of 1224%Dunn11 of 5221%Hadison0 of 2Insufficient dataMadison0 of 2Insufficient dataMacinanie0 of 110%Middieton4 of 538%Montrose3 of 2114%Oregon13 of 5226%Perry0 of 3Insufficient dataPleasant Springs10 of 4821%Springfield30 of 7739%Sun prairie4 of 1921%Vernont0 of 170%Vernont0 of 170% <th>Township</th> <th>Number of samples exceeding 10 ppb*</th> <th>% of samples exceeding 10 ppb^*</th>	Township	Number of samples exceeding 10 ppb*	% of samples exceeding 10 ppb^*
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Westport 15 of 32 50% Windsor 16 of 38 42%	Verona	7 of 39	14%
Windsor 16 of 38 42%	Vienna	31 of 48	65%
	Westport	15 of 32	50%
York 0 of 9 0%	Windsor	16 of 38	42%
	York	0 of 9	0%

*Rhynium Maximum Contaminant Level = 10 ppb (parts per billion)

Table 2

Summary of Selected Interview Results and Quotes

Concepts ¹	C1. Township Map ¹	C2. Dot Map ¹	C3. Alphanumeric Table ¹
R1. What was seen	 Geographic distribution of information (n=10) Color (n=8) <i>"where I live"</i> [map location] (n=7), Geographic trends (n=7) Reported <i>seeing</i> meaning (n=6) e.g. seeing <i>*"areas where it is</i> <i>unsafe"</i>. 	 Geographic distribution of information (n=12) Color (n=11) Dots (n=7) Wells (n=9) <i>"where I live"</i> [map location] (n=9) Geographic trends (n=3) "I'm seeing, based on color, where wells were tested in the county andwhat the results were." 	 Number of samples exceeding 10 ppb (n=10) Alphabetical township names (n=8) Percentage of samples over 10 ppb (n=7) Column headings (n=7) Column headings (n=7) "where I live" [based on township name] (n=3)
R2. Illustrative quotes	 "Tm assuming that whatever I'm looking for is the dark red. The darker the red, the more toxic." "Tm a little confused. But generally, I would look at this and say based on the color, this is a bad thing. You know what? The color helps me figure this out more than the numbers do. So even if I didn't get the numbers, I would think I was getting it by the color." 	 "It looks busy when you first look at it, then when you take it in, it's busy because it's giving you the information you wanted. You wanted to know where these tests were taking place." "it would take some time [to read], while here [township map] it just jumped right out at me." "In this version of the map it looks to me like there's a much greater number of wells that tested ok, frankly. That's the effect of the way these dots are." 	 "That one with all the dots on it made me a little nervous saying oh man! Look at all these wells with all the problems, so maybe it was the visual But with this one [table] it's like, ok, I'm fine, and I don't like numbers anyway so I wouldn't study it much." "The [township] map made it seem serious, the red, but here 8 of 23, oh, that's not so serious, but it still is 35%."
R3. Trends and causal explanations	Township patterns as county trends: • "the dark red seems to go from the upper left to the lower right [of the county], Is that because of the Yahara River watershed?"	Dot patterns as local trends: • "like the red line through here I would say there's a water crevice or something in that area"	Numerical trend: townships with more testing had higher rates of exceedances. (n=1)
R4. Meaning of uncertainty	Comments show multiple interpretations: • "I wonder what that's all about - only two private wells in Blue Mounds?"• "I'm wondering why the four [townships] have insufficient data - there shouldn't be bad access [to water] there."• "I'd think they're not finding the substance. It isn't that they haven't looked enough or asked enough, it's that it's not there"• "Um, just that whatever testing was done, was insufficient statistically"	 "And it's nice here for the townships that said insufficient data, you can really see why; because there weren't many tests done, and I would say ok, well why not? Why isn't there any sampling what were the choices in terms of why the 	Easy to understand the meaning of <i>insufficient data</i> because this term was in the percent column and exceedances per sample size was provided in an adjacent column.

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		data were collected where it was?"	
R5. Format preference	 3 of 13 participants chose the township map: "In terms of teaching me about the amount of rhynium in private wells I'd go with this one [township map]. This [dot map] gives me more information about wells but not as much about wells that really need my attention." 	 7 of 13 participants chose the dot map: "Definitely the one with the dots it gives me a little more idea of the incidence you can track the problems. It tells me that the whole township is not an issue. I think it's easier to understand, and it also tells me, you know, I would say that's a pretty fair sampling in Springfield." 	3 of 13 preferred the table: • "Not that one [Township], even though I like the color on there it didn't give me as much information. Isn't that interesting, I think I'd prefer that one. I can just go straight to the table and it's clear. This one [dot] I kind of had to study for a bit to figure out what was going on." • "The other thing you lose here is the distribution."

I Numbers in headers (C1–3) pertain to column numbers. Numbers in rows (R1–5) pertain to row numbers.