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# Perceived risk and intentions to practice health protective behaviors in a mining-impacted region

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**Abstract:** Understanding the strength of the associations between perceived risk and individuals' behavioral intentions to protect their health is important for determining appropriate risk communication strategies in communities impacted by lead contamination. We conducted a survey within communities of northern Idaho, USA (n = 306) near a Superfund megasite with legacy mining contamination. We empirically test a theoretical model based on the Health Belief Model. Survey respondents had higher intentions to practice health protective behaviors when they perceived the risk of lead contamination as severe, recognized the benefits of health protective behaviors, and considered the risks of lead contamination. Women reported higher behavioral intentions than men, but age and mining affiliation did not have an association. Survey comments indicated that perceptions about the long-term environmental remediation in the region influenced risk perceptions. Understanding risk perceptions, behavioral intentions, and related factors can aid public health agencies in tailoring risk communication for increasing protective behaviors in mining-impacted communities internationally.

**Keywords:** Health Belief Model; risk perception; behavioral intentions; lead contamination; mining

## 1. Introduction

Lead [Pb] contamination, a consequence of industrialization, is a widely publicized international environmental health risk [1,2]. When Pb is widespread in a community, both primary prevention activities, the total removal or remediation of Pb hazards, and secondary prevention, individual health protective behaviors such as handwashing reduce the risk [3]. Even the low levels of Pb contamination that remain following primary prevention efforts are linked to long-term chronic diseases such as diabetes [4–6]. Communicating Pb risks is challenging because, in addition to beliefs about health effects, social, cultural, and political factors may influence whether risk communication motivates people to practice preventive behaviors [7–11]. For instance, concerns about the health effects of environmental contaminants may become less salient relative to other community development issues following a remediation project [11,12].

Sources of and exposures to Pb declined globally following the enforcement of new regulations and the removal of Pb from gasoline [13,14], but it remains a widely dispersed contaminant, especially in and around mining communities [2]. Contaminated topsoil remains a leading source of elevated blood lead levels in children because of the wide distribution of the contaminant [13,15]. Muennig [16] estimate that reducing blood lead levels to less than 1 µg/dL among all US children between birth and age 6 years would reduce crime and increase on-time high school graduation rates later in life, resulting in net societal benefits arising of \$50,000 per child annually at a discount rate of 3%. In low- and middle-income countries, the societal burden associated with childhood Pb exposure

was estimated to amount to 1.2% of the global GDP in 2011 [17]. Secondary prevention and risk communication are important for reducing the global burdens of Pb exposure.

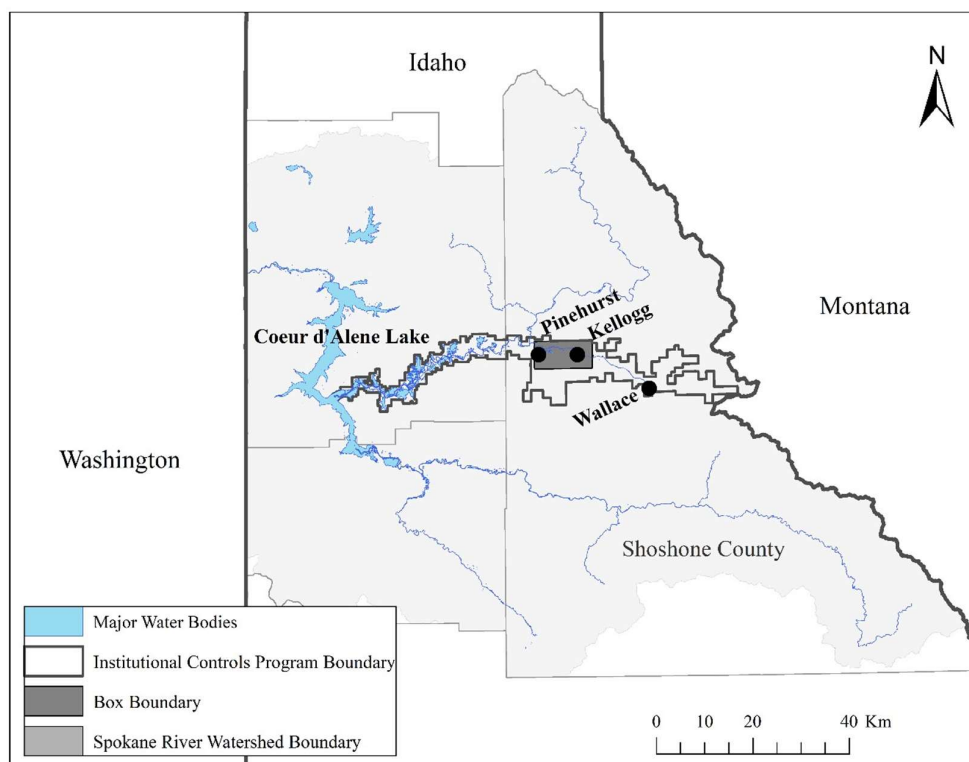
Health behavior frameworks facilitate improved understanding of the associations between perceived risk and behavioral intentions (e.g., [18,19]). The Health Belief Model (HBM) is often applied in empirical studies about environmental and health related topics (e.g., [20,21]). Identifying associations between risk perceptions and behavioral intentions can aid responsible agencies in developing or modifying risk communication strategies. Developing consistent and comparable empirical methods for measuring risk perceptions and health behavioral intentions is challenging [22,23].

Our objective was to examine the strength of associations between perceived risk and health protective behavioral intentions (hereafter, behavioral intentions) in mining-impacted communities of the Silver Valley in northern Idaho, United States (US) (Figure 1). We also wanted to identify emergent individual and contextual variables that might further influence risk perception and behavioral intentions. Communities of the Silver Valley are located in a designated Superfund site—the US program administered by the Environmental Protection Agency (EPA) for remediating contaminated areas—where widespread Pb contamination has been present for over 140 years [24]. In 1983, the several residential areas were included in the initial boundaries of the Bunker Hill Mining and Metallurgical Complex or Bunker Hill Superfund site. In 2002, the Superfund site boundaries were expanded to include all communities along the floodplains of the Silver Valley [25]. Staff with the Panhandle Health District (District) are concerned that people are exhibiting behaviors that can lead to Pb exposure, such as recreating at old mine sites [26]. To improve the District's risk communication strategy, we used the HBM to develop a community survey (n=306) for examining perceived health risks and behavioral intentions given possible exposure to Pb.

## 2. Materials and Methods

### 2.1. Study Area

Historical mining, smelting, and associated waste disposal practices in the Silver Valley resulted in the contamination of soils, sediments, groundwater and surface water with Pb as well as arsenic and other toxic metals [24]. Once the wealthiest county in Idaho, the Silver Valley's Shoshone County currently has an aging population of approximately 12,700 (U.S. Census, 2018). The population is predominantly white, and poorer than most counties in Idaho [27]. Over 20% of the county's population under the age of 65 years is on disability, compared to 13% for the state of Idaho. Nearly 11% of children (5 to 17 years old) have a disability, relative to just 5.7% of children in the state [28]. The Silver Valley also reports higher rates of non-communicable diseases (e.g., cardiovascular disease) relative to the state [29].



**Figure 1.** Communities of Kellogg, Pinehurst, and Wallace in the Silver Valley of Idaho. The dark gray rectangle incorporating Pinehurst and Kellogg represents the 54 km<sup>2</sup> area known as “the Box” – the area of the original Bunker Hill Superfund Site that included a smelter and other processing facilities. The Institutional Controls Program Boundary includes the expanded Superfund site that includes 394 km<sup>2</sup> of floodplains and wetlands.

Sources: [30,31]

Primary prevention activities, including land remediation through soil removal and replacement of city infrastructure, began in the 1980s following the designation of the Superfund site [32]. Today, most residential properties have been remediated along with the smelting areas and some of the old mine sites [31,33]. Blood lead level concentrations among children living in nearby communities fell from approximately 64 µg/dL to 2.7 µg/dL during 1974-2001 [34,35]. Yet, the Silver Valley remains contaminated at abandoned mine sites and in the floodplains of creeks and rivers where the mine waste was dumped and continues to be distributed by high flows. With the remediation of most private properties complete, Pb exposure now occurs primarily through use of recreational areas in floodplains and near mine sites [31,33].

## 2.2. The Health Belief Model (HBM)

Survey questions were based on the six primary constructs of the HBM, which are hypothesized to predict whether a person will choose to practice health protective behaviors [36]. Four of these constructs—perceived severity, perceived susceptibility, perceived barriers, perceived benefits—were developed in the original HBM while cue to action, and self-efficacy were added to the extended HBM [37]. Perceived severity and susceptibility are defined as an individual’s cognitive assessment of the likelihood and magnitude of a danger [19]. Perceived barriers and benefits relate to individuals’ expectations about the likelihood that an action will be followed by particular consequences [38]. Self-efficacy was added to the HBM because a disbelief in one’s ability to practice a behavior is also believed to influence behavior [39]. Similarly, the cue to action construct—internal and external triggers that prompt a health behavior—was added to the model because of the importance of reminders in facilitating behavior change [19]. Collective, the six constructs inform

individuals' perceived risk. Motivation to practice health protective behaviors is also influenced by demographic and psychosocial factors that affect an individual's risk perception [36]. Behavioral intentions are widely considered the most immediate and important predictor of behavior and are commonly used to evaluate behaviors when actual behaviors cannot be measured [40].

Previous reviews of empirical HBM studies indicate that the associations between the perceived health risk constructs and behavioral intentions are not the same for all the constructs. Meta-analyses of empirical HBM studies find that perceived barriers and benefits tend to be the strongest predictor of behavior [41]. Although not included in many HBM studies, self-efficacy is a strong predictor of behavioral intentions [42]. Self-efficacy is at times considered a perceived barrier, rather than a separate component of the model because, if an individual's belief in their ability to change their behavior is low because of low self-efficacy, then these beliefs could be interpreted as a perceived barrier. Meta-analyses provide limited insight about the strength of associations between the HBM constructs and behavioral intentions because associations depend on the context and behavior being examined [43,44]. Thus, while the primary associations proposed by the HBM are reinforced by empirical studies, evaluations of health risks and behaviors through the model must be reevaluated across contexts and behaviors.

### 2.2.1. Hypotheses

The HBM can be used to evaluate a causal structure, or parallel mediation model, in which an independent variable such as behavioral intention is associated with all of the HBM constructs, and then these affect an outcome variable or an actual behavior [44]. The HBM framework does not assume shared influence or paths between constructs [19]. We proposed associations among HBM constructs and behavioral intentions that can be evaluated by a parallel mediation (path) modeling approach. We hypothesized that the six HBM constructs are associated with behavioral intentions for practicing protective health behaviors in this environment of long-term, Pb contamination. For the outcome expectancy constructs, perceived benefits and barriers, we hypothesized that high perceived benefits and low perceived barriers to action will be associated with behavioral intentions.

Age, gender, and mining affiliation were included in the analysis as covariates because they have been found to influence health protective behaviors in the context of Pb contamination. Age may play a role because a person's age is an indicator of how much experience they have with Pb contamination and whether they are likely to have young children [45,46]. Gender may influence behavior because women and children are more vulnerable to negative health outcomes from Pb exposure and might be more likely to practice health behaviors [47,48]. Affiliation with mining is likely relevant because several previous studies have linked involvement in livelihoods related to a polluting industry with lower perceived health risk [49,50].

### 2.3. Survey Development

To assess the perceived risk, based on the primary constructs of the HBM, and behavioral intentions of residents, a drop-off, pick-up survey was developed by University of Idaho researchers and District staff. The study protocol was approved and certified exempt by the University of Idaho Institutional Review Board (#18-080). The survey was validated through pretesting the survey questions at community events hosted by the District in 2018 (n=87). Results from survey pretesting were submitted to a principal components analysis (varimax rotation) to determine whether the survey items aligned with HBM variables. The analysis of the pretest survey responses was deemed acceptable because alignment between survey items and the corresponding HBM variables produced factor loadings greater than 0.4 [51].

#### 2.3.1. Drop-off, Pick-up Survey Procedures

We drew stratified random samples from neighborhood clusters in Kellogg, Pinehurst, and Wallace (Table 1). These three communities were chosen from the seven communities in the Silver Valley based on their variable locations within the Superfund site, differing population sizes, and

ease of access to researchers, as we determined through consultation with the District and 2010 U.S. Census data. The samples were stratified based on proportional representation of single- and multi-family housing in each community. Neighborhood clusters increased the efficiency of house-to-house visits. A total of 773 households were identified for inclusion in the study. The DOPU method was selected because of its suitability for limiting non-response bias within hard to reach communities [52]. The survey was fielded in March 2019. Conducting the survey in March helped to ensure that the sample primarily included our target respondents—residents of the Silver Valley—rather than winter and summer second home and rental populations.

**Table 1.** Drop off, pick up survey responses

	n (%)	Household Type		Community		
		Multi-family	Single-family	Kellogg	Pinehurst	Wallace
<b>Selected households</b>	773 (100%)	193 (25%)	580 (75%)	365 (47%)	255 (33%)	159 (20%)
<b>Removed from sample</b>						
Vacant/unsafe	204 (26%)					
Refusals	126 (16%)					
Unreturned mailers	119 (15%)					
Incomplete	18 (5%)					
<b>Survey Responses</b>	306 (40%)	58 (18%)	248 (82%)	143 (47%)	113 (37%)	49 (16%)

*Note.* The final analysis was based on 306 surveys. Surveys with more than 20 incomplete items were excluded from the analysis. Towns were sampled proportionately based on number of households.

A pre-survey notification was mailed a week prior to the in-person survey drop-off period. Then, the field staff visited each household up to three times to deliver surveys. Only consenting adults (18 years of age or older) were eligible to participate, and participation was randomized by requesting the responsible adult with the closest birthday complete the survey [53]. When a respondent agreed to participate, field staff left the survey and a pen, and coordinated a time to return to the house to collect the completed survey. After three failed delivery attempts, field staff left a survey packet (including a cover letter, survey, pen, and prepaid return envelope) on the door of the residence. 306 surveys were completed, with 30 of those completed by mail. Of the 773 households in the original sample, 204 were excluded because they were determined to be either vacant or unsafe; thus, the final response rate, calculated out of a possible 569 households, was 53.8%. Completed survey data were manually entered into Qualtrics, an online survey platform. Each survey was entered twice by two different researchers and an accuracy check was performed. Discrepancies between the two entries (<1%) were manually corrected.

### 3.3.2. Survey Measures

We used a 5-point response scale for the 33 survey items conceptualized to represent the study variables – the six health belief constructs and a behavioral intentions variable. We chose a 5-point scale because some studies suggest that it offers higher data quality than 7- or 11- point scales [54], and we were concerned about overwhelming respondents with too many response options. The full survey instrument is included in Supplementary Materials, not all survey items were used in this analysis. At the end of the survey, respondents were asked to share any general comments about the survey. We used these comments to help interpret the survey results and to identify other variables not measured by the survey items.

1. **Behavioral intentions:** Respondents were asked to consider their intentions to complete six health protective behaviors related to avoiding exposure to Pb contamination over the next year. Participants responded to all items on a 1 = very unlikely to 5 = very likely scale. A “does not apply” option was included, but these responses were excluded from the analysis.
2. **HBM constructs:** twenty-seven items were included in the survey to measure the HBM constructs perceived severity, perceived susceptibility, perceived benefits, perceived

barriers, and self-efficacy. Participants responded to all items on a 1 = strongly disagree to 5 = strongly agree scale. These items were adopted from several studies related to heavy metal contamination (e.g., [21,46,55,56]). The cue to action construct was measured through two items that asked respondents about how frequently they had thought about, read, or heard about Pb contamination issues in the past year. The scale ranged from 1 = never to 5 = very often.

3. **Socio-demographic characteristics:** Eight items were about socio-demographic characteristics. Three items were included in the model as covariates due to their possible influence on behavioral intentions. Survey respondents were asked to indicate gender (male, female, prefer not to answer), age (continuous), and connections to mining. The latter item was phrased: “has a member of your household ever worked in a mining-related job in your local area?” Response options included “yes”, “no”, and “I don’t know.” Response options for “I don’t know” and “prefer not to answer” were excluded from the model analysis. Remaining items about the socio-demographic characteristics of the sample are reported in the results.

#### 2.4. Data Analysis

RStudio (version 1.2.1335) was used to analyze the data. Descriptive statistics (means, frequencies, and standard deviations) were calculated for each Likert-type question and the demographic variables. Primary analysis included structural equation modeling (SEM), a combination of factor analysis and multiple regression analysis [57], which allowed for analysis of the structural relationship between items in the survey and the latent variables of the HBM.

##### 2.4.1. Imputation

The data were analyzed for outliers and missing items – survey responses with fewer than 25% missing items, which resulted in excluding 18 surveys. While many methods exist for handling missing data within SEM, multiple imputation or maximum likelihood methods are recommended because they produce consistent parameter estimates, standard errors, and test statistics [58]. Prior to statistical modeling analysis, we conducted 20 rounds of imputation using a maximum likelihood estimation in the R package called mice for the remaining missing response items (<1%), including for responses coded as “does not apply” [59].

##### 2.4.2. Structural equation model analysis

Model testing was performed in the R package Lavaan [60]. Analysis included an exploratory factor analysis (EFA) followed by a two-step SEM to evaluate the measurement and structural properties of modeled associations between the HBM constructs and behavioral intentions. Data were first assessed for factorability using Bartlett’s Test of Sphericity and the Kaiser-Meyer-Olkin Measure (KMO) of sampling adequacy [61]. The Bartlett’s Test of Sphericity resulted in a Pearson’s Chi-square test statistic,  $\chi^2$  (465, n=306) =5,466,  $p < .001$ , and a KMO value= 0.83 above the acceptable threshold of 0.5. Because of the significance of the Bartlett’s test and the KMO value being in the acceptable range, data were deemed suitable for factor analysis. An EFA was performed to evaluate the correlation of the items, validate their groupings with the theorized health belief constructs and behavioral intentions, and establish variable parameters for modeling [51]. The EFA was performed using maximum likelihood extraction method with a direct oblimin rotation due to the expected correlation between the survey items [62]. Factor selection was performed using the Kaiser-Guttman rule based on an eigenvalue cut-off of one [51]. As a preliminary test of validity, each factor was analyzed for internal reliability using Cronbach’s Alpha and a threshold of  $\geq 0.7$  [63].

The variable groupings derived from the EFA were entered into a confirmatory factor analysis (CFA) to evaluate the measurement properties of the SEM [64]. Each factor (variable) identified in the EFA was treated as its own latent variable in the CFA. The model was estimated with a weighted least square mean and variance (WLSMV) adjusted estimator as a suitable estimator for ordinal data

because it does not assume that the data is normally distributed [65–67]. We evaluated model goodness-of-fit to the data using multiple indices and the recommendations in Kline [57]. Given the sensitivity of the chi-squared statistic to sample size, a Comparative Fit Index (CFI), a Tucker Lewis Index (TLI), and a Root Mean Square Error of Approximation (RMSEA) were used to assess model fit [68]. The acceptable threshold for CFI and TLI is  $\geq 0.9$  and for RMSEA is  $\leq 0.08$  but ideally below  $\leq 0.05$ .

After assessing the measurement properties of the SEM, we evaluated its structural properties, or the strength of associations between the perceived health risk and behavioral intentions variables. This evaluation included exploring the correlations between the variables as some studies based on the HBM indicate that variable ordering is important due to possible direct and indirect effects between variables [44]. Error correlation between the perceived health risk variables was allowed. Correlated errors assume that the latent variables share at least one omitted characteristic in common and allow the model to account for the possibility of measurement error that develops from similarly worded and measured items [51,57].

### *2.5. Survey Comments*

The accuracy and efficacy of interpretation of our results was enhanced through the inclusion of qualitative comments made during data collection. Open-ended comments entered by respondents at the end of the survey were also analyzed to identify other variables that might influence behavioral intentions and risk perceptions. The comments were organized and combined into a text document [69]. One round of coding was used to distinguish the primary themes related to Pb contamination, the Superfund site, health behaviors, and risk perception.

## **3. Results**

### *3.1. Sociodemographic Characteristics*

Survey respondents were 44% male, 91% white, with an average age of 54.5 (SD=17.7) years old, and 36% of respondents held a bachelor's degree or higher (Table 2). Relative to the Shoshone County population, respondents were more likely to be female, older, and had higher educational attainment. On average, respondents reported having lived in the Silver Valley for 62% of their lives, with over 75% reporting that they lived in the Silver Valley for at least 75% of their lives. Household income estimates align closely with the income levels of the Silver Valley with 52% reporting annual incomes under \$50,000. Ten percent of respondents opted not to provide an estimate of their household income. Slightly fewer than half (44%) of respondents reported having a family member (or being involved themselves) in a mining-related occupation.

**Table 2.** Description of sample (n=306)

Characteristic	Mean (SD) [% (Freq)]
Age (years, M [SD])	54.5 (17.7)
Years lived in Silver Valley (years, M[SD])	33.3 (21.5)
Gender (% [Freq])	
Female	54% (165)
Male	44% (134)
Prefer not to say	2% (6)
Race/Ethnicity (% [Freq])	
White	90.8% (278)
No Response	4.6% (14)
All others	5% (14)
Highest education (% [Freq])	
Advanced degree	9.8% (30)
College degree	26.1% (80)
Some college but no degree	30.1% (92)
High school graduate	28.1% (86)
Less than high school degree	5.2% (16)
Occupational status (% [Freq])	
Retired	35.6% (109)
Working full-time	36.3% (114)
Homemaker	8.8% (27)
Working part-time	7.2% (26)
Disabled/Medical Leave	4.6% (5)
Student	0.7% (2)
Unemployed	1.3% (4)
No Response	3.0% (9)
Approximate household income (% [Freq])	
Less than \$20,000	21.6% (66)
\$20,000 to \$49,999	30.7% (94)
\$50,000 to \$79,999	22.5% (69)
\$80,000 to \$99,000	8.2% (26)
\$100,000 or more	6.5% (21)
No Response	10% (30)
Family in mining (% [Freq])	
No	53.3% (163)
Yes	44.4% (136)
Not sure	1.6% (5)

Note. 'No response' categories excluded for characteristics when less than 1%

### 3.2. Exploratory Factor Analysis

The total variance explained by the EFA was 54% and six variables (factors) were extracted (Supplementary Materials, Table S1). Nine items were excluded from further analysis because they did not align with the primary EFA factor. One theorized behavioral intentions item, "how frequently do you recreate in or near the South Fork of the Coeur d'Alene River?" was excluded because it had a loading of only 0.19. Two items conceptualized as relating to self-efficacy, "I seek out information about lead contamination" and "I can prevent lead contamination from entering my home," cross-loaded >0.3 with other variables and were therefore removed from the analysis. Two items conceptualized as perceived barriers, "preventing lead contamination from entering my home is inconvenient" and "avoiding lead contamination while spending time outdoors is inconvenient," and two items conceptualized as self-efficacy, "I can avoid lead contamination while



spending time outdoors” and “I can prevent lead contamination from entering my home,” failed to load on any factor. Two other items conceptualized as perceived barriers, “I need more information about how to avoid lead contamination while spending time outdoors,” and “I need more information about how to prevent lead contamination from entering my home,” loaded with perceived severity instead of perceived barriers, and were therefore excluded from the analysis.

The items conceptualized to measure self-efficacy were divided into two variables for further analysis. Two items formed a variable of self-efficacy in individual knowledge about Pb contamination – “I know a lot about the health effects from lead contamination” and “I am better informed about the health effects of lead contamination than most people” – while two other items measured self-efficacy in accessing information and resources about Pb contamination – “I know who to ask if I have questions about preventing health effects from lead contamination” and “I am aware of the available resources for preventing health effects of lead contamination.” We named this variable “perceived barriers,” but highlight that these items relate only to barriers about awareness of information and resources. The four items conceptualized to measure perceived barriers did not form a cohesive variable, the variable was not included in the analysis. The final six variables extracted through the EFA included behavioral intentions, self-efficacy and perceived severity, susceptibility, benefits and barriers. These six variables demonstrated acceptable reliability with Cronbach’s Alphas above 0.7 [63].

### 3.3. Confirmatory Factor Analysis

The initial model demonstrated acceptable fit ( $\chi^2(194, n=306) = 550.32, p < .001; \chi^2/df = 2.83$ ). Although the chi-square test was significant – suggesting poor model fit – the RMSEA value (0.078) was within the acceptable limits, and the CFI (0.987) and TLI (0.985) were above the minimum threshold of 0.9 suggested by Kline [57]. The perceived susceptibility item, “if it is my destiny to experience health effects related to lead contamination, there is nothing that I can do to prevent it,” had a low standardized coefficient of 0.40 relative to the other three items that comprised the perceived susceptibility variable, so the item was dropped from the analysis. High correlations were found between several items and variables. The high correlation between the perceived benefits and perceived severity ( $r = 0.50, p < .001$ ) led to a decision to evaluate the structural properties of two models with and without the perceived benefits variable. The full correlation matrix with the six latent variables is in Supplementary, Table S2. Following a recommendation by Rossell [60], we accounted for high correlations in the perceived severity variable items by adding residual variances between items measuring the same cognitive concepts for indoor versus outdoor Pb contamination. The adjusted model revealed improved fit (Table 3:  $\chi^2(172, n=306) = 422.30, p < .001; CFI = 0.992; TLI = 0.990; RMSEA = 0.069$ ). The revised model did not meet the ideal threshold of  $\leq .05$  for the RMSEA value but was within the acceptable range of  $\leq .08$ . Due to the exploratory nature of the model and acceptable model fit, the revised CFA was considered plausible.

**Table 3.** Confirmatory factor analysis of the HBM and behavioral intentions variables (n=306)

Item	b(SE) <sup>ab</sup>	$\beta$
<i>Perceived Benefits</i>		
<i>Indicate to what extent you agree that completing the following actions are good for your health:</i>		
Promptly removing dirt from your clothes, toys, pets, cars, and equipment after spending time outdoors.	1.00	0.80
Staying on designated trails while recreating in areas with lead contamination warning signs posted.	1.01 (0.03)	0.87
Washing your hands with clean water or wipes before eating or drinking after recreating or working outdoors.	0.92 (0.04)	0.77

Using a protective barrier such as a blanket when sitting on a sandy beach.	1.03 (0.03)	0.86
Following the advice of a local public health official about ways to safely avoid lead contamination.	0.10 (0.03)	0.83
<i>Perceived Severity</i>		
I worry about lead contamination while spending time outdoors.	1.00	0.80
It is worth my time to avoid lead contamination while spending time outdoors.	1.02 (0.06)	0.79
I worry about lead contamination entering my home.	0.97 (0.04)	0.75
It is worth my time to clean my home to prevent lead contamination.	1.01 (0.06)	0.79
<i>Behavioral Intention</i>		
<i>Consider your recreational and outdoor activities in your local area over the next 12 months. How likely is it that you will?</i>		
Promptly removing dirt from your clothes, toys, pets, cars, and equipment after spending time outdoors.	1.00	0.80
Staying on designated trails while recreating in areas with lead contamination warning signs posted.	0.90 (0.05)	0.72
Washing your hands with clean water or wipes before eating or drinking after recreating or working outdoors.	0.90 (0.06)	0.71
Using a protective barrier such as a blanket when sitting on a sandy beach.	0.97 (0.05)	0.77
Following the advice of a local public health official about ways to safely avoid lead contamination.	1.07 (0.05)	0.85
<i>Perceived Susceptibility</i>		
I have experienced health effects related to lead contamination.	1.00	0.90
I feel I will experience health effects related to lead contamination at some time during my life.	1.10 (0.03)	0.99
I am more likely than the average person to experience health effects from lead contamination.	0.88 (0.03)	0.79
<i>Self-Efficacy</i>		
I know a lot about the health effects from lead contamination.	1.00	0.90
I am better informed about the health effects of lead contamination than most people.	0.96 (0.04)	0.90
<i>Perceived Barriers</i>		
I know who to ask if I have questions about preventing health effects from lead contamination.	1.00	0.90
I am aware of the available resources for preventing health effects of lead contamination.	1.03 (0.03)	0.96

Note. Both unstandardized (b) and standardized ( $\beta$ ) beta coefficients are reported.

Model:  $\chi^2$  (172, n=306) =422.30,  $p < .001$ ; CFI=0.992; TLI=0.990; RMSEA=0.069).

<sup>a</sup>The first items for each variable are fixed as a reference item at 1.00 in Lavaan

<sup>b</sup>Regression weights significant at  $p < .001$

### 3.4. Path Analysis

Table 4 includes the associations between the perceived health risk variables and behavioral intentions based on three path models. Model 1 shows the path coefficients for the variables included in the CFA. Only the association between perceived benefits and behavioral intentions was significant ( $\beta = 0.67$ ,  $p < .001$ ). Model 2 reflects the same model without the perceived benefits variable ( $\chi^2(92, n=306) = 186.76$ ,  $p < .001$ ; CFI=0.976; TLI=0.994; RMSEA=0.058). Model 2 had a lower chi-square value and RMSEA than Model 1, and the association between perceived severity and behavioral intentions was significant ( $\beta = 0.62$ ,  $p < .001$ ). This indicates that perceived severity had a lower effect on behavioral intentions than perceived benefits.

**Table 4.** Associations between HBM variables and behavioral intentions (dependent variable),  $n=306$

Independent Variable	Model 1		Model 2		Model 3	
	b (SE)	$\beta$	b (SE)	$\beta$	b (SE)	$\beta$
Perceived Severity	0.17 (0.09)	0.16	<b>0.57 (0.07)</b>	<b>0.62</b>	0.15 (0.09)	0.12
Perceived Susceptibility	0.00 (0.06)	0.00	-0.12 (0.07)	-0.14	0.04 (0.06)	0.04
Perceived Benefits	<b>0.64 (0.06)</b>	<b>0.67</b>			<b>0.63 (0.06)</b>	<b>0.61</b>
Perceived Barriers	-0.06 (0.09)	-0.08	0.07 (0.10)	0.08	-0.08 (0.09)	-0.09
Self-Efficacy	0.05 (0.08)	0.06	0.02 (0.09)	0.02	0.08 (0.09)	0.08
<sup>1</sup> Cue: think about	<b>0.21 (0.04)</b>	<b>0.26</b>	<b>0.21 (0.04)</b>	<b>0.26</b>	<b>0.21 (0.04)</b>	<b>0.26</b>
<sup>1</sup> Cue: read or heard about	-0.02 (0.05)	-0.03	-0.02 (0.05)	-0.03	-0.02 (0.05)	-0.03
Gender (0=F, 1=M)					<b>-0.36 (0.10)</b>	<b>-0.22</b>
Mining Affiliation (0=No, 1=Yes)					-0.13 (0.10)	-0.07
Age					-0.00 (0.00)	-0.03

Note. Model 1:  $\chi^2(172, n=306) = 422.30$ ,  $p < .001$ ; CFI=0.992; TLI=0.990; RMSEA=0.069

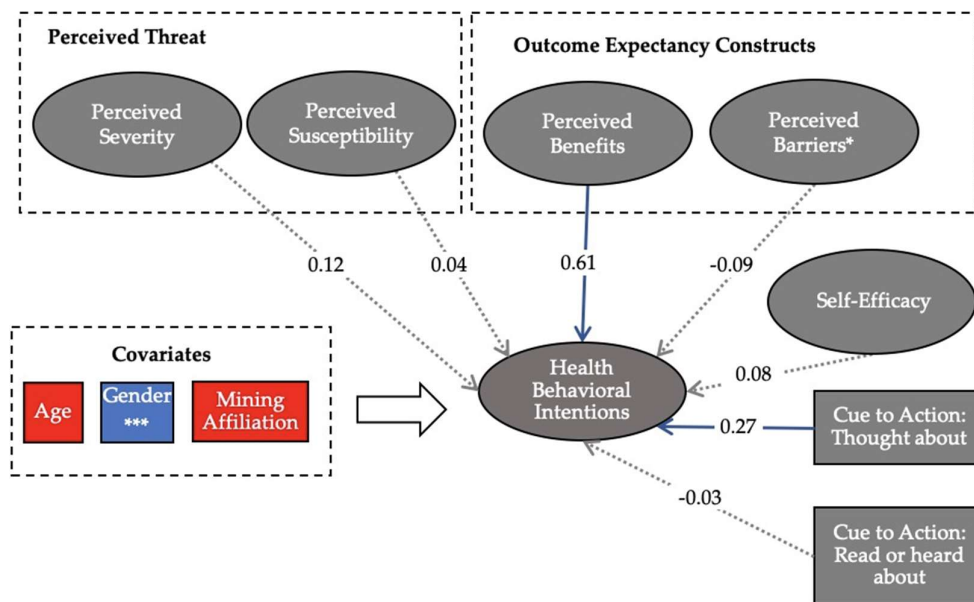
Model 2:  $\chi^2(92, n=306) = 186.76$ ,  $p < .001$ ; CFI=0.976; TLI=0.994; RMSEA=0.058

Model 3:  $\chi^2(272, n=306) = 1147.98$ ,  $p < .001$ ; CFI=0.961; TLI=0.970; RMSEA=0.103

Both unstandardized (b) and standardized ( $\beta$ ) beta coefficients are reported. The coefficients and error terms measure the strength of the statistical association. Bolded associations significant at the  $p < .001$ .

<sup>1</sup>Cue to action variables based on two observed survey items.

Model 3 included the latent variables, the two cue to action variables, and the covariates gender, age, and mining affiliation ( $\chi^2(272, n=306) = 1147.98$ ,  $p < .001$ ; CFI=0.961; TLI=0.970; RMSEA=0.103). The path coefficients for the full model are illustrated in Figure 2. The RMSEA exceeded the recommended threshold of 0.08, however, the CFI and TLI were within the acceptable range. Based on discussion in Kline [57] and Xia and Yang [68] we decided that the model fit was reasonable despite the RMSEA because it is sensitive to sample size and was not developed explicitly for ordinal categorical data. The perceived benefits variable was again significantly associated with behavioral intentions ( $\beta = 0.61$ ,  $p < .001$ ). One of the cue to action variables, the survey item that asked if respondents "thought about lead contamination issues" was significantly associated with behavioral intentions ( $\beta = 0.27$ ,  $p < .001$ ). Gender was the only covariate with a statistically significant association with behavioral intentions, with women more likely than men to report intentions to practice health protective behaviors ( $\beta = -0.36$ ,  $p < .001$ ).



**Figure 2.** Path analysis for the full model. Solid blue lines indicate significant paths. Gender had a significant association with behavioral intentions in both models with women being more likely than men to report performing health protective behaviors.

\*Perceived barriers were hypothesized to be inversely associated with behavioral intentions

Note. Ovals represent latent variables and rectangles represent observed variables

### 3.5. Emergent Contextual Variables

While most respondents did not leave comments at the end of the survey, the comments provided add nuance to the results of the path analysis and additional understanding of the contextual and individual variables that might influence risk perception and behavioral intentions. Many comments reflected back, in both supportive and unsupportive ways, on the decades long environmental remediation in the region. The 76 comments split between three primary themes about Pb contamination, the Superfund site, health behaviors, and risk perception: 28 supported efforts related to the Superfund program and/or primary prevention activities; 27 were unsupportive of these efforts; and 21 mentioned beliefs that individual health behaviors mitigate the risks posed by Pb contamination (Table 5).

**Table 5.** Illustrative excerpts from survey comments grouped by primary themes

Theme	Comment
Supportive of primary prevention and/or Superfund program (27 comments)	<ul style="list-style-type: none"> <li>• “We are not concerned about lead contamination because we see efforts every day to reverse clean up questionable areas.”</li> <li>• “My dad worked for the Bunker Hill mine. I have pictures of the early 50s. The mountains were much different. They are beautiful now. I would drive just a very short distance and the smelter smoke had a terrible odor.”</li> <li>• “In grade school all kids tested very high in lead in blood. When I left Kellogg 30 years ago, there were no trees on the mountains. Now trees! I hope the lead is gone because it is beautiful now. But scary. As I get older, I hope there are no lasting effects of lead!”</li> <li>• “It has already been taken care of. 30 years ago, they took my soil out and put new soil in.”</li> </ul>
Unsupportive of primary prevention and/or	<ul style="list-style-type: none"> <li>• “The EPA has been here it seems forever. They have been digging up everything in the Valley, spending millions of dollars on things that seem to be a waste. First, the plant where I worked for 29 years and no one seemed to care that 2,000 men didn't have a job to pay their loans off or feed their families and</li> </ul>

Superfund program (28 comments)	<p>this has been going on every year that we lost our jobs. I feel it's time to get out of dodge and find somewhere else to dig up; ruin their lives for the next 20 years."</p> <ul style="list-style-type: none"> <li>• "I feel that 99% of what the EPA is doing is a waste of time and money. Lead sulfides are not poisonous only refined lead is."</li> <li>• "Asking about lead contamination in the Silver Valley, is like saying water is wet. Half the people here work underground in the mines. I drank water from a water hose and I'm still kicking. I know the risks. Sorry, I don't care about lead, I work in a mine."</li> </ul>
Beliefs about individual behavior and Pb exposure (21 comments)	<ul style="list-style-type: none"> <li>• "If you wash hands and face before eating and take baths and clean your clothes, the risk of lead poisoning is greatly reduced."</li> <li>• "I was not raised here and haven't been here that long. I came to retire and live simply. I knew it was a Superfund area, but that didn't affect my choice. If I had children here, I would have been much more proactive in testing and facts."</li> <li>• "Over 95% of the properties in the area have been remediated which I believe has lowered the risk of lead contamination to a level comparable to most areas. We have lived here 45 years and raised a healthy family with good education over the years about how to minimize lead contamination problems. Our family was not impacted by the lead issues."</li> </ul>

*Note.* Comments edited for improved clarity.

Overall, comments indicated that factors related to the Superfund program and primary prevention influence risk perception. Many of the supportive comments described that a beneficial transformation in the Silver Valley had occurred following the closure of the smelter and the environmental remediation. Some of these comments suggested that the remediation efforts decreased or eliminated concerns about health risks. Unsupportive comments framed the remediation as costly and detrimental to the local economy, especially the mining economy. Several of these comments were dismissive of health consequences attributed to Pb contamination and contended that the remediation is a waste of taxpayer money. In these comments, respondents often mentioned an affiliation with mining both as a reason for supporting and not supporting the remediation. The comments about individual health behaviors included beliefs that Pb exposure is avoidable with the right education and that families and children are at the greatest risk of exposure or that as a retired person there was less of a reason for concern.

#### 4. Discussion

Perceived benefits and one of the cue to action variables were significantly associated with the behavioral intentions variable, while perceived severity, perceived susceptibility, perceived barriers, and self-efficacy were not. When we excluded the perceived benefits variable from the model, due to its high correlation with perceived severity, perceived severity and the same cue to action variable had significant associations with behavioral intentions. The results suggest that respondents who perceived the risk of Pb contamination as severe, believed there were benefits to protecting themselves from Pb contamination, and thought about Pb contamination frequently had higher behavioral intentions. Only gender had a significant association with behavioral intentions, indicating that women were more likely than men to report intentions to practice health protective behaviors. Factors related to primary prevention activities and the Superfund site in the study region may also influence the associations between the health belief constructs and behavioral intentions. The division in the comments identified as supportive and unsupportive also suggest that respondents may perceive risk differently depending on their perspectives about the Superfund program and environmental remediation.

#### 4.1. Mining-Impacted Communities, Risk Perception, and Behavioral Intentions

In the Silver Valley environmental and public health conditions have improved over the past several decades: hillsides that were once bare due to smoke fallout from the Pb smelter, have been revegetated [70]; the water quality and condition of rivers and streams have improved [24]; health risk warning signs are posted at public recreation areas and at old mining sites [26]; the District hosts regular workshops about Pb contamination and provides free annual blood lead screenings [31]; and extensive environmental remediation in residential and commercial areas has reduced the risk of Pb exposure [35]. Nationally, the EPA has applied a national model of community engagement at Superfund sites in an attempt to ensure that remediation and restoration efforts align with local needs [71]. Related studies demonstrate that risk perception is not only linked to the contaminants present, but also to cues such as the equipment used for remediation or how organized remediation sites appear [72]. The improved environmental conditions and focus on health risk communication may cue people to recognize and understand the health benefits to practicing recommended health protective behaviors.

Survey comments both reinforced and added nuance to the associations observed between the HBM variables and behavioral intentions. We identified a divide in comments between respondents who were supportive and unsupportive of the efforts to reduce environmental contamination. In the comments that were supportive of primary prevention and/or the Superfund program there was a theme that the efforts to improve conditions alleviated concerns about Pb contamination. Within many of the unsupportive comments, respondents expressed fatigue towards topics related to Pb contamination and a perception that the existing environmental remediation counteracted the need for concern.

The division in support within the comments reinforce challenges that have been associated with effective health risk messaging related to heavy metal contamination and remediation programs like the Superfund program. While the Superfund program is intended to reduce public health risks and improve living conditions, residents have also developed negative emotional responses towards hazards and the decision-makers associated with the program (e.g., [73–75]). Fears of stigmatization and concerns about economic development have long been associated with how people cope with risk in mining-impacted communities [74,76]. Baxter and Lee [77] found that a strong sense of community pride and a fear of stigmatization prevented people from outwardly expressing concern about the health risks of a nearby hazardous waste facility. Grasmück and Scholz [78] found that the desire for additional information about the risk of heavy metal contamination in soil was not affected by a lack of knowledge but was affected by emotional concerns. Factors like stigmatization and denial may explain why we did not identify significant associations between the HBM constructs for self-efficacy and perceived susceptibility and behavioral intentions. For instance, in the Silver Valley, a person who holds negative emotions towards the Superfund program may report high levels of self-efficacy and low behavioral intentions because the behaviors are recommended by the EPA.

Perceptions about the health conditions may also be informed by environmental remediation and risk communication efforts. In this study, perceived severity, but not perceived susceptibility, was strongly associated with behavioral intentions. The result may be explained by differences in perceptions of acute versus immediate health risks. Walpole and Wilson [79] illustrated that personal perceived risk was significantly associated with perceived severity but not perceived susceptibility for risks related to contaminated waterways, while the inverse was true for more immediate and acute risks such as extreme weather events or walking in a dangerous neighborhood. The existing primary prevention activities and a decline in childhood blood lead levels [31] may lead residents to view the negative health consequences of Pb contamination as a long-term rather than acute health issue. If this is the case, individuals may be less likely to attribute Pb contamination with negative health consequences to themselves. Several survey comments about individual behaviors suggested that some respondents believe that the health consequences of Pb contamination are negated by practicing health protective behaviors. These beliefs may influence the association between perceived susceptibility and behavioral intentions.

#### 4.2. Socio-demographic Characteristics and Behavioral Intentions

Women were more likely than men to report practicing health protective behaviors. This could be because women and children are more vulnerable to experiencing health effects from Pb contamination [4,55]. Relative to men, women are also often considered more likely to practice health behaviors intended to reduce the consequences of environmental risks [47,80]. The non-significant effects for the mining affiliation and age covariates may indicate that they do not influence behavioral intentions in the Silver Valley relative to the other study variables. Wolde et al. [9] also found that age was not a significant factor informing individual behaviors related to Pb exposure. In survey comments, several respondents mentioned that they were not personally concerned about Pb contamination but believed that families with children should be concerned. Considering that children are more sensitive to Pb's adverse health effects, future studies are needed to determine why younger study participants did not have higher behavioral intentions relative to older participants. While nearly half of respondents reported having a familial affiliation with the mining industry, mining-related employment opportunities in the Silver Valley are limited. Studies where an affiliation with a polluting industry has influenced behavioral intentions have been conducted in areas where the polluting industry plays a more influential economic role than is currently the case in the Silver Valley (e.g., [49]).

#### 4.3. Study Limitations

Habitual behaviors such as the behaviors that reduce the risk of Pb exposure are among the more difficult health behaviors to evaluate and monitor. Cross-sectional HBM studies about habitual behaviors have several limitations including: 1) relying on measures of health behavioral intentions variables rather than actual behaviors [23,40]; 2) failing to account for feedbacks between perceived risk and behavior [22,81]; and 3) not accounting for external cultural, cognitive or affective responses and biases that may influence risk perception and behavior [82]. The HBM's primary benefit in cross-sectional studies is that it is relatively easy to employ and can be applied and compared across contexts and behaviors. The survey comments add nuance and helped to understand how external factors, primarily the Superfund program and primary prevention, influence risk perception.

The social desirability bias and the intention-behavior gap were primary limitations. Social desirability bias is defined as a tendency of survey respondents to give responses that they perceive as desired by the research instead of choosing responses that are reflective of their true feelings [83]. The DOPU method improved our ability to collect data across a hard to reach population. However, the approach may have increased the influence of social desirability bias as study respondents and researchers interacted with one another directly during data collection. Findings from a meta-analysis of the intention-behavior gap, or the gap between behavioral intentions and behavior, indicate that while intention may be the best predictor of behavior, less than one-third of behavior change can be explained by behavioral intention [40]. We found that survey respondents were "likely" or "very likely" to perform health protective behaviors, yet the District observes residents practicing exposure enhancing behaviors, such as recreating in areas that may have high levels of contamination [26]. These two limitations are not easily resolved within empirical cross-sectional studies.

### 5. Conclusions

The Silver Valley provided a suitable case study for understanding behavioral intentions and the health belief constructs. Results are transferable to other contexts where frequent long-term exposure to a contaminant is linked to long-term health consequences and individual behaviors are important for reducing exposure. Results are likely to be most similar in contexts with developed programs for managing Pb contamination through primary prevention. As demonstrated, the HBM provides a useful yet incomplete conceptual framework for understanding interactions between behavioral intentions and risk perceptions. As demonstrated through the qualitative analysis and survey comments, site-specific factors, not accounted for directly through the HBM, are likely to

cause variations in risk perceptions and behavioral intentions. In the Silver Valley, ongoing primary prevention activities, changes to mining operations, prolonged psychological effects of stigmatization, and reductions in childhood blood lead levels likely influence the HBM constructs. Survey comments suggest that respondents are divided about whether the Superfund program has improved conditions. It is challenging to understand how these factors influenced the HBM constructs in this study, and in other areas a different set of factors may be more influential.

The goal of this study was to build understanding of the factors that influence how residents respond to risk communication. To remind residents of the health protective behaviors, the District could send an annual reminder postcard to residents. Because young children are especially vulnerable to Pb poisoning and we found that age did not have a statistically significant association with behavioral intentions, we suggest that risk communication strategies focus on approaches that encourage parents to practice behaviors that limit Pb exposure for their children. For instance, the District could work directly with pediatricians to share information about Pb poisoning with parents. As demonstrated through the survey comments, maintaining effective long-term risk communication is challenging in environments with persistent contaminants as perceptions of contamination are dynamic and people may begin to feel fatigued by long-term primary prevention efforts.

Comparative methods and longitudinal panel studies are important for understanding dynamic perceptions at Superfund sites and in other contexts with persistent contaminants. Without comparative studies, developing a comprehensive outlook about how risk perception and behavioral intentions are socially determined versus how they vary between contexts is not possible. Longitudinal panel studies help to build understanding of how behavioral intentions and risk perception change over time, especially when management actions such as the remediation or removal of Pb hazards alter the severity of the risk. Continuing to build knowledge about how risk perceptions interact with behavioral intentions is important for developing risk communication strategies tailored to specific contexts and population subgroups. When secondary prevention is needed to reduce risk, as was the case in this study, prioritizing improved risk communication along primary prevention is critical for reducing both the societal and human health burdens of Pb poisoning. Improving risk communication around Pb contamination and health protective behaviors is an important factor in continuing to decrease the societal burdens associated with Pb exposure.

**Supplementary Materials:** The following are available online at [www.mdpi.com/xxx/s1](http://www.mdpi.com/xxx/s1), Figure S1: survey, Table S1: Exploratory Factor Analysis; Table S2: Correlation Matrix

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## References

- Gleason, J.A.; Nanavaty, J.V.; Fagliano, J.A. Drinking water lead and socioeconomic factors as predictors of blood lead levels in New Jersey's children between two time periods. *Environ. Res.* **2019**, *169*, 409–416.
- Entwistle, J.A.; Hursthouse, A.S.; Reis, P.A.M.; Stewart, A.G. Metalliferous Mine Dust: Human Health Impacts and the Potential Determinants of Disease in Mining Communities. *Curr Pollution Rep* **2019**, *5*, 67–83, doi:10.1007/s40726-019-00108-5.
- Kegler, M.C.; Malcoe, L.H.; Kegler, S.R.; Lynch, R.A.; Tolliver, R. Caregiver beliefs and behaviors in the prevention of childhood lead poisoning. *Fam. Community Health* **1999**, *22*, 50–65.
- Needleman, H.L. *Human Lead Exposure*; CRC Press, 1991; ISBN 9780849360343.
- Rossi, E. Low level environmental lead exposure—a continuing challenge. *Clin. Biochem. Rev.* **2008**, *29*, 63.
- Vorvolakos, T.; Arseniou, S.; Samakouri, M. There is no safe threshold for lead exposure: A literature review. *Psychiatrike* **2016**, *27*, 204–214.
- McGee, T.K. Private responses and individual action: community responses to chronic environmental lead contamination. *Environ. Behav.* **1999**, *31*, 66–83.
- Harclerode, M.A.; Lal, P.; Vedwan, N.; Wolde, B.; Miller, M.E. Evaluation of the role of risk perception in stakeholder engagement to prevent lead exposure in an urban setting. *J. Environ. Manage.* **2016**, *184*, 132–142, doi:10.1016/j.jenvman.2016.07.045.
- Wolde, B.; Lal, P.; Harclerode, M.; Rossi, A. Comparative Optimism: Relative Risk Perception and Behavioral Response to Lead Exposure. *Environ. Manage.* **2019**, *63*, 691–701, doi:10.1007/s00267-019-01148-9.
- Sullivan, M.; Green, D. Misled about lead: an assessment of online public health education material from Australia's lead mining and smelting towns. *Environ. Health* **2016**, *15*, 1.
- Ramirez-Andreotta, M.D.; Brody, J.G.; Lothrop, N.; Loh, M.; Beamer, P.I.; Brown, P. Improving environmental health literacy and justice through environmental exposure results communication. *Int. J. Environ. Res. Public Health* **2016**, *13*, 690.
- Halter, A.; Acevedo, A. How a New Ecological Augmentation Remedy Option Could Advance Superfund Site Closures at Mining-Impacted Sites. *Nat. Resour. Environ.* **2019**, *34*, 22–26.
- Levin, R.; Brown, M.J.; Kashtock, M.E.; Jacobs, D.E.; Whelan, E.A.; Rodman, J.; Schock, M.R.; Padilla, A.; Sinks, T. Lead exposures in US children, 2008: implications for prevention. *Environ. Health Perspect.* **2008**, *116*, 1285–1293.
- Schoof, R.A.; Johnson, D.L.; Handziuk, E.R.; Van Landingham, C.; Feldpausch, A.M.; Gallagher, A.E.; Dell, L.D.; Kephart, A. Assessment of blood lead level declines in an area of historical mining with a holistic remediation and abatement program. *Environ. Res.* **2016**, *150*, 582–591.
- Mielke, H.W.; Gonzales, C.R.; Powell, E.T.; Mielke, P.W., Jr Spatiotemporal dynamic transformations of soil lead and children's blood lead ten years after Hurricane Katrina: new grounds for primary prevention. *Environ. Int.* **2016**, *94*, 567–575.
- Muennig, P. The Social Costs of Childhood Lead Exposure in the Post-Lead Regulation Era. *Arch. Pediatr. Adolesc. Med.* **2009**, *163*, 844–849, doi:10.1001/archpediatrics.2009.128.
- Attina, T.M.; Trasande, L. Economic costs of childhood lead exposure in low- and middle-income countries. *Environ. Health Perspect.* **2013**, *121*, 1097–1102, doi:10.1289/ehp.1206424.
- Fishbein, M.; Ajzen, I. Belief, attitude, intention, and behavior: An introduction to theory and research. **1977**.
- Glanz, K. *Health behavior: Theory, research, and practice*; John Wiley & Sons, 2015;.
- Andrade, L.; O'Malley, K.; Hynds, P.; O'Neill, E.; O'Dwyer, J. Assessment of two behavioural models (HBM and RANAS) for predicting health behaviours in response to environmental threats: Surface water flooding as a source of groundwater contamination and subsequent waterborne infection in the Republic of Ireland. *Sci. Total Environ.* **2019**, *685*, 1019–1029, doi:10.1016/j.scitotenv.2019.06.249.
- Straub, C.L.; Leahy, J.E. Application of a Modified Health Belief Model to the Pro-Environmental Behavior of Private Well Water Testing. *JAWRA Journal of the American Water Resources Association* **2014**, *50*, 1515–1526.
- Weinstein, N.D. Misleading tests of health behavior theories. *Ann. Behav. Med.* **2007**, *33*, 1–10.
- Noar, S.M.; Zimmerman, R.S. Health Behavior Theory and cumulative knowledge regarding health behaviors: are we moving in the right direction? *Health Educ. Res.* **2005**, *20*, 275–290.
- Mix, M.C. *Leaded: The Poisoning of Idaho's Silver Valley*; Oregon State University Press, 2016;.
- Gustavson, K.E.; Barnthouse, L.W.; Brierley, C.L.; Clark, E.H.; Ii, I.I.; Ward, C.H. *Superfund and mining megasites*; ACS Publications, 2007;.
- Helkey, A. Getting the Lead Out- 30 years of remediation and education in the Silver Valley 2018.
- U.S. Census *US Census QuickFacts, Shoshone County, Idaho*; 2018;.

28. ACS 2016 American Community Survey: 5-Year Data [2012-2016, Counties] Available online: <https://www.census.gov/programs-surveys/acs> (accessed on Mar 2020).
29. Panhandle Health District Community Health Assessment Available online: <http://panhandlehealthdistrict.org/wp-content/uploads/2019/06/CHA-2018-final.pdf> (accessed on Mar 2020).
30. USGS Watershed Boundary Dataset Available online: [https://www.usgs.gov/core-science-systems/ngp/national-hydrography/watershed-boundary-dataset?qt-science\\_support\\_page\\_related\\_con=4#qt-science\\_support\\_page\\_related\\_con](https://www.usgs.gov/core-science-systems/ngp/national-hydrography/watershed-boundary-dataset?qt-science_support_page_related_con=4#qt-science_support_page_related_con) (accessed on Mar 2020).
31. Alta Science and Engineering Inc 2017 and 2018 Blood Lead Data Evaluation – Bunker Hill Mining and Metallurgical Complex Superfund Site; Idaho Department of Environmental Quality and Environmental Protection Agency, 2019;.
32. Elias, R.W.; Gulson, B. Overview of lead remediation effectiveness. *Sci. Total Environ.* **2003**, *303*, 1–13, doi:10.1016/S0048-9697(02)00361-3.
33. Spalinger, S.M.; von Braun, M.C.; Petrosyan, V.; von Lindern, I.H. Northern Idaho house dust and soil lead levels compared to the Bunker Hill Superfund site. *Environ. Monit. Assess.* **2007**, *130*, 57.
34. Klemick, H.; Mason, H.; Sullivan, K. Superfund cleanups and children's lead exposure. *J. Environ. Econ. Manage.* **2020**, *100*, 102289, doi:10.1016/j.jeem.2019.102289.
35. von Lindern, I.; Spalinger, S.; Stifelman, M.L.; Stanek, L.W.; Bartrem, C. Estimating children's soil/dust ingestion rates through retrospective analyses of blood lead biomonitoring from the Bunker Hill Superfund Site in Idaho. *Environ. Health Perspect.* **2016**, *124*, 1462.
36. Janz, N.K.; Becker, M.H. The health belief model: A decade later. *Health Educ. Q.* **1984**, *11*, 1–47.
37. Rosenstock, I.M. Historical origins of the health belief model. *Health Educ. Monogr.* **1974**, *2*, 328–335.
38. Lippke, S. Outcome Expectation. In *Encyclopedia of Personality and Individual Differences*; Zeigler-Hill, V., Shackelford, T.K., Eds.; Springer International Publishing: Cham, 2017; pp. 1–2 ISBN 9783319280998.
39. Bandura, A. Self-efficacy: toward a unifying theory of behavioral change. *Psychol. Rev.* **1977**, *84*, 191–215.
40. Sheeran, P. Intention—behavior relations: a conceptual and empirical review. *European review of social psychology* **2002**, *12*, 1–36.
41. Carpenter, C.J. A meta-analysis of the effectiveness of health belief model variables in predicting behavior. *Health Commun.* **2010**, *25*, 661–669.
42. Sheeran, P.; Maki, A.; Montanaro, E.; Avishai-Yitshak, A.; Bryan, A.; Klein, W.M.P.; Miles, E.; Rothman, A.J. The impact of changing attitudes, norms, and self-efficacy on health-related intentions and behavior: a meta-analysis. *Health Psychol.* **2016**, *35*, 1178.
43. Harrison, J.A.; Mullen, P.D.; Green, L.W. A meta-analysis of studies of the health belief model with adults. *Health Educ. Res.* **1992**, *7*, 107–116.
44. Jones, C.L.; Jensen, J.D.; Scherr, C.L.; Brown, N.R.; Christy, K.; Weaver, J. The Health Belief Model as an Explanatory Framework in Communication Research: Exploring Parallel, Serial, and Moderated Mediation. *Health Commun.* **2015**, *30*, 566–576, doi:10.1080/10410236.2013.873363.
45. Halpern, M.T.; Warner, K.E. Radon risk perception and testing: Sociodemographic correlates. *J. Environ. Health* **1994**, *56*, 31.
46. Rinker, G.H.; Hahn, E.J.; Rayens, M.K. Residential radon testing intentions, perceived radon severity, and tobacco use. *J. Environ. Health* **2014**, *76*, 42–47.
47. Davidson, D.J.; Freudenburg, W.R. Gender and environmental risk concerns: A review and analysis of available research. *Environ. Behav.* **1996**, *28*, 302–339.
48. Rice, L.J.; Brandt, H.M.; Hardin, J.W.; Ingram, L.A.; Wilson, S.M. Exploring perceptions of cancer risk, neighborhood environmental risks, and health behaviors of Blacks. *J. Community Health* **2015**, *40*, 419–430.
49. Greenberg, P. Risk perceptions and the maintenance of environmental injustice in Appalachia. *Environmental Sociology* **2020**, *6*, 54–67.
50. Zhuang, J.; Cox, J.; Cruz, S.; Dearing, J.W.; Hamm, J.A.; Upham, B. Environmental stigma: Resident responses to living in a contaminated area. *Am. Behav. Sci.* **2016**, *60*, 1322–1341.
51. Brown, T.A. *Confirmatory factor analysis for applied research*; Guilford Publications, 2014;.
52. Steele, J.; Bourke, L.; Luloff, A.E.; Liao, P.-S.; Theodori, G.L.; Krannich, R.S. The drop-off/pick-up method for household survey research. *Community Dev.* **2001**, *32*, 238–250.
53. Dillman, D.A. *Mail and Internet surveys: The tailored design method—2007 Update with new Internet, visual, and mixed-mode guide*; John Wiley & Sons, 2011;.
54. Revilla, M.A.; Saris, W.E.; Krosnick, J.A. Choosing the number of categories in agree–disagree scales. *Sociol. Methods Res.* **2014**, *43*, 73–97.
55. Bland, A.D.; Kegler, M.C.; Escoffery, C.; Malcoe, L.H. Understanding childhood lead poisoning preventive behaviors: the roles of self-efficacy, subjective norms, and perceived benefits. *Prev. Med.* **2005**, *41*, 70–78.
56. Devitt, C.; O'Neill, E.; Waldron, R. Drivers and barriers among householders to managing domestic

- wastewater treatment systems in the Republic of Ireland; implications for risk prevention behaviour. *J. Hydrol.* **2016**, *535*, 534–546.
57. Kline, R.B. *Principles and practice of structural equation modeling*; Guilford publications, 2015;.
  58. Olinsky, A.; Chen, S.; Harlow, L. The comparative efficacy of imputation methods for missing data in structural equation modeling. *Eur. J. Oper. Res.* **2003**, *151*, 53–79, doi:10.1016/S0377-2217(02)00578-7.
  59. van Buuren, S.; Groothuis-Oudshoorn, K. mice: Multivariate Imputation by Chained Equations in R. *J. Stat. Softw.* **2011**, *45*, 1–67, doi:10.18637/jss.v045.i03.
  60. Rosseel, Y. Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA). *J. Stat. Softw.* **2012**, *48*, 1–36.
  61. Williams, B.; Onsman, A.; Brown, T. Exploratory factor analysis: A five-step guide for novices. *Australasian Journal of Paramedicine* **2010**, *8*, doi:10.33151/ajp.8.3.93.
  62. Costello, A.B.; Osborne, J. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical assessment, research, and evaluation* **2005**, *10*, 7.
  63. Santos, J.R.A. Cronbach's alpha: A tool for assessing the reliability of scales. *Journal of extension* **1999**, *37*, 1–5.
  64. Rahman, W.; Shah, F.A.; Rasli, A. Use of Structural Equation Modeling in Social Science Research. *Asian Social Science* **2015**, *11*, 371, doi:10.5539/ass.v11n4p371.
  65. Muthén, B. A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. *Psychometrika* **1984**, *49*, 115–132.
  66. Şimşek, G.G.; Noyan, F. Structural equation modeling with ordinal variables: a large sample case study. *Qual. Quant.* **2012**, *46*, 1571–1581, doi:10.1007/s11135-011-9467-4.
  67. Suh, Y. The Performance of Maximum Likelihood and Weighted Least Square Mean and Variance Adjusted Estimators in Testing Differential Item Functioning With Nonnormal Trait Distributions. *Struct. Equ. Modeling* **2015**, *22*, 568–580, doi:10.1080/10705511.2014.937669.
  68. Xia, Y.; Yang, Y. RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behav Res* **2019**, *51*, 409–428, doi:10.3758/s13428-018-1055-2.
  69. Saldana, J. *The Coding Manual for Qualitative Researchers*; SAGE, 2015; ISBN 9781473943599.
  70. National Research Council *Superfund and Mining Megasites: Lessons from the Coeur d'Alene River Basin*; The National Academies Press: Washington, DC, 2005; ISBN 9780309097147.
  71. Zaragoza, L.J. The Environmental Protection Agency's Use of Community Involvement to Engage Communities at Superfund Sites. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4166.
  72. Messer, C.M.; Shriver, T.E.; Adams, A.E. Collective Identity and Memory: A Comparative Analysis of Community Response to Environmental Hazards. *Rural Sociol.* **2015**, *80*, 314–339, doi:10.1111/ruso.12069.
  73. Shriver, T.E.; Messer, C.M.; Whittington, J.R.; Adams, A.E. Industrial pollution and acquiescence: living with chronic remediation. *Env. Polit.* **2019**, 1–20.
  74. Adams, A.E.; Shriver, T.E.; Saville, A.; Webb, G. Forty years on the fenceline: community, memory, and chronic contamination. *Environmental Sociology* **2018**, *4*, 210–220.
  75. Shriver, T.; Kennedy, D. Contested Environmental Hazards and Community Conflict Over Relocation\*. *Rural Sociol.* **2005**, *70*, 491–513, doi:10.1526/003601105775012679.
  76. Tang, Z.; Guo, Z.; Zhou, L.; Xue, S.; Zhu, Q.; Zhu, H. Combined and Relative Effect Levels of Perceived Risk, Knowledge, Optimism, Pessimism, and Social Trust on Anxiety among Inhabitants Concerning Living on Heavy Metal Contaminated Soil. *Int. J. Environ. Res. Public Health* **2016**, *13*, 1076, doi:10.3390/ijerph13111076.
  77. Baxter, J.; Lee, D. Understanding expressed low concern and latent concern near a hazardous waste treatment facility. *J. Risk Res.* **2004**, *7*, 705–729, doi:10.1080/1366987042000146210.
  78. Grasmück, D.; Scholz, R.W. Risk perception of heavy metal soil contamination by high-exposed and low-exposed inhabitants: The role of knowledge and emotional concerns. *Risk Analysis: An International Journal* **2005**, *25*, 611–622.
  79. Walpole, H.D.; Wilson, R.S. Extending a broadly applicable measure of risk perception: the case for susceptibility. *J. Risk Res.* **2020**, *0*, 1–13, doi:10.1080/13669877.2020.1749874.
  80. Dömötör, Z.; Nordin, S.; Witthöft, M.; Köteles, F. Modern health worries: A systematic review. *J. Psychosom. Res.* **2019**, *124*, 109781, doi:10.1016/j.jpsychores.2019.109781.
  81. Sheeran, P.; Abraham, C. The health belief model. *Predicting health behaviour* **1996**, *2*, 29–80.
  82. Radcliffe, N.M.; Klein, W.M.P. Dispositional, unrealistic, and comparative optimism: Differential relations with the knowledge and processing of risk information and beliefs about personal risk. *Pers. Soc. Psychol. Bull.* **2002**, *28*, 836–846.
  83. Grimm, P. Social Desirability Bias. In *Wiley International Encyclopedia of Marketing*; American Cancer Society, 2010 ISBN 9781444316568.

