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Tap Water Lead Monitoring through Citizen Science: Influence of Socioeconomics and Participation on Environmental Literacy, Behavior, and Communication

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Abstract

Citizen science have been increasingly applied in environmental monitoring projects as a way to address large-scale social-environmental problems, including a lack of awareness of such problems as well as the capacity for using science to inform decision making. While studies have found that citizen science can help improve environmental literacy and engage participants, knowledge about the extent of such changes in environmental literacy and behaviors as well as how these changes are influenced by participants' socioeconomic characteristics remains limited. In response, we developed a contest-based citizen science study focused on drinking water quality data collection and education. We sought to understand how socioeconomic characteristics affect participant knowledge in the context of drinking water quality and lead contamination, willingness to take preventative actions to improve health protection, and frequency of communication about water quality issues with those around them. Comparison of pre- and post-surveys showed statistically significant increases in participants' likelihood to communicate about drinking water. With regards to knowledge, this project showed success in improving scientific literacy relating to key lead information, and overall provided self-assessed educational benefits to those who participated. This project demonstrates that citizen science methods could be used to actively engage and inform participants in water quality monitoring efforts, creating a more scientifically literate and active public.

Key Words: Crowdsourcing, drinking water quality, citizen science, socioeconomics, knowledge, action, communication

Introduction

Over the last decade, citizen science has been increasingly applied in environmental monitoring. Citizen science is a method to address large-scale problems at a low cost, utilizing the collective efforts of independent, widely distributed participants who help with data collection (Howe 2006, Jeppesen and Lakhani 2010, Malone et al. 2010). By using the resources and knowledge of community volunteers, the cost, time, and labor needs associated with sample collection and analysis are reduced. This allows for increased efficiency in monitoring activities which allows for improved allocation of public resources (Bonney et al. 2009, Silvertown 2009). Researchers have also found that citizen science can serve as a venue to improve environmental literacy and engage participants in environmental decision making (Bonney et al. 2009, Den Broeder et al. 2016). For example, (Brossard et al. 2005) evaluated the Birdhouse Network, an informal science education project of the Cornell Laboratory of Ornithology, and found that the project had a positive impact on participants' knowledge of bird biology. Similarly, Cronje et al. (2011)

saw significant science literacy gains after people participated in invasive species monitoring training. Nerbonne and Nelson (2004) saw greater knowledge and involvement in civic processes for citizens involved in volunteer macroinvertebrate monitoring groups. However, knowledge about the extent of such changes in environmental literacy and behaviors as well as how these changes are influenced by participants' socioeconomic characteristics remains limited.

Of the previous citizen science-based environmental monitoring studies, many have focused on natural resources and ecosystems (Bonney et al. 2009, Bonney et al. 2014, Conrad and Hilchey 2011, Dickinson et al. 2012, Jollymore et al. 2017, Pandya 2012, Shirk et al. 2012, Silvertown 2009, Snik et al. 2014, Trumbull et al. 2000, Wiggins and Crowston 2011), while the monitoring of drinking water quality is a relatively untapped field. In the U.S., issues such as aging infrastructure and the increased detection of legacy and emerging contaminants require the continued development of drinking water treatment and monitoring solutions to better protect public health (EPA, 2015). Lead, for example, remains a recurring problem for communities. Around 20% of lead exposure in the U.S. comes from contaminated drinking water (EPA, 2018). This is partly because of the limited public resources available for continuous and widely-spread water quality monitoring at the consumer taps. A few recent citizen science-based drinking water monitoring studies occurred in response to the Flint water crisis (Goovaerts 2019, Jakositz et al. 2019, Roy and Edwards 2019). These studies investigated the effectiveness of the citizen science approach in monitoring water quality at the consumer taps. However, they did not study the influence of participation on the behavior and knowledge changes of participants to inform future designs of drinking water quality monitoring programs.

Other studies have investigated participants' changes in attitudes, behavior, and/or knowledge through a citizen science program. For example, Crall et al. (2013) examined how invasive species training affects participants' knowledge about science and behavior towards the environment, and modest changes were found in both areas. Seymour and Haklay (2017) studied participation patterns in environmental volunteering and citizen science projects. Jordan et al. (2011) investigated changes in participants' knowledge and behavior towards invasive plants. They found that participants' knowledge of relevant issues increased and participants reported changes in their behavior with respect to invasive plants, specifically in the area of communicating with other people about invasive plants. Most literature explores participant changes after engaging in outreach opportunities in which educators and/or researchers are directly interacting with participants (Adelman et al. 2000, Anderson et al. 2000, Bogner 1999, Brossard et al. 2005, Cockerill 2010, Crall et al. 2013). However, none of these studies have examined participant's knowledge and behavior changes in a drinking water quality monitoring setting. While many drinking water-related citizen science projects have recorded participants' demographic information to evaluate recruitment success (Goovaerts 2019, Jakositz et al. 2019, Roy and Edwards 2019), to our knowledge none have analyzed the effect of demographic information on citizen's behavior and/or knowledge related to the subject. Understanding participants' changes helps researchers target specific audiences or adjust their methods in order to reach a wider spectrum of participants and achieve the maximum social impact (West and Pateman 2016).

Building on this prior research, our study applied citizen science to drinking water monitoring at the consumer taps to understand how participation in such a project can potentially affect participants' knowledge about drinking water quality and lead contamination, willingness to take preventative actions to improve health protection, and frequency of communication about water quality issues with those around them. We also investigated how the participants' socioeconomic characteristics are linked to their changes. This project aims to provide an enhanced understanding regarding whether and how the citizen science method could be used to actively engage and inform citizen participants in water quality monitoring efforts, creating a more scientifically literate and active public.

Methods

Data analyzed in this study were collected through a tap water lead-testing project that took place in a New Hampshire city from August through November 2018. The lead-testing project distributed sampling packets primarily through five informational kiosks placed at highly trafficked locations across the city. Each sampling packet contained a 50-mL sample vial, sampling instructions, a sample information sheet, and a pre-survey, all housed in a pre-paid mailing envelope. Citizen participants were instructed to bring the packet home, collect a sample of their home's tap water according to instructions, and complete the sample information sheet and pre-survey. The participants could either return their completed packet to a kiosk or mail it to researchers at the University of New Hampshire (UNH) using the pre-paid mailing envelope. All samples received were assumed to be valid. Researchers at UNH then preserved and analyzed returned samples for lead concentrations using an Inductively Coupled Plasma Mass Spectrometer (ICP-MS) in accordance with EPA 200.8 (Brockhoff et al. 1999). The lead results along with information and online resources related to lead in drinking water, its health effects, action level, and the steps to minimize exposure, as well as a link to an online post-survey made using Qualtrics® were sent to participants via email. For those samples that exceed the EPA's advisory level of 15 ppb, we offered retesting. Participants who opted to retest samples were asked to follow the same methods as the original sampling event, and an additional instruction sheet was provided in the retest sample kit. Contact information was provided with both the original and retest samples for participants to reach out if they had questions regarding the instructions. A more detailed description of the project design can be found in Jakositz et al. (2019).

Out of approximately 800 packets distributed, the project received 149 returned packets with 136 packets containing pre-surveys that had more than 50% of all questions answered. All participants who submitted a packet were asked to complete a post-survey, and 41 post-surveys were submitted with more than 50% questions answered. Of the 41 post-surveys, 34 were matched with their participant's respective pre-survey for comparison. Descriptive and bivariate statistics were conducted using R.

Analysis of participants' environmental literacy

To analyze the influence of the project on the participants' environmental literacy, five true-or-false questions were included in both pre- and post-surveys. The design and the narrative of these questions were identical in both surveys. Figure 1 provides the questions and response options that were presented to participants. Particularly, two questions related to the health impacts of lead, one question related to how most lead contamination enters drinking water, one question related to methods of removing lead from drinking water, and one question related to federal regulations regarding lead in drinking water. For each of these questions, participants were given three choices: true, false, or don't know. They were also advised not to guess the answer.

All 136 aggregate pre-survey responses, 38 out of the 41 aggregate post-survey responses, and all 34 matched survey responses have more than 50% of the five statements in Figure 1 answered, and hence were included in our analyses of the participants' environmental literacy. We first calculated and visualized the percent distributions of participants who provided correct, incorrect, and missing answers for each statement for both the aggregate and the matched pre- and post-survey data. A correct answer is when a participant correctly identified whether a listed statement is true or false. An incorrect answer is when a participant either misidentified the correctness of a statement or if they selected "Don't Know". An overall percent distribution was also calculated for all statements combined.

We then used the 34 matched responses to evaluate the level and the statistical significance of the participants' changes on environmental literacy before and after participating in the project. The level of change was indicated by the *LoC* score calculated using Equation 1 below.

$$LoC = \sqrt{\sum_{i=1}^{n}(P_{i,pre} - P_{i,post})^2} \qquad \text{(Equation 1)}$$

Where *LoC* is the level of change score for a specific statement in Figure 1; i is an index of participants' responses based on the aforementioned interpretation by the authors (correct, or incorrect); n is the total number of possible responses, which equals to 2 for the environmental literacy survey question; $P_{i,pre}$ is the percent of participants who give i response to the statement of consideration in the pre-survey; and $P_{i,post}$ is the percent of participants who give i response to the statement of consideration in the post-survey. An overall *LoC* score was also calculated based on the overall percent distributions of participants' interpreted responses to all 5 statements combined. The statistical significance of the participants' changes was evaluated by the p-values obtained from the McNemar test, with p-values below or equal to 0.05 indicating a statistically significant change. The McNemar test is suitable for matched nominal datasets with binary response categories. Missing answers were not considered in this test as they do not reflect actual environmental literacy changes. To run the McNemar test, we first created contingency tables based on the matched pre- and post-survey responses for each of the statements listed in Figure 1. An example contingency table is provided in Table 1. An overall contingency table was also created by summing up the contingency tables for individual statements. A detailed list of all contingency tables can be found in the supporting information (SI). The McNemar test was run by the *mcnemar.test()* function with continuity correction embedded in the "*stats*" package in R.

We also investigated how an individual's socioeconomic characteristics might affect their changes in environmental literacy after participating in the project. We again used the 34 matched pre- and post-survey responses for this analysis. An individual's change was scored by the number of statements with a different response in the matched pre- and post-surveys. Individuals that do not show any changes in any of the five statements would be scored 0, while individuals that show changes in all five statements would be scored 5. Six types of socioeconomic characteristics were considered, including age, household income, education, gender, housing ownership, and children. These socioeconomic characteristics were recoded based on Table 2. F-tests based on the one-way ANOVA were then run to assess the statistical significance between each of the recoded socioeconomic variables and the participants' changes in their responses. The F-test was selected because of its higher efficiency as compared to a non-parametric alternative. We used the p-values from the F-tests to assess the level of statistical significance, with p-values below or equal to 0.05 indicating a statistically significant correlation. The F- test was run by the *aov()* function in R.

Analysis of participants' responses towards potential tap water quality red flags

In the pre-survey, participants were asked, "How often do you contact your drinking water utility?" to determine the frequency that participants communicated with their utility. Using Chi-square analysis, with variables re-coded as dichotomous, we tested the association between this question and participants' responses to the question, "How would you rate the quality of your drinking water at home?" to determine the relationship between perceptions about drinking water quality and intentions to contact the utility.

In an effort to understand participant's responses towards potential lead issues in tap water, we asked participants, "Imagine your water quality results indicate that you have lead in your drinking water. How likely are you to take the following actions in response to learning about lead in your water?" In the post-survey, we then asked participants, "Now that you have your water quality results, how likely are you to take the following actions in response to the lead in your drinking water?". By comparing the matched responses between the pre- and post-surveys, we were able to examine the potential changes of participants' actions in response to their knowledge of the actual water quality. Figure 2 provides the format of the question as displayed in the pre- and post-survey. We provided six potential responses to drinking water quality issues based upon their prominence in literature. We also included a space where participants could add other potential responses. However, none of the survey responses provided additional actions beyond the six that we provided. The surveys asked the participants to rate each of the responses on a Likert scale from highly unlikely, unlikely, neutral, likely, to highly likely.

Overall, 135 out of the 136 aggregate pre-survey responses, 35 out of the 41 post-survey responses, and 30 out of the matched survey responses have at least half of the six actions in Figure 2 scored, and hence were included in our analyses of the participants' responses towards potential tap water quality red flags. It has to be noted that a participant is removed from the matched survey dataset if they do not meet the inclusion criteria for either their pre- or the post-survey responses. Similar as described in Section 2.1, we first calculated and visualized the percent distributions of highly unlikely, unlikely, neutral, likely, highly likely, and missing responses for each of the actions included in Figure 2 for both the aggregate and the matched pre- and post-survey data. An overall percent distribution was also calculated for all actions combined. Particularly, the percent distribution of the "Do nothing" action was reversed (e.g., "highly unlikely" was counted as "highly likely", and vice versa) in the overall distribution calculation, given its opposite direction as compared to the other actions.

We then used the 30 matched responses to evaluate the level and the statistical significance of the participants' changes in their responses. The level of change calculation followed a similar procedure as shown in Equation 1, expect that i index became the 5 possible responses (highly unlikely, unlikely, neutral, likely, and highly likely) to each action. An overall *LoC* score was also calculated based on the overall percent distributions calculated previously for the matched responses (with the "Do nothing" responses reversely counted). The statistical significance of the participants' changes was evaluated by the p-values obtained from the McNemar-Bowker test, with p-values below or equal to 0.05 indicating a statistically significant change. The McNemar-Bowker test is a generalized form of the McNemar test, which is suitable for matched nominal datasets with more than 2 possible response categories. A similar contingency table is needed as an input to the McNemar-Bowker test. However, given the high frequency of zero occurring in the contingency table with the 5 response categories, we combined some of these response categories before running the test. Specifically, the original highly unlikely and unlikely responses were merged as one category, and the original highly likely and likely responses were also merged. An overall contingency table was created by summing up the contingency tables for individual actions except for "Do nothing". The remaining actions were assumed to be independent from each other. A detailed list of all contingency tables can be found in the SI. R utilizes the same function to run the McNemar-Bowker test as the McNemar test.

Given the difference in the question asked in the pre- and post-survey as shown in Figure 2, we investigated how the lead results the participants received might affect their changes in the pre- and post-survey responses. We again used the 30 matched pre- and post-survey responses for this analysis. An individual's change was scored by the number of actions with a different response in the matched pre- and post-surveys. Individuals that do not show any changes in any of the six actions would be scored 0, while individuals that show changes in all six actions would be scored 6. Individuals' lead results were recoded based on Table 3. A F-test was then run to assess the statistical significance between the lead results and the participants' changes in their responses. We used the p-values from the F-test to assess the level of statistical significance, with p-values below or equal to 0.05 indicating a statistically significant correlation. We also conducted a qualitative analysis on those participants who received a relatively high lead result of above 10 ppb.

Analysis of participants' communication about water quality

To analyze the influence of the project on the participants' likelihood to communicate with their social network about water quality, we asked the participants to identify their frequency of talking about drinking water quality with different groups. Figure 3 provides the questions and response options that were presented to participants. The same question was presented in both pre- and post-surveys. It has to be noted that none of the survey responses provided additional social groups beyond those that we provided.

Overall, 134 out of the 136 aggregate pre-survey responses, 36 out of the 41 post-survey responses, and 32 out of the matched survey responses have more than half of the five social groups in Figure 3 scored, and hence were included in our analyses of the participants' communication about water quality. We first calculated and visualized the percent distributions of never, rarely, sometimes, often, every time, and missing responses for each of the social groups included in Figure 3 for both the aggregate and the matched pre- and post-survey data. We then used the 32 matched responses to evaluate the level and the statistical significance of the participants' changes in their communication after participating in the project. The level of change calculation followed a similar procedure as shown in Equation 1, expect that i index became the 5 possible responses (never, rarely, sometimes, often, and every time) to each social group. An overall *LoC* score was also calculated based on the percent distributions of participants' responses to all 5 social groups combined. The statistical significance of the participants' changes was evaluated by the p-values obtained from the McNemar-Bowker test, with p-values below or equal to 0.05 indicating a statistically significant change. We combined the original "Never" and "Rarely" responses as one category, and the original "Often" and "Every Time" responses as another category to create the contingency tables used for the McNemar-Bowker test. An overall contingency table was also created by summing up the contingency tables for all 5 social groups. A detailed list of all contingency tables can be found in the SI.

We also investigated how an individual's socioeconomic characteristics might affect their changes in communication after participating in the project. We used the 32 matched pre- and post-survey responses for this analysis. An individual's change was scored by the number of social groups with a different response in the matched pre- and post-surveys. Individuals that do not show any changes in their communication with any of the five groups would be scored 0, while individuals that show changes in their communication with all five groups would be scored 5. These socioeconomic characteristics considered follow Table 2. F-tests were then run to assess the influence of each socioeconomic variable on the participants' changes in their communication. We used the p-values to indicate the level of statistical significance, with p-values below or equal to 0.05 indicating a statistically significant correlation.

Results and Discussions

Participants' environmental literacy on lead in drinking water

In the aggregate pre-survey results (n=136), 77.3% of responders indicated that they knew where their water came from and were able to indicate the source as the city's water treatment plant

(45.6%), a community shared well (7.4%), or a private well (24.3%). 5.1% of responders indicated that they did not know where their water came from. The high missing response rate of 16.2% may indicate that a higher percentage of people may not know where their water comes from than just those who reported.

Overall, respondents had high content knowledge about important health-related issues with lead in drinking water related to the physical impacts and risks to reproductive health prior to participating in the project (Figure 4). However, in the aggregate pre-survey results (n=136), around 38% of respondents did not know if boiling water was an effective method of removing lead from drinking water, and 10% falsely indicated that boiling does remove lead. Similarly, in the aggregate pre-survey results, around 51% of respondents did not know if the EPA regulates lead in public drinking water and 14% falsely indicated that the EPA does not regulate lead in public drinking water. These two points represent opportunities for sharing relevant information about lead regulation and protection measures. Comparing both the aggregate and the matched pre- and post-survey results, we observe consistent improvement in participants' content knowledge about lead in drinking water after participating in the project. Knowledge about the human health effects of lead consumption was high and consistent in both the pre- and post-surveys in both aggregate and matched results (S1 and S2 in Figure 4). The highest level of change was observed in knowledge about the efficacy of boiling water as a strategy (S5 in Figure 4), followed by knowledge about how lead enters drinking water through pipe corrosion (S3 in Figure 4), and about the role of the EPA in regulating drinking water (S4 in Figure 4), though these changes were not statistically significant based on our criteria. Nevertheless, when all statements were combined, the level of change becomes statistically significant with a p-value of

0.0162. These results indicate that a project such as ours may contribute to changes in content knowledge about drinking water quality and the effectiveness of specific strategies to flush, filter, and remove lead.

The F-test shows none of the socioeconomic variables considered have statistically significant correlations with the participants' changes in the pre- and post-survey responses (Table 4), with housing ownership and education having the relatively low p-values.

In addition to the above question, when asked whether this project improved participants' understanding about lead in drinking water in the post-survey, 81.0% of participants answered "Yes" and 16.7% answered "No". This indicates that this project has a positive effect in educating a majority of participants on the concerns about lead in drinking water and potential ways to mitigate them. This suggests that methods like those employed in this project may be useful in achieving public education recommendations set forth by the National Drinking Water Advisory Council (EPA, 2016).

Participant responses towards potential tap water quality red flags

In the pre-survey, participants were asked, "How often do you contact your drinking water utility?" 98.4% of the aggregate pre-survey respondents, both well water and public supply, indicated that they never contact their water utility, and 90.3% of participants on the public water supply indicated that they never contact their public water utility. Only ten respondents, six of them on public water, indicated that they ever contact their public water utility (Table 5). This demonstrates gaps in communication between citizens and drinking water utilities, as nearly all citizens indicate that they never contact their public water utility, even when this is their main water supply. This question was compared with the participants' responses to the pre-survey question, "How would you rate the quality of your drinking water at home?" and there was no statistical significance between perception about drinking water quality and intention to contact the utility (r_s=0.10 via Spearman's Rho). This suggests that even if people think their water is unsafe, they still may not contact their utility, indicating a potential lack of knowledge about "who to contact" about water quality concerns.

When asked about what they would do if they learned they had lead in their drinking water in the pre-survey, participants indicated that they would be most likely to flush their tap water and install a filter in both aggregate and matched results (Figure 5). There were also a significant percent of participants indicated that they are highly likely or likely to tell their neighbors about the problem or to conduct additional research in both aggregate and matched pre-survey responses. Participants indicated that they would be least likely to do nothing or move to a new home in both aggregate and matched pre-survey results. In the post- survey, participants had learned about their actual water quality results, and they were asked about how they will respond to their actual water quality outcomes. It has to be noted that a majority of the households participated in this project had a drinking water lead level of below 15 ppb – the Lead and Copper Rule's Action Level (Table 3). Hence, not surprisingly, a relatively significant level of change was observed in the "Do nothing" option in the matched responses. While the matched participants are much more likely to do nothing after receiving their results, they are less likely to install a filter (LoC = 0.5395) or tell their neighbors about the problem (LoC = 0.4434) with high statistical significance. No statistically significant changes were observed on flushing the tap, conducting additional research, or moving to a new house. Nevertheless, there is a high statistical significance in changes in the remaining individual actions, including “Do nothing” (p=0.0011), “Install a filter” (p=0.0029), “Tell my neighbors about the problem” (p=0.0351), as well as the overall change when all individual actions except for “Do nothing” are combined (p=0.0000). A relatively high percentage of participants indicated they would flush the tap even after knowing lead results, indicating a desire to take certain actions for precaution.

The F-test found that lead result is not a statistically significant indicator of participants’ changes in their pre- and post-survey responses (p=0.8830). When taking a closer look at the participants who received a relatively high lead results of above 10 ppb, the two participants that had a lead level of above the Lead and Copper Rule’s Action Level of 15 ppb indicated high likelihood to take actions in both their pre- and post-survey responses. For the two participants that had a lead result of between 10-15 ppb, one was a lot less likely to take actions overall, while the other was notably less likely to install a filter but slightly more likely to flush the tap. This may suggest that these participants may not be as concerned with their lead results as they are below the Action Level, a potential danger of assigning a limit that may not necessarily be indicative of exposure health implications.

Participant communication about water quality

In both the aggregate and matched pre- and post-survey results, the groups that participants most frequently communicated with regarding water quality were family and friends (Figure 6). This makes sense as these are the groups that participants likely have the most contact with. Also, previous research found that the strongest motivation for participation in this project was to protect the health of oneself and one's family (Jakositz et al. 2019), which may also explain why family was the group most frequently communicated with. Participants were least likely to communicate with strangers and colleagues. This may suggest that most conversation about drinking water quality takes place in or around the home.

Comparing the matched pre- and post-survey results, notable positive changes in participants' communication about water quality were observed. The highest increase in communication was observed with the colleagues and neighbors, both with statistical significance (p=0.0226 and 0.0303, respectively). High levels of changes were also observed with the family and friends groups, despite not meeting our criteria of statistical significance. Communication with the strangers group has the least change and do not have quantifiable statistical significance. When all social groups are combined, the overall level of change is statistically significant (p=0.0020).

Our F-test shows none of the socioeconomic variables considered have a statistically significant effect on the participants' changes in their communications about water quality (Table 6), with whether having children under the age of 6 in the household having the lowest p-value.

Conclusions

This project demonstrated that a well-designed citizen science approach can be used to engage participants in water quality activities that both benefit the citizen and the researchers. With regards to participants' content knowledge about lead in drinking water, this project demonstrated success in improving participants' scientific literacy relating to key lead information, and overall provided educational benefit to those who participated. This contributes to previous literature that shows that citizen science can be a meaningful way of increasing environmental and science literacy (Crall et al., 2013; Jordan et al., 2011), providing new information about how citizen science data on drinking water can contribute to these kinds of changes. Participants are mostly likely to flush their taps and install a filter towards potential water quality red flags, and least likely to do nothing or move to a new house. It was notable that most participants would be willing to take preventative actions to protect their health against water quality concerns, even with a knowingly low lead level in the household. We also found that participants that had a lead result of between 10-15 ppb may become less likely to take actions, indicating a potential danger of assigning a limit that may not necessarily be indicative of exposure health implications. However, this is based on two participants results and may not be generalized. Comparing pre- and post-surveys showed statistically significant increases in participants' likelihood to communicate about drinking water with neighbors and colleagues, while change in communication with strangers is the least significant.

Data Availability Statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1. An example contingency table based on matched pre- and post-survey responses for the 4th statement listed in Figure 1. This table serves as an input to the McNemar test. Numerical values in the table shows the participant counts based on their responses in the pre- and post-surveys.

Responses	Correct in post-survey	Incorrect in post-survey
Correct in pre-survey	4	12
Incorrect in pre-survey	7	9

Table 2. Socioeconomic variables considered in this study and their recoding scheme.

Socioeconomic Variables	Variable Levels/Values	Variable Standardization	Number of participants
Age	Less than 40	0	9
	Between 40 and less than 60	0.5	8
	More than 60	1	12
Household income	Less than $49,999	0	12
	$50,000 to $99,999	0.5	14
	More than $100,000	1	4
Education	Less than high school graduate, diploma	0	1
	Less than bachelor’s degree	0.5	16
	More than bachelor’s degree	1	16
Gender	Male	0.25	8
	Female	0.5	24
	Other	0.75	0
	Prefer not to answer	1	1
Housing ownership	Rent	0	11
	Own	0.5	22
	Other	1	1
Children	Have child(ren) under 6 years old living in household	0	7
	Do not have child(ren) under 6 years old living in household	1	25

Table 3. Number of post-survey participants in each of three lead concentration groups.

Individual Lead Result	Number of participants
< 1ppb	15
≥1 ppb & < 10ppb	11
≥ 10 ppb & < 15 ppb	2
> 15 ppb	2
Total	**30**

Table 4. P-values from the F-test indicating the statistical significance of the influence of various socioeconomic variables on participants' knowledge changes.

Socioeconomic variables	P-value from the Chi-squared test
Age	0.8220
Household income	0.4950
Education	0.1400
Gender	0.7900
Housing ownership	0.1080
Children	0.4090

Table 5. Self-reported frequency of contacting public water utility for all respondents and a subset who reported that they are on a public water supply.

Contact frequency	# based on all respondents	% based on all respondents	# based on respondents who are on a public water supply	% based on respondents who are on a public water supply
Never	124	98.4%	56	90.3%
Every couple of years	7	5.6%	5	8.1%
Every year	2	1.6%	1	1.6%
Multiple times per year	1	0.8%	0	0
Missing	2	1.6%	N/A	N/A
Total	**136**	100%	**62**	100%

Table 6. P-values from the F-test indicating the statistical significance of the influence of various socioeconomic variables on participants' knowledge changes.

Socioeconomic variables	P-value from the Chi-squared test
Age	0.3870
Household income	0.6760
Education	0.3100
Gender	0.9510
Housing ownership	0.2700
Children	0.1840

Figure 1. Question included in pre- and post-surveys to understand participants' knowledge about lead-related water quality issues.

Figure 2. Pre- (a.) and post-survey (b.) questions asking participants about their likelihood to take various actions related to combating potential lead levels in their drinking water.

Figure 3. Question included in pre- and post-surveys to understand participants' likelihood to communicate with their social network about water quality.

Figure 4. Response distributions in both the aggregate and matched pre- and post-survey responses that assessed content knowledge before and after the project. S1 to S5 corresponds to the five statements in Figure 1. Pre1 and Post1 indicate aggregate pre- and post-survey results, respectively. Pre2 and Post2 indicate matched pre- and post-survey results, respectively. * indicates statistically significant changes in the matched results before and after participating in the project.

Figure 5. Response distributions in both the aggregate and matched pre- and post-survey responses that assessed actions taken under hypothetical and real water quality results. The six actions in this figure correspond to the six potential actions listed in Figure 2. Pre1 and Post1 indicate aggregate pre- and post-survey results, respectively. Pre2 and Post2 indicate matched pre- and post-survey results, respectively. * indicates statistically significant changes in the matched pre- and post-survey responses.

Figure 6. Response distributions in both the aggregate and matched pre- and post-survey responses that assessed participants' communication with identified social groups. The five social groups correspond to the groups identified in Figure 3. Pre1 and Post1 indicate aggregate pre- and post-survey results, respectively. Pre2 and Post2 indicate matched pre- and post-survey results, respectively. * indicates statistically significant changes in the matched pre- and post-survey responses.