A Structural Equation Modeling Approach to Water Quality Perceptions

Jonas G. Levêque^{a*}, Robert C. Burns^a

^a *School of Natural Resources, West Virginia University, Morgantown, WV, 26505, United States of America*

* Corresponding author. Tel: +1.304.293.0053. *Email address:* jonas.leveque@gmail.com.

Abstract

Researches on water quality perceptions have used various techniques and models to explain relationships between specific variables. Surprisingly, Structural Equation Modelling (SEM) has received little attention in water quality perceptions studies, and reporting has been inconsistent among existing studies. One objective of this article is to provide readers with a methodological example for conducting and reporting SEM. Another objective is to build a model that explains the different relationships among the diverse factors highlighted by previous studies on water quality perceptions. Our study focuses on the factors influencing people's perceptions of water quality in the Appalachian region. As such, researchers have conducted a survey in a mid-sized city in northcentral West Virginia to assess residents' perceptions of water quality for drinking and recreational purposes. Specifically, we aimed to understand the relationships between perceived water quality, health risk perceptions, organoleptic perceptions, environmental concern, area satisfaction and perceptions of surface water quality. Our model provided a good fit that explained about 50% of the variance in health risk perceptions and 43% of the variance in organoleptic perceptions. Environmental concern, area satisfaction and perceived surface water quality are important factors in explaining these variances. Perceived water quality was dismissed in our analysis due to multicollinearity. Our study demonstrates that risk communication needs to be better addressed by local decision-makers and water managers.

Keywords: Water Quality Perceptions, Structural Equation Modeling, West Virginia.

1. Introduction

A large amount of public researches in developing countries have demonstrated evidence of a misconception regarding tap water quality. For instance, many studies reported that the general

public believes bottled water to be of higher quality, to have lower health risks and to taste better than tap water (Anadu and Harding, 2000; Hu et al., 2011; Raj, 2005; Zivin et al., 2011).

Researchers identified several factors that explain the variation of public perceptions of tap water quality (Doria, 2010; Syme and Williams, 1993). More specifically, several studies showed that perceived tap water quality is positively influenced by organoleptic perceptions and negatively influenced by health risk perceptions, with health risk perceptions being negatively influenced by organoleptic perceptions (Doria et al., 2005; Proulx et al., 2012; Turgeon et al., 2004). Different methods of analysis have been used in the past to investigate water quality perceptions, but only a few studies proposed the use of a Structural Equation Modeling (SEM) approach: Doria et al. (2005, 2009). Notably, these two studies did not investigate the relationships between tap water quality perceptions and other factors such as environmental concern. In fact, several studies have linked environmental concern, perceptions of the water quality of streams, rivers and lakes or ground water quality in the area with tap water quality perceptions (Hu et al., 2011; Merkel et al., 2012; Syme and Williams, 1993). Including these variables in an SEM model increases current knowledge on water quality perceptions as SEM is a technique that can assess different relationships between variables at the same time (Hu and Bentler, 1999; Kline, 2015).

Ultimately, SEM is used to analyze the discrepancy function between the covariance matrix of the sample under study and the fitted covariance matrix by a specified model that is based on these relationships (Hu and Bentler, 1999). This technique is a powerful statistical tool because it accounts for measurement error in the model, which is not possible in traditional regression approaches (Kline, 2015). Additionally, SEM allows researchers to investigate direct and indirect paths in their models (Kline, 2015).

In West Virginia, water management is critical, as many different human activities have the potential to affect the water quality. The Elk River pollution that occurred in Charleston (West Virginia) in early 2014 is an example of water contamination that directly impacted residents and their use of tap water (Whelton et al., 2015). In the context of global climate change and population growth, water management appears to be one of the most challenging issues for the 21st century (World Bank, 2016). Yet, the impacts of water quality are many, not only for ecosystems but also for populations (World Bank, 2016). Merkel et al. (2012) demonstrated that environmental risks associated with human activities such as mining and gas drilling can increase risk perceptions linked with drinking tap water. In contrast to natural disaster risks,

these risks are linked to technological risks (Flint and Luloff, 2005). Therefore, implementing preventive measures and risk management can reduce the likelihood of these risks. As a result, public risk perceptions may increase or decrease support for preventive measures and lead to behavioral changes. In comparison, Fessenden et al. (1987) explained the psychology of water consumption for US citizens: “if people have seen, tasted, or smelled something different about their water, whether or not the change is related to the contamination, they tend to exaggerate the risk. But if their own senses have given them no clue that a problem exists, people may feel that the risk they are being told about has been exaggerated” (p.97).

2. Study purpose

In summary, a first goal of our study is to help other researchers by designing an SEM model with an analyses report that follows SEM guidelines. Hurlimann et al. (2008) pointed to the existence of variability among the studies that report SEM results. A second goal of our study is to explain the water quality perceptions in a community of West Virginia. In order to proceed, we build on Doria et al.’s SEM model (2009) and propose to modify it by adding other factors such as environmental concern (Dutcher et al., 2006; Syme and Williams, 1993), area satisfaction (Syme and Williams, 1993), and the perceived surface water quality (Hu et al., 2011). We created the item “the likelihood of a chemical spill” in order to better understand risk perceptions. Results of this study will help further research in the region and will enable targeting risk communication and general communication about water quality and environmental protection. These are important factors in a period of elections.

More specifically, we were interested in depicting the following relationships:

Hypothesis 1: Perceived water quality (PWQ) is negatively influenced by perceived health risks (PHR) (Doria et al., 2005), the likelihood of a chemical spill (CS) and environmental concern (EC) (Dutcher et al. 2007); positively influenced by organoleptic perceptions (OR) (Doria et al., 2005), the perceived surface water quality in the area (PSWQ), the satisfaction with living in the area (AS) (Syme and Williams, 1993) and the context (CTX) (Doria et al., 2005).

Hypothesis 2: Perceived health risks are negatively influenced by organoleptic perceptions, the perceived surface water quality in the area, the satisfaction with living in the area and the context; positively influenced by environmental concern the likelihood of a chemical spill.

Hypothesis 3: Organoleptic perceptions are negatively influenced by the likelihood of a chemical spill and environmental concern; positively influenced by the perceived surface water quality in the area and the satisfaction with living in the area.

Hypothesis 4: Context is positively influenced by organoleptic perceptions (Doria et al., 2009) and we supposed it is also negatively influenced by environmental concern.

Hypothesis 5: The likelihood of a chemical spill is negatively influenced by the satisfaction with living in the area and the perceived surface water quality in the area; positively influenced by environmental concern.

Hypothesis 6: The perceived surface water quality in the area is positively influenced by the satisfaction with living in the area and negatively influenced by environmental concern.

The following conceptual model was proposed:

[insert figure 1 about here]

A description of the items used can be found in Appendix B (online supplementary content).

3. Methods:

3.1. Data collection

In order to test our model, we conducted a survey in northcentral West Virginia from November 2015 to January 2016. A sample of residents were randomly selected from a medium-sized city with an approximate population of 77,500 residents (see map in Appendix C, supplementary content). A mail-back survey was sent to 184 residents from a West Virginia University database, while an online survey was sent to another 5,492 residents from a third-party database. Later analyses of the results showed that there were no significant differences between the two survey methods for the variables of interest. A total of 603 residents completed the survey, achieving a 11.3% response rate. A non-response bias check was conducted comparing early respondents with late respondents, as suggested by Israel (1992). No significant differences were found. As the focus of the study is to build an SEM model, a non-response bias has less consequence than when analyzing univariate variables (Blair and Zinkhan, 2006). In addition, studies have shown that our non-response bias is reliable since we had a 45-day delay between initial and final respondents (Blair and Zinkhan, 2006; Dillman et al. 2014).

3.2. Results reporting

As noted by Hurlimann et al. (2008), there exists an important variety of ways to report SEM results, depending on researchers and journals. We used several recommendations from different sources throughout the following sections, especially from McDonald and Ho (2002).

3.3. Data processing and analysis

3.3.1. Software used

In order to investigate the nature of the different relationships developed through our hypotheses, we used the SEM software LInear Structural RELations (LISREL) 9.2, developed by Jöreskog and Sörbom. The SEM method was explicitly chosen because it allows the integration of error into the model, contrary to regression approaches that make the assumption of the perfect measurement of items (Kline, 2015). The Software Package for Social Sciences (SPSS) version 24 was utilized for the initial treatment of the data.

3.3.2. Missing data and outliers' treatment

As a result of missing values, the effective sample size achieved under listwise deletion was $n = 567$, corresponding to 5.9% missing data. Since missing data can affect parameter estimates (Vaske, 2008), we decided to use an imputation method. Following warnings of Jöreskog and Sörbom (1996), we used the Expectation-Maximization (EM) method available in PRELIS (treatment software from LISREL) (Du Toit and Mels, 2002; Lin, 2010). After inspecting missing data, we detected a total of 22 multivariate outliers using the Mahalanobis distance with SPSS (IBM Corp., 2016). As different techniques in handling outlier detection exist, we chose to create one dataset with outliers ($n = 603$) and another dataset without outliers ($n = 581$) and to look at the models' chi-squares and fit indices in LISREL during the measurement testing (Aguinis et al., 2013). Our results indicated no significant difference in chi-square, with fit indices that were slightly better for the dataset containing the outliers. Individual parameter estimates did not change significantly. Therefore, we decided to keep the model with more data, $n = 603$. According to Schumacker and Lomax (2004), our sample size (in both cases) was large enough to develop a model using SEM following the recommendation of 20 responses per variable in the model; using 19 observed variables and 8 latent constructs in our model (see Appendix A), our sample size met this criterion. The different inter-correlations, means and

standard deviations of the observed variables can be found online within the supplementary content (Appendix B).

3.3.3. Normality

An investigation of the descriptive statistics under PRELIS indicated the presence of univariate and multivariate non-normality. Because multivariate normality is an important assumption in SEM, we chose to use an estimation method that would be robust to non-normality (Finney and Distefano, 2006; Kline, 2015; McDonald and Ho, 2002). As such, we used the Robust Maximum-Likelihood estimation method under LISREL, using the Satorra-Bentler corrected (S-B) chi-square and fit indices. This estimation method has been found to correctly measure parameter estimates and to “outperform the ML-based chi-square” (Finney and Distefano, 2006, p.290).

3.4. Model building

This section describes the analyses and steps that were taken to assess and correct the performance of our model, especially in terms of reliability and validity.

3.4.1. Model comparison / goodness of fit

Since the chi-square test is sensitive to sample size, resulting in model rejection with $p < 0.05$, we added other fit indices to describe the model fit (Jöreskog and Sörbom, 1993). Precisely, the Comparative Fit Index (CFI), the Root Mean Square of Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) were chosen, following recommendations from Kline (2015). As the CFI and the RMSEA are based on the S-B chi-square, the SRMR is based on the discrepancies between the observed correlations and the estimated correlations (Kline, 2015). Nonetheless, the chi-square difference test was used to compare nested models. Since we used a Satorra-Bentler chi-square, the estimation did not follow a normal chi-square distribution. Using Bryant and Satorra (2012), a re-scaling of the S-B chi-square was made possible for model comparison.

3.4.2. Single-indicators

For practical reasons and following items measured in previous researches (Doria et al., 2009; Hu et al., 2011), three of the latent constructs were measured using a single-item indicator.

Sometimes seen as problematic in an SEM approach, an extensive review and discussion on the topic from Petrescu (2013) shows that single-item indicators can be used when precisely corrected. Since Doria et al. (2009) did not report the use of single-item indicators, and no other study used these items in an SEM approach, we followed the recommendations of Petrescu by setting the measurement error to $[0.95 * \text{variance}]$, based on SEM literatures (Kline, 2015; Thompson, 2000). Using Schumacker and Lomax's recommendations (2004) of a modification formula of $[(1 - \text{reliability}) * \text{variance of the indicator}]$, and using a conservative value of 0.85 for the reliability according to Jöreskog and Sörbom (1982), the single indicators were corrected as shown in table 1 (when testing for influential outliers, these corrections were recalculated for each model).

[Insert Table 1 about here]

3.4.3. Construct validity: convergence and discriminant validity

In order to determine convergence validity, we tested whether the loadings of the observed variables on their latent constructs were above 0.70 within the measurement model (Farrell and Rudd, 2009). The standardized loading of the observed variable EC5 on the environmental concern construct was not reliable (loading = 0.60), with a measurement error of 0.64, indicating 64% of the variance was imputed to error (Fornell and Larcker, 1981). Since this item did not load correctly on its latent construct, we removed it from the analyses. The next step consisted in testing the reliability at the latent level. Using Fornell and Larcker (1981), we computed the construct reliability (CR) for the different latent constructs (see table 2). All of the constructs proved to be reliable (greater than 0.70). For single-indicator latent constructs, CR and AVE are equal, simply representing the squared standardized factor loading of the indicator on its latent construct. This is also the conservative value of 0.85 that Jöreskog and Sörbom (1982) recommended.

Regarding discriminant validity, or how a latent construct is significantly distinguishable from another latent construct, we used the method proposed by Fornell and Larcker (1981). The method consists in comparing the Average Variance Explained (AVE) with the squared correlations of the different latent constructs: the AVE of each construct should be larger than the squared correlation between two constructs (Fornell and Larcker, 1981).

[Insert Table 2 about here]

According to table 2, it is possible to see that the latent construct Perceived Water Quality (PWQ) indicates issues of multicollinearity. This could be suspected from Appendix B when looking at the inter-item correlations, as PWQ1 and PWQ2 both have high correlations with other items. In order to solve the issue, we removed this latent construct from further analyses. Therefore, Hypothesis 1 was rejected. This has implications that are discussed later in this paper.

3.4.4. Model re-specification

Since PWQ was removed from the analyses, we re-specified the measurement model, and as such tested for convergence and discriminant validity in the new model. Analyses showed that two indicators within the Perceived Health Risk construct did not satisfy the condition of convergence validity with loadings less than 0.70: PHR1 and PHR4 were removed from this model. After deletion, the construct reliability was higher for PHR and the construct reliabilities for the other latent constructs were still satisfactory (see table 3). These were deemed “very good”, according to Kline (2015, p.92). No issues were encountered when testing for AVE, satisfying the validity of our model (see table 3).

[Insert Table 3 about here]

3.4.5. Two-indicator constructs

After convergent and discriminant validities were assessed and validated, there were two latent constructs that had only two reflective indicators instead of the three recommended in SEM analyses (Kline, 2015). The solution to account for this issue in SEM is to fix the two factor loadings equal. Four different models were established with and without these restrictions (see table 4). The examination of the chi-square difference tests proved that model C was not significantly different from model D, which was significantly better than model A, which was not significantly different from model B. Model C was favored, indicating that we needed to fix the loadings of PHR2 and PHR3 equally. The loadings of AS1 and AS2 did not need to be set equally.

[Insert Table 4 about here]

3.4.6. Model identification

According to Hershberger and Marcoulides (2006), our measurement model was globally overidentified since there are more equations to explain the different latent constructs than the number of latent constructs. In terms of the path model identification, we did not omit non-directed arcs (McDonald and Ho, 2002). Also, our model was found to be recursive as we tested a causal approach between the latent constructs. As such we found that the path model was identified.

3.4.7. Equivalent models

Hypotheses 1, 2, 3 and 4 for the elaboration of the path model were based on theory and previous researches. Hypothesis 5 was not based on previous researches as we introduced the likelihood of a chemical spill item, but we followed the logic from previous literatures (Hu et al. 2011; Syme and Williams 1993). Hypothesis 6 had not been seen in previous literatures, but we hypothesized that the effect of environmental concern and satisfaction of living in the area would have a significant effect on perceived surface water quality. As a result, an equivalent model to our final model is one that has correlations between CS, EC, AS and PSWQ instead of direct paths. Our model provides information about direct and indirect effects allowing us to answer hypotheses 5 and 6, unlike the equivalent model. Consequently, our final model has been retained. In fact, there is a multitude of equivalent models that replicate the same covariance matrix estimated by our model (Lee and Hershberger, 1990). Yet, it is worth noting that some of these models are diverting from previous theories, and are not representing sound causation (Kline, 2015). Using the replacing rule described by Lee and Hershberger (1990), several equivalent models were especially of interest in our research: models that have a covariance error that explains the relationships between the endogenous latent constructs CTX, OR and PHR. This change expresses the fact of a non-directionality in the relationship: causality between these variables is no longer assumed. Choosing the model with OR causing PHR should be preferred due to previous literatures (Doria et al., 2005, 2009; Syme and Williams, 1993) that found taste, odor or color to influence risk perceptions. In that sense, there is a precedence in time: we could expect one to try the water before making a judgement about its risk. However, one could argue that at the time of the survey, the risk perceptions also influenced the satisfaction with the taste, odor and color of the tap water.

4. Results

4.1. Measurement model

The measurement model (CFA) proved to have an adequate fit, with fit indices that were within recommendations (see table 6), especially in the case of the use of a S-B chi-square: CFI higher than 0.95, RMSEA and SRMR lower than 0.05 (Finney and Distefano, 2006; Yu and Muthén, 2002). Since we used the S-B chi-square, the 90% confidence interval of the RMSEA was not given by LISREL. We were able to recover this using O'Boyle and Williams (2011), and their Excel datasheet. Following their recommendation, we considered a lower bound lower than 0.05 and an upper bound lower than 0.10 as good fit. Table 5 represents the factor loadings of the CFA.

[Insert table 5 about here]

4.2. Structural model

The structural model proved to have an adequate fit as well (see table 6). Regarding the path model, we subtracted the structural model's S-B chi-square from the measurement model's S-B chi-square to find the S-B chi-square (McDonald and Ho, 2002). It is worth noting that the path model estimates fewer parameters than the measurement model, accordingly to McDonald and Ho (2002). The fit indices that are dependent on chi-square (RMSEA and CFI) were calculated and proved a good fit (see table 6). The confidence intervals of the RMSEA for the path and structural models were also recovered using O'Boyle and Williams (2011).

[Insert table 6 about here]

Figure 2 represents the path model and the different loadings among the different latent constructs.

[Insert figure 2 about here]

According to figure 2, it is possible to say that half of the variance in perceived health risks was explained by the model ($R^2 = 0.496$). The model also explained 43% of the variance in organoleptic perceptions ($R^2 = 0.430$), a third of the variance in perceived surface water quality ($R^2 = 0.314$), a quarter of the variance in the likelihood of a chemical spill ($R^2 = 0.258$) and one-eighth of the variance of context ($R^2 = 0.125$). It is interesting to note that if most paths were significant, the likelihood of a chemical spill and the environmental concern were not significant

with either of the two major latent constructs: perceived health risks and organoleptic perceptions.

4.3. Total and indirect effects

As noted earlier, SEM is a technique that allows the investigation of indirect paths. In this regard, LISREL prints the different effects between variables. It is worth noting, though, that the expression “indirect effects” here is the sum of the indirect effects of one variable onto another. The total effects are then the combination of indirect and direct effects. Table 7 summarizes the total and indirect effects between the different latent constructs. KSI represent exogenous latent constructs (AS and EC) while ETA represent endogenous constructs (PHR, CS, CTX, OR, PSWQ).

[Insert Table 7 about here]

5. Discussion

The fact that perceived water quality was removed from the model indicates a high degree of concern about the validity and reliability of the model identified by Doria et al. (2005, 2009). By using a multivariate regression analysis with multiple dependent variables, Syme and Williams (1993) indicated having high correlations between these variables and as such tested them separately. This result indicates that the items used by Doria et al. to describe water quality together with perceived health risks and organoleptic perceptions in the same model is not feasible. Our discriminant validity analysis demonstrated this issue. Solely using organoleptic perceptions and perceived health risks is encouraged for future research. Using other items to measure water quality perceptions would create a tautology effect in any sort of analyses, resulting in excessively large R^2 . This effect can be highly suspected in Doria et al. (2009), with R^2 of 0.86 and 0.98 for their U.K. and Portugal samples. The validity of their model is suspected.

The fact that the item EC5 appeared to be inconsistent with the other items of the environmental concern construct is notably due to the fact that it assesses an economic question, that underlays the willingness to pay. Removing it from the analyses makes sense conceptually, as this is not a reliable item within the environmental concern construct. This result also indicates the need for research on economic valuation of water quality.

Executing adequate validity and reliability analyses enabled us to have an overall strong model after re-specification. The fit indices of the model confirmed that our model was performing well, allowing us to affirm that our results and inferences are reliable and valid.

Regarding the explained variance of the health risk perceptions, our results are similar to Doria et al. (2009). Since we added more variables to our model, our R^2 is higher. Concerning the explained variance of context, Doria et al. found a R^2 of comparable magnitude with their U.K. sample ($R^2 = 0.14$). Context and organoleptic perceptions explained health risk perceptions in a similar fashion to Doria et al. In addition, our model explained the variance of organoleptic perceptions with a large R^2 , similar to health risk perceptions.

Even though the likelihood of a chemical spill was hypothesized to be significant with perceived health risks and organoleptic perceptions, these hypotheses were incorrect. This can be associated with the fact that the likelihood of a chemical spill was based on a single-item indicator, constructed by our team and not tested in previous researches. Further research that will better measure this risk could verify the relationship between this risk and water quality perceptions. Similarly, environmental concern did not prove to be significant with either perceived health risks or organoleptic perceptions when looking at the direct paths. In contrast, using a regression approach, Syme and Williams (1993) found that their environmental concern measures (slightly different from ours) significantly explained variance in health risk perceptions. Nonetheless, when looking at the indirect effects in our model, environmental concern was found to significantly explain variance in perceived health risks and in organoleptic perceptions. Besides, we found that environmental concern was significant with context. This is an interesting result because it shows that perceptions of tap water quality are not directly influenced by environmental concern in our study, but rather by indirect effects, and more precisely through the condition of the pipes and the state of the lakes, rivers and streams in the local area. Further analyses with replication of this result should be tested to enhance this theory.

An important result from this study is the addition of the satisfaction with living in the area variable which explained a large portion of the variance in organoleptic perceptions, health risk perceptions and perceived water quality of lakes, rivers and streams in the area. This result was similar to Syme and Williams (1993). In parallel and comparable to Hu et al.'s study (2011), we found that perceived water quality of lakes, rivers and streams in the area significantly predicted

the health risk perceptions and organoleptic perceptions. These relationships notably explain some of the significant indirect effects found earlier for environmental concern. Interestingly, environmental concern and satisfaction with living in the area were significantly negatively correlated. This indicates that the more respondents are satisfied with living in the area, the less they are concerned about the environment and the less they perceive health risks associated with the consumption of their tap water. This result has implications for risk communication, and for water managers.

Previous studies have suggested a gap between water quality perceptions and the actual water quality measured by instruments (Fessenden et al., 1987; Syme and Williams, 1993). Our results increase the evidence that communication is key in indicating the real risk that can affect populations. These results call for more and better targeted education on water quality in West Virginia.

6. Conclusions

Water quality is one of the world's most important challenges of the 21st Century. Our study is an example that the public's perceptions of water quality are complex. Using more recent statistical methods, such as SEM, provide further insight into the factors affecting water quality perceptions. Our paper has been designed following SEM reporting guidelines, setting an example for other researchers.

Our model demonstrates that water quality perceptions and especially health risk perceptions associated with drinking tap water are based on various factors that need to be understood for risk communication to be efficient. Our results prove that different populations/point of views may need different messages. In the current period of administration shifts, this is especially important for water management and local decision-makers. Further studies will be performed to replicate this model at a larger scale.

Acknowledgments

We would like to thank the US National Science Foundation-Experimental Program to Stimulate Competitive Research (through WV-HEPC-Division of Science and Research) under the Award

Number 145852 and the National Institute of Food and Agriculture (NIFA) for the funding of this study.

We would also like to thank Dr. Gerhard Mels and Dr. Mark Gavin for their advice on technical issues in SEM, as well as two anonymous reviewers.

Disclaimer

The funding source had no involvement in study design; in the collection, analysis and interpretation of data; in the writing of the report; or in the decision to submit the article for publication. Free and informed consent was asked from participants or their legal representatives was obtained. Our study protocol was approved by West Virginia University Institutional Review Board IRB, by West Virginia University, West Virginia, United States, protocol No.1510895135, November 2015.

References

Aguinis, H., Gottfredson, R. K., Joo, H., 2013. Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, 16(2), 270-301.

Anadu, E. C., Harding, A. K., 2000. Risk perception and bottled water use. *American Water Works Association Journal*, 92(11), 82.

Blair, E., Zinkhan, G. M., 2006. Nonresponse and generalizability in academic research. *Journal of the Academy of Marketing Science*, 34(1), 4-7.

Bryant, F. B., Satorra, A. 2012. Principles and practice of scaled difference chi-square testing. *Structural Equation Modeling: A Multidisciplinary Journal*, 19(3), 372-398.

Dillman D. A., Smyth J. D., Christian L. M., 2014. Internet, phone, mail, and mixed-mode surveys: The tailored design method. John Wiley & Sons.

Doria, M. F., 2010. Factors influencing public perception of drinking water quality. *Water Policy*, 12(1), 1-19.

Doria, M. F., Pidgeon, N., Hunter, P. R., 2009. Perceptions of drinking water quality and risk and its effect on behaviour: A Cross-National Study. *Science of the Total Environment*, 407(21), 5455-5464.

Doria, M. F., Pidgeon, N., Hunter, P. R., 2005. Perception of tap water risks and quality: a structural equation model approach. *Water Science and Technology*, 52(8), 143-149.

Du Toit, S. H. C., Mels, G., 2002. Supplementary Notes on Multiple Imputation. Scientific Software International, Inc. Chicago, Illinois.

Dutcher, D. D., Finley, J. C., Luloff, A. E., Johnson, J. B., 2007. Connectivity with nature as a measure of environmental values. *Environment and behavior*, 39(4), 474-493.

Farrell, A. M., Rudd, J. M., 2009. Factor analysis and discriminant validity: A brief review of some practical issues. *Anzmac*.

Fessenden-Raden, J., Fitchen, J. M., Heath, J. S., 1987. Providing risk information in communities: Factors influencing what is heard and accepted. *Science, Technology, & Human Values*, 12(3/4), 94-101.

Fornell, C., Larcker, D. F., 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 39-50.

Finney, S. J., DiStefano, C., 2006. Non-normal and categorical data in structural equation modeling, in Hancock, G. R., Mueller, R. O. (Eds.). *Structural Equation Modeling: A Second Course*. Information Age Publishing Inc., pp.269-314.

Flint, C. G., Luloff, A. E., 2005. Natural resource-based communities, risk, and disaster: An intersection of theories. *Society and Natural Resources*, 18(5), 399-412.

Hershberger, S. L., Marcoulides, G. A., 2006. The problem of equivalent structural models, in Hancock, G. R., Mueller, R. O. (Eds.). *Structural Equation Modeling: A Second Course*. Information Age Publishing Inc., pp.13-41.

Hu, L., Bentler, P. M., 1999. Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. *Structural Equation Modeling*, 6(1), 1-55.

Hu, Z., Morton, L. W., Mahler, R. L., 2011. Bottled water: United States consumers and their perceptions of water quality. *International Journal of Environmental Research and Public Health*, 8(2), 565-578.

Hurlimann, A., Hemphill, E., McKay, J., Geursen, G., 2008. Establishing components of community satisfaction with recycled water use through a structural equation model. *Journal of Environmental Management*, 88(4), 1221-1232.

IBM Corp. Released 2016. *IBM SPSS Statistics for Windows, Version 24.0*. Armonk, NY: IBM Corp.

Israel, G. D., 1992. *Sampling Issues: Nonresponse*. University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS.

- Jöreskog, K. G., Sörbom, D., 1982. Recent developments in structural equation modeling. *Journal of marketing research*, 404-416.
- Jöreskog, K., Sörbom, D., 1993. LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language. Scientific Software International, Inc.
- Jöreskog, K. G., Sörbom, D., 1996. PRELIS 2 User's Reference Guide: A Program for Multivariate Data Screening and Data Summarization: a Preprocessor for LISREL. Scientific Software International, Inc.
- Kline, R. B., 2015. Principles and Practice of Structural Equation Modeling, fourth ed. Guilford Publications.
- Lee, S., Hershberger, S., 1990. A simple rule for generating equivalent models in covariance structure modeling. *Multivariate Behavioral Research*, 25(3), 313-334.
- Lin, T. H., 2010. A comparison of multiple imputation with EM algorithm and MCMC method for quality of life missing data. *Quality & quantity*, 44(2), 277-287.
- McDonald, R. P., Ho, M. H. R., 2002. Principles and practice in reporting structural equation analyses. *Psychological methods*, 7(1), 64.
- Merkel, L., Bicking, C., Sekhar, D., 2012. Parents' perceptions of water safety and quality. *Journal of Community Health*, 37(1), 195-201.
- O'Boyle Jr, E. H., & Williams, L. J., 2011. Decomposing model fit: Measurement vs. theory in organizational research using latent variables. *Journal of Applied Psychology*, 96(1), 1-12. Excel datasheet available at:

https://www.researchgate.net/publication/265167230_O'Boyle_Williams_RMSEA-P_CI_calculator

Petrescu, M., 2013. Marketing research using single-item indicators in structural equation models. *Journal of Marketing Analytics*, 1(2), 99-117.

Proulx, F., Rodriguez, M. J., Sérodes, J. B., Bouchard, C., 2012. Spatio-temporal variability of tastes and odors of drinking water within a distribution system. *Journal of Environmental Management*, 105, 12-20.

Raj, S. D., 2005. Bottled water: How safe is it?. *Water Environment Research*, 77(7), 3013-3018.

Schumacker, R.E., Lomax, R.G., 2004. *A Beginner's Guide to Structural Equation Modeling*. Lawrence Erlbaum Associates. New Jersey.

Syme, G. J., Williams, K. D., 1993. The psychology of drinking water quality: An exploratory study. *Water Resources Research*, 29(12), 4003-4010.

Thompson, B., 2000. Ten commandments of structural equation modeling. In US Dept of Education, Office of Special Education Programs (OSEP) Project Directors' Conference, 1998, Washington, DC, US; A previous version of this chapter was presented at the aforementioned conference and at the same annual conference held in 1999. American Psychological Association.

Turgeon, S., Rodriguez, M. J., Thériault, M., Levallois, P., 2004. Perception of drinking water in the Quebec City region (Canada): The influence of water quality and consumer location in the distribution system. *Journal of Environmental Management*, 70(4), 363-373.

Vaske, J. J., 2008. Survey research and analysis: Applications in parks, recreation and human dimensions. State College, PA: Venture Publishing.

Whelton, A. J., McMillan, L., Connell, M., Kelley, K. M., Gill, J. P., White, K. D., Gupta, R., Dey, R., Novy, C., 2015. Residential tap water contamination following the Freedom Industries chemical spill: Perceptions, water quality, and health impacts. *Environmental Science & Technology*, 49(2), 813-823.

World Bank, 2016. The critical face of climate change – Water. Washington D.C.: International Bank for Reconstruction and Development/the World Bank.

Yu, C. Y., Muthen, B., 2002, April. Evaluation of model fit indices for latent variable models with categorical and continuous outcomes. In annual meeting of the American Educational Research Association, New Orleans, LA.

Zivin, J. G., Neidell, M., Schlenker, W., 2011. Water quality violations and avoidance behavior: Evidence from bottled water consumption. *American Economic Review*, 101(3), 448-453.

Table 1: Corrected measurement errors and error variances for single-item indicators (model with n = 603).

	Corrected measurement error	Corrected error variance
CS1	0.93005	0.14685
CTX1	0.76095	0.12015
PSWQ1	0.67735	0.10695

Table 2: Construct Reliability (CR), Average Variance Extracted (AVE) and squared correlations for latent constructs.

	PHR	AS	CS	PWQ	CTX	OR	EC	PSWQ
CR	0.84	0.80	0.85	0.82	0.85	0.89	0.87	0.85
PHR	0.58							
AS	0.39	0.67						
CS	0.20	0.15	0.85					
PWQ	0.83	0.44	0.17	0.69				
CTX	0.15	0.08	0.05	0.12	0.85			
OR	0.55	0.38	0.10	0.79	0.12	0.74		
EC	0.11	0.09	0.16	0.14	0.03	0.06	0.63	
PSWQ	0.29	0.26	0.15	0.35	0.03	0.28	0.14	0.85

Note 1: AVE values are represented in bold for each latent construct, grayed cells indicate issues.

Table 3: Construct Reliability (CR), Average Variance Extracted (AVE) and squared correlations for latent constructs, for final model.

	PHR	AS	CS	CTX	OR	EC	PSWQ
CR	0.87	0.80	0.85	0.85	0.89	0.87	0.85
PHR	0.77						
AS	0.29	0.66					

CS	0.13	0.15	0.85				
CTX	0.14	0.08	0.04	0.85			
OR	0.39	0.36	0.10	0.11	0.74		
EC	0.08	0.10	0.16	0.03	0.06	0.63	
PSWQ	0.24	0.26	0.15	0.03	0.27	0.14	0.85

Note 2: AVE values are represented in bold for each latent construct.

Table 4: Model with and without restrictions on two-factor loadings.

	PHR2 and PHR3 equal	PRH2 and PHR3 not equal
AS1 and AS2 equal	Model A: S-B $\chi^2 = 133.61$ df = 61	Model B: S-B $\chi^2 = 131.43$ df = 60
AS1 and AS2 not equal	Model C: S-B $\chi^2 = 124.85$ df = 60	Model D: S-B $\chi^2 = 122.68$ df = 59

Note 3: The chi-squares are Satorra-Bentler corrected (S-B χ^2).

Table 5: CFA parameter estimates, and latent standardized correlations.

Latent constructs	Observed variables	Unstandardized Estimates	Unstandardized Standard errors	z-values	Standardized Estimates
PHR	PHR2	0.99	0.03	35.67	0.93***
	PHR3	0.99	0.03	35.67	0.81***
AS	AS1	0.82	0.05	17.51	0.78***
	AS2	1.00	0.05	19.83	0.85***
CS	CS1	0.92 ^a			0.92 ^a
CTX	CTX1	0.75 ^a			0.92 ^a

OR	OR1	1.03	0.03	31.00	0.82***		
	OR2	0.78	0.04	19.70	0.83***		
	OR3	1.00	0.03	28.62	0.92***		
EC	EC1	0.91	0.04	23.25	0.82***		
	EC2	0.95	0.04	24.37	0.86***		
	EC3	0.81	0.04	19.07	0.75***		
	EC4	0.83	0.04	20.23	0.74***		
PSWQ	PSWQ	0.68 ^a			0.92 ^a		
	PHR	AS	CS	CTX	OR	EC	PSWQ
PHR	1						
AS	-0.55***	1					
CS	0.37***	-0.39***	1				
CTX	-0.39***	0.29***	-0.21***	1			
OR	-0.63***	0.60***	-0.31***	0.33***	1		
EC	0.29***	-0.31***	0.40***	-0.17***	-0.24***	1	
PSWQ	-0.49***	0.51***	-0.38***	0.17**	0.52***	-0.38***	1

Note 4: ** $p < .01$, *** $p < .001$, ^a refers to the fixed parameter estimates (single indicators).

Table 6: Fit indices for the final model.

Model	df	S-B χ^2 ($N = 603$)	CFI	SRMR	RMSEA	90% CI for RMSEA
Measurement	60	124.85	0.98	0.028	0.042	[0.031, 0.052]
Path	3	5.59	1.00	/	0.038	[0.000, 0.076]
Structural	63	130.45	0.98	0.029	0.042	[0.031, 0.052]

Note 5: These fit indices are the same for all of the equivalent models.

Table 7: Standardized total effects and (total) indirect effects of KSI and ETA on ETA.

Total effects	<i>KSI</i>		<i>ETA</i>			
	AS	EC	CS	CTX	OR	PSWQ
<i>ETA</i>						
PHR	-0.50***	0.13***	0.10	-0.17***	-0.41***	-0.28***
CS	-0.29***	0.31***				-0.17**
CTX	0.18***	-0.12*	-0.01		0.31***	0.09***
OR	0.59***	-0.05	-0.04			0.29***
PSWQ	0.43***	-0.24***				
Indirect effects	<i>KSI</i>		<i>ETA</i>			
	AS	EC	CS	CTX	OR	PSWQ
<i>ETA</i>						
PHR	-0.33***	0.10***	0.02		-0.05***	-0.13***
CS	-0.07**	0.04*				
CTX	0.18***	-0.02	-0.01			0.09***
OR	0.14***	-0.08***				0.01
PSWQ						

Note 6: * $p < .05$, ** $p < .01$, *** $p < .001$

Figure 1: Full Structural Model. Latent constructs are shown in ellipses. Observed variables are shown in rectangles. *d* represents the disturbances from the endogenous latent constructs.

Figure 2: Path model and loadings. * $p < .05$, ** $p < .01$, *** $p < .001$. Grey small arrows represent disturbances ($1 - d = R^2$).