Causal Effects of Water Conservation Behavior Patterns on Water Quality Engagement: Evidence from Latent Class Analysis and Machine Learning-Enhanced Propensity Score Matching

Dharmendra Kalauni, Emily Lang, Laura Warner, Qian Shen

Introduction

Water needs in Florida are projected to increase by 14% in 2040, resulting in a daily water demand of 7.2 billion gallons per day (Florida Department of Environmental Protection, 2024a). By 2070, demands could reach over 8 billion gallons daily (Water 2070, 2016). Current water availability does not meet future demands (Florida Department of Environmental Protection, 2024a). Public supply, which refers to the water supplied by utilities for residential and commercial use, is expected to continue representing the state's largest category of water use (Florida Department of Environmental Protection, 2024a). Water conservation is the single most important action that can be taken to sustain water supplies and to protect Florida's water-dependent ecosystems (Florida Department of Environmental Protection, 2024b). Nationally, urban landscapes consume approximately 30% of household water, but research has shown that some water users in Florida direct as much as 70% of their daily water use towards irrigation (Taylor et al., 2023). Nonpoint source pollution, such as the runoff of fertilizer and pesticides from urban landscapes, is the largest source of pollution in Florida (Florida Department of Environmental Protection, 2021). This makes the Florida urban landscape one of the largest users and polluters of water in the state, while being one of the few directly controlled by individual actions.

At the state, regional, and local levels, responsible urban landscape management has been identified as a critical component of conserving and protecting water quality in Florida. Managing landscapes according to best practices to protect water availability and quality, such as the Florida-Friendly Landscaping guidelines, is not a one-time behavior but a coalescence of behaviors that a person must adopt and maintain to successfully conserve water and prevent pollution runoff. This makes sustainable landscaping practices a series of innovations that must be adopted individually. To achieve this, it is essential to understand what motivates the audience and to design messaging that highlights how the desired behavior change will help the audience meet their own goals or interests (Rogers, 2003). Therefore, the more that is known about the target audience, the more directly messaging can be designed for that audience. We designed this study to determine whether there are patterns of water conservation behaviors and how these patterns relate to engagement in water quality protection. This audience segmentation approach would then inform Extension educators about tailoring their Extension programs to those classes that show promising water stewardship behaviors. Thus, the following two research questions guided our study:

1. What latent classes exist among residents engaged in water conservation behaviors?
2. What is the average treatment effect of different patterns of water conservation behaviors on water quality protection engagement?

Theoretical framework

Rogers (2003) discussed the attributes of both innovation and potential adopters in order to understand the diffusion of new technologies and practices. In terms of innovation, perceived characteristics of relative advantage, compatibility, complexity, observability, and trialability have been shown to explain about 50-90% of the variability in adoption rates (Rogers, 2003). These characteristics have been successfully used to predict the adoption of groups of landscape water protection behaviors related to conservation (Warner, Lamm et al., 2020) and water quality (Warner, Diaz et al., 2021). Despite the predictive power of these characteristics, some reports suggest that ownership of a particular innovation (i.e., technology) is a better predictor of the adoption of similar innovations than these five characteristics (Vishwanath & Chen, 2006). In other words, adoption of a series of innovations (here, water conservation and water quality best practices) may be better understood through the interrelated nature of these concepts (Rogers, 2003), which may also be described as the "spillover effect" (Kneebone et al., 2018; Thøgersen & Ölander, 2003). The spillover effect suggests that individuals who engage in an environmental behavior are more likely to engage in other environmental behaviors to maintain consistency (Thøgersen & Ölander, 2003). However, positive relationships do not always occur among similar behaviors; people may engage in some environmental behaviors rather than others when they perceive the latter will not benefit themselves or are too difficult to perform. In these cases, a person might engage in personally beneficial or easier behaviors and use this engagement to justify avoiding other practices (Thøgersen & Ölander, 2003). Similarly, technology clusters are considered distinct innovations that are closely related and may be adopted more rapidly when packaged together. Rogers (2003) discussed the challenge for researchers in determining where a particular innovation ends and another begins, and Vishwanath and Chen (2006) noted a concerning lack of research identifying such clusters. We initiated this research study focusing on technology clusters, recognizing that water conservation practices could potentially serve as predictors for water quality protection practices, given the interconnected nature of these behaviors. These two types of behaviors have been studied in isolation; this study fills that gap by examining them together to determine if any patterns exist in individuals who engage in water conservation and water quality protection behaviors.

Methods

Sampling and Data Collection

We employed non-probability and quota sampling to create an adult sample (i.e., individuals 18 years and older) that matched state demographics on four characteristics (age, ethnicity, race, and gender) as of the 2020 U.S. Census (Baker et al., 2013; Lamm & Lamm, 2019). Prior to the study, we obtained Institutional Review Board approval from the University of Florida (protocol # ET00043362). We collected data using an online survey. Initially, 2,464 individuals accessed the survey, and 1,562 provided complete responses. Only 370 responses were used for analysis as they met the screening criteria.

Measures and Instrumentation

We collected engagement in 38 behaviors, of which 27 related to water conservation and 11 related to water quality protection. Regarding water conservation practices, respondents were prompted to *mark the response that best describes their water-saving practices*, and the available responses were *yes*, *no*, and *not applicable*. For the water quality protection practices, respondents were prompted to *select how often they engage in the following fertilizer behaviors*, and the available responses were *never*, *rarely*, *sometimes*, *often*, *always*, and *not applicable*. These behaviors were adapted from Warner et al. (2019; 2022) and refined through an expert panel review process.

Data diagnosis and analysis

Our first step involved preparing 24 covariates, which ranged from demographic characteristics to perceived values/beliefs based on the Value Belief Norm (VBN) theory. This primarily involved recoding variables for accurate interpretation and estimation of factor scores for latent constructs. We conceptualized water conservation variables (treatment variable) as a latent construct that measures water conservation behavior using a 27-item scale. Our second step involved latent class analysis of the water conservation behavior to identify unobserved classes (Lanza et al., 2013; Weller et al., 2020). The third step involved propensity score estimation to address differences in covariate distributions between the treatment and control groups and to mitigate selection bias (Bishop et al., 2018; Rosenbaum & Rubin, 1983). Propensity scores were later used for Inverse Probability of Treatment Weighting (IPTW) and Overlap Weights (OW) to adjust for confounding and estimate treatment effects. We employed multinomial logistic regression (MLR), random forests (RF), XGBoost, and covariate balancing propensity score (CBPS) method to improve covariate balance (Ali et al., 2019; Imai & Ratkovic, 2014; Westreich et al., 2010).

Water quality protection behavior (outcome variable) was also conceptualized as a latent variable, measured by 11 items on a scale; however, there was a lack of information on its dimensionality. We implemented exploratory factor analysis (EFA) to uncover the latent structure. We used oblique rotation (Watkins, 2018), and data suitability was confirmed via the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. Parallel analysis (PA), a statistically robust method compared to other criteria like the Kaiser criterion (eigenvalues greater than 1) or the scree plot (Cattell, 1966), was used to confirm the number of underlying dimensions in the outcome variable. We used confirmatory factor analysis (CFA) to generate validity evidence for latent constructs based on internal structure. CFA tests the hypothesis that the relationships between observed variables and their underlying latent constructs are consistent with a specified model (Kline, 2017). Model fit was evaluated using chi-square (χ^2) as an exact fit index, incremental fit indices like the comparative fit index (CFI; Bentler, 1990) and the Tucker-Lewis Index (TLI; Tucker & Lewis, 1973), and absolute fit indices like the Standardized Root Mean Square Residual (SRMR; Bentler, 1995) and the Root Mean Square Error of Approximation (RMSEA; Steiger & Lind, 1980). Using CFA, we estimated factor scores for the latent construct using the lavaan package in R. We employed inverse probability of treatment-weighted linear regression to estimate the average treatment effect (ATE). Finally, to assess the robustness of our analytical results to potential unmeasured confounders, we employed the Robustness of Inference to Replacement (RIR) sensitivity analysis method (Frank et al., 2013).

Results

Latent class analysis

Latent class analysis of the treatment variable revealed four underlying behavioral classes (see Table 1). Participants in the first behavioral class and the control group had moderate engagement in water conservation practices, were basic tech users, and focused on scheduling and plant selection. So, they were named *Practical Conservers* (n = 103). Participants in the second class demonstrated low engagement in water conservation practices, limited use of technology, and focused primarily on selecting plants. They were named *Disconnected Minimalists* (n = 77). Participants in the third class were highly engaged, advanced tech users, and engaged in comprehensive or diverse conservation strategies. They were named *Innovative Eco-Champions* (n = 138). Participants in the fourth class had moderate to high engagement in water conservation behaviors, and they were intermediate tech users and focused on monitoring & calibration (more irrigation system-focused). They were named *Deliberate Tech-Conservers* (n = 53).

Table 1

Latent Class Analysis Results for Water Conservation Behaviors

Class	*AIC*	*BIC*	Likelihood Ratio
2 classes	11578.16	11793.41	7179.22
3 classes	11245.42	11570.24	6790.48
4 classes	11122.82	11557.22	6611.88

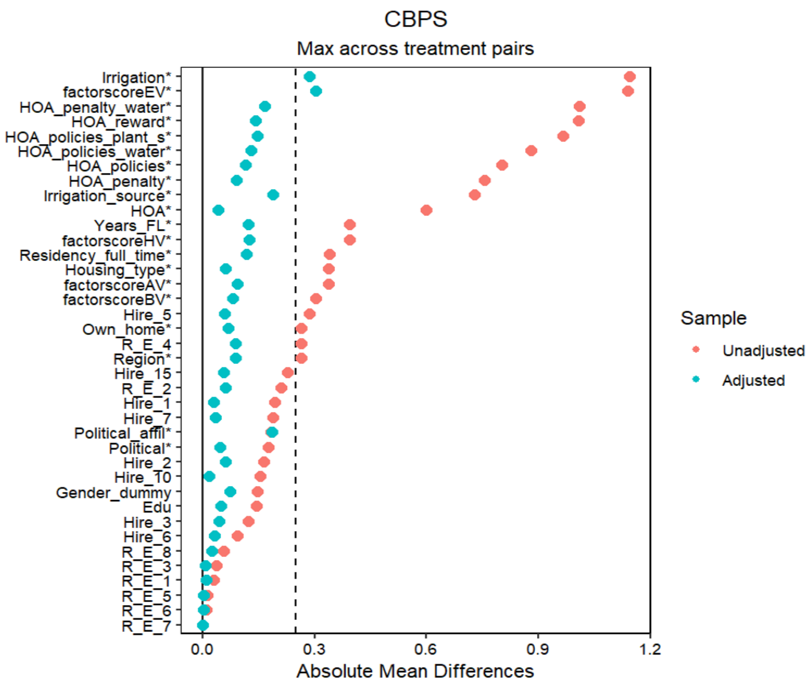
Note. *AIC* stands for Akaike Information Criterion, and *BIC* stands for Bayesian Information Criterion.

Propensity score estimation

We used CPBS and the six combinations of the three machine learning methods for propensity score estimation, along with the two weighting methods, to calculate the adjusted standardized mean difference (SMD) values for all seven methods. According to Rubin (2001), SMD values for the covariates between 0.1 and 0.25 were considered acceptable. Among the seven methods employed for covariate matching, CBPS was relatively better than the others (see Figure 1). Almost all covariates had SMD values less than 0.25, except irrigation and egoistic value.

Figure 1

Covariate Balance using CBPS



Exploratory factor analysis for the outcome variable

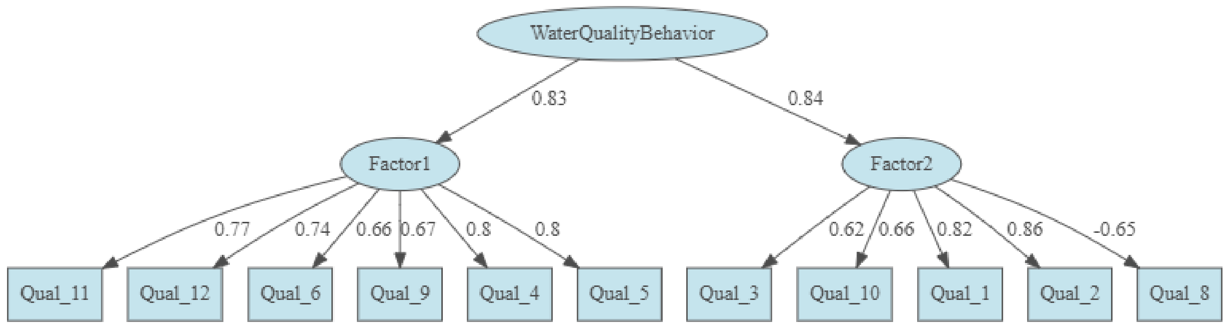
The overall measure of sampling adequacy was 0.91 for water quality protection behaviors, which was greater than the recommended threshold of 0.6 approving data for factor analysis (Kaiser, 1974), while Bartlett's test of sphericity was statistically significant (χ^2 = 5164.09, df = 55, $p < .001$), suggesting correlations among behaviors were adequately higher for factor analysis. Two factors had eigenvalues greater than 1.0, which were further validated by parallel analysis (Cattell, 1966; Watkins, 2018).

Confirmatory factor analysis for the outcome variable

After examining the dimensionality of the outcome variable, we implemented confirmatory factor analysis to calculate factor scores to use in the final regression model. The measurement model demonstrated an excellent fit. Although the chi-square test was significant ($\chi^2[42] = 462.42$, $p < 0.001$), CFI and TLI values were 0.918 and 0.893. RMSEA was 0.09, and SRMR was 0.06 (Hu & Bentler, 1995; Steiger & Lind, 1980), indicating a modest, acceptable fit. Standardized first-order factor loadings were strong and significant ($p < .001$) and exceeded 0.70 (see Figure 2), indicating strong construct measurement (Hair et al., 2019).

Figure 2.

Factor Structure of the Outcome Variable



Average treatment effect estimation

The results of the ATE estimation revealed that, compared to the latent class one (control group), individuals in latent class two did not have a significant positive effect on water quality protection behaviors (β = 0.231, p = .058). However, individuals in latent classes three (β = 0.446, p < .001) and four (β = 0.673, p < .001) exhibited a significant positive effect on water quality protection behavior. Class three, on average, had 0.446 times higher chances of engaging in water quality protection behavior compared to the control group. Similarly, class four has 0.67 times higher likelihood of engaging in water quality protection behavior (see Table 2).

Table 2.

Results of ATE Estimation

Coefficient	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.239	0.081	-3.427	<.001***
Disconnected Minimalists	0.231	0.122	1.898	.058
Innovative Eco-Champions	0.446	0.090	4.961	<.001***
Deliberate Tech-Conservers	0.673	0.116	5.801	<.001***

Note. * means significant at p = 0.05, *** means significant at p<0.001

Conclusions and Implications

Our robust methodological approach revealed a positive relationship between belonging to a group that is more engaged in conservation and engaging more frequently in water quality protection practices. These results hint that conservation practices defined as irrigation monitoring and calibration (Deliberate Tech-Conservers) have a stronger relationship, followed by Innovative Eco-Champions (who engaged in comprehensive/diverse conservation strategies), with water quality protection than other conservation measures. Extension professionals can use these findings to support their educational interventions in promoting the adoption of water quality protection behaviors among residents who own yards and make decisions about their landscapes. Specifically, our findings provide evidence about the most promising group of clients to elicit adoption of water quality protection behavior. It also assures the effective use of resources to drive community support for water quality protection behaviors.

References

Baker, R., Brick, J. M., Bates, N. A., Battaglia, M., Couper, M. P., Dever, J. A., Gile, K. J., & Tourangeau, R. (2013). Summary report of the AAPOR task force on non-probability sampling. *Journal of Survey Statistics and Methodology*, 1(2), 90–143. https://doi.org/10.1093/jssam/smt008

Bettega, F., Mendelson, M., Leyrat, C., & Bailly, S. (2024). Use and reporting inverse-probability-of-treatment weighting (IPTW) for multi-category treatments in medical research: a systematic review. *Journal of Clinical Epidemiology*, 111338. https://doi.org/10.1016/j.jclinepi.2024.111338

Bollen, K. A. (2002). Latent variables in psychology and the social sciences. *Annual Review of Psychology, 53*(1), 605. https://doi.org/10.1146/annurev.psych.53.100901.135239

Bray, B. C., Dziak, J. J., Patrick, M. E., & Lanza, S. T. (2019). Inverse propensity score weighting with a latent class exposure: Estimating the causal effect of reported reasons for alcohol use on problem alcohol use 16 years later. *Prevention Science, 20*, 394–406. https://doi.org/10.1007/s11121-018-0883-8

Cattell, R. B. (1966). The scree plot test is used to measure the number of factors. *Multivariate Behavioral Research, 1*(2), 245–276. https://doi.org/10.1207/s15327906mbr0102_10

Chesnaye, N. C., Stel, V. S., Tripepi, G., Dekker, F. W., Fu, E. L., Zoccali, C., & Jager, K. J. (2022). An introduction to inverse probability of treatment weighting in observational research. *Clinical Kidney Journal*, *15*(1), 14–20. https://doi.org/10.1093/ckj/sfab158

Courtois, É., Pariente, A., Salvo, F., Volatier, É., Tubert-Bitter, P., & Ahmed, I. (2018). Propensity score-based approaches in high dimension for pharmacovigilance signal detection: an empirical comparison on the French spontaneous reporting database. *Frontiers in Pharmacology*, 9, 1010. https://doi.org/10.3389/fphar.2018.01010

Frank, K. A., Maroulis, S. J., Duong, M. Q., & Kelcey, B. M. (2013). What Would It Take to Change an Inference? Using Rubin's Causal Model to Interpret the Robustness of Causal Inferences. *Educational Evaluation and Policy Analysis*. https://doi.org/10.3102/0162373713493129

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Organizational Research Methods, 7*(2), 191–205.

Ibtissem, M. H. (2010). Application of value beliefs norms theory to the energy conservation behaviour. *Journal of Sustainable Development*, *3*(2), 129. https://d1wqtxts1xzle7.cloudfront.net/67838851/819680c02830dc97f9fa0de83dbef9f24e75-libre.pdf?

Imai, K., & Ratkovic, M. (2014). Covariate balancing propensity score. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *76*(1), 243-263. https://doi.org/10.1111/rssb.12027

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Guilford Press.

Linzer, D. A., & Lewis, J. B. (2011). poLCA: An R Package for Polytomous Variable Latent Class Analysis. *Journal of Statistical Software*, *42*(10), 1–29. https://doi.org/10.18637/jss.v042.i10

Liu, J., Liu, Y., Zhou, Y., & Matsouaka, R. A. (2025). Assessing racial disparities in healthcare expenditure using generalized propensity score weighting. *BMC Medical Research Methodology*, *25*(1), 64. https://doi.org/10.1186/s12874-025-02508-2

Marbac, M., & Sedki, M. (2017). Variable selection for model-based clustering using the integrated complete-data likelihood. *Statistics and Computing*, *27*, 1049–1063. https://doi.org/10.1007/s11222-016-9670-1

Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*, 169–188. https://doi.org/10.1023/A:1020363010465

Setoguchi, S., Schneeweiss, S., Brookhart, M. A., Glynn, R. J., & Cook, E. F. (2008). Evaluating uses of data mining techniques in propensity score estimation: A simulation study. *Pharmacoepidemiology and drug safety*, *17*(6), 546–555. https://doi.org/10.1002/pds.1555

Taherdoost, H. (2016). Sampling methods in research methodology: How to choose a sampling technique. *International Journal of Academic Research in Management*, 5, 18–27. https://hal.archives-ouvertes.fr/hal-02546796

Warner, L. A., Diaz, J. M., Silvert, C., Hobbs, W., & Reisinger, A. J. (2021). Predicting intentions to engage in a suite of yard fertilizer behaviors: Integrated insights from the diffusion of innovations, theory of planned behavior, and contextual factors. *Society & Natural Resources, 34*(3), 373–392. https://doi.org/10.1080/08941920.2020.1831118

Warner, L. A., Kalauni, D., Diaz, J. M., Marois, E., Daniels, J. C., & Dale, A. G. (2024). Changes take place in stages! A gradational perspective on the influence of homeowners' associations on adopting wildlife-friendly landscape maintenance. *Environment and Behavior, 56*(3-4), 205–243. https://doi.org/10.1177/00139165241284741

Warner, L. A., Lamm, A. J., & Silvert, C. (2020). Diffusion of water-saving irrigation innovations in Florida's urban residential landscapes. Urban Forestry & Urban Greening, 47, 126540. https://doi.org/10.1016/j.ufug.2019.126540

Watkins, M. W. (2018). Exploratory factor analysis: A guide to best practice. *Journal of Black Psychology, 44*(3), 219–246. https://doi.org/10.1177/0095798418771807

Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent class analysis: a guide to best practice. *Journal of Black Psychology, 46*(4), 287–311. https://doi.org/10.1177/0095798420930932

Westreich, D., Lessler, J., & Funk, M. J. (2010). Propensity score estimation: neural networks, support vector machines, decision trees (CART), and meta-classifiers as alternatives to logistic regression. *Journal of Clinical Epidemiology*, 63(8), 826–833. https://doi.org/10.1016/j.jclinepi.2009.11.020

Zhao, P., Su, X., Ge, T., & Fan, J. (2016). Propensity score and proximity matching using random forest. *Contemporary clinical trials*, 47, 85-92. https://doi.org/10.1016/j.cct.2015.12.012