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Beyond Curtailment and Efficiency: Identifying Household Energy- and Water-Saving Measure Classes

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ABSTRACT

A key component of behavior-based energy conservation programs is the identification of target behaviors. A common approach is to target behaviors with the greatest energy-saving potential. The concept of behavioral spillover introduces further considerations, namely that adoption of one energy-saving behavior may increase (or decrease) the likelihood of other energy-saving behaviors. Thus, the total impact of correlated measure classes could be an important consideration when selecting target behaviors. Understanding the unique drivers and barriers for different measure classes can also support more efficient and effective interventions. However, current understanding of measure classes is limited.

This research aimed to identify household energy- and water-saving measure classes, within which positive spillover is likely to occur (e.g., adoption of energy-efficient appliances may correlate with adoption of water-efficient appliances). Nearly 1,000 households in a California city were surveyed and asked to report whether they had adopted 75 different energy- and/or water-saving measures. Cluster analysis based on correlations between adoption of these diverse measures revealed eight water-energy-saving measure classes: Water Conservation; Energy Conservation; Maintenance and Management; Efficient Appliance; Edge of Efficiency; Efficient Irrigation; Green Gardening; and Green Landscaping. Understanding these measure classes can help guide behavior-based energy program developers in selecting target behaviors and designing interventions. For example, a series of energy reports could focus on one measure class at a time, each report promoting multiple measures within a given class and particularly highlighting high-leverage, “gateway” measures, i.e., those most correlated with others in the class.

Introduction

Over the last decade, behavior change interventions have been increasingly called upon to help reach energy conservation goals. These interventions are often aimed at the residential sector. Research suggests household behavior changes, combined with energy-efficient technologies, could reduce total US residential energy consumption by up to 20% (Franckel, Heck, and Tai 2013). Attempting to capture such potential, utilities across the United States have adopted behavioral programs for residential customers, such as home energy reports (Consortium for Energy Efficiency 2018).

A key component of behavioral interventions is the identification of target behaviors. Some research suggests interventions should target one or more specific behaviors (Ignelzi et al. 2013; McKenzie-Mohr 2011). The question then becomes: Which ones? There could be many from which to choose. For example, Boudet, Flora, and Armel (2016) identified 261 behaviors that impact household energy consumption. A common approach is to target behaviors with the greatest environmental impact (Gardner and Stern 2009; Hawkin 2017; Wynes and Nicholas 2017). Stern (2011) also advises consideration of behavioral plasticity, which is the likelihood that individuals will adopt a given behavior.

The concept of behavioral spillover introduces further considerations for target behavior selection. Behavioral spillover is defined as “the extent to which engaging in one behavior influences the probability of conducting a subsequent behavior” (Nilsson, Bergquist, and Schultz 2017; 574). In the realm of behavior-based energy programs, spillover implies that an intervention targeting one energy-related behavior may increase or decrease the likelihood of others (i.e., positive and negative spillover, respectively; Thøgersen and Crompton 2009; Truelove et al. 2014). For example, Steinhorst, Klockner, and Matthies (2015) found that tips for reducing electricity use framed around environmental benefits led to intentions to perform pro-environmental behaviors in other domains (positive spillover). On the other hand, Bratt (1999) found evidence that recycling was used as a rationale for driving one’s car more (negative spillover).

Depending on the magnitude of these effects in real-world contexts, spillover could have significant implications for the design and evaluation of behavior-based energy programs. If some behaviors reduce the likelihood of others, net impacts of an intervention could be nil or negative, and evaluations that focus only on the targeted measure or on energy consumption data may not reveal the whole story. On the other hand, the ability to identify and target “gateway” behaviors prone to positive spillover could help program designers nudge consumers toward adopting suites of energy-saving measures. Interventions that trigger positive spillover could increase cost-effectiveness (Jessoe et al., 2017) and warrant increased investment (Truelove et al., 2014).

Thus, rather than prioritizing single, high impact behaviors, it might be more fruitful to consider the total impact of classes of related behaviors within which positive spillover is likely to occur. Nilsson, Bergquist, and Schultz (2017) argued: “If positive spillover can be reliably elicited, behaviors with small effects should not be ignored since they have the potential to influence other behaviors with more substantial effects on the environment” (574). Similarly, the total impact of a large class of low impact measures could be greater than that of a small class that includes some high impact measures.

Understanding distinctions between energy-saving measure classes in terms of their potentially unique drivers and barriers can also contribute to more effective and efficient interventions. For example, different demographic and psychographic profiles predict adoption of different kinds of energy-saving measures (e.g., Karlin et al. 2014). Layering more traditional market segmentation approaches with behavior segmentation (i.e., dividing behaviors into classes based on their relationships and characteristics) could support more tailored strategies.

The present research aimed to identify classes of household energy- and water-saving measures within which positive spillover is likely to occur. Household survey research in conjunction with a home water report (HWR) program in a city in Riverside County, California, collected data on self-reported engagement in 75 household energy- and water-saving measures. Measures frequently co-adopted by reporting households were identified as measure classes within which positive spillover might occur. Temporal relationships between adoption of measures within a class were not considered, but will be an important area for future research.

Background

While the behavioral mechanisms responsible for spillover are still not well understood (Nilsson et al., 2017), research and theory generally suggest positive spillover is more likely to occur amongst "similar" behaviors (Bratt 1999; Margretts and Kashima 2017; Nilsson, Bergquist, and Schultz 2017; Thøgerson and Crompton 2009; Whitmarsh and O'Neil 2010; Truelove et al. 2014). Behaviors can be similar in terms of a number of attributes, such as where and when they occur, resources required, and function. Attributes can be real or perceived, universal or idiosyncratic. A consistent understanding of what constitutes similar behavior in the context of behavioral spillover (i.e., what types of similarity predict positive spillover) is lacking.

Understanding Behavioral Similarity

Margretts and Kashima (2017) suggested that the resources required to perform behaviors may strongly determine behavioral similarity in the context of spillover, with spillover being more likely to occur between behaviors requiring similar resources (e.g., money as opposed to time or effort). Thøgersen and Olander (2003) suggested that a common goal across multiple behaviors might be the most important factor involved in spillover. Truelove et al. (2014) also seem to define the kind of behavioral similarity that leads to positive spillover as behaviors with a common goal.

The concepts of response generalization and response classes from the field of behavior analysis (Cooper, Heron, and Heward 2007; Stokes and Baer 1977; Stokes and Osnes 1989) may be useful in furthering understanding of behavioral similarity, and thus of spillover. A response class is a group of behaviors that have the same function (i.e., are functionally related to common antecedents and consequences). When one behavior in a response class is reinforced, the others also become more likely to occur in the future (this is the process of response generalization).

Thus, response generalization depends on an individual's history of reinforcement. Environmentally-relevant response classes will be different across individuals to the extent that the social and instrumental consequences of those responses have differed in each person's experience. However, many consequences will be similar, especially within a shared culture. Thus, though response classes are idiosyncratic, there are likely to be general response classes that are common across many individuals.

Response generalization could occur across any and all pro-environmental behaviors since they all share a function of protecting the environment. Truelove et al. (2014) noted that those with more environmental knowledge might perceive similarity across more behaviors compared to those with less environmental knowledge. However, pro-environmental behaviors also have more immediate and personal consequences, compared to the indirect and long-term consequence of protecting the environment, and these will also influence the development of response classes. For example, curtailment of energy or water use in the home could mean sacrifices in preferred hygiene, comfort, or entertainment habits.

Classifying Environmentally Relevant Behaviors

Several approaches have been taken to classify environmentally-relevant behaviors into categories of similar measures that could also be considered response classes within which positive spillover is likely to occur. One approach is to deduce categories based on an analysis of behavioral attributes (e.g., Boudet, Flora, and Armel 2016; Ignelzi et al. 2013; Sanguinetti, Kurani, and Davies 2017). Another approach is to assess consumers' perceptions about behavioral similarity (e.g., Kneebone et al. 2018, Thøgersen and Olander 1999; Olander and Thøgersen 2000). A third approach, which is taken in the present research, is to infer classes of similar behavior and important behavioral attributes based on actual or reported behavior (e.g., Gatersleben, Steg, and Vlek 2002; Karlin et al. 2014; Thøgersen and Olander 2003).

Boudet, Flora, and Armel (2016) provided the most comprehensive example of the deductive approach. They considered nine behavioral attributes in their classification of over 260 household energy-saving measures, based on social and behavioral theory: household function (e.g., thermal comfort, hygeine, entertainment), cost, energy savings, frequency, skill required, observability (visibility to others), locus of control (who can engage in the behavior), and home and appliance topography (where the behavior occurs and with what appliance). Using cluster analysis, they identified four measure classes based on their common attribute profiles: family style, call an expert, household management, and weekend projects.

Kneebone, Fielding, and Smith (2018) provided an example of an inductive approach to classification based on consumers' perceptions of household water-saving measures. Rather than using theoretically-derived attributes to classify measures, they asked consumers to sort 44 water-savings actions into groups and explain their rationale. Multidimensional scaling analysis was used to identify three classes of similar behaviors based on how often they co-occurred in participants' groupings; these were: mostly indoor curtailment or habitual behaviors, outdoor garden and plant-related behaviors, and efficiency and maintenance behaviors. An additional eight subgroups of behaviors were identified, characterized by attributes such as behavior type, location, ease of participation, behavioral goal, and personal practices or preferences.

The inductive approach, taken in the current study, is to arrive at measure classes by assessing what consumers actually do (or say they do), then characterize the classes, e.g., by defining attributes. Karlin et al. (2014) used this method in their survey research. They asked respondents to self-report engagement in eight household energy-saving measures. They used principal component analysis to identify two factors that best explained the variance in these eight energy-saving practices: curtailment/conservation behaviors (no cost habits and maintenance measures) and efficiency investments (some cost, low frequency).

Present Research

The systematic classifications reviewed above were limited to either energy- or water-saving behaviors. However, water and energy use often overlap in the home and spillover between the two would seem reasonable. For example, in a recent study in Burbank, California, an intervention consisting of home water reports (HWR) with feedback on water consumption and tips about water conservation led to reductions in both water and electricity consumption, despite the fact that electricity-consuming behaviors were not targeted in the reports (Jessoe et al., 2017). Only 26% of the electricity savings could be explained by water conservation activities (e.g., running only full loads in the dishwasher), which suggests there was spillover to non-water-related energy-saving measures.

The study reported in this paper was part of a follow-up to the study reported in Jessoe et al. (2017). It aimed to further explore the potential for positive behavioral spillover among household water and energy saving measures. This was accomplished through extensive survey research in conjunction with implementation of the WaterSmart, Inc. HWR report program in a city in Riverside County, California. The first objective of the research, which is the focus of this paper, was to identify classes of water- and/or energy-saving measures within which spillover would be likely to occur. Further exploratory analyses of identified potential gateway measures, i.e., those particularly likely to lead to spillover within and between classes. It was hypothesized that some identified measure classes would include both water- and energy-saving measures, indicating how spillover from water- to energy-saving measures, or vice versa, can occur, e.g., as a result of a HWR program.

Method

This section briefly reviews the HWR intervention, as background information, followed by a detailed description of the post-treatment survey used to identify measure classes. See Popovich et al. (2018) for a full description of the intervention and analysis of water and energy consumption data. Finally, analysis methods are discussed.

Smart Water-Energy Savings Project

The Center for Water-Energy Efficiency at University of California, Davis, partnered with WaterSmart Software, Inc. on a HWR project in two California cities. This project, called Smart Water-Energy Savings, aimed to quantify both water and energy savings associated with the HWR program. The current research focuses on just one of the cities, in Riverside County.

The HWR program ran from September 2016 to November 2017. Only single-family households with at least one year of observable water usage history at their current residence were eligible. Out of 56,000 eligible households, 14,359 were randomly assigned to HWR treatment, leaving 38,751 households as the control group. Treatment households were randomly assigned to two groups: WaterSmart and Hot WaterSmart. The latter added a focus on hot water savings, which was hypothesized to lead to greater energy savings from natural gas.

The WaterSmart HWR program features customized reports delivered by mail or email, and an online portal where residents can learn more about their water use and ways to save. Each report included feedback about past water consumption and tips on how to conserve water in the future. WaterSmart Software, Inc. keeps a library of tips and determines which tips each household receives (e.g., if they know a household has a pool, they may give pool-related water-saving tips). The authors of this research were provided with the tip library but not information about which tips each household received.

Post-Treatment Survey

This research focuses on data from a survey of both treatment and control households after the end of the year-long HWR program. The survey featured questions assessing self-reported engagement in 75 water- and/or energy-saving measures. These data were used to identify measure classes (looking across the whole sample), regardless of whether measures were adopted before or during the HWR program. The 75 measures assessed included many of the water-saving (including hot water-saving) measures promoted in the HWRs, as well as energy-saving measures that were representative of the different measure classes identified in previous research, particularly Boudet, Flora, and Armel (2016).

To avoid overwhelming participants, questions used a checklist response option format and were presented in multiple sets based on household topography, using two prompt formats: one directed at actions (43 measures) and the other at investments (36 measures). For actions, four items read: Which actions do you regularly take (1) at home; (2) while bathing/grooming;

(3) in the kitchen; (4) in your yard (if they had one)? For investments, two items read: Which [energy-; water-] saving investments/measures do you have in (1) your home; (2) your yard? Participants were instructed to mark all that apply and response option order was randomized except for a “None of the above” option, which was always displayed last.

The online survey was distributed via email when an email address was available, and otherwise an invitation sent by postal mail. The treatment group’s version of the survey included questions about HWRs, whereas the control group’s version did not. Only one response per household was allowed. Each participant received a $20 Starbucks gift card. Out of 5,703 households recruited, 976 surveys were completed (a 17% response rate).

Analysis

Energy- and water-saving measure classes were identified using principal component analysis (PCA) with Promax oblique rotation. PCA is a statistical method to reduce complex datasets into fewer core components, or factors, based on underlying patterns in the data. Household water- and energy-saving measures frequently selected by the same respondents loaded most strongly onto a common factor. PCA has been previously used in spillover and behavior segmentation work (Karlin et al. 2014; Kneebone, Fielding, and Smith 2018; Whitmarsh and O’Neil 2010). Promax is an oblique rotation method that allows for correlation between factors (as opposed to an orthogonal method than assumes uncorrelated factors). Measures were assigned to the class(es) for which they had a factor loading above .32; measures with no factor loadings above .32 were not assigned to a class (threshold suggested by Tabachnick and Fidell 2001).

The PCA was based on the correlation matrix of binary responses for the 75 energy- and water-saving measures (0 = not checked; 1 = checked) across the combined survey sample of control and HWR treatment households (both water-saving and non-water-saving). Respondents were excluded if they did not have a yard, since that would influence the yard-related measures to load onto a common factor. The final sample was 878.

Resultant measure classes are defined and described in relation to each other in terms of common behavioral attributes. The nine attributes defined in Boudet, Flora, and Armel (2016) were considered (adapted to be inclusive of water-saving measures), as well as the concept of resources required (Margetts and Kashima 2017; also adapted to include tools). Table 1 describes these attributes. We assessed which attributes helped define each measure class and which did not (i.e., where there was diversity among measures in a given class). These descriptions were formed inductively and qualitatively rather than using predefined attribute levels and coding.

Table 1. Behavioral attributes of energy- and/or water-saving measures

Attribute	Description
Resources Required	Objective, quantifiable resources (money, tools, effort/time)
Savings	Water and/or energy savings potential
Cost	Purchase price for investment measures
Frequency	How often the measure is likely to be performed
Skill Level	Amount of ability for an adult to perform (e.g., possible without reading instructions, skill with tools, need expert)
Observability	Degree to which others notice that the measure is performed
Locus of Decision	Household member(s) who can make the decision to adopt

Attribute	Description
Household Function	Service provided (e.g., comfort, hygiene, nourishment)
Home Topography	Where in the home or property it occurs
Appliance Topography	Relation to appliance category (e.g., large electric, water taps)

Source: Adapted from adapted from Boudet et al. (2016) and Margretts & Kashima (2017).

Results and Discussion

The PCA converged in nine iterations to reveal eight factors underlying self-reported participation in water-energy-saving measures. PCA was appropriate for the dataset per Kaiser-Meyer-Olkin Measure of Sampling Adequacy (= .848) and Bartlett's Test of Sphericity ($p <$ .0001). The criterion for factor selection was an Eigenvalue greater than 1.5. The value of 1.5 was selected because using an Eigenvalue criterion of 1 yielded too many factors (24) and Eigenvalue = 2 yielded too few (3 factors). We ran the same analysis on respondents from the HWR control group separately to ensure resultant classes from the full sample were not substantially influenced by the program; results were similar, so we completed analysis with the full sample. We named the measures class as follows (with Eigenvalues): Efficient Appliance (8.24), Maintenance & Management (3.33), Water Conservation (2.42), Efficient Irrigation (2.00), Green Landscape (1.87), Green Gardening (1.66), Energy Conservation (1.64), and Edge of Efficiency (1.50).

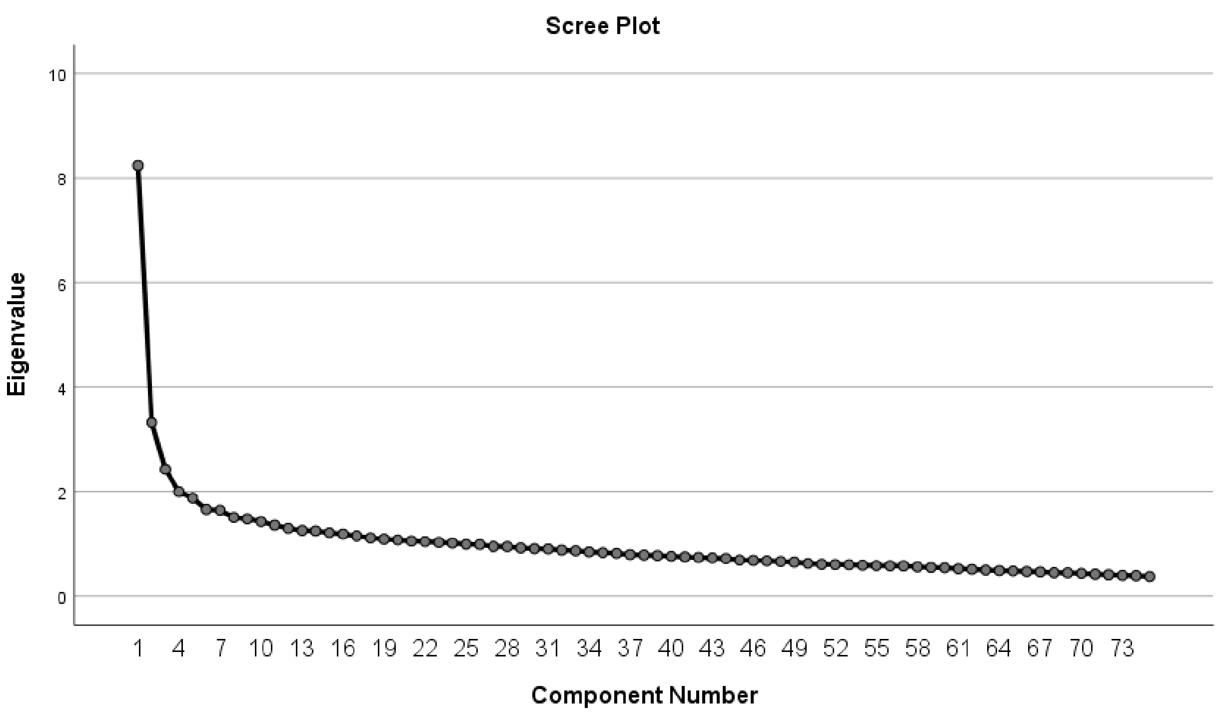

Figure 1. Scree plot from the PCA

Forty-five measures had a factor loading of at least .32 and thus were categorized as part of a measure class (per threshold given in Tabachnick and Fidell 2001). Two measures (drip irrigation and reusing boiled water) loaded onto multiple classes (two each). This leaves 30 measures that did not load strongly enough onto a factor to be categorized in a measure class. This is disappointing from one angle, because some uncategorized measures (e.g., turn off computers when not using) seem similar to measures that did load highly on one of the eight factors (e.g., turn TV off when not using) and we do not know why. On the other hand, it narrows the focus down to measures with the most implications for spillover.

In support of the study hypothesis, several of the identified measure classes contain both energy- and water-saving measures (Maintenance & Management, Water Conservation, Energy Conservation and Edge of Efficiency). Table 2 shows the rotated component matrix, including all behaviors and their factor loadings (i.e., correlation with each identified measure class), as well as frequency with which participants reported adopting them. Measures with the highest factor loadings are most indicative of a class (i.e., overall most strongly correlated with other measures in the class). Thus, these are potential intraclass "gateway" measures that, when adopted, might be most likely to lead to positive spillover to other measures in the same class. For example, checking for thermal leaks was most representative of Maintenance & Management, and would likely be the highest leverage measure to target in an intervention promoting multiple Maintenance & Management measures. We hypothesize that the more common measures within a given class may precede the less common measures, but future research is needed to explore the temporal relationships between adoption of different measures within a measure class.

Table 2. PCA results: Factor loadings of each measure onto each measure class

Water- and/or Energy-Saving Measure	Frequency (%)	Efficient Appliance	Maintenance & Management	Water Conservation	Efficient Irrigation	Green Landscaping	Green Gardening	Energy Conservation	Advanced Efficiency
ENERGY STAR TV	63	.82	-.03	.08	-.04	-.19	.01	-.02	.09
ENERGY STAR refrigerator	68	.76	-.10	.11	-.02	-.06	.00	-.01	.05
ENERGY STAR dryer	63	.76	-.11	.08	-.04	-.06	-.04	.06	.06
ENERGY STAR computer	42	.71	-.02	.07	-.01	-.03	.02	-.06	.03
Check for thermal leaks	28	-.18	.72	.06	-.01	-.16	.05	.03	.10
Caulk/seal doors/windows/baseboards	36	-.11	.71	-.02	.03	-.03	.00	.06	-.03
Check for shower/faucet/toilet leaks	75	.02	.54	.00	.14	-.09	-.01	.03	-.20
Weather-stripping on doors/windows	43	.18	.51	-.19	-.06	.16	.05	.00	-.06
Clean refrigerator coils	29	-.01	.50	.17	.02	-.06	.02	-.11	.16
Clean light bulbs	28	-.05	.41	.27	-.03	-.07	-.08	.04	.14
Low-flow faucet aerator(s)	32	.20	.35	.01	-.07	.29	.02	-.12	-.08
Set water heater temperature to 120°F	39	-.04	.33	.04	.14	-.08	.06	.15	.15

Water- and/or Energy-Saving Measure	Frequency (%)	Efficient Appliance	Maintenance & Management	Water Conservation	Efficient Irrigation	Green Landscaping	Green Gardening	Energy Conservation	Advanced Efficiency
Turn off water while soaping hands	36	.05	-.08	.65	-.01	.14	.01	-.07	.01
"…" when scrubbing fruits and veg.	51	.11	-.03	.60	.06	.05	.05	.02	-.08
"…" while scrubbing face/hair/body	38	-.07	-.02	.54	.05	.17	-.07	.01	.13
"…" while scraping/scrubbing dishes	68	.04	.04	.54	.02	.03	.01	.07	-.10
"…" while shaving	55	.15	.11	.54	.09	.13	-.12	-.07	-.05
"…" while brushing teeth	85	.15	-.05	.45	.18	.04	-.01	.08	-.26
Take short showers (5 minutes or less)	52	.10	.06	.36	-.08	.03	.04	.06	.15
Reuse cooking water after boiling (e.g., to water plants)	21	-.03	.01	.33	.00	.13	.33	-.08	.02
Check for irrig. system/sprinkler leaks	64	-.04	.07	.03	.71	-.01	-.04	.07	-.06
Trim plants around sprinkler heads	59	.00	.13	.02	.68	-.15	.01	.02	-.08
Rotating sprinkler heads	30	-.06	.10	.02	.66	-.05	-.05	-.24	-.12
Adjust irrig./sprinkler timer monthly	42	-.01	.01	.08	.64	-.09	-.05	-.04	.14
Multiple irrig./watering start times	40	-.05	-.11	-.04	.59	.15	.04	.10	.17
Weather-based irrigation controller	9	.06	-.10	.09	.37	.04	-.07	-.23	.27
Water only at dawn or dusk	80	.09	-.13	-.03	.34	-.13	.14	.29	-.15
Drip irrigation	26	-.06	-.20	-.06	.32	.45	-.02	.04	.17
Changed grass to native plants	14	-.12	-.08	.13	-.20	.77	.12	.08	-.05
Replaced high water use plants…	30	-.05	-.12	.16	-.02	.72	.13	.05	-.15
Replaced lawn with artificial turf	3	-.08	.08	.06	.00	.49	-.33	-.08	-.08
Mulch leaves and leave in yard…	25	-.02	.08	-.05	-.15	.02	.71	.02	.09
Compost grass/leaves/food…	23	-.03	-.10	.09	-.05	.08	.66	-.02	.12
Put mulch at base of tree/bush/shrub	29	.10	-.05	-.07	.00	.28	.60	-.02	-.10
Mulching lawnmower	15	.05	.12	-.10	.07	-.09	.57	-.14	.03
Water diff. plants according to needs	63	-.14	.07	.06	.12	.17	.32	.21	-.09
Turn AC down/off at night in summer	79	-.07	-.12	.07	-.10	.21	.03	.57	.13
Turn heat. down/off at night in winter	75	-.11	.02	-.02	.08	.08	-.08	.51	.12
Turn off TV when not in use	94	.01	.08	.18	-.12	.07	-.18	.39	.06
Fully load clothes washer	86	.07	.07	-.04	-.08	-.10	.10	.38	-.05
Reuse bath towels	88	-.06	.10	-.20	.01	.10	.08	.33	-.21
Tankless water heater	6	.11	-.12	-.03	-.15	-.11	.03	.10	.63
Hot water recirculation pump	6	-.01	.04	.04	.10	-.13	.07	-.15	.54
Water displacement device in toilet(s)	11	.04	.11	.05	-.01	-.09	.12	.01	.44
Smart thermostat	26	.14	-.05	-.06	.00	.22	-.06	.11	.34

Water- and/or Energy-Saving Measure	Frequency (%)	Efficient Appliance	Maintenance & Management	Water Conservation	Efficient Irrigation	Green Landscaping	Green Gardening	Energy Conservation	Advanced Efficiency
High-efficiency showerhead	48	.31	.22	.07	-.01	.24	-.01	-.01	-.08
High-efficiency toilet	46	.29	-.01	.02	-.05	.30	.02	.12	.13
LED lights	70	.25	-.03	-.01	.00	.19	.00	.05	.08
Dryer with sensor	41	.21	.05	-.14	.11	.02	.06	.02	.17
Insulation around hot water tank	29	.13	.30	-.06	-.01	.21	.11	-.10	.03
Clean/replace A/C filters	78	.13	.30	-.06	.13	.03	-.15	.21	-.06
Insulation around hot water pipes	23	.10	.24	-.10	.03	.10	-.07	.02	.31
High-eff. or double-paned windows	46	.18	.24	-.24	-.01	.17	.02	.06	-.06
Water pressure regulator valves	28	.15	.24	.00	.07	.08	.09	-.10	.15
Insulation in walls, ceilings, roof, attic	59	.13	.23	-.08	.07	.17	-.01	.07	.06
Use broom instead of hose to clean driveways/walkways/decks/patios	77	-.04	.22	.24	.00	.06	.02	.22	-.13
Use cloth instead of hose to clean lawn furniture/outdoor toys/sports eq.	44	-.10	.23	.22	-.04	.00	.03	.21	.11
Capture cold water while wait. for hot	10	-.03	.03	.22	-.01	-.04	.24	-.03	.21
Stop watering when it rains	89	.11	-.11	.09	.30	-.24	.17	.22	-.02
Ensure water isn't running onto pave.	70	.04	.06	.15	.23	.06	.09	.30	-.08
Hose faucet timer	9	-.08	.10	-.06	.23	.00	.15	-.22	.09
Graywater system	2	-.11	.03	.19	.02	.30	.00	-.29	-.02
Permeable pavement	5	.00	.02	.15	-.06	.30	.02	-.10	-.01
Solar-powered garden lights	26	.03	.04	-.08	.03	.27	.09	.03	-.08
Rainwater catchment system	5	.03	.04	.15	.11	.20	.16	-.30	-.08
Soil moisture system	1	-.15	.10	.06	.08	.13	-.04	-.24	.17
Check soil moisture before watering	28	-.03	.13	.10	.09	-.13	.28	.14	.20
Turn off lights when leaving room	95	.08	.03	.22	.02	.02	-.14	.30	-.07
Close refrigerator door quickly	89	.05	.16	.14	.02	-.08	-.09	.29	-.02
Cover pots and pans when cooking	81	-.13	.30	.12	-.11	-.02	.04	.28	-.04
Fully load dishwasher	55	.00	-.03	-.24	.21	.16	-.09	.22	.20
Turn off computers when not in use	73	.05	.15	.29	-.09	-.13	-.08	.20	.09
Motion sensor/dimmer/timer for lights	32	.01	.06	-.08	.16	.02	.08	-.04	.31
Whole house fan	25	.08	.13	.02	-.05	-.08	.13	.04	.25
Air dry laundry	40	-.10	-.07	.26	-.05	-.05	.16	.04	.16

Table 3 presents an overview of how the behavioral attributes used by Boudet, Flora, and Armel (2016) to categorize household energy-saving measures are useful in defining the measure classes identified in the PCA. Checked cells indicate a common attribute and empty cells indicate diversity within the measure class. Some classes are homogenous in terms of many attributes, while others are characterized by fewer common attributes. For example, Efficient Appliance measures require a common resource (money); have relatively high potential savings; are relatively expensive, infrequent, low skill, and observable; and are generally available only to adult household members. On the other hand, Edge of Efficiency measures (smart thermostat, tankless water heater, hot water recirculation pump and toilet tank water displacement device) are infrequent measures taken by adults only, and beyond that they have little in common. This class seems to showcase appliances at the next level of innovation in energy or water efficiency, as well as more obscure add-on measures. This might be indicative of a special type of required resource: knowledge of the existence of the measures. This is speculation that should be explored in future research.

Table 3. Behavioral attribute analysis of water-energy-saving measure classes

	Resources required	Energy and/or water savings	Cost	Occurrence frequency	Skill	Observability	Locus of decision	Household function	Home topography	Appliance topography
Edge of Efficiency				X			X			
Efficient Appliance	X	X	X	X	X	X	X			
Maintenance & Management	X		X			X	X			
Energy Conservation	X	X	X	X	X	X	X			
Water Conservation	X	X	X	X	X	X	X	X	X	X
Efficient Irrigation							X	X	X	X
Green Gardening							X	X	X	X
Green Landscape	X	X	X	X	X	X	X	X	X	X

Limitations to this study include a focus on positive *intra*class spillover. The PCA focused on identifying categories of oft-co-occurring measures, and did not explore negative spillover or *inter*class spillover (between identified measure classes). Another limitation is that we did not assess all energy-water-saving measures identified in prior research (e.g., Boudet, Flora, and Armel 2016). For example, we did not include ENERGY STAR dishwasher or clothes washer, which might have loaded with Efficient Appliance and proved it to be another category that includes both energy- and water-saving measures. Future research to confirm and extend the eight identified measure classes is crucial to continue to build knowledge in this yet relatively underexplored area of energy behavior segmentation and spillover.

Conclusion

This research builds on prior energy behavior segmentation and spillover research by classifying 75 energy- and/or water-saving measures into eight correlated measure classes within which positive spillover is likely to occur. Past important work in this area has included deductive classifications of large sets of energy measures (Boudet, Flora, and Armel 2016) and inductive classifications of relatively limited sets of measures (e.g., Karlin et al. 2014). This research attempted to blend both approaches by taking an inductive approach with a larger set of measures. Our classification confirms the importance of previously defined behavioral attributes (e.g., frequency, skill, cost) in determining the kinds of behavioral similarity that underlie spillover, but highlights how different attributes are more or less useful in defining different categories. Thus, the weighting of various attributes when deductively determining these response classes is difficult to predetermine and more inductive research is required to continue to build our understanding of pro-environmental response classes.

The findings suggest that people tend to concentrate their household energy- and/or water-saving efforts within some measure classes and not others. Understanding these measure classes can help guide behavior-based energy program developers in selecting target behaviors and designing interventions. For example, a series of energy reports could focus on one measure class at a time, each report promoting multiple measures within a given class and particularly highlighting high-leverage, “gateway” measures, i.e., those most correlated with others in the class. Additionally, if program developers collect data on baseline behavior, they could identify measures that their target audience is more likely to adopt (i.e., from classes within which they have already adopted some but not all measures). Furthermore, efforts to identify motivations, barriers, and supports for each unique measure class can support more efficient and effective interventions. Overall, understanding energy-saving measure classes can enable strategic selection of target behaviors and support more tailored and cost-effective programs.

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