Bridging the gap between sustainable technology adoption and protecting natural resources:

Predicting Intentions to Adopt Energy Management Technologies in California

Keywords

energy management technology; smart grid; technology adoption; behavior change

Abstract

To achieve energy savings, emerging energy management technologies and programs require customer adoption. Although a variety of models can be used to explain the adoption of energy management technologies and programs, they overlook the seemingly unconventional element of level of affiliation with nature. In fact, connectedness to nature has been identified as an important driver of many pro-environmental behaviors, but its role in pro-environmental technology adoption is also not well understood. Can affiliation with nature help to bridge the apparent gap—and complex chain of events—between sustainable technology adoption and protecting natural resources? Based on survey data from 856 southern California residents, this study investigated the influence of connectedness to nature and other factors on intentions to adopt five energy management technologies and programs: using three platforms to monitor home energy use (website, mobile phone application, in-home display); signing up for a time-of-use pricing plan; and participating in demand response events. Regression results showed that nature connectedness was the strongest predictor of all outcomes such that higher nature connectedness predicted greater likelihood of technology and program adoption. These findings suggest that connectedness to nature may facilitate “bridging the logic gap” between sustainable innovation adoption and environmental protection.

1 Introduction

A great deal of energy research focuses on technology fixes, with a much smaller portion (i.e., 2.2%) dedicated to understanding end user behavior (Sovacool, 2014). For instance, global investment in smart grid technologies was \$14.9 billion in 2013 (Bloomberg, 2014). Among other hardware and software upgrades, electricity meters that collect near real-time consumption data (“smart meters”) are key components of smart grid systems. In 2015, over 622 million smart meters were installed, a 15% increase from 2014 (International Trade Administration, 2016).

Despite their prevalence, smart meters alone will not save energy. However, they have expanded the variety of technologies and programs that utilities can offer directly to residential customers. Hence, to maximize energy savings, smart grid technologies require customer adoption and proper use (Ingle et.al, 2014). Although utilities already use a variety of approaches to involve customers in power systems, as has been pointed out previously (Sintov & Schultz, 2015), customers are often not the central consideration in technology or program design. Resonating with a key lines of inquiry in the field of energy research and social sciences as highlighted in Sovacool (2014), we argue that a better understanding of how people make decisions about energy use and energy technologies is urgently needed.

Focusing on end user decision-making, the present study investigates novel factors that influence decisions to adopt smart grid-enabled energy management technologies. Addressing additional key research themes, specifically, ways of leveraging energy technologies in new communication strategies and behavioral change approaches (Sovacool, 2014), findings can help practitioners to plan strategic rollouts of new programs using targeted marketing approaches, improve framing of energy feedback, and enhance adoption rates of such technologies and programs to maximize energy savings.

1.1 Smart Grid-Enabled Energy Management Technologies and Programs

Although in isolation, smart meters alone will not generate savings, smart grid infrastructure enables two-way data communication between utilities and customers. This ability to interact with customers in real time offers one key route for engaging customers. Additionally, the savings that can be achieved via new voluntary pricing (e.g., time of use) and demand response programs depends in part on program enrollment, and hence customer adoption of such programs. Below we review select smart grid-enabled energy management approaches commonly offered by electric power utilities and factors relevant to their adoption.

1.1.1 Demand Response Programs

The United States (U.S.) Federal Energy Regulatory Commission (FERC) characterizes demand response as a “bottom-up process...driven by changes in customer behavior” (2009). Although demand response forecasting models predict when, where, and how much energy will be used, solving the key problem of managing peak demand requires programs that encourage electric customers to make behavioral changes. Such programs can be effective in promoting overall energy conservation, with home energy savings as high as 21% (Ehrhardt-Martinez et al., 2010).

The most common type of demand response program is voluntary curtailment, which involves appealing to customers to temporarily curtail consumption by changing behavior in real time in response to alerts. However, program enrollment is a critical barrier to participation in both direct control and voluntary curtailment programs. Overcoming this barrier is not trivial. Current demand response program participation rates are estimated at less than 10%, and actual compliance rates are likely lower (FERC, 2009). Achieving the load reduction objectives of the coming decades will require increasing levels of customer engagement. Toward this end, utility-customer connectivity must be enhanced. Identifying

customers who are more willing to participate in these programs is a key step in tailoring marketing efforts.

1.1.2 Time-of-Use Pricing

Another method utilities can use to reduce peak demand is variable pricing plans. For instance, time-of-use pricing plans aim to discourage energy use during peak times of the day by charging higher rates during high-use periods (typically mid-afternoon hours) and lower rates during off-peak hours. Under time-of-use pricing programs, energy consumption tends to shift to off-peak hours, but the total consumption generally does not decrease (Lutzenhiser et al., 2007). Using financial (dis)incentives as a form of stimulus control, these programs attempt to shape customers' peak energy use, specifically by punishing (with higher prices) on-peak use and reinforcing (with lower prices) off-peak use (Skinner, 1953). A large body of research has shown that rewards can be effective in promoting behavior change, especially while incentives are in place, and rewards have been effective in reducing home energy consumption below baseline use levels (Walker, 1979; Winett et al., 1979) as well as below levels of information-only and control groups (Midden, 1983; Winett et al., 1979). Currently, most time-of-use pricing plans in the U.S. are voluntary, and similar to demand response voluntary curtailment programs, adoption rates remain low. As indicated by a nationwide survey conducted among utility providers in 2010 (FERC, 2011), only about 1% of residential consumers have enrolled in time-of-use pricing rate programs.

1.1.3 Energy Feedback

With the high-resolution data recorded by smart meters, utilities have advanced from providing energy feedback as part of monthly (or even annual) billing to providing near real-time data that can enhance relatability. Such energy feedback can be quite effective in changing residential energy use behavior. A wealth of research on residential electricity conservation interventions, including a meta-analysis of 156 field studies leveraging feedback

and information (Delmas et al., 2013), has shown that households can use 5-10% less direct energy without adversely impacting occupant comfort or well-being (Dietz et al., 2009). Considering that these direct energy savings do not reflect the obviation of upstream power losses at the power plant (~60-70% loss) or transmission and distribution (up to 10% loss) levels, they are actually conservative estimates—meaning changing household behavior can result in even higher savings. In addition, as noted above, smart meters can offer high resolution (15-minute interval) feedback, which better enables customers to connect their usage data to their behaviors, and to make more informed decisions about their actions. This also encourages conservation, and higher resolution feedback has been associated with greater levels of energy conservation (Ehrhardt-Martinez et al., 2010).

Smart meter data can be made available to customers through a variety of platforms, including websites, mobile phones, and in-home displays. Ford and Karlin argued that the large variation of range of energy savings for different studies could partly be due to the difference in how the information is presented to customers (2013). Though each interface can generally display the same content, users may be more likely to adopt and use different interfaces for different reasons. Froehlich found that ambient displays, a type of in-home display, require less attention, but also provide less information compared to websites or mobile phone applications (2009). Varying preferences for different displays could stem from customer preferences surrounding accessibility, mobility, or usability of the information provided. However, few studies have explored the relationship between the display preferences and customer characteristics. Such systems are costly to develop, market, and deploy, making it critical to understand customer preferences around these differences.

1.2 Theoretical Underpinnings of Smart Grid Technology Adoption

In the following section, we discuss several key theories that inform sustainable technology adoption decisions. These include Diffusion of Innovations Theory, the Technology Acceptance Model, and Value-Belief-Norm Model.

1.2.1 Diffusion of Innovations Theory

Presently, smart grid technology is regarded as an early-stage innovation. According to the Diffusion of Innovations Theory (Rogers, 1995), innovations are adopted in waves or stages throughout a given population. Under this theory, a given population consists of five categories of adopters differentiated on the basis of characteristics of the innovation itself, communication channels, time, and the given social system or context in which the innovation manifests. The five groups, in sequential order of adopters, are: innovator, early adopter, early majority, late majority, and laggard. The adopter distribution curve is assumed to be normally distributed.

What is interesting about smart grid technologies, particularly smart meters, is that while they are an “early stage” innovation, more than 50 million smart meters had been installed nationwide in the U.S. by the end of 2013, representing 37.6% of U.S. electricity customers (FERC, 2015). According to Diffusion of Innovations Theory, the first 2.5% of a given population are innovators, the subsequent 13.5% are early adopters and the next 34% are the early majority. However, smart meters have been rapidly deployed in part because of the availability of American Recovery and Reinvestment Act funds for such smart grid projects. The true “voluntary” adopters, or people with intention to actually use these innovations, may be significantly fewer than one third of the U.S. population, effectively converting those who may be more appropriately categorized as late majority or laggard into “involuntary” early adopters. Actual early adopters differ from later adopters in how they perceive new technologies. For instance, in a survey-based study of factors impacting the intention to adopt electric cars among 2,974 Dutch participants conducted in June 2012,

results showed that earlier adopters evaluated the symbolic attributes of an electric car more positively than later adopters (Noppers, et al., 2015). Although the American Recovery and Reinvestment Act helped to jumpstart the infrastructure by widely deploying smart meters, the accompanying smart grid-enabled energy management technologies and programs are largely still voluntary, and households' adoption of them is lagging behind. Thus, it is important to hone in on factors that predict adoption of these voluntary technologies and programs during this critical time period to better understand the implications of this somewhat forced technology deployment, as well as assist utilities in program development and targeted marketing efforts.

1.2.2 Technology Acceptance Model

The Technology Acceptance Model (Davis, 1989) describes perceived usefulness and perceived ease of use as two key determinants of adoption of various technologies. For instance, previous studies of implementation of new computer systems in various work settings found that higher levels of computer self-efficacy (i.e., general beliefs in abilities to operate various computer applications rooted in prior experience with computers/software), better perceived facilitating conditions (e.g. higher availability of support staff), and lower computer anxiety increased ease of use perceptions before and after hands-on experience with the specific system. Among all these antecedents, general computer self-efficacy showed a consistent and significant influence on perceived ease of use across studies, with effect sizes ranging from 0.30 to 0.57 (Venkatesh, 2000).

Digital Technology Use. Building on these findings, most emerging smart grid customer-facing platforms are digitally based, making it important to understand the impact of existing digital technology use habits on willingness to adopt these new technologies. In line with aforementioned findings on computer self-efficacy, those who rate themselves higher on measures of general technical competency are less resistant to adopting new

innovations (Ram & Jung, 1991). Based on a study of mobile internet usage (Venkatesh et al., 2012), baseline habitual use of a given technology is a positive and significant predictor of intentions and actual future use of that technology. The habit has been described as the automation of an individual using a certain technology. In other words, the more “automatically” an individual used online or mobile phone services, the more likely s/he was to report intending to continue using these platforms for other purposes, suggesting that integrating new technologies into existing platforms may be a promising route to increasing adoption. Kim and Malhotra also found that past use of certain information technologies significantly predicted current use of that technology (2005). Additionally, previous experience with certain technology has been proposed to impact perceived costs, risks, and benefits of adopting new energy management technologies. Specifically, those who use digital technologies more frequently may perceive the costs and risks of such technologies as lower, and the benefits as higher, leading to greater adoption likelihood (Huijts et al., 2012).

These previous studies have primarily focused on adoption of technologies in work settings. Given that emerging technologies are becoming available for voluntary home use, additional research is needed to understand the applicability of Technology Acceptance Model to the adoption of other technologies in new settings like households. One of the objectives of the present study is therefore to investigate the impacts of digital technology use on the adoption of home energy management technologies.

Of note, in the Technology Acceptance Model, the voluntariness of a technology indirectly impacts its likelihood of adoption (Venkatesh & Davis, 2000). As mentioned above, although smart meter deployments have made millions of people "involuntary" adopters of the meters, decisions around adopting new energy management technologies and programs enabled by these meters are typically made voluntarily by consumers. Accordingly, our study

focuses on these optional technologies and programs and investigates voluntary adoption decisions.

1.2.3 Value-Belief-Norm Theory

Adoption of smart grid technologies can be conceptualized as a type of pro-environmental behavior (PEB), defined as behavior that harms the environment as little as possible, or benefits the environment (Steg & Vlek, 2009). A variety of theories have been proposed to explain other types of PEB. A review of these theories as they apply to energy management behaviors is outside the scope of this paper. However, one of the better-supported models is the Value-Belief-Norm theory (Stern, 2000). In this theory, behavior is explained by a chain of variables: personal values (biospheric, altruistic and egoistic values) predict ecological worldview, which gives rise to awareness of consequences. This awareness increases taking responsibility for such consequences, and to the sense of obligation to take action, which most proximally predicts behavior (Stern, 2000). Thus, personal values are foundational factors that influence PEB.

Connectedness to Nature. Connectivity with nature has been regarded as a measure of environmental values (Dutcher et al., 2007), defined as “those values that are specifically related to nature or that have been found to correlate with specific environmental attitudes or concerns” (Schultz et al., 2004). Recent research has assessed levels of feeling connected to nature with the Connectedness to Nature Scale (CNS; Mayer & Frantz, 2004). CNS has been compared to alternative measures such as New Environmental Paradigm, which describe interconnectedness between human activity and a fragile biosphere (Stern, 2000). Mayer and Frantz argue that CNS better taps into an individual’s affective, experiential connection to nature (2004). Indeed, studies have shown that New Environmental Paradigm: (1) does not so much measure environmental values, but rather assesses awareness of consequences of human activities on the environment (Stern et al., 1995); and (2) best explains differences in

environmental concern and behavior based on ecological worldview instead of environmental values per se (Dutcher et al., 2007).

Meanwhile, numerous studies have found CNS to predict a range of PEBs. For instance, Lokhorst et al. found CNS to be a marginally significant predictor of intentions to conserve nature (i.e., “I plan to carry out private nature conservation in the next two years”) based on a study with 480 landowners in the Netherlands (2014). CNS has also been found to positively correlate with the protection of native vegetation and the planting of native flora to improve degraded landscapes among Australian farmers (Gosling & Williams, 2010). Expanding to a broader range of behaviors, Hoot and Friedman found CNS to positively predict a composite measure of PEB, and to do so even when New Environmental Paradigm was included in the model (2011). Perhaps most relevant to our study of energy conservation and technology adoption in a household setting, Mayer and Frantz found CNS to be positively related to a variety of low-cost curtailment PEBs, such as turning off lights, even when New Environmental Paradigm was controlled for (2004).

Despite the evidence indicating that environmental values, particularly CNS, underlie engagement and intentions to engage in various PEBs, whether and how connectedness to nature plays a role in the adoption of smart grid technologies remains unexplored. Understanding this relationship will shed light on (1) a framework for conceptualizing PEBs and (2) peoples’ motivational processes to engage in them. For instance, does connectedness to nature influence PEBs that are farther removed from their tangible effects on the natural environment, and operate further “up the chain” (e.g., sustainable technology adoption), and may be perceived as unrelated to the natural world? Answering this question can yield insights on individuals’ ability to reason through the complex causal chain of events from technology adoption to environmental betterment. This is an important area of inquiry given

the growth in technological approaches for improving the environment via energy efficiency measures that depend on end user adoption (e.g., solar panels, electric vehicles).

This is an important area of investigation because as suggested previously (Stern, 2000), different types of private-sphere PEBs might have different determinants. In particular, deciding whether or not to adopt a new energy conservation technology like compact fluorescent bulbs, may differ in important ways from other PEBs, such as taking shorter showers. In parallel, different factors have also been suggested to underlie the adoption of different smart grid technologies (Sintov & Schultz, 2015). Identifying such factors can inform a broader framework of PEB that has previously been advocated for (Abrahamse & Steg, 2011; 2013) and has practical implications for utilities.

In the following paragraphs, we discuss additional evidence surrounding household decisions around energy use and other PEBs, including demographic and residence characteristics.

1.3 Demographic Characteristics

The relationships between PEB and demographic characteristics are complex. Some evidence shows that female gender, older age, and higher education and income levels are related to household (private) PEBs (e.g., recycling, buying organic produce). This has been found across international samples (Hunter et al., 2004; Xiao & Hong, 2010). In studies of energy use, after controlling for measures of attitudes and values, there is no significant relationship between intention to reduce energy use and age or income (Abrahamse & Steg, 2011). However, Chen and Knight surveyed 584 employees from nine power utilities in China and found that males and those with higher educational attainment had higher intentions to reduce energy use at work, whereas age was not a significant predictor (2014). These findings contrast with what we describe above, and may be explained by energy saving at work being more of a public PEB, which others, in this case, colleagues, can observe. Such

behaviors may be influenced by factors different from more private-sphere PEBs performed within the walls of one's own home. These results suggest that the context in which behavior takes place moderates the influence of demographic variables on the performance of PEBs.

In contrast with its inconsistent association with PEBs, the relationship between age and technology adoption is quite robust. This aligns with Diffusion of Innovations theory, which predicts that earlier adopters of technological innovations are typically younger (Rogers, 1995). Indeed, use of information communication technologies like internet generally decreases as age grows (Selwyn et. al., 2003). Furthermore, several studies have found younger age to predict the adoption of energy-efficiency technologies in particular. For instance, based on survey of U.S. Maine residents, adopters of rooftop solar systems were significantly younger than non-adopters (Labay & Kinnear, 1981). Similarly, a survey of 1,279 United Kingdom residents found that younger residents were more inclined to adopt micro-generation technologies like solar thermal and wind power than older ones (Willis et. al, 2011). A survey of 1,500 homes in Sweden (Mahapatra & Gustavsson, 2008) found that the percentage of respondents who planned to install heating innovations like heat pumps decreased with increasing age. Taken together, these findings suggest that age has an inverse association with intentions of adopting energy management technologies. This may stem from the inverse association of age with the ability to learn new technologies (Huijts et al., 2012), as well as the tendency for pro-environmental technology adoption to involve more learning than other PEBs. Younger people may find this learning process easier, and thus have greater motivation to adopt such technologies than older ones.

In terms of political affiliation, evidence suggests that people who are more politically liberal tend to care more about environmental issues. For example, based on data from 10 universities in the Cooperative Congressional Election Study, liberal political ideology was found to be one of the strongest predictors of attitudes toward government

actions on 12 environmental issues (e.g., pollution regulations; Konisky et al., 2008). Another study based on data from 10 nationally representative Gallup Polls from 2001 to 2010, found that liberals were more likely to show concern than conservatives for specific environmental issues, like global warming (Dunlap et al., 2001; McCright & Dunlap, 2011). Notably, these studies investigated associations between political ideology and attitudes towards environmental issues. However, the relationship between political affiliation and acceptance of smart grid technologies -- now deployed among 37.6% of U.S. households-- remains to be explored.

The potential moderating role of demographic characteristics on other variables' effects on smart grid technology adoptions should also be considered. As highlighted above, some studies have found females to act more pro-environmentally (Hunter et al., 2004; Xiao & Hong, 2010) while others found the opposite (Chen & Knight, 2014). The effects of gender on PEBs may be moderated by other variables. Also, the impact of previous experience with technologies on adoption could vary as a function of ability to learn a new technology, which declines as age increases (Huijts et al., 2012), indicating a potential moderating effect of age on digital technology use.

1.4 Residence Characteristics

A variety of household characteristics may also impact home energy use, opportunities for savings, and motivations for adoption energy management technologies and programs. According to Abrahamse and Steg, the number of occupants in a household “shapes the opportunities and constraints for energy use” and thus potential for energy savings (2009). For instance, a larger number of occupants is generally associated with greater energy use (Abrahamse and Steg, 2011; Gatersleben et al., 2002). Additionally, based on a sample of 1,265 households in the United Kingdom, homes with greater environmental tendencies tended to have fewer occupants and higher rates of homeownership (Barr et al.,

2005). Another study of housing prices and energy saving investments also indicated that investment in energy-saving durable goods is efficiently reflected in housing price. The future fuel saving due to the installed energy-saving durable goods is reflected in the house price at a relatively high present value, indicating a fair return to the home owners on their investment (Johnson & Kaserman, 1983). Homeowners thus may have more incentive to invest in energy saving activities, who may be less likely to benefit long-term from investments in energy management technologies if or when they leave. Renters may also face other barriers, such as landlord approval, thereby discouraging energy efficiency investments.

1.5 Synthesis

Although connectedness to nature has been associated with a variety of PEBs as mentioned above, its impact on the adoption new energy management technologies is unclear. This is an important area of inquiry as an emerging set of PEBs now hinge in part on the adoption and use of new technological solutions, including electric vehicle adoption, solar panel installation, etc., and was one of our key study objectives. From a theoretical perspective, advancing our understanding of the role of nature connectedness in sustainable technology adoption can help inform the extent to which people can develop a sophisticated understanding of the causal chain from their (seemingly unrelated) behavior around technology adoption to impacts on the natural world. From a practical standpoint, a better understanding of these linkages can guide program rollouts and targeted marketing, and inform better-framed feedback.

1.5.1 Predictions

To address gaps in previous work as highlighted above, the present study tested the following predictions (depicted in figure 1):

P1: Higher levels of nature connectedness will positively predict intentions to adopt energy management technologies and programs.

P2: The effect of connectedness to nature on adoption intentions will be moderated by gender.

P3: Greater frequency of digital technology use will positively predict intentions to adopt energy management technologies and programs.

P4: The effect of digital technology use on adoption intentions will be moderated by gender.

P5: The effect of digital technology use on adoption intentions will be moderated by age.

P6: Younger age will positively predict intentions to adopt energy management technologies and programs.

As summarized in the literature review above, prior research suggests that other factors also influence energy management technology adoption. To adjust for these effects, we included them in analysis models.

Figure 1: Study predictions of factors influencing intentions to adopt energy management technologies and programs

Figure note: “+” means the variable is predicted to have a positive impact on adoption intentions; “-” means the opposite. Solid lines correspond to specific predictions; dotted lines represent factors adjusted for in model.

1.5.2 Study Context

As mentioned, smart grid technologies are becoming increasingly prevalent across the globe. For instance, in the U.S., residential smart meter penetration reached 38% in 2013 (FERC, 2015). Additionally, as of 2015, about 12 million California homes had smart meters installed, representing approximately one quarter of U.S. smart meters (California Public Utilities Commission, 2016), and putting the state at the forefront of U.S. smart meter deployment. In fact, California has been a leader of environmental policy since the 1960s (Sperling & Eggert, 2014). For instance, California’s Global Warming Solutions Act of 2006 was the first in the U.S. to set aggressive standards for a cap-and-trade style reduction of greenhouse emissions, and was well received by the public (Mazmanian et.al, 2008). In addition, Los Angeles (L.A.) is a recognized leader of progressive municipal energy policy (Pincetl et.al, 2015). This paints a picture of L.A., a major urban center in an environmentally progressive state, as an opinion leader in environmental policy generally and smart grid technologies specifically. Current trends in L.A. may be predictive of future national and international trends over the coming years. The following section describes how we used survey data from a sample of L.A. County residents to test our predictions.

2 Methods

2.1 Procedures

Contact information was obtained for a random sample of 200,000 residential customers of a power utility in the Southern California region in 2013. From this list, individuals were selected at random by interviewers. Those who were eligible (see Section 2.3.1 below) and agreed to participate were interviewed. Trained interviewers conducted

surveys via phone using a structured interview protocol. Calls were placed from 8am-8pm local time. Interviewers opened with an introductory recruitment statement. To mitigate the selection bias, in the verbal recruitment invitation, interviewers stressed the collaboration between the university and utility, and briefly mentioned the goal of studying perceptions of energy use. If respondents agreed to participate, interviewers read a brief IRB (Institutional Review Board)-approved information sheet before proceeding with survey questions. Sequentially, questions assessed demographic and residence characteristics, digital technology use, intentions to adopt energy management technologies and programs, and level of affiliation with nature. The mean call duration was 26 minutes. Participants could end calls at any time. No incentives were provided for participating.

2.2 Materials

2.2.1 Structured interview

The survey tool was developed for the purposes of a larger study and adapted for use as a structured interview. Questions assessed demographic and household characteristics, digital technology use, connectedness to nature, and likelihood of adopting various energy management technologies and power utility program offerings.

2.2.2 Outcomes

A total of five outcomes were examined. Respondents rated their intentions to use a free website (WEB), free mobile phone app (APP), and free in-home display monitor (IHD) to monitor home electricity usage. They also rated intentions to sign up for a time-of-use pricing plan (TOU), and participate in demand response (DR) events. Responses were given on a 7-point likert scale ranging from 1=very unlikely to 7 = very likely. Interview questions are provided in Appendix Table A.

2.2.3 Digital Technology Use (DTU)

Respondents indicated the frequency with which they used each of 10 digital technologies and platforms (e.g., surfing the web, emailing, using social media, texting, using a tablet). Responses were rated on a 7-point scale ranging from 1=never to 7=daily. Item scores were summed to create a scale score of DTU. Cronbach's alpha for the scale was 0.85.

2.2.4 Connectedness to Nature

As mentioned above, the connectedness to nature scale (CNS) is a well-established measure that has previously been shown to predict PEB. A brief 5-item version of the CNS provided by the scale authors (Mayer & Frantz, 2004) was used. Responses were given on a 7-point Likert scale ranging from 1=strongly disagree to 7 = strongly agree. Item scores were summed to create a scale score. Cronbach's alpha for the scale was 0.84.

2.2.5 Other Variables

Demographics included gender (male=1 and female=2), income (1=under \$25,000-5=more than \$100,000), age (in years), educational attainment (1=less than high school - 6=Completed graduate school or professional degree program), and political affiliation (1=very conservative – 7= very liberal). Residence characteristics included homeownership status at time of survey (1=own and 2=rent), and number of occupants residing in home (continuous integers).

2.3 Participants

2.3.1 Eligibility

Individuals were eligible to participate in the study if they were adult residential customers of a L.A. County utility. Customer status was determined based on utility data, and age was determined based on response to a screening question.

2.3.2 Multiple Imputation

The original sample comprised 1,000 participants. There are no missing data on gender and participants with any missing outcomes (WEB, APP, IHD, TOU, DR) were

excluded (n=82), leaving 918 remaining participants. Within this remaining group, those missing data on age (n=35), homeownership status (n=17), number of household occupants (n=9) or educational attainment (n=20), each of which had less than 5% of original sample missing (n≤50), were also excluded. Given that some of these participants were missing more than one of the above variables, 856 participants remained. Within this subsample, a total of 188 participants had missing data owing to participants not responding to other questions: 94 participants were missing income data, 66 were missing political affiliation, 49 were missing DTU, and 31 were missing CNS.

To investigate systematic patterns of missing data, we examined mean differences in the five outcomes based on missing predictor variable status, including: CNS, DTU, income and political affiliation. The results of ANOVA tests (see Appendix Table B) indicated that: (a) all outcomes were significantly different between participants with versus without data on income; (b) WEB, APP and IHD differed significantly between participants with versus without data on CNS, whereas TOU and DR did not; (c) WEB, IHD and TOU were differed significantly between participants with versus without data on political affiliation whereas APP and IHD did not; (d) TOU differed significantly between participants with versus without data on DTU.

As data were not missing at random, multiple imputation was used to impute values for the missing predictors, which included income, DTU, political affiliation, and CNS. Imputed datasets tend to be less vulnerable to bias arising from small datasets and/or ignoring observations with any missing data. Multiple imputation is also more reliable than other imputation techniques (e.g., single imputation) because it allows for several variations of imputed data, which better reflects sampling variability and different possible reasons for data missing, thereby mitigating a single value's impact (Allison, 2009; Rubin, 2004). We used chained equations to impute by filling in missing values iteratively using a series of

univariate imputation methods with fully conditional specifications of prediction equations. Different univariate imputation methods were used based on the different properties of imputed variables: for income and political affiliation, ordered logistic regression was used; for DTU and CNS, truncated regression was used, setting the lower and upper limit equal to each variable's minimum and maximum, respectively. Each missing value was estimated using imputed 20 values. The final regression models are based on participants who had complete data before or after imputation (n = 856).

2.3.3 Sample Characteristics

The sample roughly matched demographic and housing characteristics for L.A. County based on U.S. Census data (2010) except for educational attainment and ethnic distribution. The sample included a higher percentage of high school and college graduates relative to the L.A. County average. Additionally, the sample under-represented Latinos relative to L.A. County. Sample characteristics details are provided in appendices (Tables C1 and C2).

2.4 Analyses

To advance understanding of the role of connectedness to nature in sustainable technology adoption, we tested CNS, DTU, demographic and residence characteristics as potential predictors. The outcomes included intentions to adopt one of three energy feedback technologies: using a free website (WEB), mobile phone application (APP), or in-home display (IHD) to monitor home energy usage; intentions to sign up for a time-of-use pricing plan (TOU); and intentions to participate in demand response events (DR).

Initial examination revealed that variables were bimodally distributed, violating the assumptions of linear regression modeling. Therefore, we recoded all outcomes as binary (likely – very likely = 1, positive intentions of adoption; very unlikely – neutral = 0, no positive intentions of adoption).

Logistic regression analyses were conducted to identify the predictors of adopting each energy management outcome. Potential predictors were demographic variables, including gender, age, educational attainment, and political affiliation; DTU; CNS; and residence characteristics including tenures of residence, homeownership status, and number of occupants. Since tenure of residence was highly correlated with age ($r = 0.62$), it was dropped from further analyses. To facilitate interpretation, income and educational attainment were recoded as binary. Respondents who reported annual incomes of \$50,000 or less, which is roughly equivalent to the sample median and L.A. County median (\$49,745), were scored as “0”, whereas those who earned more than \$50,000 were scored as “1”. Similarly, respondents who earned less than 4-year college graduate, which is the median education level of our sample, were coded as 0, and those with a 4-year degree or more education were coded as 1. All analyses were performed using the STATA Version 13.1 MP software program (StataCorp, 2013).

For each outcome, the same analytic procedures were followed. A hierarchical model building procedure was used to select variables for inclusion in the final set of models. Variables were separated into four conceptual blocks: demographics (income, gender, age, educational attainment, political affiliation), residence characteristics (homeownership status, number of occupants), DTU, and CNS. Each block of predictors was regressed separately on each outcome in a logistic regression model. Predictors that were significant ($p < .05$) in any block model were retained in the set of final models used to estimate the simultaneous effects of predictors. This procedure was used to ensure the inclusion of the same set of participants in each outcome and to facilitate interpretability of results. Gender and political affiliation were not significant in their respective block models and thus were excluded from all final models.

Three interaction terms were also considered for each outcome to provide for exploration of moderation effects. The inconsistent effects of gender on PEB in the literature could be due to the interaction between gender and other important variables like CNS, DTU and age. We also considered a DTU x age interaction because of previous findings of the effects of age on DTU (Huijts et al., 2012). Each outcome was regressed on three block models of interaction terms separately: gender and CNS (gender, CNS, gender x CNS), gender and DTU (gender, DTU, gender x DTU) and age and DTU (age, DTU, age x DTU). All variables in an interaction block model with a significant interaction term for a given outcome were included in the final model for that specific outcome.

3 Results

The odd ratios (ORs) and Wald 95% confidence intervals (CIs) for each of four conceptual block models (i.e., demographics, residence characteristics, DTU, and CNS) are shown in appendix table D. The ORs and CIs for interaction block models (CNS x gender, DTU x gender and DTU x age) are shown in appendix table E.

Table 1 below displays the ORs and CIs for the final models, which include predictors that were significant in at least one conceptual block model for any outcome and predictors that showed significance in interaction models for a specific outcome (see appendix table E). We discuss findings from the final models below.

Table 1.
Odd Ratios and 95% Wald Confidence Intervals Based on Final Logistic Regression Models for Predictors of Intentions to Adopt Energy Management Technology and Programs

Predictor	WEB	APP	IHD	TOU	DR	Corresponding Predictions and Results
Key Factors						
CNS	1.07*** (1.04-1.10)	1.07*** (1.04-1.10)	1.04** (1.02-1.07)	1.14** (1.05-1.24)	1.03* (1.01-1.06)	P1: supported for WEB, APP, IHD, TOU, DR
DTU	1.06*** (1.04-1.07)	1.07*** (1.06-1.09)	0.98 (0.95-1.02)	0.97 (0.94-1.01)	1.01 (0.99-1.02)	P3: supported for WEB, APP
Demographic and Residence Characteristics						
Age	0.99* (0.98-1.00)	0.98*** (0.96-0.99)	0.94*** (0.91-0.97)	0.99 (0.98-1.00)	0.99 (0.98-1.00)	P6: supported for WEB, APP, IHD
Gender				1.99		

				(0.39-10.10)	
Income	1.11 (0.75-1.63)	1.37 (0.91-2.06)	1.43 (0.98-2.07)	0.85 (0.59-1.22)	1.38 (0.93-2.04)
Educational Attainment	1.19 (0.84-1.68)	0.86 (0.59-1.25)	1.05 (0.75-1.48)	1.02 (0.74-1.40)	1.08 (0.76-1.52)
Homeownership status	1.39 (0.95-2.04)	1.24 (0.83-1.86)	0.96 (0.66-1.39)	1.08 (0.77-1.52)	1.07 (0.74-1.55)
Number of Household Occupants	1.04 (0.94-1.15)	1.04 (0.94-1.16)	1.07 (0.97-1.18)	1.07 (0.98-1.17)	1.12* (1.01-1.23)
Interaction Terms					
CNS x Gender				0.95* (0.90-0.99)	P2: supported for TOU
DTU x Gender				1.02* (1.00-1.04)	P4: supported for TOU
DTU x Age			1.001** (1.000-1.002)		P5: supported for IHD
Pseudo R-squared ¹	0.1771	0.2518	0.1259	0.0336	0.0275

Table Note: Homeownership status, 1=own, 2=rent; gender, 1=male, 2=female; DTU=digital technology use; CNS=connectedness to nature score; WEB=intentions to use a free website to monitor home energy use; APP=intentions to use a free mobile phone application to monitor home energy use; IHD=intentions to use a free in-home display to monitor home energy use; TOU=intentions to sign up for a time-of-use pricing plan; DR=intentions to participate in demand response events.

p<.05, **p<.01, *p<.001.*

3.1 Intentions to use a free website to monitor home energy use (WEB)

Younger age, higher DTU, and higher CNS scores significantly predicted higher odds of positive intentions to use a website to monitor home energy use. The OR for age was 0.99 (95% CI=0.98, 1.00), which means for each year decrease in age, the likelihood of having positive intentions to use WEB rose by 1%. The OR for DTU was 1.06 (95% CI=1.04, 1.07), meaning each point higher DTU score was associated with a 6% higher likelihood of positive intentions to use WEB. For CNS, the OR was 1.07 (95% CI =1.04, 1.10), indicating that for each unit increase of CNS, a person was 7% more likely to have positive intentions to use a website to monitor home energy use.

3.2 Intentions to use a free mobile phone application to monitor home energy use (APP)

¹ For logistic regressions, no equivalent statistics like R-squared for OLS regression exists because logistic regression are maximum likelihood estimates and they are not calculated to minimized variance. Pseudo R-squared (McFadden 1974) used here is defined as 1-L1/L0, where L1 is the log-likelihood value of the model used in the output and L0 is the log-likelihood of model without any predictors. Also, since there are 20 sets of data used for regression due to imputation, the final Pseudo R-squared shown here is the average of the 20 pseudo R-square values calculated for each regression based on each of the 20 imputation datasets.

Mirroring findings for WEB, younger age, higher DTU scores, and higher CNS scores significantly predicted higher odds of positive intentions to use a mobile phone app to monitor home energy use. The OR for age was 0.98 (95% CI = 0.96, 0.99), meaning for each year decrease in age, the likelihood of intentions to adopt APP rose by 2%. The OR for DTU was 1.07 (95% CI = 1.06, 1.09) meaning each unit higher in DTU score was associated with a 7% higher likelihood of positive intention of adopting APP. The OR for CNS was 1.07 (95% CI = 1.04, 1.10), meaning that for each unit increase of CNS, a person was 7% more likely to have positive intentions to adopt an APP to monitor home energy use. Notably, despite having roughly similar effect sizes in both the WEB and APP models, the variables in the APP model accounted for 7.5% more explained variance than in the WEB model.

3.3 Intentions to use a free in-home display to monitor home energy use (IHD)

Younger age and higher CNS scores significantly increased the odds of positive intentions to use an IHD to monitor home energy usage. The OR for the main effect of age was 0.94 (95% CI = 0.91, 0.97), meaning for each year decrease in age, the likelihood of positive intention to use an IHD rose by 6%. The OR for CNS was 1.04 (95% CI = 1.02, 1.07), meaning for each unit increase in CNS, a person was 4% more likely to have positive intentions to use an in-home display to monitor their home energy use. In addition, the age × DTU interaction was significant. The OR was 1.001 (95% CI = 1.000, 1.002), and suggests a compounding effect. Although the effect size was small, among individuals who used digital technology relatively frequently, intentions of adopting an IHD were slightly higher among younger participants. On the other hand, odds of positive intentions to adopt an IHD were especially low among older participants with lower DTU scores (figure 2).

Figure 2: Proportion of participants with positive intentions to adopt IHD monitor as a function of DTU score and age

Figure note: IHD: in-home display; DTU: digital technology use. Median splits were used for DTU score and age to facilitate presentation of findings.

3.4 Intentions to sign up for a time-of-use pricing plan (TOU)

Higher CNS scores significantly increased the odds of positive intentions to sign up for a TOU plan. The OR for the main effect of CNS was 1.14 (95% CI = 1.05, 1.24), meaning for each unit increase in CNS, a person is 14% more likely to have a positive intention to sign up for TOU rate. No other main effects were significant in the final model, but two significant interaction effects were found: the OR for gender $\times$ DTU was 1.02 (95% CI = 1.00, 1.04) and suggests a compounding effect. Those with higher DTU scores were more likely to report positive intentions to sign up for TOU, particularly females (figure 3). Likelihood of positive intentions to sign up for TOU did not vary as a function of gender among those with low DTU scores. The gender $\times$ CNS interaction was also significant with an OR of 0.95 (95% CI = 0.90, 1.00). Among males, those with lower CNS scores were less likely to have positive intentions to sign up for TOU relative to those with higher CNS scores (figure 4). However, among females, the odds of having positive intentions to sign up for TOU were roughly consistent across high and low CNS scores. These findings should be interpreted cautiously given the small amount of explained variance (Pseudo $r^2 = .0336$) in this model.

Figure 3: Proportion of participants with positive intentions to sign up for TOU plan as a function of DTU score and gender

Figure note: TOU: time-of-use pricing; DTU: digital technology use. Median split used for DTU score to facilitate presentation of findings.

Figure 4: Proportion of participants with positive intentions to sign up for TOU plan as a function of CNS and gender.

Figure note: TOU: time-of-use pricing; CNS: connectedness to nature score. Median splits used for CNS to facilitate presentation of findings.

3.5 Intentions to participate in demand response events (DR)

A higher number of household occupants and higher CNS scores each significantly increased the odds of having positive intentions to participate in DR events. The OR for occupancy was 1.12 (95% CI=1.01, 1.23), which means with each additional household member, the likelihood of having positive intentions to participate in DR increased by 13%. For CNS, the OR was 1.03 (95% CI=1.01, 1.06) meaning for each unit increase of CNS, a person was 3%

more likely to have a positive intention to participate in DR events. These findings should be interpreted cautiously given the small amount of explained variance in the model (pseudo $r^2=.0275$).

4 Discussion

4.1 Key Findings

The present study investigated willingness to adopt a variety of smart-grid enabled home energy management technologies and programs. The results indicate that level of affiliation with nature was the strongest predictor of intentions across all outcomes examined, supporting P1. Conceiving of connectedness to nature as a measure of environmental values, and energy management technology adoption as a pro-environmental behavior, these findings lend support to and extend the Value-Belief-Norm model. A summary of the results of predictions tests is shown in the right-hand column of table 1.

Whereas previous work has shown that higher levels of affiliation with nature predict engagement and intentions to engage in a variety of PEBs, including native vegetation protection, curtailment activities like turning off lights, contributing to environmental causes, purchasing based on environmental attributes of products, and involvement in environmental groups (Gosling & Williams, 2010; Hoot & Friedman, 2011; Lokhorst et al., 2014; Mayer & Frantz, 2004), this is the first study showing that this relationship extends to the intention to adopt energy management technologies. This is a somewhat paradoxical finding given that interacting with technologies does not correspond to interacting with “nature” in a traditional sense, and suggests that human perceptions may indicate otherwise. One possibility is that people high in connectedness to nature may better understand the complex causal chain connecting human behavior to impacts on the natural world, even seemingly unrelated behaviors such as technology adoption. Their sophisticated understanding may serve to stretch their motivation to protect valued objects (nature) over extended causal chains.

Additionally, previous work rooted in the Technology Acceptance Model has shown that baseline technology use predicts willingness to adopt new technologies; we have extended this body of work by showing that baseline technology use also predicts intentions to engage in certain types of PEBs (figure 5). As Venkatesh demonstrated, more prior experience with computers and information technology systems (i.e., greater digital technology use) is associated with higher perceived ease of use of new technologies in the early stages of user experience due to the higher computer self-efficacy, and thus leads to higher intention to adopt new technologies (2000). As our study assessed voluntary adoption only, results build on prior work investigating mandatory workplace technologies (Venkatesh, 2000), and suggest routes by which to foster adoption of entirely optional technologies. Our findings therefore extend application of the Technology Acceptance Model to: (1) a residential setting; (2) sustainable technology adoption; (3) entirely voluntary technologies. Notably, in our study, people who used digital technology more frequently had significantly stronger intentions to use website and mobile phone applications to monitor home energy use, lending partial support to P3; however, there was no significant main effect of digital technology use on intentions of adopting in-home displays. This is not entirely surprising because website and mobile phone apps may be more appealing technologies than in-home displays among frequent digital technology users due to their mobility: one can bring a laptop or mobile phone outside the home, access websites anywhere an internet connection is available, or use a mobile phone app anywhere mobile phones are permitted. This convenience and accessibility may increase the appeal of mobile energy management options compared to in-home displays.

Figure 5: Modeling the role of connectedness to nature in energy management technology adoption
Figure note: Straight lines depict relationships established in prior literature; bolded lines show new relationships found in the current study.

This study also evaluated the influence of several demographic characteristics on energy management technology adoption. In contrast to previous work, we found income, educational attainment, and political affiliation were not significantly related to technology adoption intentions. However we did find an interesting gender interaction such that gender moderated the effect of connectedness to nature on intentions of signing up for time-of-use rates, lending partial support to P2. Among males, those higher in connectedness to nature were more likely to report positive intentions to sign up for time-of-use rates; among females, the odds of having positive intentions to sign up for time-of-use rates did not vary as a function of connectedness to nature. This may be explained by potentially different motivations to sign up for time-of-use rates across genders. As mentioned above, among females, saving money may be a more important motivator for adopting time-of-use rates. However, previous work has found that males have more positive attitudes toward purchasing

environmentally friendly products than females (Mostafa, 2007); it is possible that motivation to protect the environment, here reflected in higher connectedness to nature scores, is more important among males than females in signing up for time-of-use rates.

Additionally, supporting P6, younger individuals were significantly more likely to report positive intentions to use a website, a mobile phone app, or an in-home display of household energy consumption than were older participants. Such results diverge from previous studies indicating older people tend to engage in more private PEBs (Konisky et al., 2008; Xiao & Hong, 2010). One possible explanation for these differences is that the adoption of energy management technologies differs from PEBs assessed in previous studies (e.g. recycling, buying organic produce, driving less) that do not involve hands-on interaction with emerging technologies. In our study, PEBs and technology adoption overlap. Previous work has found that while younger people are less likely to behave pro-environmentally (Xiao & Hong, 2010), they tend to be more accepting of new technology than older people (Harrison & Rainer Jr, 1992), providing context for our findings and suggesting a route by which younger people can be mobilized to perform PEBs.

However, younger age was not associated with all outcomes, only intentions to adopt the energy monitoring technologies, but not to adopt time-of-use rates or demand response programs. This underscores the fact that there exist important differences across energy technologies and programs that interact with predictors of adoption. One explanation for our findings could be that direct interaction with energy management interfaces requires more learning of technology than signing up for new programs, and such ability to learn new technologies has been shown to decrease as age increases (Huijts et al., 2012). In fact, we investigated age as a potential moderator of the impacts of digital technology use. Results provided partial support for P5: age moderated the impact of digital technology use on intentions to adopt in-home displays, such that among those with lower digital technology

use scores, older people had much lower odds of positive intentions of using in-home displays compared to younger people, whereas among those with higher digital-technology-use scores, age differences were much smaller. Higher digital technology use score, which indicates more prior experience with similar technologies, may lead to lower effort expectancy, inferred from the Technology Acceptance Model (Venkatesh 2000; Venkatesh et al 2003). The current results lends support to previous research that effort expectancy can be a stronger determinant of individuals' intention of technology adoption, especially among older people (Morris & Venkatesh, 2000). This indicates that enhancing perceived ease of use of energy management technologies may be a promising route to elevating their acceptance and adoption.

4.2 Limitations

Our findings should be viewed in light of several limitations. First, relative to L.A. County, our sample underrepresented those with lower educational levels as well as those who identify as Latino, and therefore may not generalize to the population of L.A. County. Hence, our results may not extend to Latino or lower educated populations. In the future, more emphasis should be placed on energy research among underrepresented groups, including those with lower educational levels and Latinos. Second, our sample was from the U.S., so caution should be exercised in applying the findings of the present study to different countries and cultures. In particular, some cultural contexts may naturally imbue high levels of nature connectedness in its members (Medin et al., 2006; Bang et al., 2007), leading to higher baseline levels of PEB. In such contexts, the effects of nature connectedness on sustainable technology adoption may potentially plateau. For instance, if baseline nature connectedness levels are already high, beyond a certain point, an increase in such levels may have less impact on sustainable technology adoption compared to an equivalent increase

starting from lower baseline levels. Still, connectedness to nature predicts other PEBs across different countries (Lokhorst, 2014; Gosling & Williams 2010), coinciding with our findings.

Also, we obtained data only on intentions of adopting energy management technology, not actual behavior. Although research has found that intentions are among the best predictors of a variety of behaviors (Sheeran, 2002), and similarly, a meta-analytic model of 46 studies found a correlation of 0.52 between reported intentions and actual PEBs (Bamberg & Möser, 2007), future studies must address the gap between intentions and behavior by measuring observed behavior. Some of our effect sizes were also rather small, and therefore the corresponding findings should be interpreted with caution. Finally, due to the cross-sectional design of our study, the results are not causal. Future studies should provide for examination of a potential causal link between connectedness to nature and PEB.

4.3 Strengths

This is the first study to explore the effect of connectedness to nature on emerging technology-aided PEB intentions. Of theoretical importance, these results provide preliminary support for the conceptualization of technology adoption as a type of PEB. In a practical sense, this research is important given the trend of energy management solutions using technologies. As end user adoption is an important component to the success of such solutions, identifying factors that influence the adoption of these technologies can shed light on the underlying process of technology adoption, and inform strategic marketing and rollout efforts. Another strength of the study is the use of multiple imputation to impute missing data and thereby avoid potential bias associated with including only complete cases.

4.4 Conclusions and Future Directions

This study sheds light on the relationship between connectedness to nature and the adoption of energy management technologies and programs. Our findings suggest that connectedness to nature can motivate action to protect valued objects, even through

sophisticated reasoning chains. On the practical side, findings can help utility companies plan for strategical marketing and rollouts of energy management technologies and programs by targeting the “right” customers. Many utilities offer environmentally-friendly programs, such as the L.A. Department of Water and Power’s turf replacement program for water conservation, and its green power program to fund renewable energy (L.A. Dept. Water and Power, 2013a, 2013b). Utilities could potentially consider past or current customer enrollment such programs, or possibly customer membership in environmental organizations (e.g., Sierra Club- if such information is available), as proxies for nature connectedness, and target such customers for new technology and program offerings. Another possibility is for practitioners to attempt to nurture customers’ connectedness to nature, for instance through giving out plants (Weinstein et al., 2009) or promoting opportunities to spend time in nature (e.g., free parks days; Mayer et al., 2008), which may influence behavior without being perceived as overly controlling, addressing a key line of inquiry in energy research and social sciences (Sovacool, 2014). Finally, framing energy feedback in nature-relevant terms may also be helpful. Several studies have shown that framing feedback as number of trees needed to mitigate CO₂ emissions yields substantial savings (Holmes, 2007), up to 28% more than kWh-framed feedback (Jain et al., 2013). Such framing represents an innovative approach to communications and behavior change, informing current debates in this research field (Sovacool, 2014).

At the same time, our findings demonstrate heterogeneity in the factors that influence the adoption of different energy feedback management technologies and programs. Results indicate that motivations to adopt different feedback technologies—despite the fact that they are providing identical information—differ across interfaces. Thus, approaches to promote different technologies and programs can be tailored as well. For instance, to promote the adoption of website and mobile application interfaces, customers who enrolled in online

bill payments (implying a comparatively higher digital technology usage) could be targeted using email marketing.

Although connectedness to nature was the most robust predictor of intentions to adopt in our models, there may be other predictors not accounted for in the present study (e.g., perceived ease of use, symbolic attributes) that may be stronger predictors of intentions and behavior. Future work should continue to investigate additional predictors of the adoption of additional energy technologies, such as solar panels and electric vehicles. We also found several interaction effects, and as has been suggested previously, it is important to further explore the role of moderators of home energy management behavior on several levels: household characteristics, demographic variables, and psychosocial variables (Abrahamse & Steg, 2011; 2013; Sintov & Schultz, 2015). Understanding differences across these three levels can aid in identifying specific types of technologies that are likely to be accepted by different groups.

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Appendices

Table A

Interview Questions for Outcomes (WEB, APP, IHD, IOU and DR)

Outcomes	Corresponding Question
WEB	How likely are you to use a free website to manage your home energy use? Please tell me if you are very likely, likely, somewhat likely, undecided, somewhat unlikely, unlikely, or very unlikely to do this activity
APP	How likely are you to use a free smart phone app to manage your home energy use? Please tell me if you are very likely, likely, somewhat likely, undecided, somewhat unlikely, unlikely, or very unlikely to do this activity:
IHD	How likely are you to use a free in-home display to manage your home energy use? Please tell me if you are very likely, likely, somewhat likely, undecided, somewhat unlikely, unlikely, or very unlikely to do this activity.
IOU	How likely are you to switch to a time of use rate (higher rate during daytime hours, lower rate at night). Please tell me if you are very likely, likely, somewhat likely, undecided, somewhat unlikely, unlikely, or very unlikely to do this activity.
DR	At some point in the future, [your power utility] will be starting a voluntary "Save Power" program. Under this program, Save Power Events will occur an estimated 5-10 days per year and will last a few hours each. The goal will be to reduce power usage during that time period. You can participate in one event or in all of them, whatever you chose. Prior to such events, [your power utility] will notify customers to inform them that a Save Power Event is going to occur. During Events, customers who choose to participate will do energy

	<p>saving actions that are not too uncomfortable or inconvenient (e.g., turn down air conditioning a couple of degrees). How likely are you to participate in a Save Power Event? Would you say you are very likely, likely, somewhat likely, undecided, somewhat unlikely, unlikely, or very unlikely.</p>
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Table B.
ANOVA Test Results Based on Missingness of Selected Predictors

	WEB	APP	IHD	TOU	DR
Complete vs. Missing CNS					
Mean of complete group	4.33	4.19	4.49	4.47	5.23
Mean of missing group	3.28	3.06	3.85	4.41	5.14
F	11.98	12.25	4.38	0.04	0.14
p-value	0.0006*	0.0005*	0.0366*	0.8353	0.7058
Complete vs. Missing DTU					
Mean of complete group	4.30	4.16	4.47	4.50	5.25
Mean of missing group	3.81	3.65	4.24	3.94	4.99
F	3.29	3.23	0.68	4.91	1.55
p-value	0.0699	0.0728	0.4107	0.0270*	0.2134
Complete vs. Missing Age					
Mean of complete group	4.29	4.15	4.47	4.48	5.24
Mean of missing group	3.53	3.35	4	3.97	4.97
F	3.81	3.69	1.42	1.89	0.79
p	0.0512	0.0551	0.2339	0.1697	0.38
Complete vs. Missing Income					
Mean of complete group	4.37	4.21	4.52	4.55	5.28
Mean of missing group	3.62	3.59	4.02	3.90	4.89
F	14.01	8.69	5.96	11.65	6.07
p-value	0.0002*	0.0033*	0.0148*	0.0007*	0.0139*
Complete vs. Missing Educational Attainment					
Mean of complete group	4.27	4.12	4.45	4.46	5.23
Mean of missing group	4.26	4.45	4.6	4.89	5.05
F	0.00	0.41	0.10	0.83	0.22
p-value	0.9886	0.5199	0.7577	0.3633	0.6415
Complete vs. Missing Political Affiliation					
Mean of complete group	4.33	4.16	4.50	4.51	5.25
Mean of missing group	3.72	3.86	4.06	4.01	5.02
F	6.85	1.52	3.52	5.27	1.58
p-value	0.009*	0.2179	0.0611	0.0219*	0.2096
Complete vs. Missing Homeownership Status					
Mean of complete group	4.28	4.14	4.47	4.48	5.24
Mean of missing group	3.53	2.88	3.31	3.57	4.24

F	2.00	5.19	4.58	2.87	5.80
p-value	0.1576	0.0229*	0.0325*	0.0906	0.0162*
Complete vs. Missing Number of Household Occupants					
Mean of complete group	4.27	4.13	4.45	4.48	5.25
Mean of missing group	4.78	4.11	4.44	3.13	2.89
F	0.49	0.00	0.00	3.66	17.12
p-value	0.4831	0.9844	0.9905	0.0559	0.0000*

*Significant at $\alpha=.05$

Table C1.
Demographic Characteristics of Sample (n=856) Relative to Los Angeles County

Characteristic	Sample	Los Angeles County
Gender (% female)	54.9	50.3
Mean age (SD)	47.1 (17.8)	35.4a
Ethnicity		
African American	14.6	9.6
Asian / Asian American	7.9	11.1
Caucasian	42.2	38.7
Latino	20.3	48.5
Native American / Pacific Islander	1.5	0.8
Multiracial	4.0	4.6
Other	5.8	--
Primary language spoken at home		
English	83.4	60.2
Spanish	10.8	--
Other	5.8	--
Educational Attainment (≥ 25 yrs)		
Less than High School	5.4	25.8
High school diploma	12.3	19.3
Technical/trade school	1.6	--
Some college /Associate's degree	25.4	24.1
4-year college degree	30.1	20.4
Graduate / professional degree	25.2	10.4
HS degree or higher	94.6	74.2
4-year degree or higher	55.4	30.8
Political Affiliation		--
Liberal	54.4	
Moderate	20.3	
Conservative	25.3	
Annual household income		Median household income: \$49,745
<\$25,000	25.5	
\$25,001-\$50,000	24.2	
\$50,001-\$75,000	17.3	
\$75,001-\$100,000	12.1	
>\$100,000	21.0	
Marital Status		--
Never married	37.0	
Currently married	37.7	
Domestic Partnership	3.3	
Separated	3.7	
No longer married	16.0	

^a Median age

Table C2.

Residence Characteristics of Sample (n=856) Relative to Los Angeles County

	Sample	Los Angeles County
Homeownership Status		
Own	40.2	38.0
Rent	59.8	--
Residence type		--
Single family home	47.0	
Multi-family home	35.2	
Duplex/triplex/Quad	8.3	
Townhome	6.3	
Mobile home	0.2	
Other	2.8	
Housing Stability		
Mean (SD) length of tenure at current address (years)	10.7 (13.1)	--
% residing in same residence as last year	87.3	85.4
Total number of occupants	2.7	2.8

Table D

Odd Ratios And 95% Wald Confidence Intervals For Conceptual Block Models Of Predictors Of Intentions To Adopt Energy Management Technology And Programs

Block	Predictor	WEB	APP	IHD	TOU	DR
Affiliation	CNS	1.07*** (1.04-1.10)	1.06*** (1.04-1.09)	1.05*** (1.02-1.07)	1.05*** (1.02-1.07)	1.03* (1.01-1.06)
With Nature						
Technology	DTU	1.07*** (1.05-1.08)	1.09*** (1.08-1.10)	1.05*** (1.04-1.06)	1.01** (1.00-1.02)	1.02*** (1.01-1.03)
Use						
Demographic	Age	0.96*** (0.96-0.97)	0.95*** (0.94-0.96)	0.97*** (0.96-0.98)	0.99** (0.98-0.99)	0.99** (0.98-0.99)
Characteristics	Gender	0.78 (0.58-1.04)	0.96 (0.71-1.30)	0.84 (0.62-1.12)	1.08 (0.82-1.43)	1.03 (0.76-1.40)
	Income	1.55** (1.12-2.15)	2.21*** (1.57-3.11)	2.01*** (1.45-2.79)	0.94 (0.69-1.28)	1.49* (1.06-2.10)
	Educational attainment	1.39* (1.01-1.91)	1.14 (0.82-1.58)	1.11 (0.81-1.53)	1.03 (0.76-1.39)	1.03 (0.74-1.43)
	Political affiliation	0.92 (0.84-1.01)	0.93 (0.84-1.02)	0.93 (0.85-1.02)	0.98 (0.91-1.07)	0.99 (0.90-1.09)
Residence	Homeownership status	1.54** (1.17-2.03)	1.56** (1.19-2.06)	1.12 (0.84-1.48)	1.25 (0.95-1.64)	1.06 (0.78-1.43)
Characteristics	Number of household occupants	1.03 (0.95-1.12)	1.07 (0.98-1.16)	1.11* (1.02-1.21)	1.08 (0.99-1.17)	1.12* (1.01-1.23)

Notes: Homeownership status, 1=own, 2=rent; gender, 1=male, 2=female; DTU=digital technology use;

CNS=connectedness to nature score

Significance level indication: * $p < .05$, ** $p < .01$, *** $p < .001$.

Table E

Odd ratios, 95% Wald Confidence Intervals for Interaction Block Models

Block	Predictor	WEB	APP	IHD	TOU	DR
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CNS x Gender	Gender	0.47 (0.11-1.96)	0.54 (0.13-2.23)	0.96 (0.24-3.81)	4.35* (1.06-17.85)	0.93 (0.23-3.80)
	CNS	1.05 (0.97-1.14)	1.04 (0.96-1.13)	1.06 (0.98-1.15)	1.13* (1.04-1.22)	1.03 (0.95-1.12)
	Gender ×CNS	1.01 (0.96-1.06)	1.01 (0.97-1.06)	0.99 (0.94-1.04)	0.95* (0.90-1.00)	1.00 (0.95-1.05)
DTU x Gender	Gender	0.72 (0.25-2.11)	1.47 (0.40-5.48)	1.05 (0.40-2.76)	0.48 (0.20-1.15)	0.93 (0.37-2.33)
	DTU	1.06* (1.02-1.10)	1.10* (1.05-1.15)	1.06* (1.02-1.09)	0.98 (0.95-1.01)	1.01 (0.98-1.05)
	Gender ×DTU	1.00 (0.98-1.03)	0.993 (0.97-1.02)	1.00 (0.98-1.02)	1.02* (1.00-1.04)	1.00 (0.98-1.02)
DTU x Age	Age	0.97* (0.94-1.00)	0.98 (0.95-1.02)	0.94* (0.92-0.97)	0.97 (0.95-1.00)	0.99 (0.96-1.01)
	DTU	1.04* (1.00-1.07)	1.08* (1.04-1.13)	0.98 (0.95-1.02)	0.99 (0.96-1.01)	1.01 (0.98-1.04)
	Age ×DTU	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.001* (1.000-1.002)	1.00 (1.00-1.00)	1.00 (1.00-1.00)

Notes: Gender, 1=male, 2=female; DTU=digital technology use; CNS=connectedness to nature score

*Significant at $\alpha=.05$.