Understanding the Path to Smart Home Adoption: Segmenting and Describing Consumers across the Innovation-Decision Process

Abstract

The burgeoning smart home market brings opportunities for home energy management systems (HEMS)**.** Despite hundreds of smart HEM products on the market and many invested stakeholders, consumer adoption is lagging behind expectations. Past research in this space has focused on smart home technology (SHT) in general, rather than particular products with HEM potential. Conflating smart HEMS with all SHT is problematic because there is a wide range of smart home products and functions, toward which consumers may have varying attitudes. Past work has also rarely distinguished between various stages of the adoption process that lead up to smart HEMS purchase (Knowledge, Persuasion, and Decision Stages). This research used a Diffusion of Innovations framework and survey data from 709 California utility customers to assess the current market and barriers to HEM smart hardware adoption. Cluster analysis based on consumer awareness, interest, and ownership of HEMS revealed four consumer segments at different positions along the path to adoption: Unfamiliar, Unpersuaded, Persuaded, and Owners. Each group had a unique demographic and psychographic profile with implications for different sets of relevant barriers to adoption.

Keywords: Home energy management; smart home technology; consumer adoption; innovation-decision

Understanding the Path to Smart Home Adoption: Segmenting and Describing Consumers across the Innovation-Decision Process

New technology is changing the way energy is generated, distributed, and consumed. Decreasing costs and increasing performance of information and communications technology has supported the growth of “big data” in the energy sector, transforming passive power grids into smart energy systems. The burgeoning smart home technology (SHT) landscape, including a growing smart metering infrastructure, microgeneration, storage, and home energy management systems (HEMS), is placing consumers at the heart of the evolving smart energy system. SHTs offer a range of benefits to households--not only reductions in electricity costs, but also home security, comfort, and convenience, or enjoyment for the tech-savvy consumer (Balta-Ozkan, Boteler, & Amerighi, 2014; Ford, Karlin, Sanguinetti, Nersesyan, & Pritoni, 2016; Strengers & Nicholls, 2017) by enabling more precise control over appliances through feedback, scheduling, rule-setting, remote control, and automation.

Policymakers and energy utilities are investing time and money in the smart home. For example, the UK government recently put out a call for evidence to explore how smart appliances enable consumers to support “the development of a more efficient, smart, and flexible energy system” (BEIS & Ofgem, 2016, p. 59). In the US, legislation like California’s Assembly Bill 793 (2015) mandates that utilities promote and rebate HEM products.

Major technology companies are also investing in SHT; for example, Google’s purchase of Nest and Amazon’s Echo. Retailers are promoting the smart home through dedicated displays and venues, such as Sears “Connected Solutions”, a smart home retail and demonstration display that is being rolled out in 200 Sears and 300 Kmart stores in the US (Wolf, 2015). Target has deployed “Connected Life” departments in 1,800 stores (Wollerton, 2015), and Walmart has created a smart home technology website called “Your Life. Connected: Home Automation” (Walmart, 2016).

Hundreds of smart home products are currently available worldwide. Ford et al. (2016) identified a subset of these products as HEM smart hardware: smart thermostats, smart appliances, smart lights, smart plugs, smart switches, and smart hubs. With the exception of hubs, smart hardware products enable direct management of energy consumption in the home without additional products. Hubs enable HEM by networking multiple devices for centralized control.

Despite the abundance and variety of products, marketing efforts, and great expectations, awareness and adoption of SHT remains low (Harms, 2015; Harris Poll, 2015; “Americans don’t totally ‘get’ smart home,” 2015; Where the smart is, 2016). However, market characterization studies indicate high consumer interest in SHT (Shelton Group, 2015; Wilson, Hargreaves, & Hauxwell-Baldwin, 2017). Therefore, there seem to be signifcant gaps or barriers in the SHT market. For example, potentially interested consumers may be unaware of the technology, or knowledgeable and even highly interested consumers may be stopping short of adoption.

This study investigates these gaps in the context of HEM smart hardware adoption. We assert, and demonstrate, that differentiating consumers according to dimensions of the adoption-decision process (awareness, interest, and ownership) can shed considerable light on the current SHT market and barriers to further diffusion. The next sections review past research on SHT adoption and introduce the Diffusion of Innovations (Rogers, 1971, 2003) framework used in the present research.

Smart Home Technology Adoption

Past research on HEMS adoption has focused on energy feedback products without control capabilties (i.e., not *smart*) or SHT broadly, which includes many products without implications for HEM. The current study is unique in its focus on HEM smart hardware. That said, smart hardware is part of the SHT landscape, and often includes energy feedback features, therefore these literatures are relevant and shed light on smart hardware adoption.

A number of studies describe consumers’ perceived benefits and risks of SHT (Balta-Ozkan et al., 2013; Balta-Ozkan et al., 2014; Daws, 2016; Hargreaves et al., 2015; Hargreaves, Wilson, & Hauxwell-Baldwin, 2017; Icontrol Networks, 2015; Harris Poll, 2015; Honeywell, 2015; Coldwell Banker and CNET, 2015; Paetz, Dütschke, & Fichtner, 2012). Many of these focus on the general population (mostly not owners of SHT). In one such study, Balta-Ozkan et al. (2014) concluded that non-energy benefits, such as health and security, are crucial for consumers to appreciate the benefits of smart homes. Balta-Ozkan et al. (2013) inventoried 45 barriers to SHT adoption in 7 categories: (1) fit to current and changing lifestyles, (2) administration, (3) interoperability, (4) reliability, (5) privacy and security, (6) trust, and (7) costs.

A few studies have described SHT users' or owners' experiences. For example, Hargreaves et al. (2015) and Hargreaves, Wilson, and Hauxwell-Baldwin (2017) assessed SHT field study participants' experience, including motivations for agreeing to participate in the field study, which included energy and associated cost savings, interest in technology and automation, environmental values, and control (Hargreaves et al., 2017). Limited research has been conducted with naturalistic SHT adopters (as noted by Gram-Hanssen & Darby, 2018, and Wilson, Hargreaves, & Hauxwell-Baldwin, 2015). An early exception is Mennicken and Huang (2012), who interviewed members of seven households to explore their motivations for naturalistically adopting SHT. They described four themes: adopters perceive smart homes as modern; experiencing SHT leads to further adoption; "hacking the home" as a hobby; and a desire to save energy.

In these studies it is difficult to distinguish between benefits that are sufficiently valuable to persuade consumers to adopt from those that are simply widely acknowledged but perhaps not very valuable. Similarly, it is different to determine barriers that truly impede adoption from risks that consumers may widely recognize but be willing to overlook. Testing for predictors of interest and ownership can help identify which benefits and barriers most influence adoption, and for whom (in terms of demographic and psychographic profiles).

For example, Karlin et al. (2015b) surveyed naturalistic adopters and non-adopters of home energy feedback technology, and found that adopters were more likely to be male, older, married, homeowners, with a higher income, more liberal political ideology, more environmental concern, and more conscious of their energy bill; barriers for non-adopters featured lack of knowledge, including awareness of the technology, where to buy, and how to install/set-up products. More recently, Parag and Butbul (2018) surveyed prospective SHT adopters (defined as non-technophobic consumers) in Israel and assessed predictors of interest in SHT adoption and interest in demand flexibility through SHT. They found that higher income, openness to experience, and general trust in technology predicted interest in SHT adoption among non-technophobic consumers. The excluded technophobic group included more women and senior citizens.

Adoption as a Multi-stage Process

Identifying predictors of interest and adoption provides insight into barriers to SHT and HEMS adoption for non-interested consumers and non-adopters, respectively. However, Diffusion of Innovations Theory (DoI; Rogers, 1971, 2003) posits that adoption is a multi-stage process consumers go through, from learning about a technology to forming attitudes about it, making a purchase, and using the technology. Thus, more nuanced consumer segmentation and study based on these dimensions is needed to build a more complete understanding of who is getting stuck in the SHT adoption process, where, and why. For example, rather than lumping all non-adopters together into a single group, there may be a number of distinct non-adopter groups, ranging from those with no knowledge of the technology but latent interest, to those with a desire to purchase but have not acted on it, and those who are knowledgeable but not interested. These groups may be characterized by distinct demographic and psychographic profiles and they may experience different barriers.

Wilson et al. (2017) used a DoI framework to characterize and compare "actual adopters" (from a field study of smart HEMS in 18 households) to a national survey sample of "prospective users" (filtering out those without knowledge of SHT) and subsets of prospective users defined by their knowledge of SHT. Specifically, they considered high, medium, and low levels of knowledge proxies for early adopters, early majority, and late majority (adopter categories in DoI Theory). Participants in their early adopter group were comparable to the field study participants; they were younger, more likely to be male, live in larger households, and have higher household income compared to all prospective users. The early adopter group also perceived more potential benefits of SHTs than both the early majority and late majority groups. However, comparisons regarding perceived risks were not straightforward. Overall, prospective users were most concerned with loss of autonomy and independence to technological control.

The direction taken by Wilson et al. (2017), drawing on DoI and distinguishing between consumer segments based on their position along the path to adoption, is an important start. They also made interesting comparisons between consumer perceptions and industry marketing content. However, their study is limited by their small sample of "actual" adopters who were not naturalistic adopters. Any naturalistic adopters in their study were included in the early adopter group with non-owners that had high knowledge. Those without prior SHT knowledge were excluded, therefore no insights were gained about consumers who marketing efforts are not reaching at all. Finally, using knowledge as a proxy for adopter categories is an incomplete application of DoI theory, since knowledge does not necessarily portend interest or purchase. Knowledge is a requisite precursor to the adoption decision, but the decision can also be to reject the innovation.

DoI provides a more appropriate framework for understanding the *intra*personal adoption-decision process for a given individual, as opposed to the *inter*personal process of innovations diffusing across different groups in society (i.e., the oft-cited adopter categories: innovators, early adopters, early majority, late majority, and laggards). This framework is called the *innovation-decision process* (Rogers, 1971, 2003), which describes how an individual adopts a new technology in five iterative stages:

1. **Knowledge Stage:** Awareness and understanding of the technology
2. **Persuasion Stage:** Attitudes regarding the degree to which the technology aligns with one's needs and values
3. **Decision Stage:** The choice to purchase/acquire the technology or not (adopt or reject)
4. **Implementation Stage:** User experience after acquisition
5. **Confirmation Stage:** Mirrors the Persuasion Stage in that the customer can reassess the degree to which the technology aligns with their values and goals

The first three stages are particularly relevant to adoption studies that include all consumers, whereas the Implementation and Confirmation Stages are relevant after adoption.

Rogers notes that the innovation-decision process is not a linear path through these stages. For example, persuasion can begin as soon as a consumer becomes aware of a technology and knowledge can continue to develop after interest and the decision to adopt. Therefore, innovation-decision stages can also be characterized as dimensions, e.g., consumers can lack awareness of a technology but have high potential for interest, or they can be quite knowledgeable but uninterested. Thus, consumers may be classified according to their position along the dimensions of Knowledge, Persuasion, and Decision.

Present Research and Hypotheses

The present study applies the innovation-decision model (Rogers, 2003) to the case of HEM smart hardware to better understand how far in the adoption journey different segments of consumers are and how they are getting stuck along the way. This framework, along with the inclusion of all consumers (not just non-technophobic consumers as in Parag & Butbul, 2018, or those with pre-existing knowledge of SHT as in Wilson et al., 2017), allows for a more complete and nuanced segmentation of consumers than previous studies of SHT adoption, and more targeted analysis of barriers at different stages of the adoption decision process. The focus on HEM smart hardware rather than a broader conceptualization of SHT allows for a more targeted analysis of SHT adoption as it relates to the goal of HEM, in a similar vein as the focus on SHT demand flexibility in Parag and Butbul (2018). Based on the innovation-decision framework and literature reviewed above, this study tested the following hypotheses:

H_1: Clustering consumers based on HEM smart hardware awareness, interest, and ownership will reveal distinct groups along the adoption spectrum, including multiple groups of non-adopters, such as those with low awareness but high potential interest, those with some awareness but low interest, and those with awareness and interest.

$H_{2\_A, B, C}$: Each identified cluster will have a unique demographic and psychographic profile. The following relationships are predicted:

A. Demographics and housing characteristics: Higher income, being male, homeownership, and larger home size will predict membership in any cluster that has high knowledge, interest, or owns smart hardware (as suggested by Karlin et al., 2015b; Parag & Butbul, 2018; Wilson et al., 2017).
B. Technology adoption and use: Adoption of other innovative energy-related household technologies (solar PV and plug-in electric vehicles) and higher use of personal technologies will predict membership in any cluster that has high interest or owns smart hardware as suggested by Hargreaves et al., 2017; Karlin et al, 2015b; Mennicken & Huang, 2012; Parag & Butbul, 2018; Rogers, 2003).
C. Perceived smart home benefits and barriers: Perception of more salient SHT benefits, especially non-energy benefits, and less concern with risks will predict membership in any

cluster that has high interest or owns a smart hardware product; the converse, perception of fewer potential SHT benefits and more risks will predict membership in any cluster with low interest (as suggested by Balta-Ozkan et al., 2014; Parag & Butbul, 2018). Finally, informational barriers, such as not knowing where to find information on or purchase SHT, and concerns about hassles of installation and setup will predict membership in any cluster with low awareness (as suggested by Karlin et al., 2015b).

Method

This study was part of a broader research project conducted on behalf of Pacific Gas and Electric (PG&E), the largest energy utility in California. The overall project included a HEM technology inventory, stakeholder analysis, and consumer research and findings were synthesized into a report (Ford et al., 2016). The present research focuses on one aspect of the consumer research--an online survey of 709 PG&E residential customers.

The survey was conducted in March 2016 using PG&E's Customer Voice Panel, a voluntary pool of more than 15,000 customers who agreed to be contacted for research recruitment. Stratified sampling was used to increase the representativeness of the sample in terms of region (Northern, Central Valley, Central Coast, Bay Area), gender, age, income, and housing tenure (own or rent). The resultant sample consisted of 709 customers (a 28% response rate). Sample characteristics are listed in Figure 1.

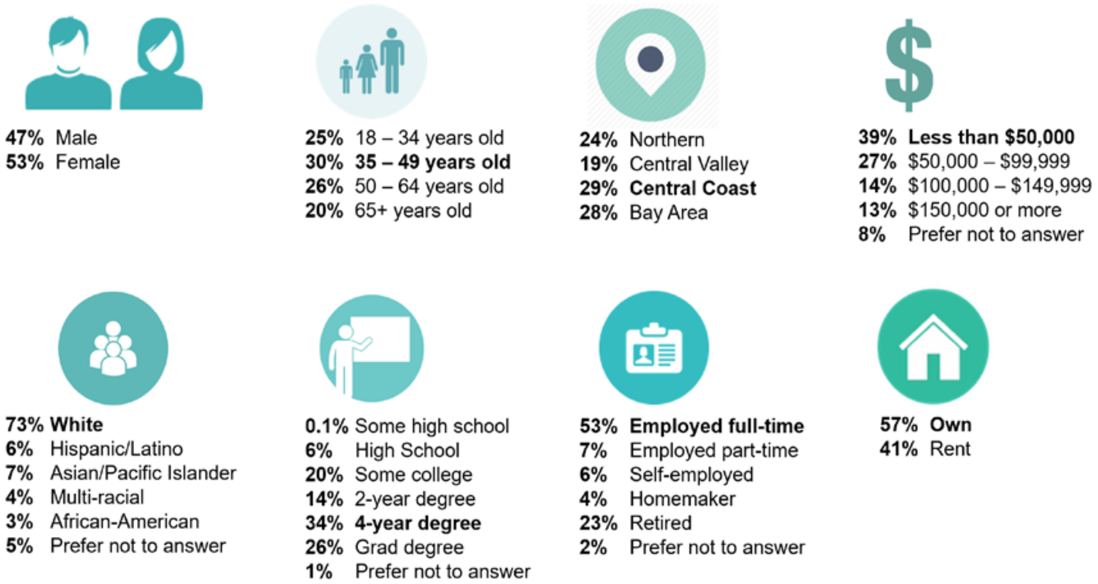

Figure 1. Sample characteristics; mode levels bolded.

The survey focused on the smart hardware product categories identified in Karlin et al. (2015) that have independent capacities to support home energy management: smart thermostats, appliances, lights, and plugs (excluding hubs, which only have an impact through their relationship to other smart products). Smart switches, which are similar to smart plugs (with an interface at the switch rather than the outlet), were not explicitly mentioned in the survey; Karlin and colleagues identified smart switches as a separate category (Ford et al., 2016) after our survey was conducted. However, several respondents who indicated they had a smart *plug* mentioned smart *switches* in open-ended responses, and in other cases we assigned responses regarding smart switches to the smart plug category; thus, we captured information about switches in the plug category.

Survey questions aimed to measure indicators of the innovation-decision process (knowledge, persuasion, and decision) with regard to smart hardware products, as well as variables hypothesized to predict consumer segments based on these indicators; Table 1 lists questions, response options, and supplementary data. The survey proceeded as follows: The first questions concerned respondents' knowledge of SHT, which was followed by an infographic to introduce the concept to those who may have been unfamiliar (Figure 2). After the smart home infographic, additional questions gauged perceived benefits and risks of SHT. Then, questions focused on each smart hardware product type in turn, following a similar sequence--beginning with a knowledge question, then an infographic (Figure 3), then questions about attitudes about and ownership of each product type. The last part of the survey included the items measuring demographics and housing characteristics, and more general technology adoption and use.

Table 1. Survey questions, response options, and supplementary data.

	Construct	Item	Options (coding for cluster analysis and regression)
Innovation-decision indicators	Knowledge	How familiar are you with [smart appliances; smart thermostats; smart plugs; smart lights]?	Not at all (1); A little bit (2); Somewhat (3); Very (4) (summary score used for clustering)
	Persuasion	How much does the idea of [smart appliances; smart thermostats; smart plugs; smart lights] appeal to you?	
	Decision	Do you own [a smart appliance; a smart thermostat (one with features beyond those of a programmable thermostat); any smart lights; any smart plugs]?	Yes; No; Not sure (Yes to any product type = 1; Else = 0 for clustering)
Demographics & housing	Gender	Provided by the utility (PG&E)	Male (0); Female (1)
	Age		18-34 (1), 35-49 (2), 50-64 (3), 65+ (4)
	Household income		under $30,000 (1); $30-49,999 (2); $50-74,999 (3); $75-99,999 (4); $100-149,999 (5); $150-199,999 (6); $200,000+ (7); Unknown
	Tenure		Own (1); Rent (0); Unknown
	Home size	How many bedrooms are in your home?	None (0); 1; 2; 3; 4; 5; 6 or more (6)
Technology adoption & use	PV ownership	Do you own solar photovoltaic (PV) panels for home energy?	Yes; No; Not sure (Yes = 1; Else = 0)
	PEV ownership	Do you own a plug-in hybrid or all-electric vehicle?	
	Personal technology use	How often, if ever, do you use or access the following? Laptop/desktop computer; Tablet; E-reader; Mobile phone with Internet; Wearable health/fitness tracker; Health/fitness tracking app; Energy consumption tracking app/service; Money management app; Gaming/music mobile app	At least once a day (4); A few times a week (3); A few times a month or less (2); Never (1) (summary score used in regression)
Perceived SHT benefits & barriers	Benefits	In which of the following ways, if any, might smart home products benefit your household?	Options listed in Table 5 (Unselected = 0, Selected = 1)
	Barriers	Which, if any, of the following concerns do you have with smart (or connected) home technology?	Options listed in Table 6 (Unselected = 0, Selected = 1)
		Information about SHT is readily available	Strongly disagree; Disagree; Neutral; Agree; Strongly agree (Strongly disagree and Disagree = 1; Else = 0)
		I know where to buy smart home products	

Figure 2. Smart home technology infographic show to familiarize participants with the concept before questions about perceived benefits and barriers.

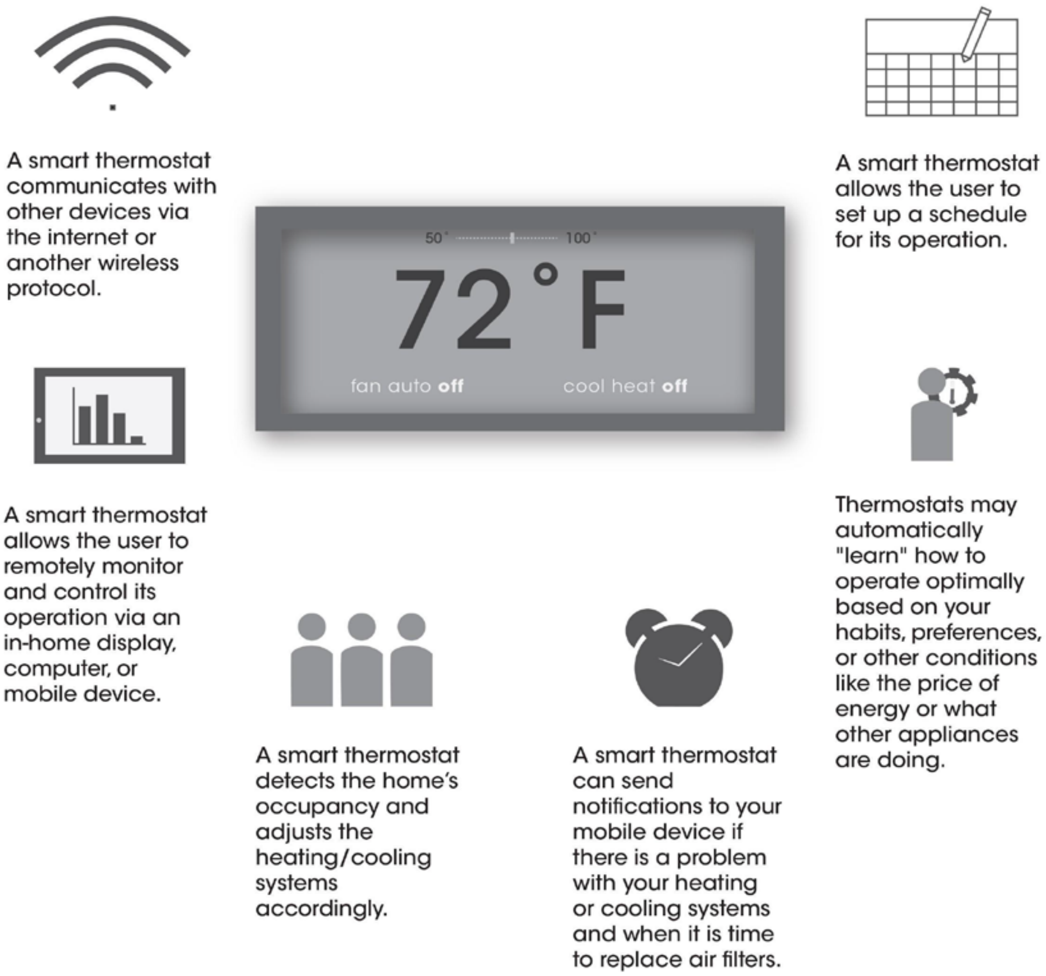

Figure 3. Smart thermostat infographic in the survey. A similar infographic for each smart plugs, lights and appliances was also included. Each infographic appeared after a question about familiarity and before questions about appeal and ownership of the particular product type.

Analysis and Results

Survey data were analyzed to segment consumers based on their position in the innovation-decision process (knowledge, persuasion, decision) and demographic and psychographic predictors of these segments, including their characteristic perceptions of SHT benefits and barriers.

Clustering Consumers based on their Position in the Innovation-decision Process

To cluster participants into types based on position in the innovation-decision process, we ran two-step cluster analysis in SPSS statistical software, with log-likelihood distance measurement and Schwarz's Bayesian Criterion, on the following three variables corresponding to the decision stages:

1) Knowledge: Sum of the four items assessing familiarity with each product type (1 = Not at all familiar, 4 = Very familiar);
2) Persuasion: Sum of the four items assessing appeal of each product type (1 = Not at all appealing, 4 = Very appealing); and
3) Decision: Owns any smart appliance, thermostat, plug/switch, and/or light (1 = Yes, 0 = No).

Two-step cluster analysis was selected because it is appropriate for multiple and mixed types of data, and it can automatically determine the appropriate number of clusters (Norušis, 2009; Sarstedt & Mooi, 2014). The procedure assumes normality of cluster variable distributions for continuous data. Histograms for Knowledge and Persuasion scores (Figures 4 and 5) illustrate some deviation from normality. In particular, there are high frequencies for scores that are multiples of 4 (4, 8, 12, 16) because many respondents selected the same level of knowledge or persuasion for each of the four product types. However, Q-Q plots for these variables do not indicate significant deviation from normality. Furthermore, Norušis (2009) noted that the procedure is robust against violations of distribution assumptions.

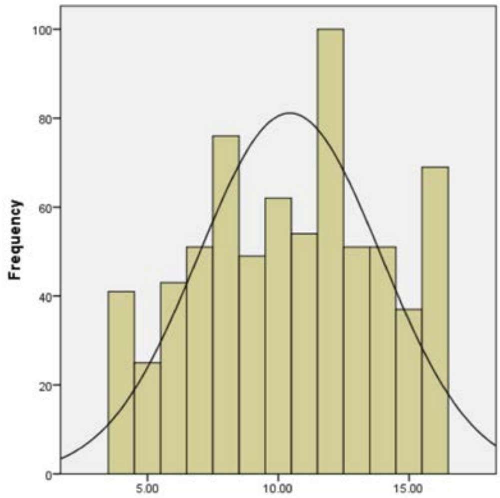

Figure 4. Knowledge score histogram

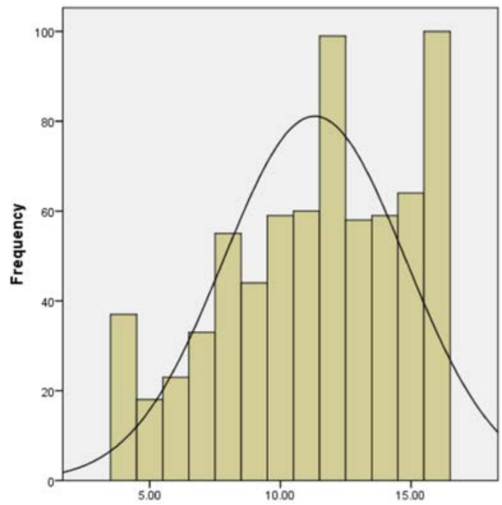

Figure 5. Persuasion score histogram

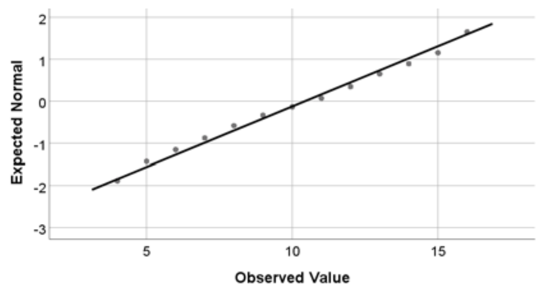

Figure 6. Knowledge score normal Q-Q plot

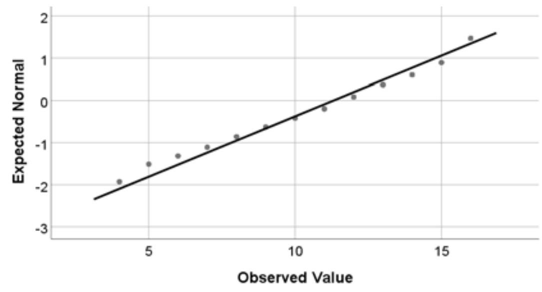

Figure 7. Persuasion score normal Q-Q plot

Our two-step cluster analysis yielded four groups, which we named *Unfamiliar, Unpersuaded, Persuaded*, and *Owners*. Table 2 and Figures 8-9 describe these clusters. This solution had a "good" fit, indicated by a silhouette measure of cohesion and separation of 0.6. This index, which ranges from -1 to 1, reflects the average fit of each case to its assigned cluster; the closer to 1 the better the fit.

The *Unfamiliar* cluster reported significantly less familiarity with HEM smart hardware than the other clusters, but upon introduction found the products appealing. The *Unpersuaded* cluster was differentiated by a low persuasion score, i.e., they found smart hardware significantly less appealing than the other clusters. The *Persuaded* had the highest mean knowledge and persuasion scores, even compared to *Owners*, a cluster entirely comprised of those who owned at least one of the smart hardware product types.

Table 2. Clusters described by variables used in cluster analysis (i.e., sum scores for Knowledge, Persuasion, and Decision indicators across the four smart hardware types). Means and ordinal scales noted for context. Lowercase letters (a, b, c) denote comparisons between clusters; if two cells in the same row have a different letter it means the data for those two clusters differ significantly.

	Unpersuaded (n = 197)	Unfamiliar (n = 150)	Persuaded (n = 205)	Owners (n = 157)	ANOVA or Chi-square
Knowledge					
Familiarity with smart hardware 1 = *Not at all* 2 = *A little bit*	9.47 (0.22) a (per item μ = 2.4)	6.49 (0.14) b (per item μ = 1.6)	12.70 (0.14) c (per item μ = 3.2)	12.48 (0.24) c (per item μ = 3.1)	F = 227***

3 = *Somewhat* 4 = *Very*					
Persuasion Finds HEM smart hardware appealing 1 = *Not at all* 2 = *A little bit* 3 = *Somewhat* 4 = *Very*	6.97 (0.14) a (per item μ = 1.7)	12.40 (0.18) b (per item μ = 3.1)	13.66 (0.13) c (per item μ = 3.4)	12.65 (0.21) b (per item μ = 3.2)	F = 366***
Decision Owns smart hardware	0 a	0 a	0 a	100% b	χ^2 = 709***

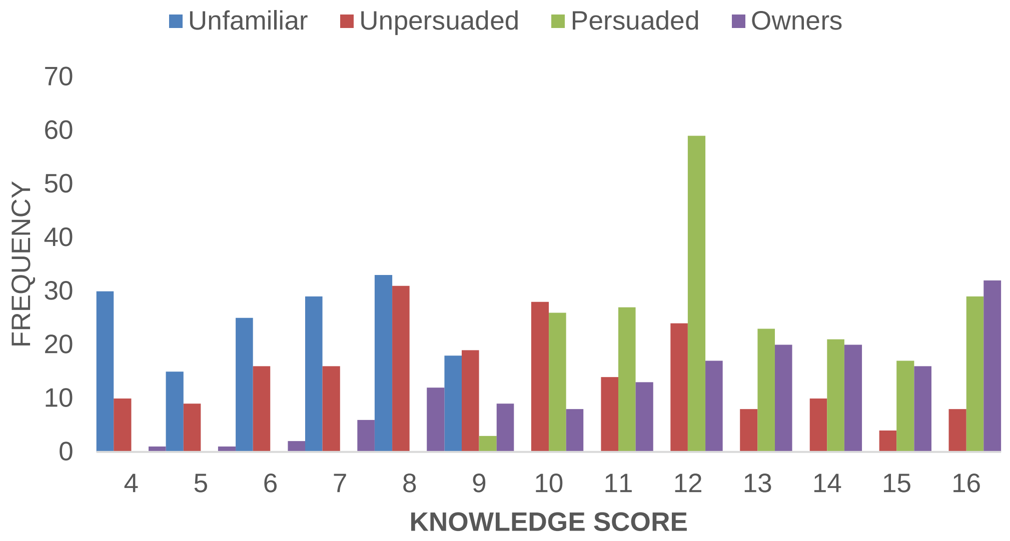

Figure 8. Distribution of smart hardware knowledge scores for each of the four clusters.

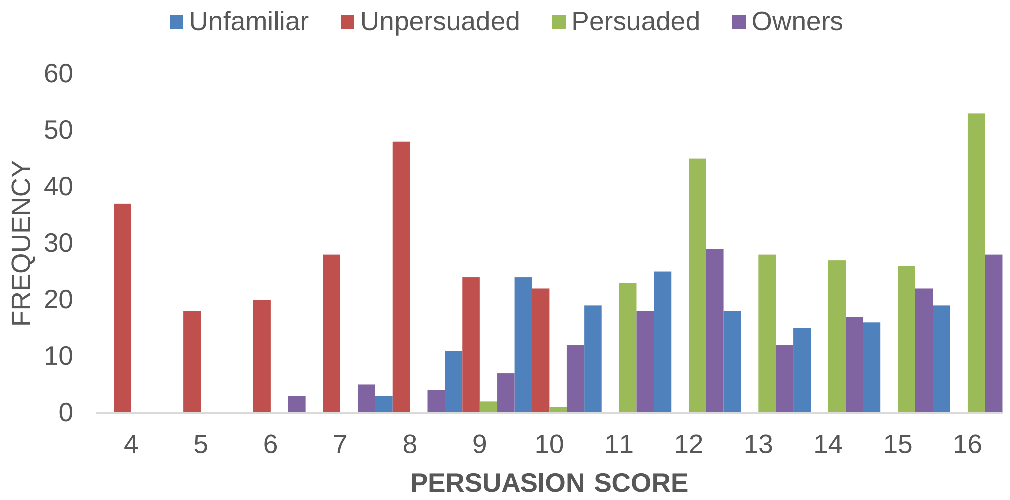

Figure 9. Distribution of smart hardware persuasion scores for each of the four clusters.

Clusters included consumers across Knowledge, Persuasion, and Decision Stages (Figure 10). The Unfamiliar cluster was early on in the Knowledge Stage, with very low familiarity with smart hardware prior to taking the survey. The Unpersuaded and Persuaded clusters were significantly more knowledgeable of smart hardware that the Unfamiliar cluster and had formed opinions in one direction or the other regarding the appeal of smart hardware; specifically, the Unpersuaded found smart hardware relatively unappealing and the Persuaded found smart hardware significantly more appealing compared to every other cluster. Owners had passed into the Decision Stage by purchasing one of the smart hardware product types under study.

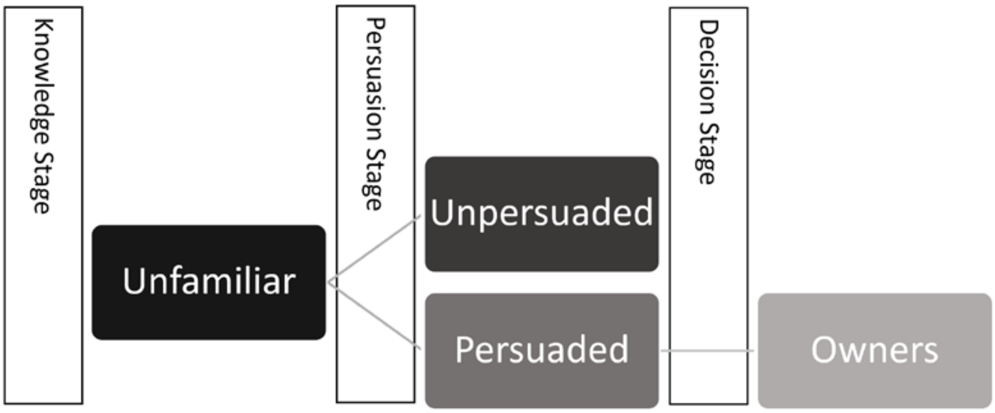

Figure 10. Clusters mapped onto innovation-decision stages.

Predictors of Innovation-decision Clusters

We created a hierarchical binary logistic regression model for each cluster, regressing membership in the cluster (0 = non-membership, 1 = membership) on all potential predictor variables, to identify demographic and psychographic profiles. Variables were entered stepwise to ensure that all meaningful variables were included. Only variables that were significant at the $\alpha = .05$ level when first entered in the model were included in subsequent steps, and these variables were not excluded if the p-value rose over .05 in subsequent steps. The order proceeded from demographic and contextual variables to behaviors and psychographic variables more relevant to smart hardware adoption, as follows:

Step 1: Demographics (gender, age, and income)
Step 2: Housing characteristics (housing tenure and house size)
Step 3: Technology adoption and use (PV ownership, PEV ownership, and personal technology use)
Step 4: Perceived smart home benefits and barriers

We also compared demographic and psychographic characteristics of the resultant clusters via Chi-squared and one-way ANOVA tests. Chi-squared tests were used to compare proportions for categorical variables and ordinal variables with fewer than five levels. ANOVAs were used to compare means for continuous variables and ordinal variables with five or more levels, respectively. These tests were included to reveal pairwise comparisons (differences as well as similarities between any two clusters) that the regression models may obscure. Specifically, if two clusters were similar to each other but significantly different from a third cluster on some variable (e.g., age), that variable might not emerge as a significant predictor of the two similar clusters.

The regression model for each cluster was statistically significant (Table 3), explaining roughly 20-45% of the variation in cluster membership. Interpretation of these effects should take into account that each predictor variable could be related to multiple clusters in the same way (e.g., higher personal technology use scores predicted membership in both the Persuaded and Owners clusters). The following sections summarize significant predictor variables in each regression model, and highlight pairwise differences in means and proportions tests. Tables 4-6 summarize all descriptive statistics and difference in means or proportions tests.

Demographics and housing characteristics. Being female and having lower income predicted membership in the Unfamiliar cluster, whereas being male and having higher income predicted membership in the Owners cluster. Older age predicted membership in the Unpersuaded cluster. No demographic variables were significant predictors of the Persuaded cluster in the regression model, although means and proportions difference tests showed the Persuaded were younger than the Unpersuaded; they also had lower income and were less likely to be male compared to Owners (Table 4).

No housing characteristics were significant predictors of the Unfamiliar cluster in the regression model, although means and proportions difference tests showed the Unfamiliar group included fewer homeowners compared to both the Unpersuaded and Owners; they also had smaller homes, as measured by number of bedrooms, compared to Owners. Smaller home size predicted membership in the Unpersuaded cluster. The Unpersuaded also included more homeowners compared to the Unfamiliar and the Persuaded, and had smaller homes on average. Renting one's home was a significant predictor of membership in the Persuaded cluster. Housing characteristics were not significant predictors of HEM smart hardware ownership in the regression model, although the significance was marginal for homeownership (as opposed to renting; $p = .060$) and larger home size (i.e., more bedrooms; $p = .051$) when entered.

Technology adoption and use. Not owning solar PV predicted membership in the Unfamiliar cluster. Difference in means and proportions tests revealed that the Unfamiliar reported lower levels of personal technology use than the Persuaded and Owners, but higher than the Unpersuaded. Low levels of personal technology use did predict membership in the Unpersuaded cluster, whereas higher levels of technology use predicted membership in each the Persuaded and Owners clusters. The Unpersuaded were also less likely to own solar PV compared to Owners and the Persuaded, but more likely than the Unfamiliar. Owners were more likely than each other cluster to own plug-in vehicles.

Perceived smart home benefits and barriers. Owners and the Persuaded had similar perceptions of smart home benefits. Owners and/or the Persuaded were more likely than the Unfamiliar to perceive smart home benefits of comfort, convenience (i.e., making chores easier), health, security, and enjoyment, but not energy savings, cost savings, energy management, or environmental impact. The Unpersuaded recognized each smart home benefit less than all other clusters.

Compared to each other cluster, the Unfamiliar were significantly less likely to agree that SHT is readily available, less knowledgeable about where to buy products, and more concerned that products could be a hassle to install or set-up. Although the Unpersuaded were also less confident in where to find SHT information and buy products compared to Persuaded and Owners, it was their greater skepticism about product value and performance that distinguished them from all other clusters. The Persuaded's concerns with SHT risks were similar to that of Owners, except they were significantly less concerned than SHT could make simple tasks unnecessarily complicated. Although concerns about privacy and security were prevalent for all groups, there were no between-group differences; e.g., Owners were just as concerned as the Unpersuaded.

Table 3. Regression models predicting membership in each HEM smart hardware decision cluster with predictor β (SE); the dependent variables are binary (e.g., Unfamiliar = 1; Other = 0), as are the perceived benefits and barriers variables (Checked = 1; Unchecked = 0).

	Unpersuaded	Unfamiliar	Persuaded	Owners
Constant	2.09(0.64)***	-6.16(1.29)***	-1.13(0.52)*	-2.35(0.61)****
Age	0.18(0.10)*			
Gender		0.88(0.24)****		-0.67(0.23)***
Income		-0.15(0.06)**		0.14(0.06)**
Housing tenure			-0.61(0.19)***	
Home size	-0.22(0.10)**			
Owns PV (solar)		1.36(0.63)**		0.85(0.31)***

Personal technology use	-0.07(0.02)***		0.03(.02)*	0.07(0.02)****
Benefit: Make my home more comfortable	-1.12(0.24)****		0.61(.20)***	0.87(0.23)****
Benefit: Reduce energy use	-1.48(0.29)****			
Benefit: Reduce negative environmental impact				-0.37(0.24)
Benefit: Enjoyable to have and/or use	-0.86(0.28)***			
Benefit: Improve home resale value			0.39(.19)**	
Benefit: Enable better management of household energy use	-0.81(0.22)****	0.97(0.25)****		
Benefit: Protect health of household members		-0.43(0.26)*		
Barrier: Don't know where to buy products		1.65(0.22)****	-0.94(.22)****	-1.22(0.30)****
Barrier: Skeptical whether they perform as well as basic devices	0.64(0.23)***			
Barrier: Hassle to set-up/install	-0.61(0.24)**			
Barrier: Not worth the price	0.64(0.22)***			
Barrier: Makes simple tasks unnecessarily complicated	0.75(0.24)***		-0.82(.22)****	
Barrier: Easier for others to access my personal information without my permission	0.52(0.22)**			-0.43(0.21)**
Nagelkerke R Square	.448	.267	.199	.256
N, -2 log likelihood	706, 572	646, 541	693, 734.10	646, 571.33
Chi-square	262****	121****	104.09****	119.12****

*, **, ***, **** indicates significance at the 90%, 95%, 99%, and 99.9% level, respectively

Table 4. Clusters described by demographics, housing characteristics, and technology adoption and use variables. Differences in column proportions or means denoted by lowercase letters a, b, c.

	Unpersuaded	Unfamiliar	Persuaded	Owners	Chi-square or ANOVA
Gender	44% Male a 56% Female a	25% Male b 75% Female b	52% Male a 48% Female a	67% Male c 33% Female c	χ^2 = 58***
Age	18% 18-34 a 22% 35-49 a 31% 50-64 a 29% 65+ a	25% 18-34 a, b 39% 35-49 b 24% 50-64 a, b 12% 65+ b	29% 18-34 b 31% 35-49 b 21% 50-64 b 20% 65+ b	26% 18-34 a, b 33% 35-49 b 26% 50-64 a, b 15% 65+ b	χ^2 = 32***
Income (median range)	$30-49,999/ $50-74,999 a, b	$30-49,999 a	$50-74,999 b	$75-99,999 c	*F* = 15***
Housing tenure	64% Own a	44% Own b	50% Own b	71% Own a	χ^2 = 37***

	34% Rent a	51% Rent b	49% Rent b	28% Rent a	
Home size	2.57 (1.04) a	2.57 (1.10) a	2.55 (1.07) a	2.94 (1.05) b	F = 5**
Technology use	19.58 (5.32) a	21.21 (4.66) b	23.65 (5.06) c	24.40 (5.31) c	F = 34***
Owns solar PV	12% a	2% b	10% a	21% c	χ^2 = 29***
Owns plug-in vehicle	5% a	3% a	6% a	12% b	χ^2 = 14**

*, **, ***, **** indicates significance at the 90%, 95%, 99%, and 99.9% level, respectively

Table 5. Clusters described by percent of sample who agreed to each potential benefit of smart home technology for their household. Differences in column proportions denoted by lowercase letters a, b, c.

	Unpersuaded	Unfamiliar	Persuaded	Owners	Chi-square
Make my home more comfortable	19% a	43% b	67% c	68% c	122.1***
Make household chores easier	9% a	20% b	34% c	32% c	43.2***
Save time	16% a	40% b	48% b	48% b	54.8***
Save money on energy bills	62% a	91% b	95% b	92% b	100.9***
Reduce energy use	63% a	91% b	96% b	94% b	108.3***
Reduce negative environmental impact	37% a	61% b	72% c	64% b, c	54.1***
Enjoyable to have and/or use	13% a	35% b	46% c	47% c	62.9***
Improve home resale value	20% a	35% b	44% b	44% b	31.9***
Enable better management of household energy use	40% a	75% b	79% b	75% b	84.5***
Protect home from theft or vandalism	25% a	40% b	49% b, c	58% c	42.7***
Protect health of household members	11% a	21% b	37% c	36% c	46.3***
Alert me when household equipment needs attention	41% a	69% b	73% b	73% b	58.0***
Enable better care for children or elderly	8% a	18% b	24% b	27% b	24.7***
Enable better care for pets	9% a	27% b	30% b	28% b	30.1***

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

Table 6. Clusters described by percent of sample who agreed to each potential barrier and risk to smart home adoption. Differences in column proportions denoted by lowercase letters a, b, c.

	Unpersuaded	Unfamiliar	Persuaded	Owners	Chi-square
Information is not readily available	24% a	39% b	13% c	10% c	51.2***

Don’t know where to buy products	37% a	63% b	17% c	10% c	129.0***
Skeptical whether they perform as well as basic devices	44% a	30% b	24% b	25% b	23.6***
Hassle to set-up/install	37% a	51% b	34% a	34% a	12.3**
Not worth the price	55% a	43% b	34% b	34% b	22.9***
Makes simple tasks unnecessarily complicated	46% a	31% b	17% c	27% b	41.5***
Easier for others to access my personal information without my permission	62% a	55% a, b	51% a	49% a	7.4

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$

Discussion

Statistically clustering consumers based on their awareness, interest, and ownership of HEM smart hardware revealed four groups: Owners, Persuaded, Unfamiliar, and Unpersuaded. These findings supported H_1, which predicted several distinct groups of non-adopters, i.e., those who were unfamiliar but interested upon learning about smart hardware (Unfamiliar), those who were aware but not interested (Unpersuaded), and those who were aware and interested but did not own (Persuaded). The sets of hypotheses outlined as $H_{2\_A, B, C}$ predicted demographic and psychographic profiles of these clusters, which were largely supported. Specifically, higher income, being male, homeownership, larger home size, higher rates of technology adoption and use, greater perception of SHT benefits, and less concern with SHT risks were characteristic of Owners and/or the Persuaded. Less perception of SHT benefits and greater concern with SHT risks was characteristic of the Unpersuaded, and informational barriers (not knowing where to find information on or purchase SHT, and concerns about hassles of installation and setup) were characteristic of the Unfamiliar.

Results have implications for understanding, and perhaps accelerating, HEM smart hardware adoption. We discuss implications for each cluster, including comparisons to Rogers’ adopter categories (innovators, early adopters, early majority, late majority, laggards). However, we remind the reader that Rogers’ interpersonal adopter categories are based on latency of adoption after an innovation is introduced and an individual consumer is limited to a single category. In contrast, our clusters are based on the intrapersonal innovation-decision process and we assume individuals move between clusters, e.g., from Unfamiliar to Persuaded to Owner.

Unfamiliar

Largely unfamiliar with HEM smart hardware prior to taking the survey, this group found the products appealing once introduced. Information is the key barrier to adoption for this group. In particular, the Unfamiliar did not believe information about SHT was readily available, they did not know where to buy smart home products, and they were concerned that installation and set-up might be too much of a hassle.

Implications for HEMS product development to better reach this segment include the need for plug-and-play products that are accessible for less tech-savvy consumers. Implications for service providers and utility program design include proactive customer service strategies to help with installation, set-up, and troubleshooting. Findings also imply a need for better marketing to women, who made up the majority of this group and found HEM smart hardware equally appealing as did the male-dominated Owners cluster. This correlation between gender and technology adoption has been found previously, both with regard to HEMS adoption (e.g., Karlin et al., 2014) and technology adoption more broadly (e.g., He & Freeman, 2010; Venkatesh & Morris, 2000).

Unpersuaded

The Unpersuaded resemble the group Rogers’ (1971, 2003) referred to as laggards, who tend to be older, traditionalists, and suspicious of innovations. Compared to other groups, the Unpersuaded were older, had lower rates of personal technology use, and expressed significantly less acknowledgement of SHT benefits and more skepticism about product performance and value. However, they were no more concerned than other groups about data privacy and security, which is consistent with Wilson et al. (2017) who found that other risks were more detrimental to adoption.

An inverse relationship between perceived benefits and barriers in our findings, especially evident in the Unpersuaded cluster, aligns with previous research (Slovic, 1987), and has been attributed to an innate human desire for consistency among diverse beliefs. People tend to reduce their perception of risk for technologies they find to be beneficial (Alhakami & Slovic, 1994; Frewer et al., 1998), and perceived benefits often outweigh perceived risks in consumers' evaluation of new technologies (Starr, 1969) These findings suggest fostering adoption among this consumer segment requires better communicating the benefits of SHT rather than assuaging perceptions of risks. In particular, benefits related to safety, health, comfort, and energy cost savings might be more compelling than benefits that could be perceived as frivolous or unnecessary, e.g., entertainment, novelty, and convenience.

Persuaded

The Persuaded actually found HEM smart hardware more appealing than did Owners. It is difficult to guess what barriers for this group might be, but compared to Owners they had lower income and included fewer homeowners. There may be contextual and psychological barriers to HEM smart hardware adoption for renters. For example, property managers may provide appliances and renters may hesitate to replace large appliances, thermostats, and even plug outlets and switches if they would have to store and reinstall old equipment upon moving. In terms of psychological barriers, renters may not be in the habit of investing in home improvements.

Owners

Consumers who have reached the Decision Stage and chosen to adopt HEM smart hardware likely include the groups Rogers (1971, 2003) called innovators and early adopters. Consistent with Rogers' characterization of early adopters, Owners had higher income compared to other clusters, and higher levels of adoption of solar PV and plug-in vehicles. The latter is also suggestive of the theme Mennicken and Huang (2012) identified among SHT adopters, that adoption of SHT can be reinforcing, leading to adoption of further SHTs.

The fact that Owners and/or the Persuaded were more likely than the Unfamiliar to perceive smart home benefits of comfort, convenience (making chores easier), health, security, and enjoyment, but *not* energy savings, cost savings, energy management, or environmental impact suggests that non-energy benefits are driving HEM smart hardware adoption. If HEM smart hardware is being adopted and used mainly for non-energy benefits, energy-conserving and/or demand response default settings could be critical features to ensure energy benefits (see discussion of default settings in Sintov & Schultz, 2017). See also Peffer, Pritoni, Meier, Aragon, and Perry (2011) for an example of the impotence of energy efficient technologies that rely on user behavior rather than default settings (i.e., programmable thermosats).

Limitations and Future Research

Participants in this study volunteered to be part of a research panel for their energy utility, so they may have more interest in energy than the general population, and the fact that the survey came from their utility may have led to some response bias. The results are also limited to California consumers. Replications of this research in other locations might result in different clusters. For example, in places where awareness of HEM smart hardware products is lower, we might have found multiple clusters with low awareness, differentiated by level of interest.

The R-squared values for the regression models were relatively low for the Unfamiliar, Owners, and particularly the Persuaded cluster. This is likely in part because these clusters had positive appraisals of HEMS, thus were similar in terms of characteristics that predict finding HEMS appealing, which would deflate the power of these characteristics to predict membership in one cluster over the others. However, it may also indicate that the survey did not assess important barriers for these groups at the Knowledge and Decision Stages, such as the complexities of choosing between multiple similar HEM product types (Sanguinetti, Karlin, Ford, Salmon, & Dombrovski, 2018).

Future research would also benefit from considering other theoretical models for predictors of innovative technology adoption, and particularly sustainable technology adoption. For example, Noppers, Keizer, Milovanovic, and Steg (2016) recently demonstrated the utility of a model that includes consumer perception of instrumental, environmental, and symbolic attributes of sustainable technologies as predictors of HEMS adoption. In particular, the present study did not account for symbolic attributes, i.e., perceptions of how HEMS adoption affects one's social image or status.

This research shed light on factors influencing adoption up to the decision to purchase HEM smart hardware, but did not consider factors influencing adoption in the Implementation and Confirmation Stages of the innovation-decision process. Future research could cluster smart hardware adopters based on dimensions of Implementation and Confirmation (e.g., whether owners use the energy saving features of these products). Longitudinal research is needed to understand how consumers' perceptions change as they move between clusters (e.g., from Unfamiliar to Persuaded to Owner). Furthermore, if and when smart home technologies begin to be integrated into buildings at the construction stage or become commonplace in appliances, this type of research could be replicated to understand which consumers use (or disable) HEM features.

Future research should also consider whether smart hardware products are being used independently or as part of multi-product smart home systems. We did explore using the number of different product types owned as a Decision Stage indicator in the cluster analysis for this study, but no unique clusters emerged. In a different or larger sample, or if and when HEM hardware products are more widely adopted, there may be interesting distinctions between clusters of consumers who own one particular product type and others who own multiple types.

Conclusion

In conclusion, this research demonstrated that consumers can be clustered according to their position in the smart home adoption-decision process. Categorizing consumers along multiple dimensions of the innovation-decision process is a novel contribution to Diffusion of Innovations Theory that can be applied to different domains. The practical utility of this research is the identification and description of market segments for HEM smart hardware and barriers that impede each segment's progression in the adoption-decision process. Further research is needed to better understand how diffusion of HEM smart hardware might enable energy conservation and support grid resilience.

References

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In *Action control* (pp. 11-39). Springer Berlin Heidelberg.

Americans don't totally 'get' smart home. (2015, September 10). Retrieved from http://www.hbsdealer.com/article/survey-americans-dont-totally-get-smart-home

Assembly Bill 793. (2015). Chapter 589. California State.

Balta-Ozkan, N., Boteler, B., & Amerighi, O. (2014). European smart home market development: Public views on technical and economic aspects across the United Kingdom, Germany and Italy. *Energy Research & Social Science*, *3*, 65-77.

Balta-Ozkan, N., Davidson, R., Bicket, M., & Whitmarsh, L. (2013). Social barriers to the adoption of smart homes. *Energy Policy*, *63*, 363-374.

BEIS & Ofgem (2016). A smart, flexible energy system: A call for evidence. Retrieved from https://www.ofgem.gov.uk/ofgem-publications/108609

Coldwell Banker, & CNET. (2015). Americans ready for the smart home: Results of the Coldwell Banker and CNET smart home survey. Retrieved from https://www.coldwellbanker.com/content/pdfs/survey_final.pdf

Daws, R. (2016, May 4). Research: Nest reveals consumer feelings about IoT. Retrieved from http://www.iottechnews.com/news/2016/may/04/research-nest-reveals-consumer-feelings-about-iot/

Ford, R., Karlin, B., Sanguinetti, A., Nersesyan, A., & Pritoni, M. (2016). Assessing Players, Products, and Perceptions of Home Energy Management. San Francisco, CA: Pacific Gas and Electric.

Gram-Hanssen, K., & Darby, S. J. (2018). "Home is where the smart is"? Evaluating smart home research and approaches against the concept of home. *Energy Research & Social Science*, *37*, 94-101.

Hargreaves, T., Hauxwell-Baldwin, R., Coleman, M., Wilson, C., Stankovic, L., Stankovic, V., ... & Hassan, T. M. (2015). Smart homes, control and energy management: How do smart home technologies influence control over energy use and domestic life? Paper presented at the European Council for an Energy Efficient Economy (ECEEE) 2015 Summer Study, Toulon/Hyères, France, June 2015, pp. 1021-1032.

Hargreaves, T., Wilson, C., & Hauxwell-Baldwin, R. (2017). Learning to live in a smart home. *Building Research & Information*, 1-13.

Harris Poll. (2015). Consumers beginning to embrace smart home technology – even if they don't know it yet. Retrieved from http://www.theharrispoll.com/business/Consumers Embrace-Smart-Home-Technology.html

He, J., & Freeman, L. A. (2010). Are men more technology-oriented than women? The role of gender on the development of general computer self-efficacy of college students. Journal of Information Systems Education, 21(2), 203.

Honeywell. (2015). *More than Two-Thirds of Americans Don't feel Totally Safe in their own Homes, According to Honeywell Survey* [Press release]. Retrieved from https://honeywell.com/News/Pages/More-Than-Two-Thirds-Of-Americans-Dont-Feel-Totally-Safe-In-Their-Own-Homes-According-To-Honeywell-S.aspx

Icontrol Networks. (2015). 2015 State of the Smart Home Report. Retrieved from http://www.icontrol.com/wp-content/uploads/2015/06/Smart_Home_Report_2015.pdf

Karlin, B., Davis, N., Sanguinetti, A., Gamble, K., Kirkby, D., & Stokols, D. (2014). Dimensions of conservation: exploring differences among energy behaviors. *Environment and Behavior, 46*(4), 423-452.

Karlin, B., Ford, R., & Squiers, C. (2014). Energy feedback technology: a review and taxonomy of products and platforms. *Energy Efficiency, 7*(3), 377-399.

Karlin, B., Ford, R., Sanguinetti, A., Squiers, C., Gannon, J., Rajukumar, M., & Donnelly, K.A. (2015). Characterization and Potential of Home Energy Management (HEM) Technology. San Francisco, CA: Pacific Gas and Electric.

Karlin, B., Sanguinetti, A., Davis, N., Bendanna, K., Holdsworth, K., Baker, J., ... & Stokols, D. (2015b, August). Diffusion of Feedback: Perceptions and Adoption of Devices in the Residential Market. In *International Conference of Design, User Experience, and Usability* (pp. 368-379). Springer, Cham.

Karlin, B., & Ford R. (2013). *Beyond kWh: A new tool for assessing behavior-based energy interventions*. Report prepared for the International Energy Agency Demand Side Management Program (IEA-DSM) Task 24-Behaviour Change in DSM.

Mennicken, S., & Huang, E. M. (2012, June). Hacking the natural habitat: an in-the-wild study of smart homes, their development, and the people who live in them. In *International Conference on Pervasive Computing* (pp. 143-160). Springer Berlin Heidelberg

Noppers, E. H., Keizer, K., Milovanovic, M., & Steg, L. (2016). The importance of instrumental, symbolic, and environmental attributes for the adoption of smart energy systems. *Energy Policy*, *98*, 12-18.

Norušis, M. J. (2009). PASW Statistic 18. Statistical Procedures Companion.

Ozaki, R., & Sevastyanova, K. (2011). Going hybrid: An analysis of consumer purchase motivations. *Energy Policy*, *39*(5), 2217-2227.

Paetz, A. G., Dütschke, E., & Fichtner, W. (2012). Smart homes as a means to sustainable energy consumption: A study of consumer perceptions. *Journal of Consumer Policy*, *35*(1), 23-41.

Parag, Y., & Butbul, G. (2018). Flexiwatts and seamless technology: Public perceptions of demand flexibility through smart home technology. *Energy Research & Social Science*, *39*, 177-191.

Peffer, T., Pritoni, M., Meier, A., Aragon, C., & Perry, D. (2011). How people use thermostats in homes:

A review. *Building and Environment, 46*, 2529-2541.

Rogers, E. M. (2003). Diffusion of innovations. Free Press. *New York*, 551.

Rogers, E. M., & Shoemaker, F. F. (1971). Communication of Innovations; A Cross-Cultural Approach.

Sanguinetti, A., Karlin, B., Ford, R., Salmon, K., & Dombrovski, K. (2018). What's energy management got to do with it? Exploring the role of energy management in the smart home adoption process. *Energy Efficiency*, 1-15.

Sarstedt, M., & Mooi, E. (2014). Cluster analysis. In *A concise guide to market research* (pp. 273-324). Springer, Berlin, Heidelberg.

Shelton Group. (2015). What utility customers want: The foundation for future utility-customer relationships. Retrieved from https://storage.googleapis.com/shelton-group/Content%20Library/SmartHomeStrategiesForUtilities_SpecialReportEnergyPulse2015.pdf

Sintov, N.D., & Schultz, P.W. (2017). Making smart homes more sustainable with adjustable green defaults. *Sustainability, Special Issue on the Advent of Smart Homes, 9*, doi:10.3390/su9040622

Stern, P. C. (2000). New environmental theories: toward a coherent theory of environmentally significant behavior. *Journal of Social Issues*, *56*(3), 407-424.

Schwartz, S. H. (1977). Normative influences on altruism. *Advances in Experimental Social Psychology*, *10*, 221-279.

Strengers, Y., & Nicholls, L. (2017). Convenience and energy consumption in the smart home of the future: Industry visions from australia and beyond. *Energy Research & Social Science*, *32*, 86-93.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. MIS quarterly, 115-139.

Walmart. Home Automation. (2016). Retrieved from http://www.walmart.com/cp/Your-Life.-Connected-Home- Automation/1155673.

Where the smart is. (2016, June 11). Retrieved from http://www.economist.com/news/business/21700380-connected-homes-will-take-longer-materialise-expected-where-smart

Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2017). Benefits and risks of smart home technologies. *Energy Policy*, *103*, 72-83.

Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2015). Smart homes and their users: a systematic analysis and key challenges. *Personal and Ubiquitous Computing*, *19*(2), 463-476.

Wolf, A. (2015, January 16). TWICE Exclusive: Sears rolling out connected-home shops. Retrieved from http://www.twice.com/news/retail/twice-exclusive- sears-rolling- out-connected-home-shops/55658

Wollerton, M. (2015, May 12). Target stores to introduce dedicated smart-home sections. http://www.cnet.com/news/target-stores- to-introduce- dedicated-smart- home-sections/.