Energy Research and Development Division

FINAL PROJECT REPORT

Cybernetic Research Across California

Documenting Technological Adoption and Behavior Change Across Diverse Geographies and Populations to Inform Energy Efficiency Program Design

PREPARED BY:

Primary Authors:

Susan Mazur-Stommen[1*]	Stephen Paff[2]	Katherine Farley[1]
Amy Bayersdorfer[1]	Helena Ottoson[1]	Adam Molnar[1]
Haley Gilbert[1]	Disha Vora[1]	Chris Granda[3]

*Corresponding author (susanmazur@indiciaconsulting.com)
[1] Indicia Consulting, 431 Oglethorpe Street NW, Washington, DC 20011, http://indiciaconsulting.com/
[2] University of Memphis, Memphis, TN 38152, http://www.memphis.edu/
[3] Grasteu Associates, 422 White Hill Road, Richmond, VT 05477, http://www.grasteu.com

Contract Number: EPC-14-038

PREPARED FOR:
California Energy Commission

David Hungerford
Project Manager

Virginia Lew
Office Manager
ENERGY EFFICIENCY RESEARCH OFFICE

Laurie ten Hope
Deputy Director
ENERGY RESEARCH AND DEVELOPMENT DIVISION

Drew Bohan
Executive Director

ACKNOWLEDGEMENTS

PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation and bring ideas from the lab to the marketplace. The CEC and the state's three largest investor-owned utilities—Pacific Gas and Electric Company, San Diego Gas & Electric Company, and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.

- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.

- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.

- Supporting low-emission vehicles and transportation.

- Providing economic development.

- Using ratepayer funds efficiently.

Cybernetic Research Across California: Documenting Technological Adoption and Behavior Change Across Diverse Geographies and Populations to Inform Energy Efficiency is the final report for the Cybernetic Research across California: Documenting Technological Adoption and Behavior Change across Diverse Geographies and Populations to Inform Energy Efficiency project (Contract Number EPC-14-038) conducted by Indicia Consulting, LLC. The information from this project contributes to Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the [CEC's research website](www.energy.ca.gov/research/) at www.energy.ca.gov/research/ or contact the CEC at 916-327-1551.

ABSTRACT

This project investigated households with personal consumer electronics (such as smartphones, tablets, and laptops) in two utility territories in California. The research team sought to demonstrate a psychosocial characteristic termed "cybersensitivity." Cybersensitives are people who appear to exhibit a greater emotional connection to their phones, tablets, and other personal technology such as wearables (for example, smart watches and fitness trackers). Cyberawares are distinguished from cybersensitives by their preference for tracking information or using wearables. This project collected qualitative data via indepth interviews with 48 households and a questionnaire with 298 respondents. The research team found that households fell into segments according to different behaviors and attitudes about engagement with devices and electricity consumption and conservation. This market segmentation is a form of psychographic segmentation (based on shared personality traits, beliefs, values, attitudes, interests, and lifestyles) or behavioral market segmentation. Households sorted into five segments: cybersensitive, cyberaware, mainstream, low mainstream, and null.

The research team used the data to construct two decision tree models. The first model was an ethnographic decision tree model used to diagram the best process for segmenting a population according to the presence or absence of cybersensitivity traits. The second model used machine-learning techniques to produce a classification and regression tree model that predicted the percentage of segment membership across a synthetic population. These two models support the assertion that distribution of cybersensitives within a population will remain similar even when sample sizes are scaled up. The research team recommends that utilities and policymakers who seek larger energy savings begin by targeting cybersensitives and cyberawares for participation in feedback programs using opt-in program design. This recommendation is supported by an extensive literature review of behavior-based energy efficiency programs.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

Introduction

Technological innovation has been an impressive driver of efficiency gains; however, over time it has become clear that without a greater understanding of the human factors, potential energy savings will remain unlocked. Documenting and analyzing emerging attitudes, emotions, experiences, habits, and practices around technology adoption are essential to devising predictive indicators for on-going potential studies regarding energy consumption in California.

"Cybersensitive" refers to a phenomenon whereby some people appear to exhibit a greater emotional connection to their phones, tablets, and other personal technology; enjoy interacting with technology in their everyday lives; and are otherwise more viscerally responsive to technological interventions than their class, gender, neighborhood, age, or income demographic peers. This project advanced and tested the hypothesis that Cybersensitives are more likely to take energy-savings actions in response to feedback information and technology-focused efficiency and demand response programs. In addition, the project team developed critical insights into determining how to more effectively support residential engagement in energy efficient behaviors and identifying target subpopulations for whom energy savings have the potential of being more sustainable.

Project Purpose

The project had two goals: (1) to establish the presence or absence of a trait the research team termed cybersensitivity, and (2) to use this trait to divide consumers into segments and model the distribution of the segments across a population.

Once the presence of cybersensitivity is established, the specific psychosocial drivers of cybersensitive behavior (such as shared personality traits, beliefs, values, attitudes, interests, and lifestyles) could be used to segment households within California investor-owned utility territories. The primary aim with any market segmentation is to establish groupings with similarity within segments and differences among segments. Programs to change consumer behavior can then be targeted to specific segments.

A decision tree model is a tool that uses a tree-like graph or model of decisions and their potential consequences. Using a decision-tree model, populations can be divided according to traits of cybersensitivity. The researchers designed two complementary decision trees to assign the membership to a segment and then predict the distribution of segments in a population.

The research team intended for insights from this project to be useful in developing utility-run residential energy efficiency programs designed to improve consumer knowledge of, and engagement with, their electricity consumption with the aim of changing their consumption behavior. Demand response programs are designed to

encourage people to reduce electricity consumption during specific times of day or in response to specific signals that reflect electric grid conditions such as peak demand or grid emergencies. These programs commonly include features and services like smart meters, time-of-use or critical peak pricing rate provisions, smart thermostats or in-home displays, and home energy reports. Many such programs are offered as "opt-out" or "default" programs in which customers are automatically enrolled and must take action should they not wish to participate. The rationale behind this approach is often framed as a desire to treat all customers equally. However, opt-out residential energy efficiency programs have produced uneven outcomes because of differences among types of residential consumers, energy load profiles, and even attitudes.

According to classical economic theory, people are rational actors who, as consumers, always choose to get the most usefulness given their monetary constraints. Following this model, it has been argued that people use energy based on their willingness to pay, and that the way to shift behavior is through subsidies, penalties, credits, or other market mechanisms. Alternatively, in the past, energy efficiency was framed as merely a technological problem with technological solutions, to the point where funding for energy efficiency research has often focused on "device-centered" solutions to the problem. Yet such framings of the energy efficiency problem have not been enough for achieving predicted gains from energy efficiency because these framings, and the models they produce, do not take observable human behavior into account.

The knowledge-action gap produces an "efficiency gap," which is the distance between the amount of anticipated investment in energy efficiency and the actual realized amount of investment. These two gaps pose a challenge for achieving California's clean energy goals because said goals are based on models proven inadequate for predicting actual behavior and resulting energy savings.

To close the efficiency gap, decision-makers must improve their understanding of consumer behavior. Since around 2007, behavior-based energy efficiency programs that incorporate social and behavioral science theories and methods in the associated designs and applications have increasingly become part of residential energy efficiency program portfolios. This project helps address this growing interest in consumer behavior by developing a form of market segmentation to improve the adoption of energy efficiency recommendations. Market segmentation is a strategy for classifying potential consumers based on a set of identifiable common characteristics. These can include factors, such as shared needs, common interests, similar lifestyles, or demographic profiles. This research project segmented consumers by degrees of "cybersensitivity". This form of segmentation produced what is termed a "psychographic" segment because these consumers diverge from the mainstream in several identifiable ways, many of which relate to lifestyle. At the same time, this form of segmentation is also a "behavioral" segmentation because this project engaged with such aspects as device purchase and usage, as well as attitudes and habits concerning energy consumption, conservation, and efficiency measures. The authors differentiated

five segments using the sample data, and labeled them cybersensitive, cyberaware, mainstream, low mainstream, and null.

The ability to deliver real-time energy information has accelerated with the roll-out of advanced metering initiatives and the proliferation of networked personal devices, such as smartphones and tablets. The availability of such devices allows people to access energy information almost anywhere at any time. This project focuses particularly on people who seek to do just that and may respond to energy information delivered via device with higher levels of engagement and thus act with respect to investment in energy efficiency measures and energy conservation behaviors.

Project Process

The research team observed and collected energy consumption behavior for 48 households in two utility service territories in California. The researchers used ethnographic methods for collecting data to be used in identifying and understanding cybersensitive behaviors. Ethnography relates to scientific description of peoples and cultures including customs, habits, and mutual differences. Ethnographic methods are effective in collecting data related to innovation, adoption, and usage of new technologies. The research team was interested in talking to people about the ways that they think and feel about their personal technology. The research team focused on the effects of technology engagement with personal consumer electronics (such as smartphones, tablets, and laptops). The research team examined a variety of households and lifestyles, including purchase and usage behaviors around technology.

The research team developed a recruitment questionnaire to solicit participants for the interviews. The questionnaire consisted of nine questions about device ownership (smartphones, laptops, tablets, home automation or security, wearables [such as smart watches or fitness trackers]), usage (such as downloads, applications, tracking, storage), attitudes towards technology and energy consumption generally; and seven demographic questions inquiring about age, gender, and income, as well as location (Northern vs. Southern California, urban vs. rural).

Across California 415 people started the recruitment questionnaire and completed some or all of it. Of the 298 completed questionnaires, 56 percent provided an email address or phone number and indicated interest in participating in an in-depth interview. Potential participants were also required to reside within the territories of the large California investor-owned utilities. In total, researchers contacted 167 eligible interview participants, and a personal attempt was made by the regional ethnographers to organize a time to visit them at their home at a time and day of their convenience. From those 167 potential participants, the research team conducted interviews in 48 households: 22 households in Northern California's Bay Area (primarily Marin County), and 26 households in Southern California (primarily Long Beach).

One objective for this research was the construction of an ethnographic decision tree model to replicate the traits during research, and ultimately reproduce them such that

the model might be predictive. Applying the ethnographic decision tree model will organize any given population into four of the five identified segments: cybersensitive, cyberaware, mainstream, and null.

The research team used the work done in constructing the ethnographic decision tree model as the foundation for building a classification and regression tree through machine learning processes (a form of artificial in intelligence that enables a system to learn from data). Classification and regression trees are a quantitative decision tree modeling approach that uses a set of machine learning, computational-based strategies. Classification and regression tree algorithms work better on a larger dataset, so the research team used bootstrap resampling (testing that relies on random sampling with replacement) to create a dataset of 300 virtual persons. The research team then carried out preliminary testing using a synthetic population constructed from American Census Questionnaire and American Time Use Questionnaire provided by the Network Dynamics Simulation Science Laboratory at Virginia Tech University. The research team then tested the classification and regression tree for accuracy on the original sample and resampled populations. In terms of classifying the cybersensitivity of members of a cohort, the research team's model had overall an accuracy of 76 percent.

As with the ethnographic model, the classification and regression model will be untested in the real world, requiring more/larger sets of data to run before it reliably replicates real world behaviors. However, as with the ethnographic model, the construction of the model will be robust enough that another entity, with its own resources and access to data, could launch and test the model for use as a tool for organizing consumers into segments and estimating the size of the segments (and thus the effect of programs aimed at segments).

In addition to the fieldwork described, the research team selected, trained, and supervised a diverse group of 16 students from the California State University system to conduct the ethnography projects. The students conducted research projects under the umbrella of the project goals. The student research project topics explored the intersection of technology, behavior, and energy. Projects included an examination of fitness culture and wearable technologies, a comparison of solar panel owners vs. lessors, and an ethnography of a group of Southeast Asian refugees who temporarily lacked water and power in their Fresno apartment complex. The work produced by the students was important to the project because it added ethnographic context for energy consumption across California, which often corroborated the findings from the in-depth interviews conducted in the two utility territories.

Project Results

The in-home interviews offered evidence that several psychographic traits were common to cybersensitives (and the closely aligned segment, cyberawares). These characteristics show up in multiple areas of participants lives:

- Cybersensitives and cyberawares tend to have multiple careers.

- Cybersensitives tend to be engaged with learning new things.

- Cyberawares tend to be interested in tracking information and performance, not only with energy but also money and fitness.

- Cyberawares are more likely to report possessing wearables such as Fitbit or Strava.

One thing cybersensitives and cyberawares have in common is that they are planners and implementers. Cybersensitives and cyberawares show such behavior with respect to technology and how they buy other products, select/use services, pay bills, and show meticulousness/fastidiousness in other areas. The research team found the cybersensitives methodical in their decision-making, especially around technology adoption and use. For cybersensitives, technology solves problems or provides them with solutions rather than entertains or enhances status.

While cybersensitives and noncybersensitives may participate in energy efficiency programs, the pathways to uptake are different, as is their receptivity to offers, their engagement with data from their utility, and other dimensions. For example, the transcripts revealed that cybersensitives and cyberawares are more likely to be aware of their electricity consumption, and to analyze their electricity consumption. They are aware of the availability of energy efficiency programs, are interested in participating in said programs, and are willing to seek out additional energy efficiency measures that they can undertake. They pay attention to a variety of rebates, tax credits, and efficiency ratings.

The research team next examined the demographic data for the interview participants to confirm that cybersensitivity cannot be substituted for specific demographic variables such as gender, age, or income as well as region. Members of any segment could be male or female and the segments distributed themselves across various age and income ranges.

- The assignment of cybersensitivity produced cybersegments almost identical in terms of gender percentage.

- All segments have members from all age ranges

- The percentage of cybersensitives and cyberawares in each income strata remained roughly the same, supporting the point that income and cybersensitivity are not synonymous with one another.

- The distribution of segments by percentage are roughly similar when regions are compared. This finding supports the hypothesis that cybersensitivity is independent of a specific geography (such as the San Francisco Bay Area).

With the development of the ethnographic decision tree model, it became evident that the relationships among the segments were not located along a continuum with respect to one another. The research team concluded that the primary difference between the

two cybersegments lies in a preference for tracking information or using wearables, which is demonstrated by cyberawares and not by cybersensitives. So too, the relationship of nulls to the cyber-segments is that all three tend to share some traits (an attraction to or facility with technology) but nulls lack an emotional component of engagement with feedback. Mainstreams and low mainstreams tend to be distinguishable more by their lack of any of these traits, rather than possessing specific traits unique to their segment.

Based on the initial coding and analysis of the fieldwork data, the research team found that cybersensitives and cyberawares made up 17 percent each of the combined cohort (Northern and Southern California). This is a higher percentage for both than the original estimate, which was based on the literature review and posited 10 percent for each segment. The classification and regression tree model predicted 18 percent for cybersensitives and 3 percent for cyberawares, which is closer to the original estimate. The classification and regression tree model, which used a larger sample (300 virtual persons) is likely more accurate than the initial assignments, both due to small sample size. Furthermore, the classification and regression tree model and the ethnographic decision tree model were the products of iteration and refinement.

Technology/Knowledge Transfer

The project plan included several knowledge transfer activities intended to share information about the project generally, as well as demonstrate the segmentation schema and promote the decision tree models developed by the authors. One project task related specifically to the outreach and communication of project results to promote the knowledge gained, experimental results, and lessons learned available to the public and key decision makers. To accomplish these goals, the author conducted planned and spontaneous knowledge transfer activities.

The planned activities by the research team included presenting at several conferences, including the annual Behavior Energy and Climate Change Conference which brings together social scientists, practitioners, utilities, academics, governments, businesses, and non-profits to share and disseminate best practices and research to encourage behavior change for energy and carbon reduction. Members of the research team provided updates on the project progress via social media, including Facebook, Twitter, and LinkedIn. The Indicia Consulting website made downloads available of all task reports, promoted the student ethnographers and their projects, and hosted video presentations of their finished projects. The authors submitted work for publication in peer-reviewed journals and academic presses.

Additional knowledge sharing performed by the research team included writing about the project at the blog, "Small Signs and Omens." A slide deck about the project was made available on SlideShare. Finally, the research team prepared and submitted a video presentation of the project for the EPIC 2019 Symposium.

Utilities can likely use the segmentation model in this research to organize populations of energy consumers and testing receptiveness to energy efficiency messaging and the adoption of energy efficiency measures. The authors have used a modified version of the segmentation schema presented in this report for proprietary work conducted on behalf of a large Northeastern utility aiming to introduce an advanced metering initiative and associated demand response programs to its customer base.

The authors work as subcontractors to marketing agencies handling utility accounts. The use of this segmentation plan continues to be put into practice, adapted, and tested in terms of messaging up-take. There are considerations to test the segmentation with actual consumer electricity consumption, but to date they have not been approved. The authors intend to continue to refine the methods and findings from this research and apply them commercially.

The authors recommend that public organizations re-examine the design of residential energy efficiency programs in favor of allowing opt-in programs where appropriate. Current utility policy appears to favor opt-out program (default enrollment). This research discusses how combining segmentation with opt-in designs could increase savings from residential energy efficiency programs.

A technical advisory committee was formed to assist the research team. The technical advisory committee brought together a group of experts in the fields of behavior and energy research. They reviewed the task reports and provided insights, feedback, and technical assistance.

Benefits to California

Identifying the attributes and characteristics of cybersensitives will add to the overall scientific understanding of behavior and energy consumption. The research team anticipated that, by building and sharing the models constructed, other entities, such as the California investor-owned utilities, could use them to target their ratepayers with appropriate programs and incentives, reaping higher rates of energy savings in return.

The research team has developed a plan for classifying consumers of electricity in terms of their psychographic and behavioral profiles. The fieldwork observations led the research team to conclude that cybersensitives are interested in more ambitious and innovative energy efficiency measures, while cyberawares appear to be more interested in tools and applications for tracking energy consumption and savings.

By better understanding customer energy profiles, utilities can solve problems and improve energy efficiency returns across the state, thus improving grid reliability, reducing the requirement for additional power plants, and reducing carbon emissions.

CHAPTER 1:
Introduction

Segmentation and Energy Efficiency Programs

The goals of the project were two-fold: the first goal was to establish the characteristics of a psycho-social trait the research team termed "cybersensitivity" and the second goal was to use this trait to segment consumers and then model the segmentation. Mazur-Stommen coined the term "cybersensitive" (Foster and Mazur-Stommen, 2012) to refer to a phenomenon whereby some people seem to be more sensitive and responsive to energy consumption information delivered via an electronic device. Cybersensitives are people who appear to exhibit a greater emotional connection to their phones, tablets, and other personal technology, such as "wearables" (for example, Fitbit).

The research team intended for insights from this project to be useful in developing residential energy efficiency programs. Such programs—which often fall under the rubric of "demand-response—"are designed to improve consumer knowledge of, and engagement with, their energy consumption. Specifically, the goal of such programs is often to provide residential energy consumers with information about their energy consumption such that behavior change with respect to energy efficiency and/or energy conservation will ensue. Demand response programs commonly include some mix of components such as advanced meter installation, time-of-use, or critical peak pricing rate provision, smart thermostats, or in-home displays, and home energy reports. Many of these utility-run residential energy efficiency programs are offered as "opt-out" or "default" programs, where customers are automatically enrolled. The rationale behind this is often framed as an equity issue, treating all customers the same—being fair. However, opt-out residential energy efficiency programs have produced uneven outcomes due to differences among types of residential consumers, their energy load profile, and even their household attitudes (Fenrick, et al., 2014).

Efficiency Gap and Consumer Behavior

According to classical economic theory, people are rational actors who, as consumers, will always choose to maximize utility given their monetary constraints. Following this model, it can be argued that people use an optimal quantity of energy given their willingness to pay, and that the way to shift behavior is through subsidies, penalties, credits, or other manipulations to the market (Frederiks, Stenner, and Hobman, 2015). Alternatively, in the past, energy efficiency was framed as merely a technological problem with technological solutions, to the point where funding for energy efficiency research has often in the past gone to "device-centered" solutions to the problem (Wilhite et al., 2000). Yet such economic-rational or techno-scientific framings of the energy efficiency problem have not been enough for achieving predicted gains from

energy efficiency because these framings, and the models they produce, do not take observable human behavior into account:

"[E]ven with adequate knowledge of how to save energy and a professed desire to do so, many consumers still fail to take noticeable steps towards energy efficiency and conservation. There is often a sizeable discrepancy between people's self-reported knowledge, values, attitudes and intentions, and their observable behavior—examples include the well-known knowledge-action gap and value-action gap." (Frederiks, Stenner, and Hobman, 2015).

Thus, the knowledge-action gap produces an "efficiency gap," which is the distance between the amount of anticipated investment in energy efficiency and the actual realized amount of investment (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012). These two gaps pose a challenge for achieving California's clean energy goals because said goals are based on models which have proven to be inadequate for predicting actual behavior and resulting energy savings.

Findings from social science and behavioral economics indicate that individuals make decisions based on such things as social norms, personal emotions, and cultural notions of reciprocity, in addition to economic factors (Wilson and Dowlatabadi, 2007; Lutzenhiser, 1993; Hofmeister, 2010). Acknowledging this reality, behavioral economists have moved past neoclassical explanations. Michael G. Pollitt and Irina Shaorshadze (2011) point out that, "[r]esearch in behavioural economics and psychology has demonstrated that non-pecuniary interventions compare favourably to monetary interventions in changing consumer behaviour. It was also shown that judiciously applied pecuniary interventions increase the impact of monetary interventions if used in combinations."

In a chapter for his book, *Cultures of Energy,* titled "Energy Consumption as Social Practice," author Hal Wilhite (2013) recommends the use of social practice theory "to encompass the contributions to consumption of embodied knowledge, habit, and artifacts." Unpacking this sentence, Wilhite is arguing that one should consider how consumers are in physical bodies that get hot or cold and require light or warmth, and that these physical states require the services energy provides. These bodies carry around brains that have accumulated information about their requirements and their environment over decades of living. The decisions that people make with those brains are also culturally mediated; heating or cooling one's home to a certain temperature may differ depending on whether one has guests, for example. Finally, the consumption of energy is directed and constrained by the technologies available, from individual thermostats to the presence or absence of air-conditioning, to the availability and cost of fuel.

Wilhite proposes a conceptual move "from viewing energy consumption as something performed by individuals and individual devices to something that is a result of the interaction between things, people, knowledge and social contexts." His

recommendation is that one must understand the relationship between people and the technologies they interact with to understand (and potentially shift) patterns of consumption around energy. The better one can understand the forces acting on individual's decision-making—or the tension between their agency as individuals and the structures which constrain them—the better one can design effective models for encouraging energy efficiency on a larger scale.

Wilhite's proposal to view energy consumption through the lens of interaction is like the argument propounded by Loren Lutzenhiser, who recommends a move away from the physical-technical-economic model that has long dominated discourses of energy (Lutzenhiser et al., 2009). The physical-technical-economic model is a worldview that has "characterized consumer behavior and choice as instrumental, purposeful, rational, and secondary to the devices, machines, and appliances that are seen as the actual users of energy." In the not too distant past, human beings have either been left out of the equation all together, with devices holding the responsibility for managing usage, or they have been treated as if they were themselves machine-like; rational and responsive to inputs with predictable outputs.

The efficiency gap left by the deployment of physical-technical-economic model approaches created an opportunity for more nuanced behavior-based energy efficiency programs. In recent years there has been a shift away from research using the rational actor principle (that is, information received is information acted upon) or which uses neo-classical economic models (pricing produces decision-making and action), towards those based on innovative social and behavioral science findings. Since approximately 2007, behavior-based energy efficiency programs that incorporate social and behavioral science theories and methods in their designs and applications, have increasingly become part of residential energy efficiency program portfolios. The ability to deliver real-time energy information has accelerated with the deployment of advanced meter initiatives, and with the proliferation of networked personal devices such as smartphones and tablets. The availability and wide distribution of such devices means that people can access energy information almost anywhere, and at any time. This project focuses particularly on people who seek to do just that, and who may respond to energy information delivered via device with higher levels of engagement.

The cybersensitivity hypothesis of this project does not require a demonstrable baseline-level of technical knowledge. Rather, the hypothesis is that participants should have an emotional attachment to their device and that this cybernetic quality will be distributed equally across generations. The cybersensitivity hypothesis also does not anticipate that gender will affect emotional attachment to devices. Finally, although a tendency to invest in energy efficient measures has been linked to income (Roberts, 2015), the psych-social trait of cybersensitivity has not. This research further hypothesizes that cybersensitives do not purchase consumer electronics/personal technology for enhancement of social status, but instead have a more utilitarian perspective.

Marketing Energy Efficiency Programs

The research team believes that to close the gaps described above, particularly via behavior-based energy efficiency programs, advocates for said programs must increase and improve the collective understanding around consumer behavior. For example, utilities could apply modern market segmentation methods (such as those identified in this report) to improve uptake of energy efficiency recommendations.

For many years, utilities did not differentiate among their customers except by sector: residential, commercial, industrial. More recently emphasis has been placed on "low income residential" and "small to medium commercial"—both of which are means of moving towards a more differentiated approach to marketing. Yet these attempts at differentiated marketing still face challenges. They both remain poorly defined, and are not situated within a larger, more nuanced attempt to understand energy consumption (Wilhite et al., 2000). In *Trusted Partners: Every-day Energy Efficiency in the South* (Mazur-Stommen et al., 2013)*,* the authors discussed how using income as the primary variable does not explain wide differences in attitudes and behaviors among even the most narrowly defined "low-income" households. Similarly, with respect to small to medium commercial enterprises, the ethnographic research conducted for that project suggested that levels of interest regarding offers from the utility had more to do with things like monthly cash flow, or access to credit, as opposed to size of the establishment in square footage, number of employees, or total revenue. While these two attempts at organizing and understanding consumer decision-making around energy may seem to be distinct from one another, both use structural and economic variables such as income or revenue to explain responsiveness to outreach and messaging around energy (primarily electricity). The authors argue that responsiveness to messaging around energy consumption is related to behavioral and psycho-social traits, as opposed to structural and economic variables.

Market Segmentation

In contrast to a sectoral approach, market segmentation is a strategy for classifying potential consumers based on a set of identifiable common characteristics (Cano, 2001). These can include factors such as shared requirements, common interests, similar lifestyles, or demographic profiles. Psychographic, or behavioral segmentation, is a method used in marketing for organizing the customer base along such principles as lifestyle propensities or the purchase and use patterns of products—in this research—personal technology, such as smartphones, tablets, laptops, and wearables. The primary goal with market segmentation is to establish groupings that possess both internal homogeneity (similarity within segments) and external homogeneity (differences between segments). Segments, once identified, can receive various treatments or interventions which align best with their propensities.

Forms of Market Segmentation

There are several classic forms of market segmentation (Table 1)

Table 1: Various Marketing Segment Types for Classifying Consumers

Segment Type	Exemplified	Description
Demographic	Personal attributes	Use quantifiable population characteristics, such as income and age; includes common labels like *"DINKs"* for double-income no kids
Geographic	Urban or rural	Focus on population distribution and settlement patterns as keys to attitudes and behaviors
Psychographic	Lifestyle	Look for lifestyle patterns, such as "socially aware" or "conservative"
Behavioral	Purchase decision-making	Use purchasing, consumption, or usage behavior such as benefit sought or buyer readiness to group people

Source: Indicia Consulting

This research project segmented consumers by degrees of cybersensitivity. This form of segmentation produced what is called a psycho-graphic segment because these consumers diverge from the mainstream in several identifiable ways, many of which are related to lifestyle. At the same time, this form of segmentation is also a behavioral segmentation because it grouped participants based on their device purchase and usage, as well as attitudes and habits concerning energy consumption, conservation, and efficiency measures. Therefore, the authors refer to the segmentation schema in this paper as a psycho-graphic/behavioral form.

Types of Market Segmentation

In addition to these forms, there is also a range of market segmentation *output types*. These types are termed undifferentiated, differentiated, and hyper-segmented. These types range from those containing the smallest number of sub-populations/segments to those with the largest number of sub-populations/segments. Undifferentiated segmentation is the broadest type of segmentation, where everyone in a population receives the same message regardless of factors such as demographics, geography, or ideology. An example of undifferentiated segmentation would be how 19th century manufacturers sold soap (to the masses). There was not a men's soap and a women's soap. There was only soap, and purveyors competed on the quality of ingredients or reputation, but for members of the same audience. The example of a soap advertisement from the late 1800s in Figure 1 below aims for universal appeal based solely on quality and gift with purchase.

Figure 1: Larkin Soap Advertisement, 19th Century
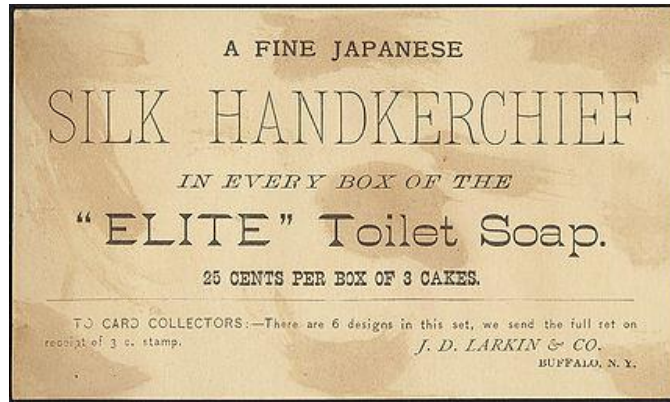
Source: Wikicommons

A differentiated segmentation strategy takes these variables into account and offers slightly different messages depending on the characteristics of the desired audience, such as age, income, region, or political leanings. The example of a soap advertisement from the 1920s in Figure 2 appeals to women specifically.

Figure 2: Palmolive Soap Advertisement, Early 20th Century

Source: Wikicommons

Finally, a hyper-segmented approach combines variables to precisely align messaging with target audiences. The concept of psycho-graphics, pioneered by firms such as Nielsen, with its Prizm database (now Claritas) is a form of hyper-segmentation. The example of soap advertising in Figure 3, which uses a psycho-graphic profile, to appeal to people who have disposable income, time to be discretionary in their soap purchases, and a "green" (or environmental) philosophy.

Figure 3: Lush Brand Soap Advertisement, 21st Century

Source: Wikicommons

Cybersensitivity as Market Segmentation Principle

The research into cybersensitivity as a potential segmenting principle began with a data anomaly. When members of the research team reviewed the literature on electricity consumption and feedback for a previous project, (Foster and Mazur-Stommen, 2012) the members noticed a group of people who achieved out-sized energy savings, seemingly irrespective of pilot design, intervention mechanism, geographic location, or demographic variables such as age, gender, or income. Allcott discussed a similar effect in his 2011 paper writing that, "…effects are heterogeneous: households in the highest decile of pre-treatment consumption decrease usage by 6.3%, while consumption by the lowest decile decreases by only 0.3%" (Allcott, 2011). From the literature, the research team noted a recurrent pattern of some households returning greater than average energy savings, such as 8.1 percent versus a control group result of 0.8 percent (Grønhøj and Thøgersen, 2011). However, the distribution and frequency of these households were open to question, as were other factors such as the presence or absence of any specific forms of technology in the home (Carroll, Lyons, and Denny, 2014).

The research team hypothesized the data anomaly as being a trait it labeled cybersensitivity where the cybernetic aspect refers to the emotional relationship between a person and their personal technology, and a heightened propensity for

15

acting on information delivered via a given device. Using this data anomaly as a clue, the research team designed this project to identify the characteristics of this trait (Appendix A), and group participants into segments based on the distribution of this trait across a cohort.

The research team felt that "data anomaly" was the key to something important. Specifically, the research team hypothesized that this was a signal registering a pattern of behavior that could best be identified ethnographically, by going into people's homes, and having in-depth conversations with them about their use of the goods (devices, appliances) and services (heating, and others) provided by electricity.

Within the social science disciplines, and with respect to energy consumption, several authors over the years have pointed out that humans are not, "socially disembodied consumers" [Wilhite, 2013]. Instead, humans inhabit bodies, interact with tools, engage with friends, and are constrained by social institutions such as law and religion. Human beings are never alone in their decision-making, because the values, beliefs, and habits of individuals are shaped by the process of enculturation since before birth. Humans are always social creatures living in a culturally encoded environment.

Theories of Cybernetics, Feedback, and Cybersensitivity

"Cybernetics is the study of processes of information, communication and control within…systems where feedback is the mechanism for that communication and control" (Ramage, 2009).

The author's hypotheses around cybersensitivity have their origins in anthropological theories of cybernetics. Cybernetics is the term for "the scientific study of control and communication in the animal and the machine" (Weiner, 1948) and thus is the organizing theoretical basis for this project. The anthropological branch of cybernetics has traditionally focused on how groups of people manage socially derived information, or "feedback", about their behavior. For anthropologists, a positive feedback loop is a process whereby a person's behavioral response to stimuli is socially channeled in such a way that subsequent iterations of the feedback/response cycle intensifies and reinforces, the effect. Gregory Bateson, an anthropologist working in Papua New Guinea in the 1930s, extracted the principles that would form the basis for cybernetics through observing a ritual among the Naven people called Iatmul (Bateson, 1936). In so doing, he saw how the behavior of performers in the ritual was influenced through audience feedback (cheers and boos), and how the more deeply the audience engaged the more intense the ritual became. In a break for his time, Bateson went beyond merely describing these activities in a socially realistic manner, and instead evaluated them as examples for the schema he was forming around more general laws of human behavior. For Bateson, there existed two types of feedback: positive (reinforcing or intensifying) and negative (dampening, delimiting). These types were social mechanisms that controlled behavior among larger sets of members of a society, who could find themselves in either a complementary/unequal dynamic (such as audience and

performers) or else a symmetrical/equal dynamic (such as two opposing teams in a sport).

While today, many people know the terms feedback in relation to technology, it nevertheless retains its original meaning of being a form of information management by groups (possibly mediated by technology). Anthropologists since Bateson, particularly those working on environmental topics, have identified several classic examples of how feedback loops operate to regulate overall consumption of resources (Appendix A). The role of feedback as outlined in cybernetics theory is useful in describing the effectiveness of personal technology on achieving desired energy behaviors. Understanding this process and its associated meaning is key to developing energy management technology and tools that people will use consistently to manage their requirements and surroundings.

Feedback and Energy Efficiency Programs

This research project was tasked to:

- Develop critical insights for supporting residential engagement in energy efficient behaviors.

- Recommend redesign of approaches geared towards this population segment.

To this end, the research team reviewed the literature on behavior-based energy efficiency programs. The research team focused specifically on "feedback" programs, which provide information about energy consumption through a variety of mechanisms intended to affect behavioral outcomes (for example, cybernetics). The term *feedback* with respect to energy efficiency programs refers to how outputs of a system (in this case energy consumption) are fed back as inputs into the system (in this case consumer awareness of energy consumption) to form a continuous loop. Feedback programs are those that, "provide customers with information to encourage shifting of loads to off-peak periods and/or to encourage lower levels of overall consumption" (Ehrhardt-Martinez, et al., 2010).

The research team focused on feedback programs because the implementation of these programs could be informed by project results of how people respond to information delivered via technology to change their energy consumption patterns. Thanks to on-going evaluation efforts, data shows that feedback programs generate the highest documentable savings among behavior-based residential energy efficiency programs, for individual households and utility portfolios (Sussman and Chikumbo, 2016).

Mazur-Stommen and Farley (2013) defined two types of feedback programs—asynchronous and real-time. These two forms of feedback programs have undergone substantial evaluation (Sussman and Chikumbo, 2016). Asynchronous feedback is when information about energy consumption and usage is delivered at a time distanced from the actual moment of consumption (such as monthly or quarterly). Programs that

deliver energy consumption information in real time in hourly or smaller intervals (on an in-home device, app, or online) are referred to as real-time feedback programs.

Opower (now owned by Intel) works in partnership with electric utilities to provide information to customers via monthly Home Energy Reports about their own energy consumption, in addition to an assessment of how consumers energy use compares to that of others. Their Home Energy Reports are one of the most studied feedback programs (Allcott, 2011; Ayres, Raseman, and Shih, 2011; Costa and Kahn, 2010; PG&E, 2014). Allcott studied Opower's program and found that it led to a decrease in energy consumption comparable to the decrease in consumption caused by a price increase of 11 percent to 20 percent in the short run and 5 percent overall (Allcott, 2011). Other studies of Opower programs have also found energy reductions ranging from about 1.2 percent to 2.2 percent per household (Ayres, Raseman, and Shih, 2011; Wu, 2012).

Studies of non-Opower programs have also found positive results. A 2010 meta-analysis by the American Council of an Energy-Efficient Economy (Ehrhardt-Martinez et al., 2010) found that residential energy consumption decreases on average between 4 percent and 12 percent in response across a variety of feedback programs, and estimates that in the United States residential energy demand could decrease by as much as 6 percent after implementing feedback programs nationally. In general, home energy reports were found to deliver 1 percent to 3 percent of energy savings when applied to a population (Sussman and Chikumbo, 2016).

There are fewer real-time feedback programs than home energy reports for several reasons. Home Energy Reports, as they are known today, were deployed in 2008, soon after the first smart meter rollouts in California in 2006. Real-time feedback programs, meanwhile, were more expensive to deploy on a per household basis, because they relied on either providing an in-home device (costing approximately $250 per unit) or building a new web portal where customers could retrieve real-time data. However, there have been a few studies that investigated their energy savings. An American Council of an Energy-Efficient Economy study looked specifically at residential real-time feedback programs and found a wide-range of energy savings with some individual households reporting no savings at all while others reduced energy consumption by as much as 25 percent (Foster and Mazur-Stommen, 2012). A study of a Denmark-based real-time feedback program found that families receiving feedback reduced energy use by 8.1 percent, compared to 0.7 percent in the control group, with the largest savings found in households with teenage children at home. The authors attribute the success of the intervention to the fact that it clearly and easily brought information about energy use to the attention of household members (Grønhøj and Thøgersen, 2011).

Opt-In vs. Opt-Out Energy Efficiency Programs

When designing pilot residential energy efficiency programs, there are two ways to assess the effectiveness of a measure, each with its own pros and cons. One method is

called "opt-in" treatment and the other is called "opt-out," also called "default enrollment." Opt-in programs offer a treatment, incentive, or opportunity to a group of individuals and allows them to choose whether to participate. Opt-out programs automatically enroll people in the treatment, incentive, or opportunity, and then require them to formally request exclusion from it. Opt-in programs are great for getting engaged and committed participants, but there is usually some form of selection bias influencing the decision. Opt-out programs are great in that they remove selection bias, and since the entire population is selected there is little to no researcher bias. However, they may result in lower rates of active participation.

A favorite example for proponents of opt-out programs are the extremely high rates of organ donation in countries where default enrollment is policy (Davidai et al., 2012). Rates of participation of up to 90 percent are pointed to as a measure of success for these programs (and are assumed to be a feature of opt-out programs). In contrast, in the case of energy efficiency, the level of savings generated by default enrollment is 1 percent to 2 percent (Sussman and Chikumbo, 2016). For Home Energy Reports, the maximum savings for opt-out style programs appears to be about 3 percent aggregated across a population (Sussman and Chikumbo, 2016). Most opt-out programs average less than this, whereby "[t]raditional opt-out programs save 1.2 to 2.2% of electricity, and 0.3—1.6% of gas by the second year." (Sussman and Chikumbo, 2016). The same home energy report program, with the identical treatments/incentives, when run as opt-in generate closer to 15 percent to 17 percent energy savings.

"Opt-in programs may save up to 16% of electricity per customer, but for fewer people (in one study approximately 20% of customers participated in an opt-in program, approximately 98% participated in an equivalent opt-out program)."

According to the American Council of an Energy-Efficient Economy (Sussman and Chikumbo, 2016), real-time feedback programs using opt-in designs average 5 percent to 8 percent savings across the wide range of pilot projects. However, one of the most rigorous studies of energy savings from real-time feedback programs was conducted by the Sacramento Municipal Utility District (Potter et al., 2014) where they demonstrated energy savings between 6 percent and 26 percent for opt-in programs (Dougherty, et al., 2015;Table 2).

Table 2: SMUD Feedback Pilot Program Outcomes (Adapted from Dougherty, et al., 2015)

SMUD pilot program	Mode of Feedback	Design	% of population participati	# of participant	Savings
SmartPricing Options: CPP	Feedback via IHD, web portal	Opt-in	18.20%	1,651	26%
SmartPricing Options: CPP	Feedback via IHD, web portal	Opt-out	95.90%	701	12%
SmartPricing Options: TOU	Feedback via IHD, web portal	Opt-in	17.50%	2,199	13%
SmartPricing Options: TOU	Feedback via IHD, web portal	Opt-out	97.60%	2,018	6%
SmartPricing Options: CPP	Feedback via Web portal only	Opt-in	18.80%	223	22%
SmartPricing Options: TOU	Feedback via Web portal only	Opt-in	16.40%	1,229	10%
SmartPricing Options:	Feedback via IHD, web portal	Opt-out	92.90%	588	8% summer
TOU+CPP					peak; 13% critical peak

This is the range of energy savings and program details for SMUD pilot programs investigating smart pricing options including Critical Peak Pricing, Time-of-Use, using web portals and In-home Devices.

Source: Indicia ConsultingAuthors

Objective and Scope

The research team set out to:

- Document/analyze emerging attitudes, emotions, experiences, habits and practices around tech adoption.

- Identify attributes and characteristics and latent psychological drivers of cybersensitives.

- Assess if cybersensitives enjoy interacting with technology in their everyday lives.

- Develop critical insights useful for determining how to more effectively support residential engagement in energy efficient behaviors.

The research team hypothesized that cybersensitivity might be a key to explaining the different energy-savings outcomes which resulted when groups of residential households were exposed to feedback concerning their energy consumption. The research team conducted in-home interviews to understand device purchase and usage, interaction with the utility and energy data, and psycho-social attributes. From this data, the research team aimed to find characteristics that were representative of the cybersensitive[1] mindset, distinguishable from their peers and neighbors based on their attitudes and behaviors.

---

[1] Cybersensitive with a lower case 'c' refers to the generic combination of Cybersensitives and Cyberawares. Written with an upper-case C refers to the actual segments.

CHAPTER 2:
Project Approach

Overview

The process of distinguishing groups of consumers from one another is known as market segmentation. The goals of this research included the identification of characteristics distinguishing cybersensitives from other members of similar cohorts (demographic or regional) to perform a market segmentation. The literature review conducted for this project suggested that there might be two deciles, comprising approximately 20 percent of the population making up this segment (Allcott, 2011).

The authors hypothesized that cybersensitives[2] are people with a greater than average emotional response to, and affinity for, technological engagement. The authors' approach was the use of ethnographic methods for collecting data to be used identifying and understanding cybersensitive behaviors. Ethnographic methodology has been shown to be effective in collecting data around questions of innovation, adoption, and usage of new technologies (for an extended discussion of this please see Appendix A).

Fieldwork and Data Collection

Over the course of this project the team collected two primary sets of data

- Answers to a recruitment questionnaire which ran for 18 months, and

- Responses to questions posed by ethnographers during in-home interviews.

The qualitative data collected during the project also included the observations made by the ethnographer during the interview (preserved in field notes); and finally, the photos and videos shot by the ethnographer on site. These different sets of data were used to characterize the cohort of households who participated in the in-depth interviews.

Qualitative data collection began in September 2015 and ran through April 2017. Prior to conducting the in-home interviews, the research team fielded a recruitment questionnaire to attract customers of California Investor Owned Electric Utilities including Pacific Gas $ Electric (PG&E), Southern California Edison (SCE), San Diego Gas & Electric (SDG&E), as well as Community Choice Aggregators such as Marin Clean Energy. During this period, members of the research team conducted ethnographic fieldwork in households in northern and southern California, particularly in Marin County and the City of Long Beach.

Households generally consist of more than one individual and thus are sociocultural units rather than strictly psychological ones where the unit may be an individual. Therefore, the research team opted for a psycho-social examination of household behavior, where psycho-social refers to the inter-relationship between an individual's

behavior and social factors. The locus within the household was generally the person who was primarily responsible for engaging with the electricity utility, but in some cases multiple people within the household participated in the in-depth interview (and in the questionnaire). It is common in segmentation strategies to treat the household as a unit for consumption of products, for example Claritas 360 has organized American consumers into 68 different segments, in three life-stage categories. These segments are households, an example can be seen in Figure 4

Figure 4: Claritas Segments

54 Struggling Singles Downscale Middle Age Mostly w/o Kids	**42 Multi-Culti Mosaic** Midscale Middle Age Family Mix	**31 Connected Bohemians** Midscale Younger Mostly w/o Kids	**32 Traditional Times** Upper Mid(Scale) Mature w/o Kids
33 Second City Startups Upper Mid(Scale) Younger Mostly w/ Kids	**34 Young & Influential** Midscale Younger Mostly w/o Kids	**35 Urban Achievers** Midscale Middle Age Mostly w/o Kids	**36 Toolbelt Traditionalists** Upper Mid(Scale) Older Mostly w/o Kids
37 Bright Lights, Li'l City Upper Mid(Scale) Younger Family Mix	**38 Hometown Retired** Midscale Older Mostly w/o Kids	**39 Kid Country, USA** Midscale Younger Mostly w/ Kids	**40 Aspiring A-Listers** Downscale Older Mostly w/o Kids
41 Domestic Duos Lower Mid(Scale) Mature w/o Kids	**43 City Roots** Upscale Younger Family Mix	**44 Country Strong** Lower Mid(Scale) Middle Age Family Mix	**45 Urban Modern Mix** Midscale Middle Age Mostly w/o Kids
46 Heartlanders Lower Mid(Scale) Older Mostly w/o Kids	**47 Striving Selfies** Low Income Middle Age Mostly w/o Kids	**48 Generation Web** Low Income Middle Age Family Mix	**49 American Classics** Lower Mid(Scale) Older w/o Kids

Screenshot of Claritas website listing the types and characteristics of household segments

Source: Indicia Consulting

23

Recruitment Questionnaire

The research team developed a recruitment questionnaire aimed to solicit people to participate in the interview. It is common practice in ethnographic research to use a questionnaire to recruit respondents into a study.

The questionnaire consisted of nine questions about device ownership (such as smartphones, laptops, tablets, home automation or security, wearables), use (for example downloads, applications, tracking, storage), attitudes towards technology and energy consumption generally; and seven demographic questions inquiring about age, gender, and income, as well as location (such as northern vs. southern California, urban location). In terms of demographic questions, the research team chose to focus on age, gender, and income, as well as region (Northern vs. Southern California, urban location). The research team explicitly did not ask about race or ethnicity because the research team considered those traits tend to be more fluid, more subjective, and more difficult to codify. At the end of the set of questions, the research team asked for their contact information if they wanted to take part in the interview.

Four of the core questions from the survey are reproduced in this section. The complete questionnaire is provided as an attachment to Appendix A. All questions were required, and all used a Five-point Likert Scale from Strongly Agree to Strongly Disagree.

- Consider the level of energy consumption in your household. Which of the following statements would you agree with the most?
    - I am fully aware of and monitor the level of energy consumption in my household. I have made and continue to make many changes wherever possible to our energy usage and lead the charge in this aspect in my household.
    - I am generally aware of some aspects of energy consumption in my household. I do not monitor all aspects of energy usage in great detail but participate in making changes to our energy consumption whenever it is convenient.
    - I am not aware of the level of energy consumption in my household. I generally do not participate in making changes around the house to reduce our energy consumption.
- To what extent, if at all, do you agree with the following statements?
    - When I find something useful, I explore it in as much detail as possible
    - When I find a new app or service that will enhance my life in some way, I adopt it right away
    - Friends often ask for my advice before buying new devices

- o I try new things all the time, but do not pursue most of them in great depth; I quickly move on to the next new thing

- To what extent, if at all, do you agree with the following statements?
  - o Energy saving is important to me.
  - o Saving money on energy bills is important to me
  - o Technology is easy
  - o Technology is fun
  - o I regularly keep up with the latest news and information about technology

- Which of the following statements best describes you?
  - o I am usually among the first ones to buy the latest electronic devices
  - o I wait for new technologies to be somewhat widely adopted before adopting them myself
  - o I am usually the last one to adopt any new technology

Recruiting Participants for In-Depth Interviews

During the period the questionnaire was live (2015–2017), it went out to Marin Clean Energy customers, Sierra Club members in investor-owned utility territories across California, and via a proprietary Constant Contact email list from Indicia Consulting. Marin Clean Energy was the projects utility partner in Northern California, and they included information about the questionnaire in their regular customer newsletters (Figure 5). Marin Clean Energy also promoted the research and the link to the questionnaire through their social media channels, including Facebook and Twitter. Links to the questionnaire were also delivered to a variety of audiences via Facebook, LinkedIn, Twitter, and NextDoor. Posts were created on Indicia Consulting's Facebook page and Twitter feed (see Appendix A for further details on social media recruitment).

Figure 5: Recruitment Poster Included in Marin Clean Energy Newsletters

Some messaging relied on a certain "California" pride to provide incentives to respondents.

Source: Indicia Consulting

Measuring Recruitment Effectiveness in Terms of Response Rates

The research team created a unique link for each deployment of the questionnaire across different platforms (such as email vs social media), and applications (specifically Facebook, Twitter, LinkedIn). These links allowed the research team to track where the respondents were coming from, and therefore measure the effectiveness of each source of recruitment (discussed in detail in Appendix A). Tracking and measuring the placement of links for effectiveness was helpful in refining recruitment for maximum payoff in terms of attracting respondents. This step also provided data that has not often been collected or analyzed formally for ethnographic research, which often uses "snowball sampling" in recruiting participants (Trotter, 2012). Snowball sampling is a

sample recruiting technique that relies heavily on activating the social networks of the community under study. With a goal for the project of conducting interviews on a larger geographic scale, snowball sampling would not be an effective technique for recruiting all participants, though it was used to a limited extent for this project[2].

Intrinsic vs. Extrinsic Motivations

Over the course of recruiting for questionnaire respondents and interview participants, the protocol shifted from an approach without incentives to offering a small incentive ($25 Amazon gift card). This was also a shift from intrinsic to extrinsic motivation, and therefore was of interest in examining. Researchers who are outside of the qualitative field of social science research (including some members of the technical advisory committee) raised the concern that offering incentives for participation in qualitative research could affect the rate and quality of responses. To address some of these questions and concerns, the research team sought to identify response rate differences between groups where the research team relied upon intrinsic motivations, such as messaging around environmentalist stances, religion, altruism, or civic pride; versus those to whom the research team offered an extrinsic motivation, via a cash award, gift, or product.

Singer (2012) found the following reasons for survey participation: "altruistic reasons (such as wanting to be helpful to research, researchers, society), egoistic reasons (including monetary incentives) and reasons associated with aspects of the questionnaire (for example topic interest, trust in sponsor or research organization)." Intrinsically driven respondents are rare, because with the increasingly common recruiting companies and market research firms, answering questionnaires and participating in interviews have become a money-making business. Professional recruitment agencies regularly provide respondents with incentives of $200-$400 for in-home interviews. Research from Church (1993) and Singer et. al (1999) found in two meta-analysis reviews of telephone, mail, and face-to-face questionnaires that incentives improve response rates. Incentives include gift cards, products, discounts, and cash payments. There is evidence that shows the use of incentives does not appear to affect response quality (Singer, 2002).

There is also not a large body of peer-reviewed research demonstrating how large incentives have to be to increase rates of participation in interviews (Singer, 2012). Therefore, the research team collected data to examine if differences in approaches would translate into differences of participation rates.

---

[2] Respondents who participated in Marin Clean Energy in-home interviews were requested to pass along information about this study to their friends and family in the area who might be interested in participating. This method of social network recruiting, aka 'snowball sampling'—resulted in eleven completed surveys, of which four respondents left their contact information, but no interviews resulted.

Table 3 compares metrics across the various recruitment channels. From left to right, the columns report on:

- $: Cost associated with placement of link (binary yes or no)

- Impressions: the number of people who had the information presented to them, either through receiving it in their email inbox, or having it presented to them in their social media feed.

- Opens: Only applicable to email campaigns, where the number of people who open the email can be identified.

- Open Rate: The ratio of people presented the information to the number who opened it.

- Likes: Available on social media, as opposed to email. The number of people who took a positive action on a post.

- Clicks: The number of people who clicked on the link to the questionnaire.

- CTOR: Click to Open Rate, the ratio of people who acted and clicked to view the questionnaire in comparison to those who acted to review the email. One of the most important numbers in social media metrics.

- Surveys: The number of people from the original campaign email or post who engaged with the questionnaire to completion.

- Completion rate: The ratio of people who took the questionnaire to completion to the overall audience.

- Contacts: The number of respondents who left their contact information indicating their willingness to be interviewed.

- Contact rate: Percentage of respondents expressing willingness to be interviewed.

- Conversion rate: Percentage of respondents who completed an interview.

Table 3: Recruitment for Northern California Interviews – Marin

Platform	$	Impression	Opens	Open Rate	Likes	Clicks	Click Rate	CTOR	Surveys	Completion Rate	Contacts	Contact Rate	Interviews	Conversion Rate
MCE (spring email)	Yes	3291	769	23%		23	0.7%	2.9%	14	0.04%	9	64%	6	43%
MCE (fall email wave 1)	No	1840	464	28%		78	4.2%	16.8%	111	3.0%	71	64%	14	13%
MCE (fall email wave 2)	No	2149	438	27%		60	2.8%	13.7%	111	3.0%	71	64%	14	13%
Indicia email	No	1241	325	28%		44	3.5%	14.0%	7	0.01%	7		2	22%
Nextdoor (ethnographer)	No	Unknown							30				3	10%
Nextdoor (snowball)	No	Unknown											2	0%
Sierra Club email	No	16	6	40%	0		0%	0%	0	0%	0	0%	0	0%
MCE (snowball)	No	n/a							11	n/a	4	36%	0	0%
Facebook (organic)	No	4389			96	87	2.0%		0		0	0%	0	0%
Facebook (paid)	Yes	6391			0	30	0.04%		2		0	0%	0	0%
Twitter (organic) 1/26	Yes	227				11	5.0%		28	9.0	0	0%	0	0%

Platform	$	Impression	Opens	Open Rate	Likes	Clicks	Click Rate	CTOR	Surveys	Completion Rate	Contacts	Contact Rate	Interviews	Conversion Rate
Twitter (organic) 1/30	Yes	100				1	1.0%		28	9.0	0	0%	0	0%
Linkedin (organic) 4 posts	Yes	347				0	0%		0	0	0	0%	0	0%

Source: Indicia Consulting

Tracking and measuring the effectiveness of delivery platforms also allowed the team to document the scale of outreach across California, and thus gain a sense for how representative the final recruitment pool might be. As an example, during recruitment for Northern California fieldwork, the research team documented 20,000 impressions, or people seeing the link to the questionnaire.

Characterizing the Initial Questionnaire Respondents

The research team had 298 fully completed questionnaires for recruitment purposes. The research team analyzed the questionnaire respondents as compared to the California general population with respect to urban location (urban, suburban, and rural), their homeownership levels, household composition, as well as demographic variables such as age, gender, and income (see Results section to establish if the initial recruitment sample was *reasonably* representative of California.

Characterizing the Interview Participants

One aim for the research team was disentangling demographic variables from cybernetic characteristics—the argument being that the cybernetic traits identified in this research are not simply attitudes and behaviors which are reflective of such things as affluence, life-stage, or gender. The authors hypothesized that age should not necessarily preclude someone from demonstrating cybersensitive traits. Though people born after 1981 have been referred to as "digital natives" (Prensky, 2001 as cited in Moran, 2016[3]) it was not anticipated that they would demonstrate a greater propensity towards a positive emotional engagement with technology than their elders.

The research team cast a wide net in terms of recruitment and periodically examined the set of interview participants in terms of the distribution of demographic variables. The goal was to achieve a reasonable diverse set of participants so that a variety of viewpoints would be captured. The aim was not to construct a representative and/or weighted sample as might occur with a survey.

Conducting Fieldwork

The ethnographic team members included the principal investigator and three experienced ethnographers. They conducted the in-depth interviews in homes in Northern and Southern California. The in-depth interviews focused on questions around device purchase and usage, energy consumption, interaction with the utility and energy data, and psychosocial attributes (Appendix A).

From the pool of 298 completed questionnaire respondents, the research team contacted the 56 percent who provided an email address or phone number. The 167

---

[3] "The term "digital native" was coined by Marc Prensky, an education consultant, in 2001. He argued that digital-native children have vastly different learning requirements than what he called 'digital immigrants,' and that digital natives "think and process information fundamentally differently."" https://www.nngroup.com/articles/millennials-digital-natives/ (Accessed 3/4/2019)

potential[4] interview participants were contacted, and an attempt was made to organize a time to visit them at their home, at the time and day of their convenience. From the 167 potential participants, the research team ended up conducting interviews in 48 households: 22 households in Northern California's Bay Area (primarily Marin), and 26 households in Southern California (primarily Long Beach). The research team went into every home using the same field guide, returning to the collected interview data later for coding and analysis.

The research team conducted fieldwork primarily in the territories of Marin Clean Energy, PG&E, and SCE. Northern California fieldwork ran from October 2015 through April 2016. Southern California fieldwork began in April 2016 and ran through February 2017. Time in the field totaled 18 months.

Interview Protocol

Interviewing is the primary technique used in ethnography. Interviewing can mean applying a set questionnaire (closed-ended interviewing), using free-ranging questions and discussion (open-ended interviewing), or anything in-between. The research team used a semi-structured interview style. During a semi-structured interview, a field guide is followed to ensure that the same questions are covered in each interview. The semi-structured format allows the respondent to lead within the question topic and enables the ethnographer to capture unanticipated information (Bernard, 2006). The semi-structured interview type allows the ethnographer to probe new or surprising answers, while still providing a common structure and set of questions. By asking all informants the same set of questions, textual analysis of the resulting narratives is both easier and more robust. At the same time, consistency enables coding, or the tagging of themes or topics with short descriptions whether numerical or narrative. Coding qualitative data allows a research team to more easily find and document details, such as the number of times a topic recurs, and the distribution of topics across participant responses.

The ethnographers studied the interview guide (reproduced as an attachment in Appendix A) thoroughly before applying it in an improvisational manner during the interview. The ethnographer did not allow the interview to end without getting all the questions answered, but instead allowed some free play to happen, so the interviewee could clarify meanings, provide detail and context for their answers, and clear up any ambiguities arising during the process. The ethnographers spent between two to four hours visiting the participating households.

As discussed in detail in Appendix A, the research team developed an interview guide containing questions and activities to be conducted during all household interviews. Every participant was asked the same set of questions. The interviews followed the same protocol: introductions, signing consent forms, house tour, and finally the in-depth interview (outlined in detail in Appendix A). Each interview was of similar duration.

---

[4] Participants were required to live within the territory of one of the California IOUs

Most interviews lasted 90 minutes, with a few lasting up to 120 minutes. The length of the interview depended on how engaged the respondent was with the questions, and how much they decided to share. The research team took photos during both the house tour (appliances, larger items such as televisions, thermostats with settings) and while conducting the interviews (phones, tablets, laptops). The research team recorded audio from all interviews. Post interview, the anthropologists produced fieldnotes of any specific impressions they wanted to capture, such as environmental surroundings, house descriptions, personalities.

Analyzing Qualitative Data

The entire set of data collected during the recruitment and interview process is referred to as fieldwork data. This dataset includes the answers participants gave to the recruitment questionnaire, as well as the participant responses to questions posed by the ethnographer during the in-depth interviews. This data also includes the observations made by the ethnographer during the interview (preserved in field notes); and finally, any photos and videos taken on site.

These different sets of data referenced the same cohort of participants in the in-depth interviews, which allowed us to triangulate the findings. Triangulation is the method of verifying data drawn from one source with data drawn from two or more other sources (Rothbauer, 2008). Analysts in the social science disciplines use the triangulation concept in addition to more traditional concepts such as validity and reliability. By combining multiple observers, theories, methods, and empirical materials, researchers seek to overcome bias introduced via studies reliant on a single method of data collection.

Coding Data for Analysis

The fieldwork data described is initially qualitative. That is, the data consists of words, whether these are answers such as agree/disagree in response to a question posed on the recruitment questionnaire, or answers to open-ended questions such as "Tell us about a website or mobile app you use at least once a week that you think is interesting, fun, or useful, and why." The answers from the questions posed during the interviews were also collected as open-ends, in that people answered in their own words. Analyzing this kind of data is time-consuming but necessary if observable patterns are to be extracted with any degree of confidence. Coding qualitative data allows a research team to more easily find and document details, such as the number of times a topic recurs, and the distribution of topics across participant responses. Coding is the tagging of themes or topics with short descriptions whether numerical or narrative.

Converting narrative, qualitative data (such as that collected in surveys and interviews) into variables that can be assessed quantitatively enables researchers to note aspects within the data such as the frequency of occurrence of a word or phrase, the rate of its usage of a within a given period of time, or even the distribution of a word geographically.

Researchers can then extract quantitative information from the fieldwork data, and make direct comparisons across question types, participants, and collection instrument (for example questionnaire vs in-depth interview).

Coding Questionnaire Responses

Both the questionnaire answers and the interview transcripts were coded. The coding process for these two sets of data was different. Coding of the questionnaire responses included assigning numerical values to qualitative data (words). For example, converting answers to a Five Point Likert Scale—strongly agree to strongly disagree—into numerical values 1 through 5. This process makes the data easier to work with for data cleaning, numerical simulation, statistical modeling, data visualization, and machine learning.

Coding the questionnaire answers in this manner enables the data to be imported from an Excel spreadsheet into an analysis program. For this project, the research team used Jupyter which is an open-source web application that is used for data cleaning, numerical simulation, statistical modeling, data visualization, and machine learning (Project Jupyter, 2019). Jupyter is language agnostic and its name is a reference to core programming languages supported by Jupyter, which are Julia, Python, and R (Wikipedia, 2019). One of the team members set up the data frames and other coding infrastructure used in this analysis in Jupyter. Then the coding machinery (objects and functions) for the statistical analysis was developed. The scripts for this (and other) analysis are available upon request.

Coding Interview Transcripts

> "[R]esearchers who consider themselves part of the qualitative tradition in social science induce themes from texts. This is what grounded theorists call open coding, and what classic content analysts call qualitative analysis (Berleson, 1952) or latent coding (Shapiro and Markoff, 1997)." (Ryan and Bernard, 2006)

Coding interview transcripts in this manner allows researchers to distill various conversational styles and unique wording of answers into something that can be compared across a set of interviews:

> "Coding refers to the identification of topics, issues, similarities, and differences that are revealed through the participants narratives and interpreted by the researcher." (Sutton and Austin, 2015)

Interview transcripts were coded to distill various conversational styles and unique wording of answers into something that can be compared across a set of interviews. Each code is a short descriptive tag that stands for a topic in the conversation. An example of a topic might be "friends" or "pets". The research team identified codes during their review of the interview data when topics recurred across multiple interviews. The ethnographer responsible for the interview reviewed the transcript and

then (for example) highlighted the section discussing a specific topic on energy saving behaviors, such as "turn the power strip with the internet off at night" as can be seen in the following excerpt from a transcripted interview:

> "And then I turn my phone off when I go to bed unless I need it for the alarm which is very rare, and (my husband) does not turn his off but he does not like look at it in bed so I know some people check email in bed and we don't do that so we cut it off and then we turn the power strip with the internet off at night just to not be consuming that electricity."

Later, when another anthropologist reviewed the transcription data, he/she may come across another instance when a different interviewee referred to this topic, but citing another kind of energy-saving behavior such as turning out the lights or washing clothes on cold. All kinds of energy-saving behaviors mentioned would receive the descriptive tag, "energy saving behavior" as a code. The team developed 40 codes that reflected and captured topics that emerged during the interviews. For the sake of consistency, the research team held an internal team discussion about what was found in the interview data, and how to code the various topics covered in the interviews.

Human Relations Area Files

The research team originally thought that the Human Relations Area Files (HRAF) database might contain codes developed by other anthropologists that would be relevant and useful for this project. However, while the existence of Human Relations Area Files as an example was useful, the dated nature of the technology codes it contained rendered it meaningless for the purposes of this project.

The Human Relations Area Files is the best-known example of ethnographic coding. The HRAF database facilitates cross-cultural research of human behavior and society, as it contains ethnographic and archaeological information for cultures and regions across the world (Clements, 2002). The Human Relations Area Files is a database that originally began at Yale in 1949 (Clements, 2002), with one of the main founders and leaders being George Murdock, an anthropologist known for his contributions to systematic cross-cultural analysis (Kottak, 2010). Most documents included in the database are descriptions of cultures or communities, written by social scientists (Clements, 2002).

Human Relations Area Files analysts code all entries into the database, using what are called the Outlines of Cultural Materials codes. Rather than coding societies into different "cultures," these codes work to provide specific locations of where certain information can be found, down to the paragraph-level, like the team's goal with respect to the interview transcripts. The research team cross-checked the project codes against codes in the Human Relations Area Files (Table 4).

Table 4: Comparison of Cybersensitive Project Codes with Outlines of Cultural Materials Codes

Cybersensitive Project Codes	Outlines of Cultural Materials Codes
A/C	Heating and lighting equipment
Amazon shopping and products	NONE
Anticipated device usage (practical)	NONE
App e.g., banking tools downloaded on phone	NONE
Appliances	Electrical machines and appliances
Banking	Banking
Billing	Bills of exchange (credit)
Bluetooth	NONE
Brand	Property marks in movables
Building structure	Structures
Car	Vehicles
Charger	NONE
Classes/learning (SC)	Education
Cloud/external storage device (SC)	NONE
Communication	Communication

Source: Indicia Consulting

For basic terms, like "banking" and "communication" the research team's codes corresponded very well with codes listed in the Outlines of Cultural Materials. However, for technology-based codes, whether referring to devices and accessories (such as chargers) or energy related technologies (for example HVAC) the Human Relations Area Files/Outlines of Cultural Materials had few or dated entries. For example, there was nothing in the Outlines of Cultural Materials for "apps", "Bluetooth", "chargers", or "cloud [storage]" all of which figured prominently in the research team's conversations with participants. It is also apparent that Human Relations Area Files codes were too general for these purposes: heating and lighting equipment is bundled, whereas the authors treated them as separate topics/codes. "Appliances" was another topic where the Human Relations Area Files codes were too broad.

In summary, while coding fieldwork data is a commonly used ethnographic method and has an established history and an illustrious progenitor in the Human Relations Area Files, the codes in the Human Relations Area Files were too general, dated, or missing recent technological developments to be useful. In comparison, the project codes generated by the research team were specific, topical, and captured up-to-date technological developments.

Atlas.ti and Outputs

Once the complete list of 40 codes had been agreed upon, the ethnographers reviewed all the interview transcripts again and identified sections, words, sentences that aligned with a specific code. The code is attached to the transcript using the program Atlas.ti. Atlas.ti was the projects qualitative data analysis software tool. The tool was the platform used to transcribe, code, and annotate interviews. For example, a research team member coded the transcript for "energy saving behavior" and the Atlas.ti output is reproduced in Figure 6.

Figure 6: Example of Coding Output from Atlas.ti
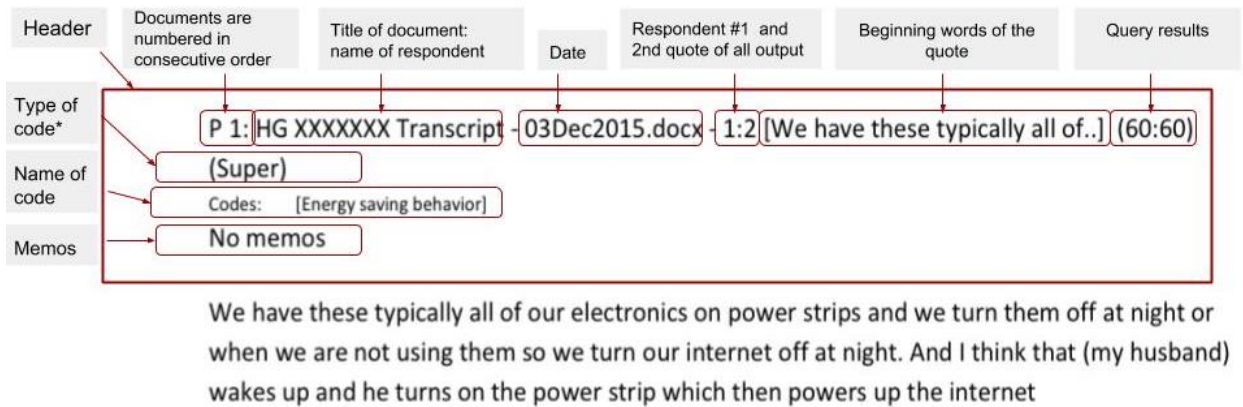
An example of a coding output from Atlas.ti of an excerpt of a transcription that was coded with "energy saving behavior". The different components of the Atlas.ti output are labeled here. (*A "super" code runs a query in the background to calculate up to date results.)

Source: Indicia Consulting

The interview data (once input into Atlas.ti and coded) can be sorted within Atlas.ti in a variety of ways: by code, by participant, or by verbatim answer. The example above is output produced by sorting on the code, energy saving behavior. That same section of the transcript may have other codes attached as well, such as "night", or "spouse". This enables review of transcript data from a variety of perspectives. Team members then exported Atlas.ti data to Excel, and then ran frequency counts of the codes. Frequency counts are a common method in cognitive anthropology:

Words that occur a lot are often seen as being salient in the minds of respondents. D'Andrade notes that "perhaps the simplest and most direct indication of schematic organization in naturalistic discourse is the repetition of associative linkages" (1991:294). He observes that "indeed, anyone who has listened to long stretches of talk, whether generated by a friend, spouse, workmate, informant, or patient, knows how frequently people circle through the same network of ideas" (1991:287). (Ryan and Bernard, 2006)

Frequency counts simply tally the number of times a given code appears in a file. Using Excel, team members sorted codes by interviewee, to see who was speaking on which

topics during the interviews, and how salient said topics were for them. For example, during the interviews, it appeared that some participants answered questions in greater detail, and often at greater length, regardless of topic. These people also spent more time on any given topic than did other members of the cohort. Through coding, members of the research team were able to verify that participants who answered the same set of questions from the interview guide—posed under circumstances designed to be similar—answered them differently in ways that were patterned and observable. For example, one way the research team ultimately identified Cyberawares as distinct from cybersensitives was because they appeared to spend more time discussing devices during interviews, and this distinction was corroborated through the coding process.

Using Excel, the research team was able to perform operations such as counts and sorts on codes, which represent topics that occurred during each interview. By coding the topics, the research team could compare them with each other, both across the cohort, and within subsets of the cohort (Appendix B). Coding the topics and sorting by their frequency of occurrence across the various cohorts allowed the research team to interrogate subjective perceptions derived from the fieldwork observations with greater empirical validity.

Categories of Codes (Psych, Energy, Device)

The goal with the interviews was to elicit broader conversations about technology usage, the emotions it elicited, and any relevant attitudes around energy consumption within the household. As discussed above in section 2.4.1.2, codes were developed for repeated topics in the interviews. The 40 codes were organized into three categories: "Device" codes, "Energy" codes, and "Psych" codes. These categories of codes represent the main themes of the research project. A category, such as Device, groups together all the codes from the interviews that pertain to personal technology usage. The 40 codes organized into three categories featured

- Nine codes in the Energy category,

- Ten codes in the Device category.

- Twenty-one codes in the Psych category.

Table 5 is an excerpt from the Master Data Set collated for the project, which shows how often a subset of specific codes for the category Psych showed up for four participants in Southern California.

Table 5: Frequency of Psych Codes for Four Participants in Southern California

Participant	Psych: Privacy	Psych: Regret	Psych: Security	Psych: Work
A	1	0	0	2
B	2	0	0	5
C	3	0	0	2
D	1	0	0	7

How often a subset of specific codes for the category Psych showed up for four participants in Southern California

Source: Indicia Consulting

There are several ways to define a cultural domain, but a good starting point is: a set of items that are of the same type. For example, "animals" is a cultural domain. The members of the *cultural* domain of animals[5] may include living organisms such as birds, mammals, and reptiles but not insects or invertebrates. Implicit in the notion is that assignment to the domain is not determined by any one individual respondent, but that it exists "out there" in the language of the culture. For the purposes of this project, a category such as Device is a cultural domain in that it groups together all the coded topics discussed in the in-depth interviews that pertain to personal technology usage (see Glossary for definitions).

There are nine different codes in the Energy category.

1. Energy: Appliances
2. Energy: Billing
3. Energy: Electric Car
4. Energy: Energy meaning
5. Energy: Energy programs
6. Energy: Energy saving behavior
7. Energy: Energy tracking
8. Energy: Energy usage
9. Energy: Saving money

There are ten different codes in the Device category.

1. Device: Amazon shopping and products
2. Device: Banking

---

[5] Different from biological taxonomy.

3. Device: Communication

4. Device: Computer

5. Device: Connectivity

6. Device: Friends devices

7. Device: Older tech

8. Device: Purchase process

9. Device: Dispose of old devices

There are 21 different codes in the Psych category.

1. Psych: Addiction

2. Psych: Aging/age

3. Psych: Anxiety

4. Psych: Artistic

5. Psych: Disconnect

6. Psych: Excitement

7. Psych: Expensive

8. Psych: Family

9. Psych: Fastidious

10. Psych: Friends

11. Psych: Health

12. Psych: Indulgence

13. Psych: Love

14. Psych: Nature

15. Psych: Passion

16. Psych: Philanthropy/volunteer

17. Psych: Pragmatic

18. Psych: Privacy

19. Psych: Regret

20. Psych: Security

In addition to simply tallying the occurrence of various codes the research team also looked at the cumulative totals for all occurrences of the codes within the categories.

This enabled the comparison of the cumulative totals of codes for the three categories for each participant. The cumulative code totals for each category was a means by which level of interest or engagement with each categories' topics could be compared across the cohort(s). A participant with 32 total codes in one category suggests that category is more salient to their interests than does someone with only eight codes in the same category.

Ranking Participants Within Categories

For each category (Psych, Energy, Device), a participant was ranked as more or less cybersensitive before the category rankings were then combined into a final rank/status. The research team could have imposed an arbitrary cutoff (e.g., top five, bottom ten) to stand for ranks in each category. Instead, the research team looked for what conditions, or rules, appeared to underlie the pattern of responses. This assignment of status considered the total number of codes per category, but also the variety of different codes represented. For example, interviewee C.K. may have had a total of eight codes in the Energy category, but they are all for the single code, energy tracking. In contrast, H.G. had 32 total Energy codes, but those codes were also distributed across all nine different codes. H.G. is more interested in a range of energy topics and behaviors, which is an important aspect of the overall trait of cybersensitivity.

Psych category Rankings

If a respondent gave 20 or more total responses in this category they were ranked as cybersensitive for that category. The rank of Cyberaware was defined by multiple codes having more than one response. The rank of Mainstream required a minimum of five codes. Participants with three or four codes were ranked as Low Mainstream. Those participants who gave a maximum of two codes across the full set of 21 different codes were ranked as null. People who had a wider variety of codes showed they were interested in a range of psych topics and behaviors, which is an important aspect of the overall trait of cybersensitivity.

Energy Category Rankings

Participants with a minimum of 10 codes, and four to five codes in individual categories were ranked as cybersensitive for that category. Participants who had a minimum of eight codes, with up to three instances of a single code, were ranked as cyberaware. Participants with at least six codes ranked as mainstream. Participants with a maximum of four total across all nine codes were ranked as null. People who had a wider variety of codes showed they were interested in a range of energy topics and behaviors, which is an important aspect of the overall trait of cybersensitivity.

Device Category Rankings

Participants with between 10 and 20 responses, but also having a minimum of six different codes represented were ranked as cybersensitive for that category.

Participants with totals of between seven and nine codes and having at least two different codes represented were ranked as mainstream. Meanwhile, participants with four or fewer code totals were ranked as null. People who had a wider variety of codes showed they were interested in a range of device topics and behaviors, which is an important aspect of the overall trait of cybersensitivity.

Finalizing Segment Membership

The final determination of segment status was derived from combining the ranks from all three categories. The research team gave the most importance to the Psych category, as the research teams definition of cybersensitivity primarily rests upon the existence of a strong and potentially measurable emotional/psychological relationship with technology.

Our final segmentation schema had five segments (discussed in Section 3.3):

- Cybersensitive

- Cyberaware

- Mainstream

- Low Mainstream

- Null

A participant had to have ranked as cybersensitive in at least two categories to be assigned to the Cybersensitive segment. Similarly, a participant had to have ranked as cyberaware in at least two categories to be assigned to the Cyberaware segment. A participant ranked as mainstream in two categories would be assigned to the Mainstream segment. A participant with at least two categories where they ranked as low mainstream would be assigned to the segment Low Mainstream. A participant ranked as null in at least two categories would be assigned to the Null segment.

Post segmentation, the research team returned to the interview transcripts and reviewed them once again to identify patterns related to segment membership. The team also returned to the recruitment questionnaire answers given by participants and examined them in terms of answers given by segment members. Those findings as they pertain to the development of the Ethnographic Decision Tree Model are discussed in the Results section.

Decision Tree Models

One objective of this research was to recommend an alternative energy efficiency model using decision tree modeling.

> "In decision tree modeling, an empirical tree represents a segmentation of the data that is created by applying a series of simple rules. These models

generate a set of rules which can be used for prediction through the repetitive process of splitting." (Tso and Yao, 2005)

Researchers define decision trees as "classification systems that predict or classify future observations based on a set of decision rules" (IBM, 2012). There are two basic functions that decision trees normally address: predict the membership of someone in a category, or predict the behavior of a group member with respect to certain decisions. The authors designed two complementary decision-trees to predict the membership of someone in a segment, and from there extrapolate their prevalence in a synthetic population based on American Time Use Survey data.

Decision rules are generally a set of binary Boolean decisions or criteria, such as true/false or yes/no, which the model then branches into a hierarchical tree structure (IBM, 2012). Often, researchers use decision tree models to represent a decision process, such as the car buying model example shown in Figure 7.

Figure 7: Example Decision Tree Model
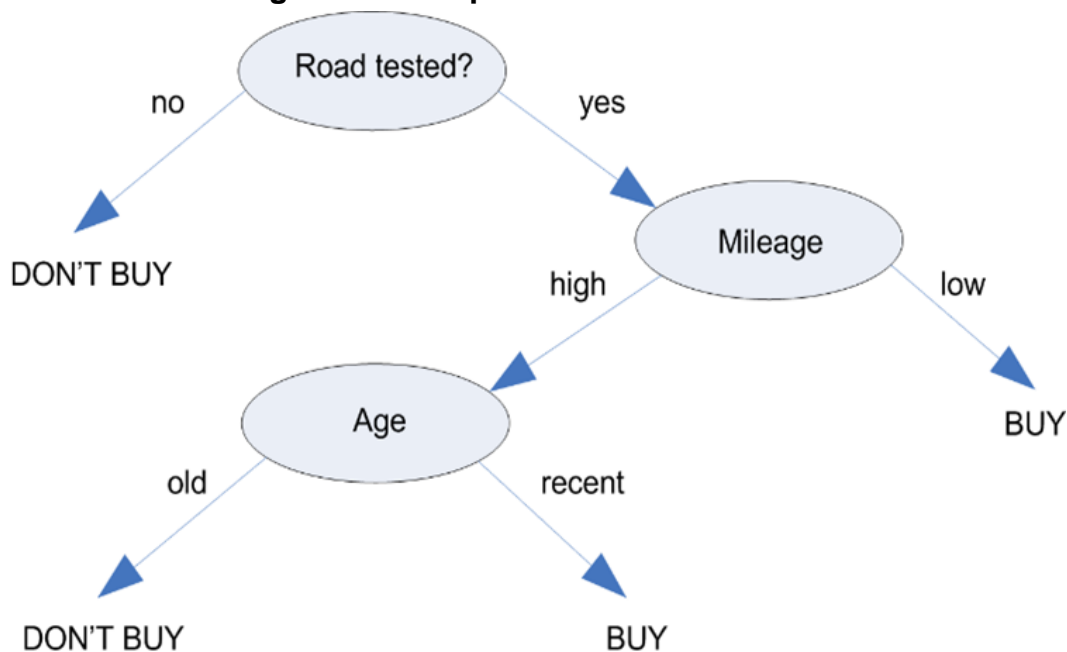
A decision tree illustrating the decisions involved in buying a used car.

Source: IBM, 2012

Types of decision-tree models include ethnographic and machine learning, also known as computational. The former builds the model from qualitative observations and questioning based on ethnographic observations, and the latter codes machine learning algorithms based on (generally) quantitative data. The research team constructed one of each: an ethnographic decision tree model (EDTM), and a machine learning based Classification and Regression Tree (CART). Both decision tree types build a structure based on the data through a fluid set of procedures, although each uses different data

and thus employs similar but different protocol. Both forms of decision tree modeling are inductive since they build the model from observations and theory. "In brief, the object of the game is to frame criteria, order or arrange them into a tree-like structure, and then test and revise the tree model" (Gladwin et al., 2001).

Ethnographic Decision Tree Models

The aim of this research project is to construct a tool capable of segmenting a population using a fresh dataset. The EDTM used the most salient questions from the questionnaire and interview guide to build a formal model representing how people interact with their devices and consumer energy. One question for the team was, "What were specific things that Cybersensitives and Cyberawares reported doing that was different from the rest of their cohort?" For this project the research team employed ethnographic methods to provide the data that formed the basis for an ethnographic decision tree model:

> "The method is called ethnographic decision tree modeling because it uses ethnographic fieldwork techniques to elicit from the decision-makers themselves their decision criteria, which are then combined in the form of a decision tree, table, flowchart, or set of if-then rules or expert systems which can be programmed on the computer." (Gladwin, 1989).

EDTMs, "are qualitative causal analyses that predict real, episodic behaviors, rather than—as does so much social research—the intent to behave in a certain way." (Ryan and Bernard, 2006). Researchers analyze and consolidate multiple informants' explanations of their decision-making processes into an overall decision tree model. "There are direct and indirect eliciting methods, but both require the ethnographic model builder to look for contrasts in decision behavior, ask the informant to explain the contrast (e.g., Why did you decide to evacuate with Hurricane Andrew but not with Hurricane Erin?) and then test that explanation on another informant" (Gladwin et al., 2001).

Ethnographic decision tree modeling is a tool used to represent decision-making made by groups, rather than by individuals. The objective is to represent the decision-making process made by members of a group in response to a certain set of circumstances, e.g., freshmen deciding about a meal-plan at college. For this research, the decision-making being represented is that a *new* set of participants could answer a set of questions about device usage, energy consumption, and communication preferences and those answers would end up replicating the segmentation performed by coding and analysis.

The first phase of any EDTM development consists of conducting a series of ethnographic interviews with the members of the group under scrutiny. The interviews are designed in such a way as to elicit the process of decision-making in the words of the group themselves. In the second phase of EDTM development, the ethnographer(s) reviews the verbatim responses, and organizes the steps in the decision-process as captured in the ethnographic data. The third phase of EDTM development is to run the now

44

diagrammed set of choices past another, similar, set of group members, to see where the ethnographer may have misunderstood or missed pertinent information. If the EDTM model is generally predictive, (the literature suggests that a minimum 80 percent of cases should be properly accounted for by a well-done model) then the modeler can stop, although ideally the process of refinement can continue *ad infinitum*.

Building an Ethnographic Decision Tree Model

One objective for this research was the construction of an Ethnographic Decision Tree Model to replicate the behaviors identified during research, and ultimately reproduce them such that the model might be predictive. EDTMs "are built from interviews with a relatively small sample of people (20—60) and are usually tested on a similarly small and local sample" (Ryan and Bernard, 2006). The authors collected qualitative and ethnographic data from 48 households in both Northern and Southern California. Ethnographic data collection methods provide for a uniquely rich dataset, which allows researchers to explore in depth the features with which to build their model.

Most studies that model decision behavior through decision trees, whether ethnographic or machine learning in their approach, build their model on their sample data set and then test that data off a larger sample of the entire population (such as Ryan and Bernard, 2006; Wright 1996; Bell et al., 2018; Chapnick, 1984; Murtaugh, 1984). In most instances that means constructing the decision-tree model based on the answers given by an initial small set of local respondents (e.g., car buyers in California) that they are studying and then testing those responses against the data collected via another method (e.g., national data on car purchases).

It is important to note that the research team built an EDTM but did not test it with a subsequent set of new participants. Testing ethnographic decision-tree models in this manner is an integral part of the overall process in constructing a reliably predictive model (Gladwin, 1989). Ideally, there would be two additional rounds of recruitment and testing, with two different cohorts: one to initially test assumptions and refine the model, and one to validate the findings. However, that lies beyond the scope of this project.

The research team returned to the transcripts from the interviews to look for verbatim examples of patterns of behavior for inclusion in the EDTM. The research team reviewed the answers made by all segment types to specific questions about appliances, energy bills, energy programs they may have heard about, and their tracking of household energy use.

In the review of the transcripts, it soon became clear, that while all households *may* participate in energy efficiency programs, the pathways to uptake are very different, as is their receptivity to offers, and their engagement with data from their utility. Cybersensitive and Cyberaware households were more active in acquiring information about energy efficiency measures and programs, than were other households. Participants in these segments used more detail and description in their answers, and

more often reported taking direct action in response to information received from their utility.

It is helpful to remember that the EDTM is not a survey of attitudes where it is desirable to capture responses from the entire group. Instead it is a means to represent decision-making. It would also likely be administered face-to-face in an interview-type setting[6]. That means that people would be able to give some context, clues, even corrections, as the questions are asked[7].

A segmentation schema must possess both internal homogeneity (similarity within segments) and external homogeneity (differences between segments). Because Mainstream and Low Mainstream households were the only households where someone reported *not* actively pursuing saving energy this was considered to be a distinguishing characteristic, separating them from the remaining segments (Cybersensitive, Cyberaware, and Null). Therefore, the first question for building the decision tree becomes "Have you tried to save energy?" Answering "no" to this question would tag them as Mainstream and they would exit the decision-tree[8]. Answering "yes" to the question "Have you tried to save energy?" requires the model to next establish *how* they acquired information about saving energy. The following questions help to establish this:

- Do you read your monthly electricity bill?
- Did any information from utility change your energy behavior?
- Do you get information about saving energy from other sources (internet?)

Again, if participants are interested in saving energy, but did not pursue it in any meaningful way, they will answer "no" to one or more of these questions, which will tag them as Mainstream and they would exit decision tree. The next few questions identify potential Nulls, based on their previously established characteristics (facility with technology/lack of emotional engagement with technology):

- Technology is easy for me
- My friends ask my advice about tech issues
- I have a lot of devices (laptop, phone, tablet)
- I feel uncomfortable when separated from my devices

---

[6] It could also be administered online via a website or an application.

[7] Particularly if administered as a step in testing the model.

[8] If we were asking freshmen about their meal plan at college and someone were to answer that they do not go to college, they would similarly be disqualified. It is not that they might not have interesting or valid opinions, but they lack membership in the group under investigation.

One can be Cybersensitive without a deep understanding of technology. Conversely, people can be sophisticated in their understanding about technology, without evincing cybersensitivity. These questions allow people to give us enough context without prematurely winnowing them from the pool. From the ethnographic observations, the research team established a few common aspects to cybersensitive lifestyles (the psychographic element), one of which was the pursuit of multiple, in-depth hobbies and a sort of zest for life/inquisitiveness about things in general. The next questions help them to self-identify:

- I have several hobbies

- I try new things all the time

At the same time, based on their answers to survey questions, these participants report immersing themselves in the details of the things they are interested in. The next two questions help identify people who may be more superficial in terms of their engagement with new ideas and interests:

- I quickly move on to the next new thing

- I spend a great deal of time on details

The next set of questions helps us to flesh out the mode of communication and engagement they are most comfortable with. Since the research team was interested in people receiving information on their devices, the next question is about applications and platforms.

- Do you communicate with friends and family primarily via phone call?

- Do you communicate with friends and family primarily via email?

- Do you communicate with friends and family primarily via video call (Skype/Facetime)?

- Do you communicate with friends and family primarily via text/WhatsApp?

- Do you communicate with friends and family primarily via social media (Facebook)?

The next section deals with engagement with the utility, but also with devices, platforms, and applications, the modes of engagement with energy consumption, billing, and information about both. This will help further identify Mainstreams who slipped through earlier questions. People who do not engage with their utility online/via device or who receive information about their energy consumption solely through paper means, are not Cybersensitive, Cyberaware, or Null.

- Do you receive your electric bill via email?

- Do you pay your electric bill online?

- Do you log in to pay your electric bill?

- Is your monthly payment automated?

The final set of questions help distinguish Cyberawares from Cybersensitives because the primary distinction between the two cyber-segments are preferences with respect to tracking information (in a variety of contexts and activities) and for wearing personal devices such as Fitbit or Strava that purport to use feedback to change behavior (Sullivan and Lachman, 2017):

- Do you use any device to track your energy?

- Do you have any devices that track other things, like health/fitness?

- Have those devices changed your behavior?

At the end of the model, the questions posed should have:

- Identified Mainstream and Low Mainstream participants at an early stage

- Distinguished Nulls from Cybersensitives and Cyberawares

- Distinguished Cybersensitives from Cyberawares

At the conclusion of the administration of the EDTM, the researcher should have four segments:

- Cybersensitives

- Cyberawares

- Mainstreams[9]

- Null

Classification and Regression Trees

The research team combined the data from the recruitment questionnaire and the coded responses from the in-depth interviews to build a Classification and Regression Tree. CART is a quantitative decision tree modeling approach that uses a set of machine learning, computational-based strategies. Like most machine learning models, CART modeling requires balance between accuracy and reliability. A perfectly accurate model can account for every individual in the dataset and correctly predict it. For CART, that means adding as many levels or branches as possible until it classifies correctly. A model is reliable if it is robust enough to be able to accurately classify or predict cases from new datasets, samples, surveys, and/or studies.

---

[9] This version of an EDTM is not nuanced enough to distinguish Low Mainstream from Mainstream. A testing round of the EDTM, in particular with a larger sample size, and household energy data, might be able to refine the model.

The biggest advantages of quantitative decision tree models are that results are easy to visualize and understand intuitively (unlike many other machine learning processes with obscure, unintelligible processes). Unlike other methods, CART can handle a mixture of data types. CART models do not require normalization or extensive data preparation, typically required by machine learning methods for which all data must be of one type and/or of the same scale. CART models are easy to create and because of its branching style, it is easy to edit or prune one branch or part of the tree, and this makes it easy to build and synthesize the results from several decision trees coherently. By creating and testing between several CART different decision trees, this process addresses potential tendency towards variation and overfitting inherent in decision trees, since they pick up the wide patterns between many specific decision tree models, filtering out any irregular variation of a model by looking at the patterns of the models as a whole (see Appendix E-1).

CART algorithms work better on a larger dataset so the research team used "bootstrap resampling" to create a dataset of 300 virtual persons. Resampling refers to the addition of dummy cases that maintain the same distribution and other data patterns as the given data. Bootstrap resampling works by randomly adding the dataset values with replacement (in other words, each new time a value is selected it does not exclude past values, so values can be selected more than once) from the initial dataset until 300 is reached.

The research team carried out preliminary testing using a synthetic population constructed from American Census Questionnaire and American Time Use Questionnaire provided by the Network Dynamics Simulation Science Laboratory at Virginia Tech University. As with the EDTM, the CART (as of this writing) will be an untested (in the real world) model, requiring more/larger sets of data to run before it reliably replicates real world behaviors. However, as with the EDTM, the model's construction will be robust enough that another entity, with their own resources and access to data, would be able to deploy the model and test it for use as a tool for better understanding and predicting consumer behavior.

Process

CART models typically involve three basic steps: pre-development or data preparation, model development, and pruning through testing and/or ensemble methods. Data preparation refers to the process of organizing the data for the model, including developing independent and dependent variables, splitting the data into training, and testing sets, resampling the data, data cleaning, etc.

Next in developing the model, the most important consideration in this process is the method used to determine branching: that is, the equation and algorithm used to determine when to split the data into smaller branches and the variable to use to split it (Appendix E-1 for detailed development of the algorithm).

After creating the initial model, developers test the accuracy model with cross-validation techniques and based on those results prune (or strategically adjust) the tree further. Pruning refines the nodes on the branches to ensure better accuracy and reliability (on both the data set and on potentially new potential data sets respectively).

Various ensemble methods—algorithms that combine several models together into a single modeling approach to improve the results—are often performed parallel to pruning. Ensemble methods combine several models together to improve the results, based on a collaborative approach. Random forest generation is a way to compare several different CART decision trees to improve the accuracy. A random forest algorithm produces several CART decision trees (called forests, because they build many trees) based on randomly selected subsets of data points within the sample.

California State University Student Ethnographies

In addition to the fieldwork described and analyzed above, the research team also selected, trained, and supervised a diverse group of 16 students from the California State University (CSU) system. This group included undergraduates and early-stage graduate students in social and behavioral majors with a focus on qualitative methods. The students conducted individual research projects under the umbrella of the project goals. Each student created their own research proposal. The students began in August 2016 and wrapped up in August 2017. On-campus advisors supervised these projects, in addition to team members from California State University San Marcos and San Diego State University (SDSU). The support from the CSU system included assistance from the Language Acquisition Resource Center at SDSU, which hosted an online course for the students (Fall 2016/Spring 2017) which trained them in ethics and methods appropriate for collecting data for supporting the research objectives.

These student researchers were "embedded" within California communities of their choosing for their ethnography project including Latino communities in San Diego, the homeless in Los Angeles, as well as surfers, commuters, and coffee-shop patrons. The student research project topics explored the intersection of technology, behavior, and energy and their projects included an examination of fitness culture and wearable technologies, a comparison of solar panel owners vs. lessors, and an ethnography of a group of Southeast Asian refugees who temporarily lacked water and power in their Fresno apartment complex.

The work produced by the students was important to the project because it added ethnographic context for energy consumption across California that was often corroborative of the findings from the in-depth interviews conducted in the two utility territories. As one example, the research produced by a graduate student on the project suggested that, "personal and emotional feelings about appliances seemed to affect accuracy [regarding the actual energy consumption of the appliance] …the more frequently a subject used an appliance, the more accurate their estimate was of its power consumption." (Ehlers, 2016, reproduced as an attachment in Appendix D). Each

of the 16 students produced a written report and presented in a video-conference format that was recorded. [Student biographies, and links to the recorded presentations](http://indiciaconsulting.com/students/) can be found at http://indiciaconsulting.com/students/.

CHAPTER 3:
Project Results

Insights from Recruitment

Characteristics of Questionnaire Respondents

The research team fielded a recruitment questionnaire from September 2015 through April 2017. Four hundred and fifteen persons across California started the recruitment questionnaire and completed some or all of it. Due to the wide distribution of the questionnaire, the research team ended up with a reasonable cross-section of Californians as respondents, though no claims are made to have a statistically representative population, such as might occur with a Randomized Control Trial. Respondents who made up the recruitment pool had the following characteristics:

- Respondents resided in different types of locales across California, including urban, suburban, and rural (Figure 8A).

- Respondents to the questionnaire tended to own their own homes (75 percent) more than the average Californian[10] (Figure 8B).

- Respondents were more likely to live in a household with children (Figure 8C).

- Respondents were more likely to be women than men at 59 percent to 41 percent[11] (Figure 8D).

- Respondents represented a good cross-section of the population age-wise, skewing slightly older[12] (Figure 8E).

- Respondents reported a spectrum of incomes, even if they may have skewed slightly wealthier (Figure 8F)[13].

---

[10] US Census data from 2016 shows California owner-occupied housing to be around 54 percent
https://www.census.gov/quickfacts/fact/table/ca/AGE775217#viewtop

[11] Census figures for 2016 show women to make-up 50.3 percent of the California population

[12] Census data shows that Californians aged 65+ make up 14 percent of the population, while in this survey they made up 18 percent. Conversely, under-18s were not represented, but the recruitment was aimed at ratepayers, people with utility accounts in their name.

[13] Because the research team asked for ranges of incomes, it is hard to compare directly with Census data but California 2016 median income was approximately $64,000 according to Census data

Figure 8: Household and Demographic Characteristics for Respondents

A — Residential Distribution of Respondents
- Rural 8%
- City/Urban 34%
- Suburban 58%

B — Homeownership Among Respondents
- Rent 25%
- Own 75%

C — Households with Children
- Children under 18 40%
- No children under 18 60%

D — Gender of Respondents
- Male 41%
- Female 59%

E — Age of Respondents
- 75+ 4%
- 65-74 14%
- 55-64 20%
- 45-54 26%
- 35-44 15%
- 25-34 19%
- 18-24

F — Income of Respondents
- 200K+ 13%
- 150-199K 15%
- 100-149K 23%
- 50-99K 21%
- 20-49K 10%
- Less than 20K 5%
- Prefer not to state 13%

Source: Indicia Consulting

53

Characteristics of Interview Participants

The research team fielded a recruitment questionnaire from September 2015 through April 2017. Two hundred and ninety-eight individuals *completed* the recruitment questionnaire. Of those 298, 56 percent provided an email address or phone number and indicated an interest in participating in an in-depth interview. Several respondents—who completed the questionnaire and provided their contact information for an interview—did not respond positively to follow-up requests by the ethnographers to schedule an in-home interview. Some of the reasons stated are listed:

- Some simply did not reply to any of the emails or phone calls.

- Some respondents explained that they simply did not have time to participate in an interview of that duration, despite a moderate degree of interest.

- A few respondents initially showed interest in the study but were deterred by the prospect of the interview being conducted in their homes; they (or their families) found this methodology "invasive."

- Several respondents filled out the questionnaire, and then inquired if there was compensation for the interview. Some of these respondents chose not to participate in the interview, stating that the $25 Amazon gift card was not adequate compensation for their time.

- Also, potential participants were required to reside within the territories of the large California investor-owned utilities.

In total, 167 potential interview participants were contacted, and a personal attempt was made by the ethnographer in the region to organize a time to visit them at their home, at the time and day of their convenience. From those 167 potential participants, the research team ended up conducting interviews in 48 households: 22 households in the Bay Area (primarily Marin), and 26 households in Southern California (primarily Long Beach).

For this project, when the research team asked interview participants what had motivated them to do an in-home interview, most people who decided to participate in the research reported doing it for one of the following reasons:

- They were invested in the topic (of energy savings) personally.

- They wanted to help.

- They believed they have something to offer.

The research team found that the most effective means of recruiting participants for in-home interviews about energy consumption and devices was via channels that took advantage of a pre-existing, positive relationship, such as that existing between a utility and their customer base. The presence of incentives in social media campaigns did not produce greater participation than did the email campaigns deployed without

incentives, but where an established relationship between sender and recipient existed previously (such as as a customer of a utility, or as a member of Sierra Club).

However, offering small cash incentives ($25 Amazon gift cards) did affect the conversion rate of people from survey participant to in-home interview participant: click rates for the October 2015 email campaigns without an incentive ran between 2.8 percent and 4.2 percent, while the March 2016 email with an incentive returned a 0.7 percent click rate. The research team found that the click rate was only 20 percent to 25 percent that of the earlier emails, possibly signifying some fatigue with the subject (having been sent to the same Marin Clean Energy customer base repeatedly). Yet, despite the much lower click rate, respondents left their contact information at the same rate as the earlier emails had elicited (64 percent). Further, the conversion rate from questionnaire respondent to in-home interview was three times as high (43 percent vs 13 percent, see Table 1 for details). The interpretation of these results is that *an incentive cannot substitute for the intrinsic interest of the content offering, nor does it necessarily motivate people to participate in a questionnaire, but it can strengthen the willingness to continue participating in the process leading to an interview.*

Demographic Variables of Interview Participants

As discussed in the approach section, the goal of recruitment was to achieve a reasonably diverse cohort of interview participants. The aim was that regional cohorts should also be largely reflective of their local demographics. The interviews conducted in Marin between October 2015 and May 2016 skewed slightly older, wealthier, and slightly more female than the general population of California (see above), however they were representative of Marin's population (see Appendix A for further details).

Gender of Interview Participants

The Northern California cohort had roughly the same ratio of women to men as the respondent pool (60 percent/40 percent). Both ratios are higher than California's general population (51 percent /49 percent) (Figure 9).

Figure 9: Male-to-Female Ratio of Northern California Participants
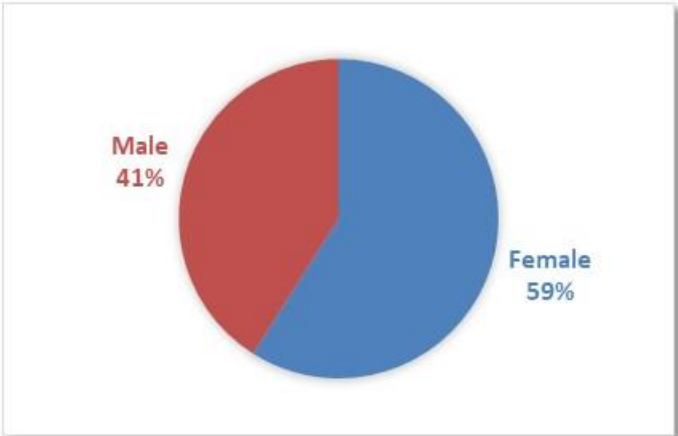
Source: Indicia Consulting

The Southern California cohort had more women (64 percent) when compared with the recruitment questionnaire respondents, the Northern California cohort or California generally (Figure 10). This discrepancy is likely due to snowball sampling by the Southern California ethnographer.

Figure 10: Male-to-Female Ratio of Southern California Participants
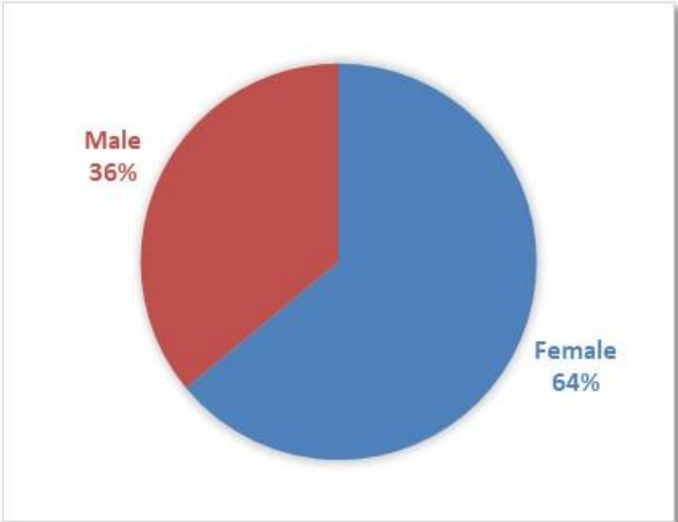
Source: Indicia Consulting

Age of Interview Participants

Northern California participants were on average older than the initial pool of respondents. In Northern California 32 percent of the participants were 65 and older (Figure 11).

Figure 11: Age of Northern California Interviewees

65-74	32%
55-64	27%
45-54	23%
35-44	9%
25-34	9%
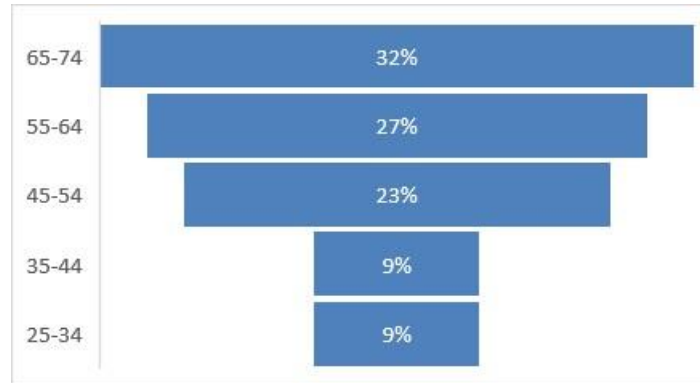
Source: Indicia Consulting

The age of the Southern California participants was younger than the Northern California cohort, and the respondents. Only 9 percent of the participants in Southern California were over 65 (Figure 12). This discrepancy is likely due to snowball sampling by the Southern California ethnographer.

Figure 12: Age of Southern California Interviewees

65-74	9%
55-64	9%
45-54	50%
35-44	23%
25-34	9%
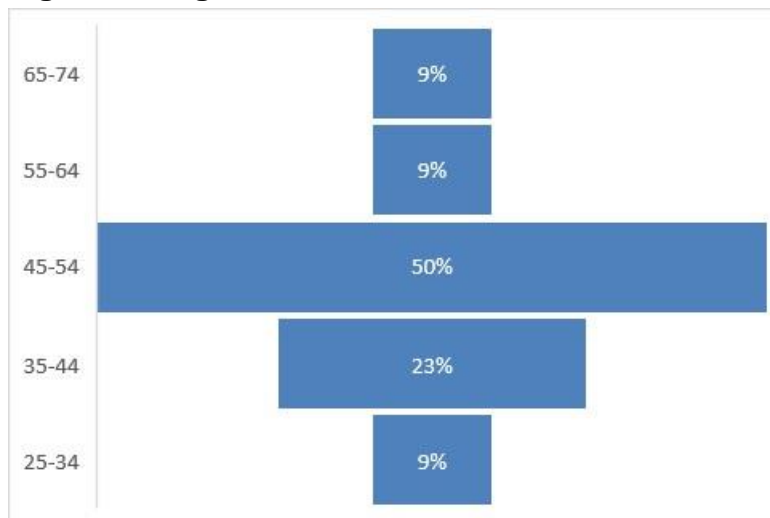
Source: Indicia Consulting

Income of Interview Participants

The Northern California interview participants were more likely to live in affluent households than were the initial pool of respondents (Figure 13). However, a range of incomes was still represented which is important for capturing diverse viewpoints and lifestyles.

Figure 13: Income in Dollars of Northern California Interviewees
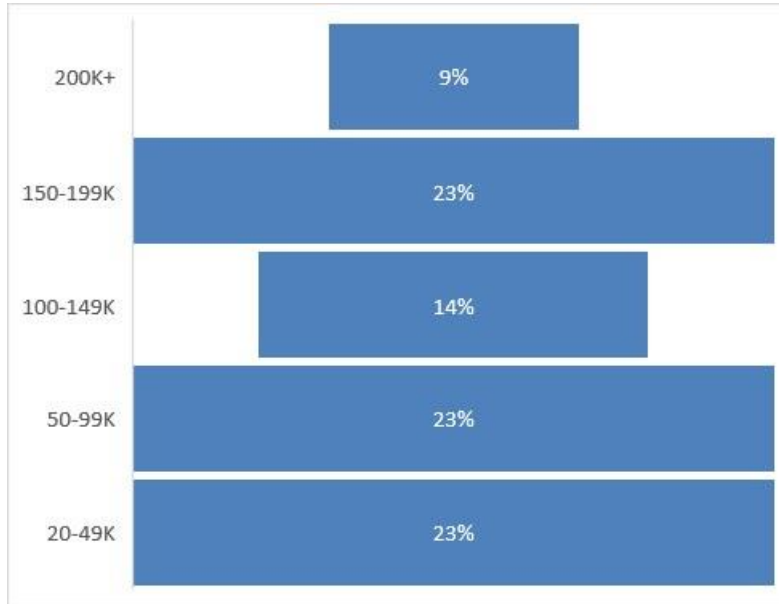
Source: Indicia Consulting

The Southern California participants were less likely to live in affluent households than was the case with the Northern California cohort (Figure 14). In Southern California, 28 percent of the participants lived in households making more than $100,000, while 54 percent were in households making less than $100,000. A larger percentage (16 percent) Southern California participants "declined to state" household income.

Figure 14: Income in Dollars of Southern California Interviewees
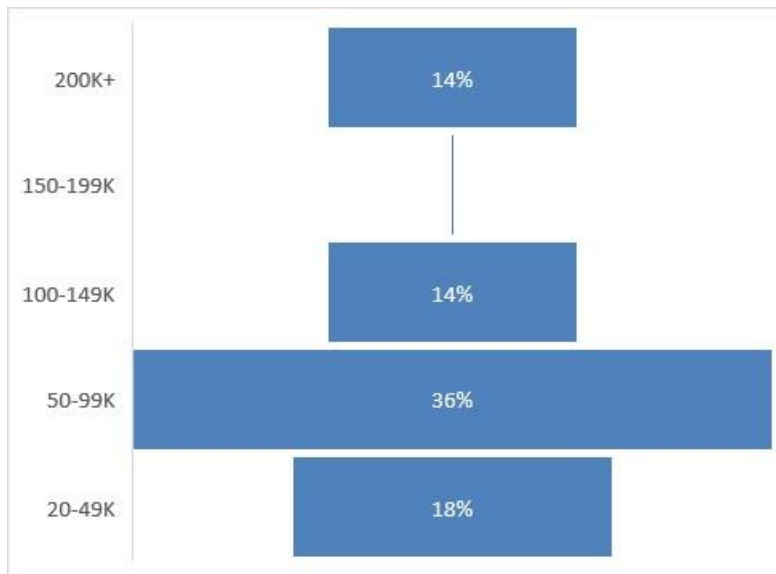
Source: Indicia Consulting

Despite differences in income between the two cohorts, the percentage of Cybersensitives and Cyberawares remained roughly the same, supporting the hypothesis that income and cybersensitivity are not synonymous with one another (Appendix C). Cybersensitivity is a psycho-graphic/behavioral trait and does not stand-in for a demographic trait.

Results from In-Depth Interviews

At the outset of the research, the research team hypothesized that there were degrees of intensity, also known as valency (Appendix B), among the segments that was the differentiating factor. As the research progressed, the research team found that the relationships among the segments was more complex than originally anticipated, and that the relationships among the segments were distinguishable through various traits, and not by the level of intensity of the emotional relationship with technologies.

The research team identified several traits common to Cybersensitives (and the closely aligned segment, Cyberawares). Cybersensitives have an intense cybernetic relationship with devices for example, while Cyberawares focus on tracking.

Differentiating groups using replicable methods is an important part of producing a viable segmentation schema, and for that reason understanding Nulls was critical. Nulls appeared to share some overlapping traits with the Cybersensitive and Cyberaware segments (such as facility and familiarity with technology) while lacking others (for example expressions of emotional engagement with technology during the interviews).

The data collected does not demonstrate distinct traits which differentiate the Mainstream/Low Mainstream segments, only that they lack the traits that define the other three segments. Both are relatively large, comprising approximately half of the sample when considered together.

Psycho-Social Drivers

The in-home observations, recorded as fieldnotes, video, and photography, offered evidence that certain psycho-social drivers were present in some households, but not in others. These characteristics of cybersensitivity show up in multiple areas of participants lives:

- Cybersensitives have a lot going on in their personal lives, which may be the precursor to desiring to track and record activities.

- Cybersensitives and Cyberawares tend to have multiple chapters in their careers, and often juggle multiple simultaneous revenue streams.

- Cybersensitives tend to be highly engaged with learning new things, they tend to have serious hobbies and be on the lookout for new projects particularly those involving the home.

- In response to the survey question, "I try new things all the time, but do not pursue most of them in great depth; I quickly move on to the next new thing," cybersensitives were the most apt to strongly disagree.

- Cybersensitives are likely to strongly disagree with any characterization that they are lightweight.

- Cyberawares tend to be more interested in tracking information and performance, not only with energy but also money and fitness.

- Cyberawares are more likely to report possessing wearables.

Device Usage and Other Technology-Related Behaviors

The ethnography team members focused primarily on the presence or absence of specific devices (e.g., smartphones, laptops) in making their initial assessments. However, as one of the senior ethnographers later observed after conducting the in-home observations:

> "Don't get hung up on the device itself or the number of devices they own. Devices are just proxies. Focus instead on their feelings about the device, what it represents in the respondents' mind, and their attitudes/behavior towards the device. Look to what motivations it invokes and whether they are detail-oriented with their usage."

Cybersensitives

The research team found the Cybersensitives to be methodical in their decision-making, especially around technology adoption and usage. All Cybersensitives answered "Yes" to the recruitment questionnaire question, "I wait for new technologies to be somewhat widely adopted before adopting them myself."

Cybersensitives tend not to buy new devices for novelty's sake; for Cybersensitives, technology solves problems or provides them with solutions rather than entertains or enhances status. These interviewees are very practical in their decision-making and articulate well thought out rationales for their purchases. RR said that he, "owns the devices he needs, but if he had more money, he would update a few of them."

DW has a schedule to buy new devices as soon as they "don't do what they are supposed to do." Meanwhile, KST only purchases devices that he requires although there are a few devices that he likes because they are fun, such as the Amazon Echo, because "it takes voice commands." CJ goes about her purchases and decision-making in a very systematic fashion: she only buys devices that she decides that her family require, and each device has a specific function within the household electronic ecosystem. In a similar vein, BH said that her members of her household have devices "only for their use-value, nothing extra."

- Cybersensitives often have multiple computers in use in the home, and not just work computers vs. home computers, but multiple personal computers, often with multiple screen setups.

- Building home brew devices is a common activity among the cybersensitives. JA builds his own computers to achieve his precise specifications.

- Cybersensitives are not afraid of unconventional or imaginative ways to extend the uses of technology.

    o The research team interviewed a father and daughter, and the daughter NZ said that she would like a water bottle that beeps if she is not drinking enough water throughout the day.

    o Meanwhile, the father PZ would like a watering system for his garden hooked up to a weather report and automated.

Cyberawares

One thing the Cybersensitives and Cyberawares in the cohort have in common is that they are planners and implementers. Both Cybersensitives and Cyberawares will not only show such behavior with respect to technology, but also in the way they buy other products, select/use services, pay bills, and show meticulousness/fastidiousness in other areas as well. For instance, tracking is a common topic among Cyberawares particularly. BBL, 70, is an avid biker and tracker of his own health stats. He is also very meticulous about his schedule and food intake, tracking them using his device (Figure 15). Here he discusses some of his process with devices:

"So, I got a bike computer, a heart rate monitor, and cadence monitor, it tells you [how many revolutions you are doing per minute] and that the bike upstairs will do as well. and that is just another device, but your bike computer tracks that. So, I mean, I show you. (walks away) So, this is the bike computer, it tracks everything on it. in fact, let's turn it on ok, so when I am riding, let's turn the light on. So, you got speed, you got distance, how long you have been doing it, and your heart rate. And then you can upload that to a program.

61

Figure 15: Participant Shows-Off a Wearable Tracking Device

Source: Indicia Consulting

- In response to the survey question, "When I find something useful, I explore it in as much detail as possible," Cyberawares tended to strongly agree.

- The more Cyberaware a participant was, the more likely they strongly agreed with this statement.

- There is a trend for Cyberawares to take an interest in life-long learning, with taking classes getting regular mentions in the interviews.

Nulls

The authors recommend disentangling the concept of cybersensitivity from being equated with familiarity and facility with technology, particularly personal computing devices, laptops, tablet, or smartphones. The interviews and subsequent analysis showed that people with occupations in technology, which is assumed to be an indicator of technical skill and knowledge, often ranked the lowest in terms of cybersensitivity, even with respect to questions about technology and devices. Ones skill or employment regarding computers or engineering does not translate into engagement with a device, or responsiveness to feedback via device (Houde et al., 2013). As an example, JC scored low in terms of device codes (rank eighteenth), which was unexpected in that he works as a software engineer. Several of the most highly skilled technical people, in terms of occupation, such as JC above ranked low in terms of their off duty interest and investment in buying devices. JJ, like JC, was highly skilled

in terms of technical aptitude and knowledge. Yet, all his equipment was old, he did little with it, and was not using it either in his everyday life or to maximize his lifestyle.

From field notes:

> "Very little emotional phrasing in terms of tech, no likes, loves, needs. In the living room where I chat is a massive television, with expensive speakers ("four or five years old," which are not calibrated, or positioned for maximum sound enjoyment, "Eh, I would have to put them behind the couch," JJ says wearily, "and I don't really listen to music anymore."

Meanwhile, IS's interview is an example of how the lack of emotional relationship to technology becomes salient in differentiating a cybersensitive from more mainstream peers. IS was a great interviewee, fun, candid, engaging; she worked and volunteered. They have a lot of technology among the family members, and she is an avid user of technologies, for example using Snapchat with her kids. But despite living in Silicon Valley and surrounding herself with devices, technology did not mean as much to her as they did to others in the cohort. With the same amount of time allotted, and the same questions asked in her interview as in others, the frequency count for codes in each category was not merely fewer for her, but several times fewer (e.g., four Device category codes vs. HG's 20 Device category codes).

Mainstream/Low Mainstream

Finally, the research team learned something about the rest of the cohort as well: they may superficially resemble cybersensitives at times, with interests in technology or energy, but this tends to be superficial. Those participants who were later determined to be Mainstream/Low Mainstream had often answered the research team's questions about their purchasing decisions with, "because I liked it" or something similarly non-descriptive and lacking in detail.

Energy Attitudes and Behaviors

While both cybersensitives and non-cybersensitives may participate in energy efficiency programs, the pathways to uptake are very different, as is their receptivity to offers, their engagement with data from their utility, and other dimensions. Repeatedly, the transcripts show that cybersensitives are much more likely to be aware of the availability of energy efficiency programs, to be interested in participating, to conduct cost-benefit analyses on their own behalf, and to be willing to actively seek out additional efficiency measures that they can undertake. For the question "Energy consumption tracking devices, apps or services: Which of the following, if any, do you own?" the only persons to own them were four Cybersensitives/Cyberawares had them: Mainstreams, Low Mainstreams, or Nulls owned none. Cybersensitives are aware of their energy consumption. They pay attention to rebates, tax credits, efficiency ratings. They take advantage of efficiency programs and actively seek out more measures. Cybersensitives can be critical of offers that do not meet their requirements/are not specific enough. DMC tells us, "We do get things occasionally and I'm trying to

remember what their subject really is. Its virtually always something we've already done."

Summing up, cybersensitives are more active in acquiring information about energy efficiency measures and programs, than are non-cybersensitives. They use more detail and description in their answers, and more often report taking direct action in response to information received from their utility.

Student Ethnography

The fieldwork conducted by students on the project also yielded interesting insights regarding energy consumption knowledge and attitudes more generally. Graduate student John Ehlers wrote:

> "One correlation[14] that defies explanation is that the more frequently a subject used an appliance, the more accurate their estimate was of its power consumption….There is no clear reason why subjects should be more accurate in their perceptions of appliances that they use more often. The appliances themselves, preferred or not, give no feedback to the user about how much energy they consumed. Also, it is unlikely that the monthly electricity bill would provide useful feedback, as the amount of electricity kitchen appliances use is dwarfed by the amount used to heat water and heat and cool the home. The additional energy consumed by, say, using the coffeemaker more frequently in a given month would be effectively invisible on a power bill. Yet the data shows that, somehow, if a person uses an appliance more often, they get a better sense of how much power it uses. If the cause of this unusual result could be determined, might it offer another way to inform consumers about their appliances energy consumption?"

Personal Feelings

Personal feelings about appliances seemed to affect accuracy too. L. said during the interview about her family's coffee bean grinder "I never use that, my parents do. It terrifies me." When answering comparison questions about the coffee bean grinder, she was 50 percent correct, lower than her average of 59 percent. She viewed the bean grinder as consuming more power than some of the most energy intensive appliances like the coffeemaker, toaster, and waffle maker. It is possible that her strong feelings about the bean grinder contribute to her perception of it as a "stronger" appliance, as its effect on her emotionally is outsized." (Ehlers, 2016, Appendix D).

Results from Coding

The initial ethnographic observations made by the senior anthropologists during the in-depth corresponded well with the results generated through coding. For example, in the fieldnotes containing direct observations of households, research team members

---

[14] His word.

described certain participants as fastidious and pragmatic. After transcribing the interviews, the research team reviewed the transcripts during the coding process, and found that fastidious, and pragmatic were topics that recurred in interviews with the same participants. These became codes in the Psych category. Within the set of 21 codes for the Psych category, pragmatic fastidious, were in the top three.

Code Totals by Category Across the Cohort

Recall that the higher the frequency a topic occurs in a conversation, the more salient it is to the concerns of the interview participant.

The team tallied 837 codes for the Psych category (Northern and Southern California combined)

- Pragmatic had the highest tally in the category (216)

- Family had the second highest tally in the category (87).

- Fastidious had the third highest tally in the category (74).

- Work had the fourth highest tally in the category (72)

The team tallied 217 codes for the Energy category (Northern and Southern California combined)

- Energy savings had the highest tally in the category (47)

- Energy tracking had the second highest tally in the category (29).

- Saving money had the lowest tally in the category (2)

  o Saving money was less salient to the cohort than other aspects of energy

The team tallied 486 codes for the Device category (Northern and Southern California combined)

- Older tech had the highest tally in the category (112)

- Purchase process had the second highest tally in the category (76).

- Dispose of old device had the third highest tally in the category (46)

Code Totals by Individual

The research team showed that certain individuals gravitated towards the top or bottom rankings in terms of intensity and engagement with the category as evidenced by the frequency and distribution of codes related to that category (Table 3). This created a spectrum which was segmented as discussed above in the Approach section.

- The Psych category code totals present in transcribed interviews ran from zero (CK[15], JJ) to 42 (HG).

- The Energy category code totals present in transcribed interviews ran from three (JJ) to 27 (HG).

  o Cybersensitives gave as many as three responses apiece across all nine codes.

- The Device category code totals present in transcribed interviews ran from three (AM) to 21 (DMC).

The strongest cybersensitive participant was HG. She ranked number one in Psych codes with 42 instances. She ranked second in energy codes with 27 instances. Finally, she ranked number two with respect to device codes, with 20 instances (Table 6). ANV was the strongest Southern California cybersensitive. She ranked first in Device category, fourth in Energy, and Fifth in Psych.

Table 6: Northern California Cybersensitives and Cyberawares Ranked Across Categories

Energy	Device	Psych
HG	DMC	HG
BB	HG	SR
SR	MLP	DMC
DA	JR	BB
DL	DL	JC
DM	LC	DL
JR	SR	MLP
CK	AN	JR

Source: Indicia Consulting

At the other end of the scale there are participants who showed NO inclinations toward cyber-awareness or cybersensitivity. The research team termed these individuals Nulls as they show little or no propensity towards cybersensitivity in terms of their code frequencies. Nulls scored below ten in terms of Psych category responses, as low as zero (thus the labeling of them as Nulls). As an example, JJ was last place in the energy category with three responses (compared with HG's 27). He was fourth from the bottom in terms of Device category codes, with six responses. Similarly, CK tied for last place in Psych category codes with zero responses. Despite his career in an energy-related profession he only ranked in the middle of the pack (eight) for Energy category codes. CK's low rank for the Device category was also interesting, considering his work is technical in nature (another pattern demonstrated repeatedly for Nulls).

---

[15] Participant initials.

The Device category was interesting, because someone could have an overall higher score by being extremely passionate about a single topic, thus appearing to be more into devices than they really are (in general). A good example would be CK, who had five instances for the code older tech but zero in seven of the nine other codes in the Device category.

Demographic and Geographic Variables

As discussed above the research team examined the demographic data for the in-depth interviews to support the hypothesis that traits of cybersensitivity cut across a variety of demographic variables. Members of any segment were male or female and distributed themselves across various age and income ranges.

Distribution of Segments Regionally

Based on the coding and analysis described in Chapter 2, the research team found that Cybersensitives and Cyberawares made up 17 percent of the combined cohort each (Northern and Southern California) in Figure 16. This is a higher percentage for both than the original hypothesis, which was based on the literature review and posited 10 percent for each. The CART model, discussed below, predicted 18 percent for Cybersensitives and 3 percent for Cyberawares The CART model, which used a larger sample (300 virtual persons) is likely more accurate than the initial assignments, not only due to small sample size, but also because the CART model (and the EDTM which proceeded it) were the products of iteration and refinement (Figure 17).

Figure 16: Segment Percentiles, All California
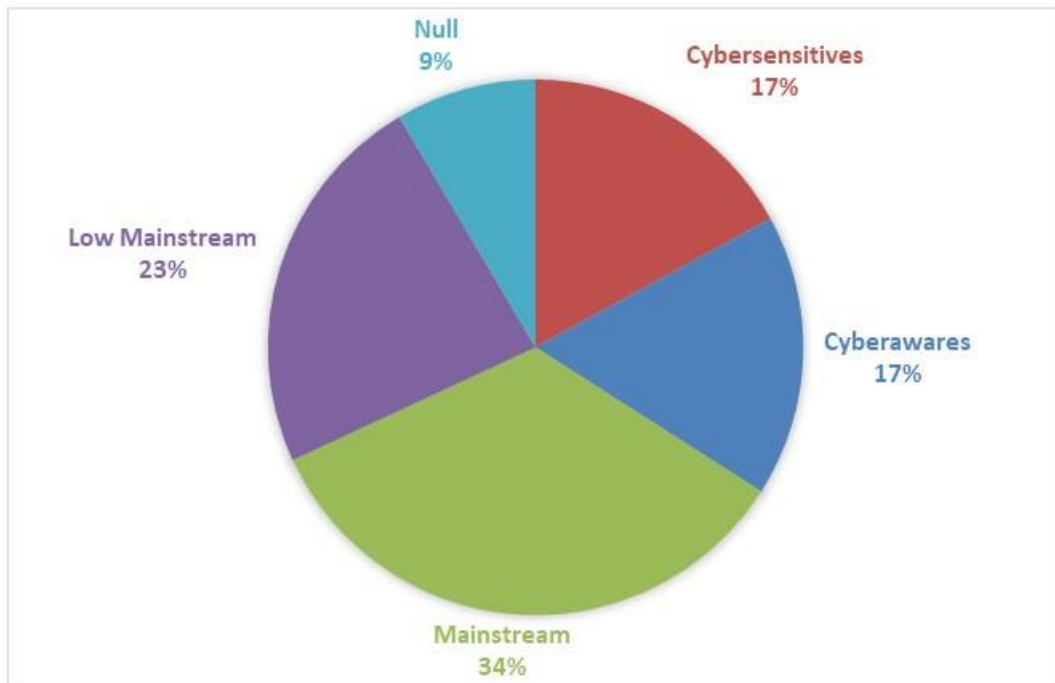
Source: Indicia Consulting

Figure 17: Segment Percentiles Classification and Regression Tree Prediction
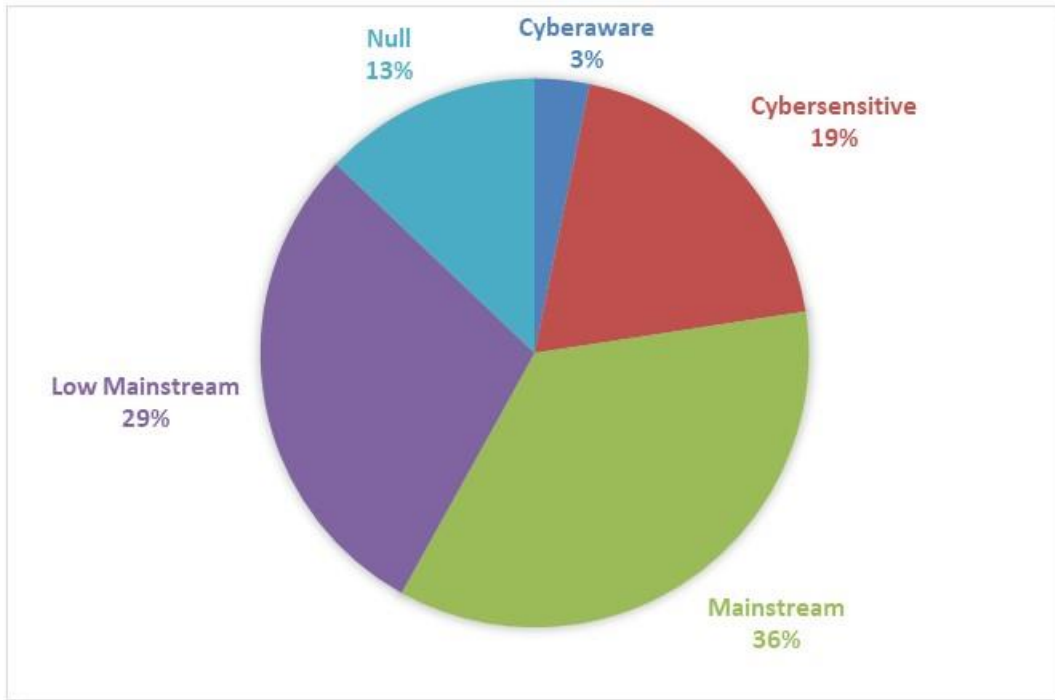
Source: Indicia Consulting

Based on the coding and analysis described in Chapter 2, the research team found:

- Five Cybersensitives in Northern California

- Three Cybersensitives in Southern California.

- Four Cyberawares in Southern California

- Three Cyberawares in Northern California.

- In both cohorts, the joint set (Cybersensitives plus Cyberawares) as a percentage of the whole was close—30 percent and 35 percent, in Northern vs. Southern California respectively (Figure 18).

  - The analysis revealed that there was a lower percentage of cybersensitives in the Southern California cohort than in the Northern California cohort—13 percent and 23 percent, respectively.

  - Conversely, there were slightly MORE Cyberawares in the Southern California cohort than in the Northern California cohort—17 percent and 13 percent, respectively.

Figure 18: Segment Percentiles by Region
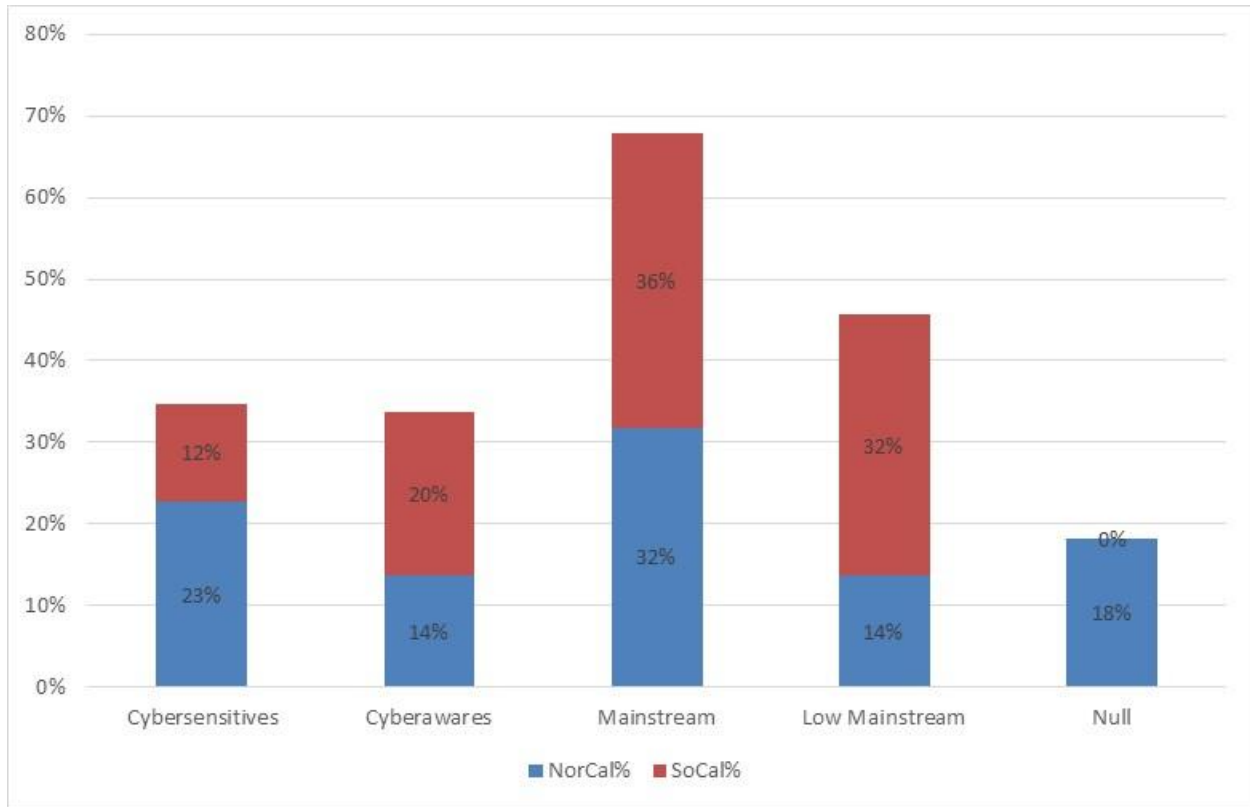
Source: Indicia Consulting

The Northern California and Southern California fieldwork was conducted at different times and with different ethnographers yet the distribution of segments by percentage are roughly similar when regions are compared. This is supportive of the hypothesis that cybersensitivity is independent of geography (discussed in detail in Appendix C).

The fact that 51 percent of the cohort was assigned Mainstream/Low Mainstream suggests that very little bias was introduced during the recruitment process. If *self-selection bias* was present, then one could expect to see more potential cybers raising their hands to participate. If *researcher* or *confirmation bias* were present, in either the recruitment or coding of the cohort, then it would be likely that the distribution would more likely match the hypothesized distribution.

Membership in Segments by Gender

Despite the recruitment pool and the cohort skewing female, the ultimate assignment of assignment of cybersensitivity, based on coding, gave us cyber-segments that were almost identical in terms of gender percentage (with one interesting difference) in Figure 19.

Figure 19: Gender Composition of Segments by Percent
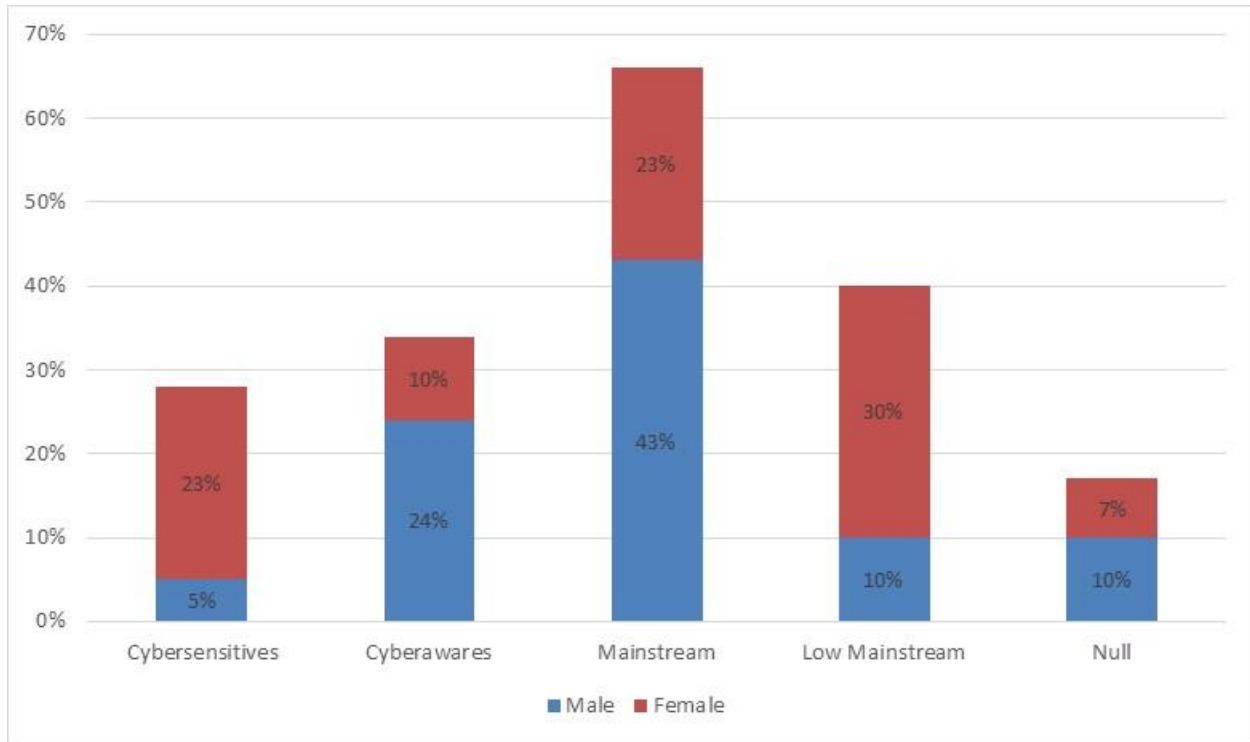
Source: Indicia Consulting

29 percent of the males in the cohort were assigned to either the Cybersensitive or Cyberaware segment, 33 percent of the female population were assigned to either the Cybersensitive or Cyberaware segment. The percentages are roughly similar for either gender, despite having more women in the cohort. This supports the hypothesis that the segmentation is fairly gender neutral.

However, one interesting difference emerged: within the cohort sample, cybersensitives were overwhelmingly women, while Cyberawares tended to be men: 24 percent of the male population were assigned to Cyberawares while only 10 percent of the female population was. Conversely, only 5 percent of males were assigned to cybersensitive while 23 percent of women were so assigned. This assignment was completely data-driven, and the outcome was a surprise to the team, as this difference was noted well after coding and segment assignment had occurred. This could simply be an artifact of a small sample, but it points in a direction for future research.

Membership in Segments by Age

Another hypothesis was that age and cybersensitivity would be independent of one another (discussed in detail in Appendix C). The chart below is supportive of this hypothesis in that segment membership was assigned seemingly independent of age, because all segments have members from all age ranges. At the same time, most age ranges are found in most segments (Figure 20).

Figure 20: Age Composition of Segments by Percent
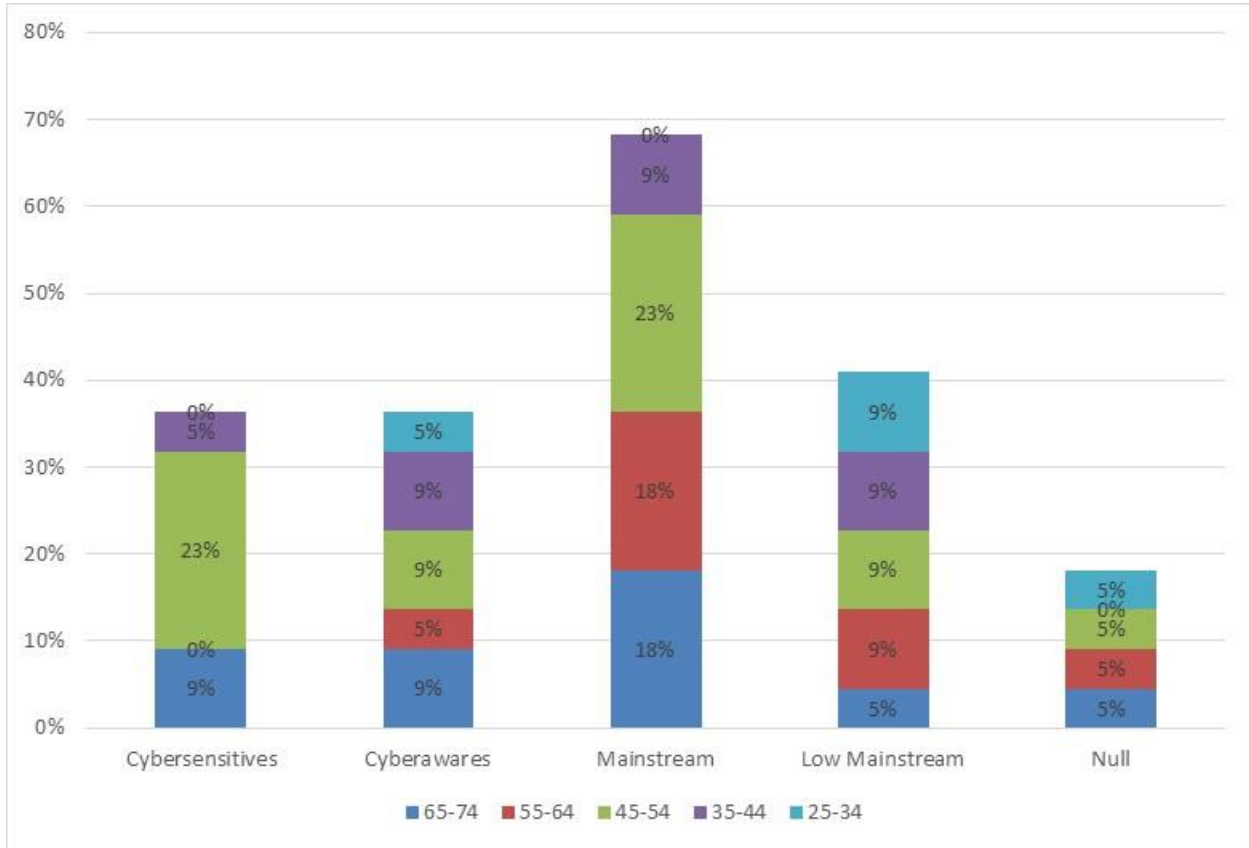
Source: Indicia Consulting

If cybersensitivity was linked to age, aka the digital native hypothesis, then there should be more younger people in the cyber-segments, despite the fact the sample skewed older. As with gender, there is a role for future research on this topic with a larger sample.

Household Composition by Segment

Because the participating households were distributed across all ages and incomes, they also differed in terms of where they were on the life-cycle. The participating households were at various stages of coupling, uncoupling, raising children, and living as empty-nesters. The research team had recent graduates living with their parents and older folks living alone. This diversity of housing types and sizes in the cohort reflects the diversity of household composition (Table 7).

Table 7: Household Sizes by Segment

Segment	4-person Household	3-person Household	2-person Household	1-person Household
Cybersensitive	4	2	0	2
Cyberaware	1	3	1	3
Mainstream	5	2	4	5
Low Mainstream	2	0	4	3
Null	1	2	1	0

Source: Indicia Consulting

Cybersensitives in the cohort tended to have larger household sizes than the other segments. Three and four-person households make up 75 percent of their composition, more than most of the other segments. Cyberawares evince more diversity of household composition. Only 49 percent of Cyberawares live in three-or four-person households. Cyberawares are evenly split between 1- to 2-person and 3- to 4-person households: Nulls also live in larger households at the same rate (75 percent) as cybersensitives, and yet they have very different electricity consumption patterns. Even fewer Mainstream participants live in larger households. The majority (56 percent) live in 1- to 2-person households.

Housing Type and Square Footage

The research team interviewed Californians living in apartments, condominiums, smaller single-family homes, and larger single-family homes. The research team interviewed urban households, rural households, and everything in-between. In terms of square footage, every segment occupies a wide range of house sizes. Both the smallest residence, at 534 square feet, and the largest residence, with 3,200 square feet, were found in the combined Cyber segments. A Cybersensitive household owned the largest house, while a Mainstream household rented the smallest apartment. The research team has been asked how the research team can assert that cybersensitivity is a trait independent of housing type and square footage. While the research team cannot definitively answer that question, the fact that a mix of housing types and sizes was present in the various segments is strong evidence that cybersensitives live in any setting (Figure 16), just like they occupy any life-stage.

Decision Tree Models

Ethnographic Decision Tree Model

The research team constructed an Ethnographic Decision Tree Model (Figure 21), which can be administered to assign a participant to the segments: Cybersensitive, Cyberaware, Mainstream, or Null. This model sorts people, based on their answers, into one of the segments—mainstream, null, cybersensitive, or cyberaware. Thus, the EDTM:

- Identified mainstreams who were not engaged with their energy consumption information.

- Distinguished those Nulls who possess technical skills from the Cybersensitives and Cyberawares who engage with technology from a more affective perspective.

- Distinguished Cyberawares from cybersensitives via the emphasis on tracking information (as opposed to merely receiving and responding to it).

With the development of the EDTM it became evident that the relationships among the segments were not located along a continuum of valency with respect to one another. The research team concluded that the primary difference between the two cyber-segments lies in a preference for tracking information or using wearables, which is demonstrated by Cyberawares and not by Cybersensitives. So too, the relationship of Nulls to cyber-segments is that all three tend to share some traits (attraction to/facility with technology) but nulls lack the emotional component of engagement with feedback that is at the heart of cybersensitivity. Mainstreams and Low Mainstreams tend to be distinguishable more by their lack of any of these traits, rather than possessing specific traits unique to their segment.

Figure 21: Ethnographic Decision Tree Model
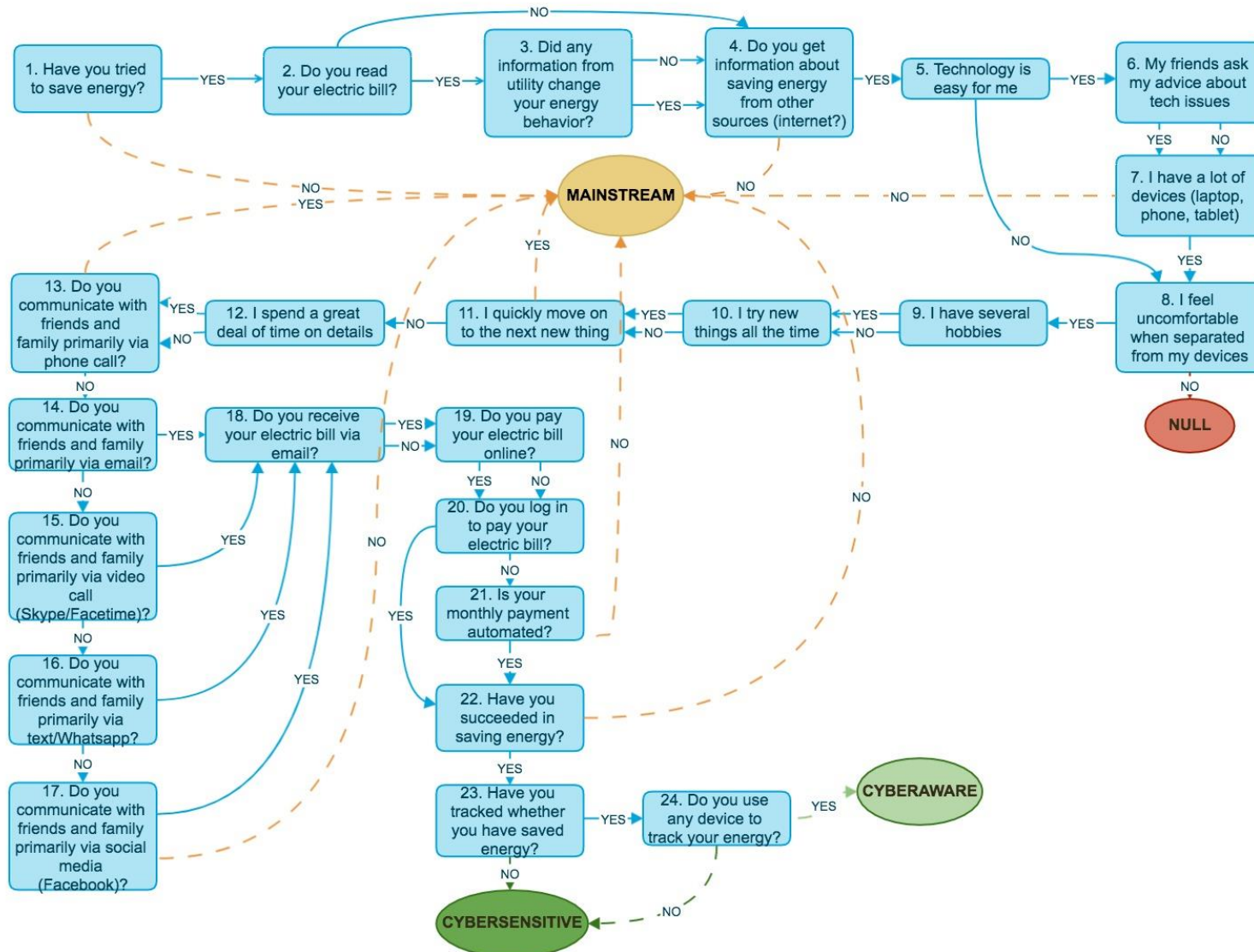
The Ethnographic Decision Tree Model provides a means whereby any interested party can segment a population according to cybersensitivity. The questions could be administered during a home energy audit, or even taken by a customer via a self-administered questionnaire on a website. Applying the EDTM will organize any given population into four segments: Cybersensitive, Cyberaware, Mainstream, and Null. While the research team recognizes that this method is labor intensive, the research team asserted that this could be mitigated through incorporation into a home energy audit, which would assist the managers of home energy audits to make and test some predictions concerning uptake of recommendations and energy efficiency investments..

Classification and Regression Tree

The research team used the work done in constructing the EDTM as the foundation for building a CART through machine learning processes. The research team then tested the CART for accuracy on both the resampled population and the original sample. The former provides an internal test of the models own ability to predict its own behavior, and the latter provides an initial external test of a similar but different model.

As discussed above, the research teams CART model has overall an accuracy of 76 percent, in terms of classifying the cybersensitivity of members of a cohort. Because the research teams random forest model produced a CART decision tree with 100 percent accuracy, a rarity since develops these trees probabilistically, that tree is reproduced below. Even though as a single tree, it is one among one thousand in the random forest modeling, it demonstrates the most accurate CART decision tree model developed so far by the team (Figure 22).

Figure 22: Classification and Regression Decision Tree
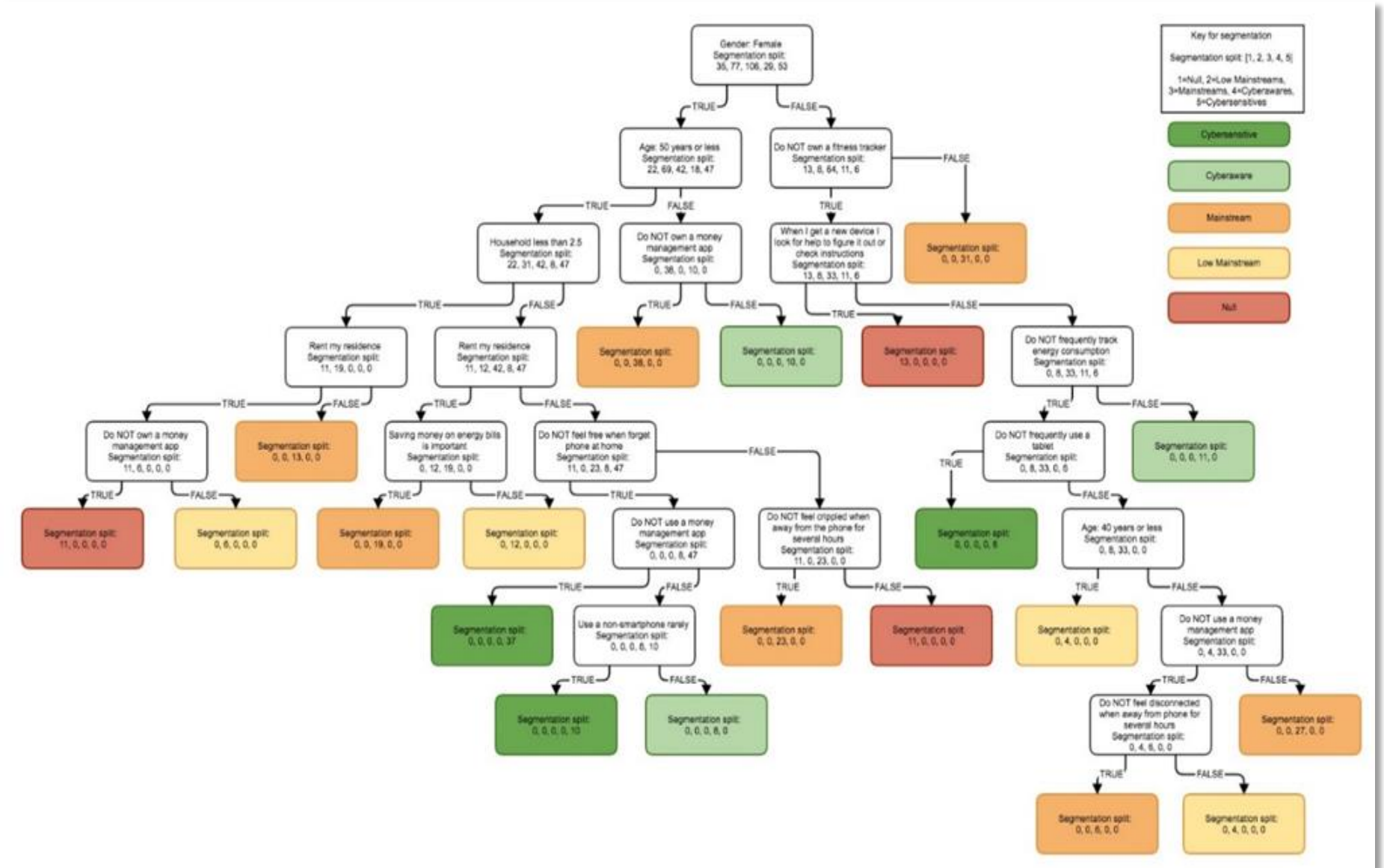
Source: Indicia Consulting

CHAPTER 4: Technology/Knowledge/Market Transfer Activities

The primary goal in the project *"Cybernetic Research across California: Documenting Technological Adoption and Behavior Change across Diverse Geographies and Populations to Inform Energy Efficiency"* was the development of critical insights for supporting residential engagement in energy-efficient behaviors.

To accomplish this, the project plan includes many technology transfer activities. One of the project's tasks (Task 8: Knowledge and Technology Transfer) is specifically related to the outreach and communication of project results to promote the knowledge gained, experimental results, and lessons learned available to the public and key decision makers.

Planned Activities Completed

Presentations
The research team presented at several conferences:

- Mazur-Stommen, S. 2016. Behavior, Energy, and Climate Change Conference October 2016 (Baltimore, MD) titled "Using Behavioral, Cultural, and Social Insights to Expand Uptake of Residential Energy Efficiency."

- Mazur-Stommen, S. 2017. Talk to School of Public Policy, University of California, Riverside April 2017 (Riverside, California) titled "Behavior, Energy, and Climate Change: Ethnographies of Energy as Policy Tools".

- Mazur-Stommen, S. and Gilbert, H. 2018. Society for Applied Anthropology Annual Meeting April 2018 (Philadelphia, Pennsylvania) titled "Ethnographies of energy: Recruiting participants for in-home interviews."

- Paff, S. 2018. Society for Applied Anthropology Annual Meeting April 2018 (Philadelphia, Pennsylvania) titled "Anthropology of Machine Learning."

- Mazur-Stommen, S. 2018. American Anthropology Department Leaders Institute June 2018 (Washington, D.C.) ["Preparing Students to Practice Anthropology."](#)

- Paff, S. 2018. American Society for Cybernetics Conference August 2018 (Chicago, IL) Machine Stories: Machine Learning as Computerized Narrative Design."

- Mazur-Stommen, S. 2018. Behavior, Energy, and Climate Change Conference October 2018 (Washington, D.C.) titled "Cybersensitive Electricity Consumption Patterns."

Social Media

Members of the research team provided updates on the project progress via social media:

- Twitter: @IndiciaInfo (250+ followers, 5K monthly impressions)
  - Our Interns tweeted regularly about project related literature and activities
  - Used #EPIC
  - Our CSU Students had their own twitter @EPICCSUstudents
- Facebook: https://www.facebook.com/indiciaconsulting/
  - Twitter and Facebook are linked and used in tandem to promote #EPIC activities
- LinkedIn: posts summing up findings and announcing milestones:
  - "Behavioral incentives to change energy consumption: Pros and cons" January 2016
  - "Cybernetic Fieldwork: First Look" October 2016
  - "Anthropology of Technology: Student Presentations Fall 2016" January 2017
  - "Cybersensitives and their emotional drivers around technology" March 2017
  - "Videos from the California Cybernetic Project" May 2017
  - "Differentiating consumers of energy information" May 2017
  - "Cybersensitive Electricity Consumption Patterns" February 2018
  - "Engaging Cybersensitives and Cyberawares in Energy Efficiency" August 2018

Press

The project received some press attention:

- "Searching for The Outlier Energy User Who Saves 8-20%" Lisa Cohn in Microgridknowledge.com, September 15, 2015

Website

There is a section dedicated to the project on the Indicia Consulting website here:

- http://indiciaconsulting.com/#cbp=/projects/ethnography-cybernetic-fieldwork-across-california.html

The website hosted pdfs of the project task reports here:

- http://indiciaconsulting.com/downloads/Indicia-EPIC-Task-Deliverable-2-Report-on-Cybersensitives-and-Technology.pdf
- http://indiciaconsulting.com/downloads/Indicia-EPIC-Task-Deliverable-3-Psychosocial-Drivers-of-Technology-Engagement-Among-Cybersensitives.pdf
- http://indiciaconsulting.com/downloads/Indicia-EPIC-Task-Deliverable-4-Cybersensitive-Response-to-Technology.pdf
- http://indiciaconsulting.com/downloads/Indicia-EPIC-Task-Deliverable-5-Cybersensitive-Electricity-Consumption-Patterns.pdf
- http://indiciaconsulting.com/downloads/Indicia-EPIC-Task-Deliverable-6-Engaging-Cybersensitives-and-Cyberawares-Part-1.pdf
- http://indiciaconsulting.com/downloads/Indicia-EPIC-Task-Deliverable-6-Engaging-Cybersensitives-and-Cyberawares-Part-2.pdf

There is a page dedicated to student ethnography projects here:

- http://indiciaconsulting.com/students/

Additional Activities Completed

Publications

The authors submitted work for publication in peer reviewed journals and academic presses:

- Mazur-Stommen, S., Gilbert. H., Vora, D., Ottoson. H., Farley, K., Sauer, A., and Bayersdorfer, A. 2017. "Ethnographies of energy: Recruiting participants for in-home interviews" Energy, Research, and Social Science (Withdrawn)
- Mazur-Stommen, S. 2019. Ethnographies of Energy: Effective Strategies for Conducting Qualitative Research on Energy Consumption and Climate Change. Springer Briefs in Energy Series. Editor Denise Penrose (In Proposal)

Blogging

The research team blogged about the project at the blog "Small Signs and Omens:"

- "Cybersensitives: who are they?" July 2015
- "Our EPIC project -- Cybernetic Fieldwork" August 2015

SlideShare

A slide deck about the project is hosted here:

- "Cybernetic Research across California: Documenting Technological Adoption and Behavior Change across Diverse Geographies and Populations to Inform Energy Efficiency Program Design"

Student Video Presentations of Research

Video presentations of student ethnography research projects is hosted here:

- Student Reports on Research Conducted Fall 2016 for EPIC Cybersensitive Project
    - http://indiciaconsulting.com/students/12.15.2016.chang.lopez.bowen.mp4
    - http://indiciaconsulting.com/students/12.16.2016.wurtz.parrett.grant.mp4
- Student Reports on Research Conducted Spring 2017 for EPIC Cybersensitive Project
    - http://indiciaconsulting.com/students/05.19.2017.all.mp4

Other Video

A video presentation of the project was prepared and submitted for the EPIC 2019 Symposium and is hosted here:

- https://www.youtube.com/watch?v=XJngOkvHfvo&t=12s

CHAPTER 5:
Conclusions

Summary

In this paper, the authors provide an overview of the *Cybernetic Research Across California* project, including the background on the development of the main thesis around cybersensitivity, the theoretical basis for the project in the field of cybernetics and the concept of feedback, as well as the approach and results.

The goals of the project were two-fold. The first goal was to establish the presence or absence of a trait the research team termed "cybersensitivity." The second goal was to use this trait to segment consumers and model the impact of the segmentation. The project began with the hypothesis that some households might be more responsive to energy information delivered via device (smartphone, wearable, in-home device), because of a greater emotional affinity for the device in question. This hypothesis rested upon secondary data, gleaned from the literature on behavior-based energy efficiency programs, which provided evidence that two deciles of the population tended to have higher than average savings when exposed to information about their energy consumption, or feedback.

This phenomenon, or data anomaly, was apparent upon review of several programs (pilot and otherwise) that used synchronous (real-time) or asynchronous (monthly Home Energy Report) type of data to prompt households to change energy consumption behaviors. Because these various programs differed in terms of both type of delivery mechanism, but also in terms of the population under treatment, it appeared that demographic explanations for the differing responses were inadequate to the task.

Thus, it was proposed that the missing element was a better understanding of the emotional/affective relationship between the people receiving energy data on a device, and the device itself. This is a cybernetic relationship, because cybernetics is the "the scientific study of control and communication in the animal and the machine" (Weiner, 1948). Feedback is a concept based in cybernetics, and therefore it made sense to look at the problem as one in which people manage information that affects a social group, the household. Because the problem is a psycho-social question, ethnography was chosen as the best approach for understanding its complexities, since anthropologists have been pursuing lines of cybernetic inquiry since the 1930s.

The authors of this paper discussed the design and implementation of a recruitment strategy for conducting in-depth interviews on the topics of device purchase and usage, attitudes and behaviors concerned with energy consumption, and the emotional aspects of managing these aspects. This recruitment strategy involved the development of an online recruitment questionnaire—an assessment of potential participants attitudes

towards personal electronics and energy consumption—as well as a series of email and social media campaigns designed to distribute the questionnaire across California. The research team described the results of the recruitment methods in detail. The research team explored how intrinsic vs. extrinsic motivations affected recruitment.

The research team revisited the methodology behind the interview process, the transcription of audio recordings, and the subsequent coding and analysis. The research team outlined the data that was derived from the ethnographic in-home observations and from transcribing the audio from the in-depth interviews.

Using the data collected during fieldwork, the research team segmented consumers by degrees of cybersensitivity. The research team tentatively identified five segments through their differing responses to questions posed by the ethnographers during the in-depth interviews, as well as observations captured in fieldnotes. The research team then reviewed how the coding from the interview transcripts grouped participants into the five distinct segments the research team termed Cybersensitive, Cyberaware, Mainstream, Low Mainstream, and Null.

This segmentation is probably most akin to a classic psychographic segment because these consumers diverge one another in several identifiable ways, many of which are related to lifestyle. On the other hand, this type of segmentation is also like a behavioral segmentation because they also differ with respect to device purchase and usage, as well as in their attitudes towards energy efficiency and conservation measures. Because the research team identified five segments, the segmentation approach is a differentiated type of segmentation. The research team reviewed the distribution of these segments regionally, as well as according to the demographic variables of age, gender, and income.

The extensive qualitative data allowed the research team to make the case that distinct behavioral patterns existed between cybers and non-cybers when it came to energy efficiency measure installation, as well as program awareness and participation. The research team returned to the interview transcripts and set the now-identified Cybersensitive and Cyberaware responses alongside non-cybersensitive responses to establish patterns of difference. Repeatedly, the transcripts show that Cybersensitives and Cyberawares are much more likely to be aware of the availability of energy efficiency programs, to be interested in participating, to conduct cost-benefit analyses on their own behalf, and to be willing to actively seek out additional efficiency measures that they can undertake.

The research team provided a model for reproducing the segmentation in the forms of an EDTM and a CART. Both models are constructed to sort people, based on their answers, into one of the segments—Cybersensitive, Cyberaware, Mainstream, Low Mainstream, and Null. Thus, the EDTM:

- Identified mainstreams who were not engaged with their energy consumption information.

- Distinguished those Nulls who possess technical skills from the Cybersensitives and Cyberawares who engage with technology from a more affective perspective.

- Distinguished Cyberawares from Cybersensitives via the emphasis on tracking information (as opposed to merely receiving and responding to it).

The CART goes a step further and also provides an estimate for the prevalence of segment membership using a synthetic population constructed from American Census Questionnaire and American Time Use Questionnaire provided by the Network Dynamics Simulation Science Laboratory at Virginia Tech University. The CART model predicted approximately 21 percent of the synthetic population studied will fall into cyber segments, which is close to the research teams original estimate that Cybersensitives and Cyberawares might make up two deciles, or 20 percent of any given population. The CART model had a predictive accuracy of 76 percent. This is close to the goal of 80 percent accuracy considered to be the goal for ethnographically derived decision tree models. In the future, using the segmentation schema, and models from this research, it should be possible for future researchers to estimate exact effects from differing energy efficiency uptake among segments.

Recommendations

One goal for the project was the development of critical insights for supporting residential engagement in energy-efficient behaviors. Another goal was to identify a consistently repeating set of characteristics, including behavioral, demographic, and energy use that can be attributed to the cybersensitive profile. The organization of a consumer base by such characteristics is called market segmentation. Based on the research conducted for this project, the research team urges utility programs to understand these psychographic and behavioral distinctions among their customer base, and market appropriately to them.

The Cybersensitive and Cyberaware segments interviewed for this research report being up for more of a challenge regarding energy-efficiency programs. Aligning messages with these segments' interests could deliver a much higher return on investment in terms of energy savings harvested, with lower outlays in marketing dollars and materials. Simply providing energy information, or feedback, does appear likely to deliver higher savings via these segments; however, addressing these segments desires for greater control, or tracking tools, will improve them further. The cyber-segments should be messaged about more ambitious energy savings projects. Current literature suggests that simply marketing compact fluorescent lights and generic energy efficiency recommendations is missing the mark when it comes to actual drivers of energy savings achieved through behavior change (Khawaja, et al., 2017). Whether the program goal is lower energy consumption on an aggregate level (such as states, or utility territories) or higher rates of savings per program, or higher rates of participation in a program, the research team believe that targeting cyber-segments is a sound strategy.

The findings from the research and accompanying review of the literature discussed in the Introduction support the idea that that utilities should target the Cybersensitive and Cyberaware segments specifically for opt-in enrollment (as opposed to using opt-out or default enrollment) in residential energy efficiency programs, particularly those that use feedback. Fischer (2008), drawing on psychological theory and empirical evidence, asserts that a successful energy feedback program must capture consumers attention, draw a close link between specific actions and their effects, and activate various motives that may appeal to different consumer groups. The research described in this report delineates the various psycho-social drivers, or motives, that induce the cyber-segments to enroll in such programs. The research from this project provides evidence that these segments comprise approximately 20 percent of the population[16], and depending on the program type and design employed, could reach savings of up to 26 percent. This strategy should result in higher total savings rates than are achieved when programs treat general populations.

In the literature on opt-in versus opt-out programs, the point has been made that while opt-in programs have participants with much higher savings rates, the scale of opt-out (automatically enrolled) participants implies that overall savings will end up being higher (Sussman and Chikumbo, 2016). Upon review, the research team does not think this math holds up.

The example here uses the savings and participation estimates informed by the literature discussed. These estimates are within a range that has been achieved by both Home Energy Reports and real-time feedback programs:

Given a population of 100 households, each of which uses 100 kWh per month, the population consumes 10,000 kWh per month total.

- Assumption 1: An opt-in program might have a participation rate of 20 percent who saves 15 percent of their energy per month in response to an intervention.

    o Opt-in population of 20 households will collectively save 300 kWh per month (20 x [100 x 0.15]). Total population savings = 300 kWh

- Assumption 2: The same intervention, structured as opt-out, may garner 96 percent of the population, who save between 1 percent and 2 percent per month on their energy consumption.

    o Opt-out population of 96 households will collectively save 96—192 kWh per month (96 x [100 x 0.02]). Total population savings = 192 kWh

As can be seen, the opt-in program delivers greater energy savings. Even if the savings for the opt-in program drop to only 10 percent, that is still 200 kWh per month in savings for the population, which is still more than the savings from the opt-out program.

---

[16] See Appendix E-1

Properly targeting these two segments (as opposed to the general population) will also likely result in lowered soft costs for utilities that are implementing behavior-based energy efficiency programs, particularly for Home Energy Reports. These soft costs would include such aspects as labor, materials (printing), postage, etc. Smaller outlays in terms of fixed cost items should provide a budget savings. Cost per premise has not been included in previous analyses comparing the savings from opt-in to opt-out programs. The authors argue that lowered soft costs should also be considered when evaluating and promoting behavior programs overall.

In conclusion, while there are policy imperatives set by the state to give consumers access to the same information, the potential for improved savings through changes in program design and implementation should at least be considered.

Finally, the research in this paper is not the only way to segment energy consumers for more effective uptake of program recommendations, for example, "greater savings have also been reported among households with fewer occupants, smaller square footage, and older heads of household" (Davis, 2011). The overall lesson here is, the right tactic, to the right audience, delivers greater savings.

Future Research

The next step in furthering the research conducted for this project would be to conduct a research project using a larger dataset and the EDTM. A goal for future research would be to administer the EDTM the research team developed to a randomly selected group of utility customers, and then compare the electricity consumption for the resulting segments.

Future variations on this work might attempt to look at cybersensitivity and whether it correlates to race, ethnicity, or political affiliation—three variables not examined in this research project. The research team are skeptical that correlations would be found, given that they did not occur with other, simpler, demographic variables but it would be productive to have them ruled out. Further, the ways in which race, ethnicity, and other forms of identity complicate engagement with technology and/or energy consumption have not often been examined in the past.

The Mainstream and Low Mainstream segments may have unique but unknown characteristics of their own, in contrast to the cyber and null segments. The research team think future research on these segments might be warranted, for example, using the EDTM to identify them and then conduct in-depth interviews with a reasonably large cohort to validate their assignment within the segment.

CHAPTER 6:
Benefits to Ratepayers

Identifying the attributes and characteristics of cybersensitives will add to the overall scientific understanding of behavior and energy consumption. The research team anticipated that, by building and sharing the models the research team constructed, other entities such as the California investor-owned utilities, could make use of them to better segment their audiences, and target them with appropriate programs and incentives, reaping higher rates of energy savings in return.

The research team has developed a schema for classifying consumers of electricity in terms of their distinct psychographic and behavioral profiles. The fieldwork observations led the research team to conclude that cybersensitives are interested in more ambitious and innovative energy efficiency measures, while Cyberawares appear to be more interested in tools and applications for tracking energy consumption and savings.

By better understanding customer energy profiles, utilities can solve multiple problems, and can improve energy efficiency returns across the state, improving grid reliability, reducing the requirement for additional power plants, and reducing carbon emissions.

GLOSSARY

Term	Definition
CART	Classification and Regression Tree, a model that represents the branching path of decision-making using machine learning algorithms
Category	A collection of codes related to project themes (e.g., Psych, Device, Energy)
Code	Descriptive tag added to qualitative data for analysis purposes
CSU	California State University
Cultural Domain	A related set of topics that forms a culturally relevant whole, such as crime or entertainment
Device	A category of codes related to topics covered in the in-depth interviews such as personal technology, accessories, and purchase and usage behaviors
EDTM	Ethnographic Decision Tree Model, a model that represents the branching path of decision-making using data collected during ethnographic research
Energy	A category of codes related to topics covered in the in-depth interviews such as energy consumption, energy savings, and energy efficiency or conservation measures
HRAF	Human Relations Area Files, a database of cultural and social information aggregated from across the discipline of cultural anthropology
IDI	In-depth interviews
IOU	Investor-owned utility, e.g., a publicly owned utility such a Pacific Gas and Electric or Southern California Edison
OCM	Outline of Cultural Materials, a set of codes used by anthropologists in the classification of cultural traits and topics
Psych	A category of codes related to topics covered in the in-depth interviews such as emotions, feelings, and attitudes.
TAC	Technical Advisory Committee
Theme	The larger takeaway from analysis of narrative data
Topic	A subject of conversation captured in in-depth interviews

REFERENCES

Allcott, H. 2011. Social Norms and Energy Conservation. Journal of Public Economics, Special Issue: The Role of Firms in Tax Systems, 95 (9–10), 1082–95.

Allcott, H., Greenstone, M. 2012. Is There an Energy Efficiency Gap? Working Paper 17766. National Bureau of Economic Research. Retrieved 2016-08-20 from http://www.nber.org/papers/w17766.

Ayres I, Raseman S, Shih A. 2011. Evidence from Two Large Field Experiments That Peer Comparison Feedback Can Reduce Residential Energy Usage. Yale Law & Economics Research Paper No. 437. Retrieved 2016-08-20 from http://papers.ssrn.com/abstract=1858813Bateson G. 1936. Naven: A survey of the problems suggested by a composite picture of the culture of a New Guinea tribe drawn from 3 points of view. University Press.

Bell, A., Cheek, J.Z., Mataya, F., and Ward, P. 2018. "Do As They Did: Peer Effects Explain Adoption of Conservation Agriculture in Malawi." *Water* 10, no. 1:51.

Bernard, R.H. 2006. *Research Methods in Anthropology: Qualitative and Quantitative Approaches*. Fourth Edition. Lanham, MD: AltaMira Press.

Clements, H. 2002. EHRAF: Electronic Human Relations Area Files, Ethnography and Archaeology. Reference Reviews 16(6):14–15.

Cano, C. 2001 "The Recent Evolution of Market Segmentation Concepts and Thoughts Primarily by Marketing Academics," in E. Shaw (ed) The Romance of Marketing History, Proceedings of the 11th Conference on Historical Analysis and Research in Marketing (CHARM), Boca Raton, FL, AHRIM

Carroll, J., Lyons, S., and Denny, E. 2014. Reducing Household Electricity Demand through Smart Metering: The Role of Improved Information about Energy Saving. Energy Economics 45 (C), 234–43.

Costa DL, Kahn ME. 2010. Energy Conservation 'Nudges' and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment. Working Paper 15939. National Bureau of Economic Research. Retrieved 2016-08-20 from http://www.nber.org/papers/w15939.

Davidai, S., Gilovich, T., and Ross, L.D. "The Meaning of Default Options for Potential Organ Donors." Proceedings of the National Academy of Sciences 109, no. 38 (2012): 15201–5205.

Davis, M. (2011). Behavior and Energy Savings Evidence from a Series of Experimental Interventions. Retrieved from

http://blogs.edf.org/energyexchange/files/2011/05/BehaviorAndEnergySavings.pdf. Cited in Dougherty, et al., 2015

Dougherty, A., Henderson, C., Ph.D., Dwelley, A., Jayaraman, M., Vine, E., Ph.D., and Mazur-Stommen, S., Ph.D. Energy Efficiency Behavioral Programs: Literature Review, Benchmarking Analysis, and Evaluation Guidelines. Report. Conservation Applied Research & Development (CARD) Final Report. Madison, WI: Illume Advising, 2015. 1–114. Prepared for Minnesota Department of Commerce, Division of Energy Resources.

Ehrhardt-Martinez, K., Donnelly, K.A., Laitner, J.A., York, D., Talbot, J., and Friedrich, K. 2010. Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities. Report no. E105. Washington, D.C.: American Council for an Energy-Efficient Economy, 2010. 1–128.

Fenrick, S., Getachew, L., Ivanov, C., and Smith, J. 2014. Demand Impact of a Critical Peak Pricing Program: Opt-in and Opt-out Options, Green Attitudes and Other Customer Characteristics. The Energy Journal, 35(3), 1–24. Retrieved from http://www.jstor.org/stable/24694916

Fischer C. 2008. Feedback on Household Electricity Consumption: A Tool for Saving Energy? Energy Efficiency 1 (1), 79–104.

Foster, B., and Mazur-Stommen, S. 2012. Results from Recent Real-Time Feedback Studies. Research Report B122. American Council for an Energy-Efficient Economy Washington, DC. Retrieved 2016-08-20 from http://aceee.org/research-report/b122.

Frederiks, E., Stenner, K., and Hobman, E. 2015. Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. Renewable and Sustainable Energy Reviews. 41. 1385–1394. 10.1016/j.rser.2014.09.026.

George, S., Ph.D., Bell, E., Ph.D., Savage, A., Dunn., A., Ph.D., and Messer, B., Ph.D. California Statewide Opt-in-Time-of-Use Pricing Pilot: Interim Evaluation. Report. Nexant and Research Into Action, 2017. 1–451. Prepared for The TOU Working Group, under contract to Southern California Edison Company.

Gladwin, C.H. 1989. *Ethnographic Decision Tree Modeling*. Newbury, CA: Sage, 1997.

Gladwin, Hugh, and Michael Murtaugh. 1984. "Test of a Hierarchical Model of Auto Choice on Data from the National Transportation Questionnaire." *Human Organization* 43, no. 3: 217–26.

Gladwin, Christina H., Hugh Gladwin, and Walter Gillis Peacock. "Modeling Hurricane Evacuation Decisions with Ethnographic Methods" International Journal of Mass Emergencies and Disasters 19, no. 2 (2001): 117-143

Grønhøj, A., and Thøgersen, J. 2011. Feedback on Household Electricity Consumption: Learning and Social Influence Processes. International Journal of Consumer Studies 35(2), 138–45.

Hendricks, B., Campbell, B., and Goodale, P. Efficiency Works: Creating Good Jobs and New Markets Through Energy Efficiency. Publication. Center for American Progress and Energy Resource Management, 2010. 1-48.

Hofmeister, B. 2010. Bridging the Gap: Using Social Psychology to Design Market Interventions to Overcome the Energy Efficiency Gap in Residential Energy Markets. Southeastern Environmental Law Journal, 19, 1; Wayne State University Law School Research Paper No. 2012-07. Retrieved 2016-08-20 from http://ssrn.com/abstract=1892906

Houde, S., Sudarshan, A., Todd, A., Armel, C., and Flora, J. 2013. Real-Time Feedback and Electricity Consumption: A Field Experiment Assessing the Potential for Savings and Persistence. *Energy Journal* 34(1):87–102.

IBM Corporation. 2012. Decision Tree Models. Retrieved from IBM Knowledge Center: https://www.ibm.com/support/knowledgecenter/en/SS3RA7_15.0.0/com.ibm.spss.modeler.help/nodes_treebuilding.htm.

Jaffe, A.B., and Stavins, R.N. 1994. Markets for Energy efficiency: The Energy-Efficiency Gap What Does It Mean? Energy Policy 22(10), 804–10.

Khawaja, M. Sami, PhD, and James Stewart, PhD. Long-run Savings and Cost-effectiveness of Home Energy Report Program. Report. Waltham, MA: Cadmus Group, 2017. 1-20.Kottak, C.P. 2010. Melvin Ember and HRAF, Anthropologys Archive. Cross-Cultural Research 45(1): 11–15.

Lutzenhiser, L. 1993. Social and Behavioral Aspects of Energy Use. Annual Review of Energy and the Environment 18(1), 247–89.

Lutzenhiser, L., Mithra Moezzi, and James Woods. 2009. Behavioral Assumptions Underlying California Residential Sector Energy Efficiency Programs. February. Prepared for the California Institute for Energy and Environment (CIEE). Oakland, Calif

Mazur-Stommen, S., and Farley, K. 2013. ACEEE Field Guide to Utility-Run Behavior Programs. Research Report B132. American Council for an Energy-Efficient

Economy Washington, DC. Retrieved 2016-08-20 from http://aceee.org/research-report/b132

Mazur-Stommen, S., Vigen, M., Farley, K., el Hattab, S., and Huff, P. 2013. Trusted Partners: Everyday Energy Efficiency Across the South. Report no. B131. Washington, DC: American Council for an Energy-Efficient Economy.

Murtaugh, M. 1984 "A Model of Grocery Shopping Decision Process Based on Verbal Protocol Data." Human Organization 43, no. 3: 243–51.

PG&E. 2014. Findings from the Opower/Honeywell Smart Thermostat Field Assessment. Project number ET11PGE3074. Pacific Gas and Electric Company, San Francisco, CA. Retrieved 2016-08-20 from http://www.etcc-ca.com/reports/findings-opowerhoneywell-smart-thermostat-field-assessment

Pollitt, M.G., and Shaorshadze, I. 2011. The Role of Behavioural Economics in Energy and Climate Policy. Cambridge Working Paper in Economics # 1165 and Electricity Policy Research Group Working Paper # 1130. Retrieved 2016-08-20 from http://www.econ.cam.ac.uk/dae/repec/cam/pdf/cwpe1165.pdf.

Potter, Jennifer M., George, S.S., Ph.D., and Jimenez, L.R. Smart Pricing Options Final Evaluation: The Final Report on Pilot Design, Implementation, and Evaluation of the Sacramento Municipal Utility Districts Consumer Behavior Study. Report. Sacramento, CA: Sacramento Municipal Utility District, 2014. 4–192. Prepared for U.S. Department of Energy.

Ramage M. 2009. Norbert and Gregory: Two Strands of Cybernetics. Information, Communication & Society 12(5), 735–49.

Roberts D. 2015. Clean energy tax credits mostly go to the affluent. Is there a better way? Vox, 24 November 2015. Retrieved 22 August 2016 from http://www.vox.com/2015/11/24/9792474/energy-tax-credits-inequitable

Rothbauer, P. 2008. Triangulation. In "The SAGE Encyclopedia of Qualitative Research Methods", ed. L. Given, Sage Publications: 892–894.

Ryan, G.W., and Bernard, H.R. 2006. "Testing an Ethnographic Decision Tree Model on a National Sample: Recycling Beverage Cans." Human Organization 65, no. 1: 103–14.

Singer, E. 2002. The Use of Incentives to Reduce Nonresponse in Household Questionnaires. Questionnaire Methodology Program No. 051. In Questionnaire Nonresponse, New York, Wiley.

Singer, E., Van Hoewyk, J., and Maher, M.P. 1999. Experiments with Incentives in Telephone Questionnaires. Public Opinion Quarterly 64, 171–188.

Singer, E., and Ye, C. 2012. The Use and Effects of Incentives in Questionnaires. Annals of the American Academy of Political and Social Science 645(1), 112–141.

Sullivan, A.N., and Lachman, M.E. 2017. Behavior Change with Fitness Technology in Sedentary Adults: A Review of the Evidence for Increasing Physical Activity. Frontiers in public health, 4, 289. doi:10.3389/fpubh.2016.00289

Sussman, R., and Chikumbo, M. 2016. Behavior Change Programs: Status and Impact. Report no. B1601. Washington, DC: American Council for an Energy-Efficient Economy 2016. 1–94.

Trotter, R. 2012. Qualitative research sample design and sample size: resolving and unresolved issues and inferential imperatives. Prev. Med. 2012 Nov;55(5):398–400

Weiner, N. 1948. Cybernetics: Or Control and Communication in the Animal and the Machine. MIT Press.

Wilhite, H. 2013. Energy Consumption as a Cultural Practice: Implications for the Theory and Policy of Sustainable Energy Use. In Cultures of Energy: Power, Practices and Technologies, 60–72. Walnut Creek, Left Coast Press.

Wilhite, H., Shove, E., Lutzenhiser, L., and Kempton, K. 2000. The Legacy of Twenty Years of Energy Demand Management: We Know More About Individual Behavior But Next To Nothing About Demand. In *Society, Behaviour, and Climate Change Mitigation*. Volume 8 of the series [Advances in Global Change Research](#), 109–126. Springer Netherlands.

Wilson, C., and Dowlatabadi, H. 2007. Models of Decision Making and Residential Energy Use. Annual Review of Environment and Resources 32(1), 169–203.

Wu M. 2012. Impact and Persistence Evaluation Report: Sacramento Municipal Utilities District Home Energy Report Program. Prepared by Integral Analytics, Inc. for Sacramento Municipal Utilities District, Sacramento CA. Wu M. 2012. Impact and Persistence Evaluation Report: Sacramento Municipal Utilities District Home Energy Report Program. Prepared by Integral Analytics, Inc. for Sacramento Municipal Utilities District, Sacramento CA.

APPENDICES

APPENDIX A: Preliminary Ethnographic Report on Cybersensitives and Technology Detailing the Fieldwork and Early Findings

APPENDIX B: Psychosocial Drivers of Technology Engagement Among Cybersensitives

APPENDIX C: Cybersensitive Response to Technology

APPENDIX D: Cybersensitive Electricity Consumption Patterns

APPENDIX E-1: Engaging Cybersensitives and Cyberawares in Energy Efficiency

APPENDIX E-2: Engaging Cybersensitives and Cyberawares in Energy Efficiency Part 2: Recommendations

APPENDIX F: Student Work and Biographies

Appendices A through F are available upon request (Publication Number CEC-500-2020-017-APA-F) by contacting:

Susan Mazur-Stommen
Indicia Consulting
susanmazur@indiciaconsulting.com
Website: indiciaconsulting.com