Cybersensitive Response to Technology

Produced for the California Energy Commission by Indicia Consulting in fulfillment of Task 4 Deliverable 1 of the project *Cybernetic Research across California: Documenting Technological Adoption and Behavior Change across Diverse Geographies and Populations to Inform Energy Efficiency Program Design* Funded by EPIC PON 14-306

August 31, 2017

Contents

1 Introduction

This report assesses whether cybersensitives enjoy interacting with technology in their everyday lives, and/or are otherwise more viscerally responsive to technological interventions than peers. We refer to this quality by the term from psychological literature called valency.

It has been the goal of this project, Cybernetic Fieldwork Across California, to find a set of cybersensitives/cyberawares, interview them, and analyze the collected data to show clear psychological and/or behavioral differences between them and their peers. In the previous Task 3 report, "Psychosocial Drivers of Technology Engagement among Cybersensitives," we asserted that we found a set of both cybersensitives and cyberawares who distinguish themselves from the rest of the interview cohort through the frequency of coded responses to interview questions.

In this paper, we dig deeply into what we believe are the key characteristics of cybersensitivity. For this paper, which is our third deliverable for the project (Task 4), we integrated the datasets from the recruitment survey and the in-depth interviews, and then performed statistical analysis on the combined set. We looked for correlations between the cybersensitive status (or lack thereof) of an individual and that individual's answers to survey questions. We looked for whether cybersensitive status correlated with any of the demographic variables we have mentioned. We looked for correlation between geography and cybersensitive status, because it was of special interest to determine whether what we call cybersensitive was the result of technologically engaged persons being clustered in the Bay Area, for instance. Finally, we looked at the distribution of code frequencies derived from the Atlas.ti analysis and the assigned cybersensitive status, to see whether or not statistical correlations would support our ethnographic findings.

In this paper, we explore the statistical operations we conducted on our data sets in detail, showing the results and discussing our interpretations. To summarize those findings briefly, cybersensitivity correlates to the answers given in the Device and Energy categories, and less definitively seems to not correlate with answers given in the Psych codes category. This means that our identification of clusters of cybersensitives using frequency counts of codes derived from in-depth interviews was accurate, and that this is a plausible method for identifying this unique segment of consumers.

Cybersensitivity does not correlate with any demographic or geographic variable. In other words, as we initially hypothesized, cybersensitives were found in every age group, gender, and income strata. They were also equally likely to be found in Northern and Southern California. This finding validates our original hypothesis that cybersensitivity is a unique personality trait that is distributed across a population. Despite a small, qualitative-study-appropriate sample size, the use of statistical analysis on our data supports our belief that the distribution of cybersensitives will remain similar, even when sample sizes are scaled up.

2 Background

Our goal in developing this project was to demonstrate the evidence of a new kind of characteristic, cybersensitivity. Cybersensitivity is a personality trait whereby an individual responds more intensely to feedback provided by an electronic device than their peers. We believe the root cause of cybersensitivity is an emotional relationship between an individual and their personal technology. Our hypothesis is that, the more positive emotion is expressed with respect to a device,

the higher the likelihood is that someone has the trait of being a cybersensitive. We believe this trait is identifiable and measurable.

Our hypotheses around cybersensitivity have their origins in theories of cybernetics that date back to the 1930s, and which are still influential today. These theories, first developed by anthropologist Gregory Bateson (husband to Margaret Mead) are concerned with how groups of people manage socially derived information, or 'feedback', about their behavior. The concept of a "positive feedback loop" comes from his original work, conducted in the highlands of Papua New Guinea approximately 80 years ago. A positive feedback loop is a process whereby a person's behavioral response to stimuli is channeled in such a way that subsequent iterations of the feedback/response cycle intensifies and reinforces the effect. Bateson referred to the entire phenomenon as "schismogenesis" with feedback being one component (Bateson, 1938). While today, most people understand the terms 'feedback' and 'cybernetics' to refer to technology, it nevertheless retains its original meaning of being a form of information management. As we will discuss, Mazur-Stommen coined the term 'cybersensitive' to refer to a phenomenon whereby some people seem to be more sensitive and responsive to information delivered via an electronic device.

By way of explaining how this works, we must briefly digress. Fans of science fiction may be familiar with the term, 'cyborg.' A cyborg is a human who has incorporated technology into their body – and relies upon it for basic human functions. To a large degree, many of us are cyborgs, though we may not think of ourselves as such. If you wear contact lenses, a hearing aid, have a pacemaker, or any artificial joints, you are a cyborg. One can argue that any tool that enhances or replaces fundamental human functions is a form of cyborgism: glasses, walkers, canes, crutches, wheelchairs, the list goes on. The point is that we have adapted ourselves to our environment using tools, thereby enhancing our abilities, extending our lifespan. We have done this for so long that we barely register such additions to our functioning as 'tech' any longer.

This is also true with personal electronic devices, with the most recent example being the smartphone. Whereas they were formerly something featured on science fiction shows like Star Trek (the tricorder) now it is fair to say that many people can hardly imagine navigating their day without one in their hand. Even before internet-enabled smartphones, cellphones and their ubiquity had swiftly transformed many aspects of our society. Once plausible movie plots now fall apart because someone can reach some else anywhere at any time, as an example. Cellphones, and other personal devices such as tablets and laptops, have changed human behavior dramatically. We use them as portable memory extenders, relying upon them to tell us, "What year was the infamous white Bronco chase again?"

Again, as with contact lenses or crutches, a tool starts to enhance, and then even substitute for, a basic human function. This is another milestone in a process that has been going on for a very long time. In the Heroic Age of Ancient Greece, Homer's Iliad and the Odyssey were transmitted orally by people who memorized thousands of complex stanzas to recite them. Try to imagine one of your modern-day peers pulling off such a feat, and you will find it is almost impossible. This kind of memorization, as a basic human faculty, began to be eroded with the invention of writing, sped up with the invention of movable type, went hyper-speed in the age of mass communication, and has now been almost completely surrendered in the face of ubiquitous, portable external memory machines which are connected to the entire world's knowledge base at all times.

We believe that this relationship, between a human being and the devices they depend on in a very basic fashion, is worth investigating. We further believe that the emotional aspects of this relationship have not received as much attention as they warrant. Human beings have long exhibited the ability to cherish, even love, inanimate objects. Archaeologists have found many lovingly carved and decorated tools, such as weapons, dating back thousands of years. These had been given the kind of attention and lavish care many people now devote to detailing their cars.

We may say we 'love' something so often and so carelessly ("I love that dress!") that is may have seemed to have lost some of its power, but we would argue that is nevertheless does not render the expression void of meaning, nor is it nullified when applied to an inanimate object instead of a person. In fact, it was through asking about the love of inanimate objects that this project has its origins. We began the data collection process for this project, albeit unwittingly, with the simple question: "Do you love your phone?" Such a basic, even silly question, but the answers were revealing. About one-third of respondents answered "yes" quite forthrightly. Another third hesitated at 'love' and substituted 'like' instead. A final third thought the question was so bizarre as to be practically nonsensical. The reason we asked this question in the first place was that we had observed how various were the ways with which people interacted with their phones. There were clearly different levels of absorption and delight, regardless of the overall technical orientation of the person under observation.

The reason this project's data collection process began unwittingly is because the genesis of the project predates the submission of our proposal by several years. Over the past decades, much of the work of our principal investigator Mazur-Stommen has focused around 1) how people make decisions in general, and 2) how people make decisions about their built environment more specifically.

- In 1995, for her undergraduate honor's thesis, she looked at Iranian-American marriage choice using ethnographic decision tree modeling.
- In 2002, she defended her dissertation on the city of Rostock, focusing on how people choose what parts of their collective history to salvage or scrap in the process of historic preservation and urban revitalization.
- In 2009-2010, she worked with Lawrence Berkeley National Laboratories on their Cool Communities project, seeking to understand the decision-making process around material selection.
- In 2012, she worked with Benjamin Foster at the American Council for an Energy Efficient Economy on the paper "Recent Results from Real-time Feedback" and coined the term 'cybersensitive.'
- Also in 2012, she presented the paper, "Tamagotchi Building Project: Environmental Cues in Context" at ACEEE's Summer Study in Buildings, looking at the role of sensory input in decision-making with respect to buildings.
- Then in 2013, she and her co-authors at ACEEE published the paper, "Trusted Partners: Everyday Energy Efficiency in the South" examining how consumers of energy in the Southeastern United States acquire information and institute decisions, with the aid of their social networks.

At every step of the way, our research agenda has been to push back against the idea of an individual rational actor, in favor of an embodied, socially embedded, person, who navigates their world using their emotions and senses.

Given the longstanding interest in this area, it is not overstating it to say that simple observation and questioning of people, in situ, with their devices in hand, could be considered the beginning of the data collection process for a project that had not yet been funded. In anthropology we refer to this methodology as 'participant-observation.' At the same time, the specific genesis for the premise behind the Cybernetic Fieldwork Project Across California dates to the period following the 2012 publication of "Recent Results from Real-Time Feedback" wherein the authors realized that further work in this area was needed (Foster and Mazur-Stommen, 2012).

This report was a meta-review of recent research investigating the power of providing 'feedback' to consumers. In that report, Foster and Mazur-Stommen looked at nine pilots that had used in-home devices to offer real-time energy consumption information to customers. The results from those nine pilots ranged from 0% energy savings to 19.5% energy savings, depending on the pilot reviewed, and the specific cohort under treatment within the pilot. Among the data offered by these pilots, we noticed something interesting. The Commonwealth Edison pilot, a large-scale pilot of smart meter-enabled dynamic pricing and real-time feedback technologies, was one of the largest and most rigorous, and reported 0% savings in aggregate, but with one intriguing outlier (Foster and Mazur-Stommen, 2012:7):

"A subset of participants (estimated to be ~5-10%), however, did respond to event-day price signals enough to get significant reductions in load of approximately 5.6-21.8%, corresponding to a total load reduction of approximately 0.3-2.2%."

Reviewing the data collected by the project designers (and also personal communication with the project designers), it appeared that demographic variables were not responsible for differences among who responded to the intervention from those who did not. Another project documented in the paper, the Cape Light Compact Residential Smart Energy Monitoring Pilot, similarly demonstrated that, "savings were not spread evenly over the participants: a small percentage of households had savings greater than 11%" (Foster and Mazur-Stommen, 2012:11). Our hypothesis for this phenomenon was that something other than traditional variables (e.g. demographic or psychographic) was responsible for this difference within cohorts of customers. The authors hypothesized that energy feedback delivered via device was likely most effective among a group of people who had an emotional relationship with their technology. Foster and Mazur-Stommen also wrote about how the larger energy savings seen among members of this group may depend on new kinds of motivation or habits, and proposed calling them 'cybersensitive,' "because they seem to respond more readily to feedback, either as a predisposition or, we can speculate, as the result of some new type of learning, new motivation or habit formation that emerges from the process of getting feedback on their energy consumption."

Several of the foundational ideas for this current project trace to our findings from this meta-review. After the conclusion of that project, authors Foster and Mazur-Stommen felt that they had just begun to chip away at questions that remained, and that the concept of 'cybersensitivity' might hold the key to answering. After the conclusion of this project, the authors did a preliminary model of how the segments might break out, imagining an almost topographical depiction of the consumer landscape, where the vast majority of consumers form a flat plane of null (even negative) response

to feedback, with two exceptions rising from the plains: a piedmont region of cyberawares, those who responded to feedback with between 4–8% savings, and a mountainous region of super savers, cybersensitives who save as much as 25% under certain circumstances. It was clearly important to dig into these different response rates more deeply, but without further funding at the time, the authors were forced to shelve the concept and move on. In 2014, when the potential for funding from the California Energy Commission's EPIC grant raised the possibility that the concept of cybersensitivity could be explored in detail through ethnographic fieldwork we jumped on the opportunity. Our goals for this project became to first identify people we felt had traits of cybersensitivity, and then demonstrate that these traits were differently expressed from those of similarly situated peers in terms of age, gender, and income.

2.1 Valence

The literature review conducted for this project's grant application supported our hypothesis that a subset of consumers (~10-20%) respond more readily to feedback via device. Grønhøj and Thoegersen (2011) saw, "a generally recurrent pattern of individuals returning greater than average energy savings, e.g., 8.1% versus a control group result of 0.8%." Grønhøj and Thoegersen's work supported our thesis that closing a cybernetic 'loop' in terms of feedback delivered via device would be most effective among a group of people who had an emotional relationship with their technology. We termed this group 'cybernetically sensitive' or cybersensitive for short. For this project, we incorporated the idea of 'valence' from psychology as a means of defining that the level of intensity of emotion experienced by an individual (instead of a binary of presence or absence) was an important component in our thinking.

Valence originated from the Latin valentia, meaning "power" or "competence." The term was first used in chemistry in the concept of atomic or the charge of an atom's electrons. Psychological literature uses the term valence when discussing emotions and emotion theory. Valence refers to both the positive and negative aspects of emotions, with the concept first coming in to psychology in the 1930s (Colombetti, 2005). In psychology, valence refers to emotions and how "good" or "bad" an emotion feels (affect valence), or the positive and negative character of an emotion (emotion valence). It also describes phenomena that 'inherently' feel good or bad (Colombetti, 2005). According to Frijda (1986) valence may also refer to events, objects, or situations and the "intrinsic attractiveness or aversiveness" (p. 207) associated with them. Valence also refers to behaviors that have a positive valence, such as tolerance, or a negative valence, such as aggression (Schneirla, 1959).

Valence is not only connected to emotions, but also to decision making. Shuman et al. (2013) connects a multifaceted view of valence to appraisal theory, where different emotions arise as events or situations are appraised, or subjectively evaluated, based off several aspects or criteria. For example, appraisals of situations or events relate to pleasantness or goal conduciveness, which are then described as being 'valenced.' Shuman et al. (2013) also argue that in addition to the pleasantness and goal conduciveness of a situation, other types of appraisals can be valenced, such as power, compatibility with the self, and compatibility with norms. Even within a type of appraisal of a situation, different levels or conflicting feelings may be present, such as a woman wearing high heels. Wearing these shoes may be pleasant in that they look nice, but unpleasant in that they are uncomfortable.

Shuman et al. (2013) also describe the one-dimensional view of valency regarding how behaviors are prioritized. This view of valency may serve as a "common currency" that can help researchers

understand how people choose between options. However, the complexity of emotions and behaviors make using a one-dimensional view of valency alone problematic, in that some behaviors be both positive and negative, while others are valence-ambiguous. Additionally, people experience mixed emotions, or many different emotions at once. Colombetti (2005) also explains how emotions are often conflated with the negative causes, and consequences associated with them, and how a one-dimensional view of valence may lead to dichotomous thinking (i.e. positive versus negative). Instead of favoring one view over the other, Shuman et al. (2013) argue for a new framework that includes a consideration of the combination of the two views to better understand the complexities behind valence, emotions, and decision making.

When weighing information in decision making, people differ in the extent to which they place importance on the positive and the negative. Pietri et al. (2013) explored the "valence asymmetries" or bias of individuals and their attitudes towards novel objects or situations. In their studies, they saw that individuals who were more likely to have a negative bias, that is placing more importance on the negative aspects, feared rejection and/or felt a threat within their situations. Individual differences in weighting positive and negative information were also connected to the risks associated with a situation. Pietri et al. (2013) offer explanations for negative bias in individuals, including the possibility for a genetic pre-disposition, but also mention other factors related to childhood socialization.

Within a defined time-period, and with a circumscribed set of questions asked by the interviewer, the ability of some of our participants to discuss topics in much greater detail than others, is evidence of greater emotional engagement with the topic. The fact that some participants' transcripts had up to ten times the number of codes within the same category, is indicative of intensity, aka valency.

Finally, the persistent pattern of the same participants being emotionally engaged at the same level across disparate topic categories, suggests strongly that this valency is a personality trait, something that should be identifiable at a behavioral level, and thus open to empirical study. We feel that using the frequency of codes in different categories (psych, energy, and device) as discussed in "Psychosocial Drivers of Technology Engagement among Cybersensitives," is a good proxy for valence.

3 Method

In our first deliverable for this project, we discussed our recruitment and selection methods. In that paper, we showed how our Marin-based set of respondents were representative of the county with respect to the three demographic variables we focused on, which were age, gender, and income. For this paper, we used statistical analysis to show that cybersensitive status is independent of the demographic variables of gender, income level, and age.

We focused on these three because stereotypes persist about who engages in what kinds of behavior around electronic devices, and in our opinion such stereotypes have introduced bias into discussions about technology usage. For example, many writers have used the term, 'digital natives.' This is read to refer to a specific age group or generational cohort. It encapsulates the idea that younger people are inherently more familiar, at ease, or adept with personal electronic devices than are older people.

Similarly, sexist perceptions that coders tend to be male erase women's contributions to and involvement with technology and innovation. It is often presumed that consumers of technology trend male even when there is evidence for the prevalence of women consumers. For example, there is a perception that games are exclusively the territory of teenage boys. In reality, according to 2013 figures put out by the Entertainment Software Association, 58% of all Americans play video games. There are actually more female gamers over 18 (31% of the total number of players) than male gamers under 17 (19%). The average age of gamer is 30, with one third of gamers under the age of 18, one third between 18 and 35 years of age, and the remainder aged 36 and up. The gender divide among gamers is also less stark than is popularly imagined, with 55% of all gamers being male, and 45% female.

Finally, many studies on technology adoption and usage focus primarily on the acquisition of new devices, an angle that tends to favor the attitudes and habits of wealthier strata of society, because they have the disposable income available to purchase items, as well as more leisure time available for investment in learning the new device, system, or even just the habit of using it. Our project is NOT focused on acquisition or adoption, but rather on engagement and usage. We assert that an individual who displays cybersensitivity could come from any demographic cohort.

We combined attitudinal survey data with ethnographic observational and interview data to produce a robust dataset for our analysis. These three different sets of data reference the same population, allowing us to triangulate our findings. Triangulation is the method of verifying data drawn from one source with data drawn from two or more other sources (Rothbauer, 2008). For example, the observer can directly take note of devices, appliances, and other technology *in situ* and in use. By taking photos and videos on site, we later see aspects of home life which researchers overlooked in the development of the interview guide, or when conducting the interview. 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.

From our research, we have amassed several sets of data that we are using to triangulate our findings. These sets include:

- Answers to questions posed on our recruitment survey
- Verbatim answers given to questions posed by ethnographers during IDIs
- Frequency of codes for topics appearing in the transcripts of the IDIs
- Respondent answers to survey questions
- Sorts of code frequencies output by Atlas.ti[1]

In this set, the variety and validity of our total data collected compensates for the relative small scale of the project (45 households interviewed, divided between Northern and Southern California). This type of mixed methods research is a powerful means to confirming (through

[1] Discussed in "Psychosocial Drivers of Technology Engagement among Cybersensitives."

repetition) findings that may otherwise seem idiosyncratic or non-representative due to smaller sample sizes. Sutton and Austin (2015) discuss this issue:

> "One of the questions that arises about qualitative research relates to the reliability of the interpretation and representation of the participants' narratives. There are no statistical tests that can be used to check reliability and validity as there are in quantitative research. However, work by Lincoln and Guba suggests that there are other ways to "establish confidence in the 'truth' of the findings" (p. 218). They call this confidence "trustworthiness" and suggest that there are four criteria of trustworthiness: credibility (confidence in the "truth" of the findings), transferability (showing that the findings have applicability in other contexts), dependability (showing that the findings are consistent and could be repeated), and confirmability (the extent to which the findings of a study are shaped by the respondents and not researcher bias, motivation, or interest)."

Our research demonstrates 'transferability' in several ways. At the outset, out literature review should that an anomalous group of individuals was responding differently to interventions using real-time feedback, irrespective of the goals, methods, or design of a variety of pilot projects. Our identification of the personality trait, 'cybersensitive' is not restricted to a particular topic (e.g., energy efficiency) and as we show in this paper, it is not limited to age, income, gender status, or geographic location.

The goal of our research is to demonstrate 'dependability' via the repetition of results. This is one of the strengths of mixed methods research, in that if a finding crops up in different data sets, the likelihood that it can be relied upon increases. Credibility is also a strength of mixed methods research: whereas one ethnographer might be biased in what they see and report, having three ethnographers working with 45 different households in locations 400 miles apart and reporting similar findings weakens, if not eliminates, the likelihood of research bias being introduced.

Our results demonstrate confirmability in that they are ethnographically derived. Within a framework, respondents had a great amount of latitude concerning how they chose to answer the interviewer's questions. As such, any measurable variation within the datasets is the product of individual respondents and their answers, and not on the ethnographer deviating from the script. We discussed this issue in "Psychosocial Drivers of Technology," showing how two different ethnographers (and their potential biases) did not change to distribution of the data.

3.1 Coding

"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)

Our dataset consists of the answers to survey questions we asked at the beginning of the recruitment period; answers to questions posed by the ethnographer during the in-depth interviews (IDIs); 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. We transcribed all interviews completely, and coded them topically in Atlas.ti as discussed in the Task 3 Deliverable. We also coded photos and video via Atlas.ti and the 295 valid survey responses. Coding, in this case, means that we have assigned a shorter descriptive tag (usually a number) to a piece of qualitative

data (e.g., spoken words) such that it can be more easily analyzed using quantitative methods (e.g., frequency).

3.1.1 Atlas.ti coding

The ethnographers coded topics from the interviews in a systematic manner using the program Atlas.ti, and we were thus able to extract the frequencies with which codes for topics occurred. We could then compare them with each other, both across the sample, and within subsets of the sample (as discussed in Task 3). We also recoded qualitative survey answers to for statistical packages like SPSS to interpret them as a variable (or in our case, a custom written program in Python by one of our analysts).

In terms of the coding and analysis using Atlas.ti, we found that, whichever the topic, cybersensitives and cyberawares had more to say than their peers – despite the questions, format of the interview, and time allotted remaining consistent across all interviews. In addition to cybersensitives and cyberawares, we also categorized people in three additional groups:

- Mainstream
- Low Mainstream
- Null

Referring back to our original question discussed in the background section, cybersensitives and cyberawares are the people who say, "I love my phone," while mainstreams are those who think their phone is "ok" and nulls are the folks who think the question being posed doesn't make any sense. Nulls consistently had less to say on any of the topics than their peers – by a factor of ten in some cases! Low mainstream are those respondents who straddle the line between mainstream and null: perhaps having mainstream answers in two of the three categories, but then a deeply null answer in the third category. We broke them out as a counterpoint to cyberawares, who conversely show often as lightly cybersensitives in two categories, but mainstream in a third. We go into depth on these issues in the report, "Psychosocial Drivers of Technology Engagement Among Cybersensitives."

3.1.2 Human Relations Area Files

The classic example of ethnographic coding is the Human Relations Area Files (HRAF). The HRAF 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, 2011).

"The HRAF Collection of Ethnography contains mostly primary source materials – mainly published books and articles, but including some unpublished manuscripts and dissertations – on selected cultures or societies representing all major regions of the world. The materials are organized and indexed by a unique method designed for rapid and accurate retrieval of specific data on given cultures and topics."

Cybersensitive Project Codes	OCM Codes
A/C (SC)	Heating and lighting equipment
Amazon shopping and products	NONE
Anticipated device usage (practical) (SC)	NONE
App (SC) e.g. application on phone	NONE
Appliances	Electrical machines and appliances
Banking	Banking
Billing	Bills of exchange (credit)
bluetooth (SC)	NONE
Brand (SC)	Property Marks in Movables
building structure (SC)	Structures
Car (SC)	Vehicles
charger (SC)	NONE
Classes/learning (SC)	Education
cloud/external storage device (SC)	NONE
Communication	Communication

Figure 1 Excerpt of the comparison of our Cybersensitive project codes with the codes from the Outlines of Cultural Materials in HRAF. SC refers to codes added by the Southern California ethnographer.

This 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). Originally in paper form, HRAF was later moved to microform, and is now accessible online as eHRAF World Cultures. The online ethnography database includes over 300 cultures and 600,000 pages Entries from thousands of journals are included, dating back to the late 19th century (Gardner and Eng, 2006), which can be browsed by cultures or subjects. Searches are also possible using keywords, authors, journals, titles, and subjects, while advanced search tools can narrow searches to dates and languages (Gardner and Eng, 2006).

"The OCM serves two primary purposes: first, to assist scholars in classifying and annotating cultural materials for all societies; and, second, to aid researchers in readily locating material pertinent to their interests… The OCM is now maintained in digital format in an information retrieval thesaurus structure. As such, in addition to being a classifying system, it is also a terminology cross-referencing system. The OCM Index matches a researcher's or an author's terms for a subject with the OCM categories used to index the concept."

Most documents included in the database are descriptions of cultures or communities, written by social scientists (Clements, 2002). Cultures can be browsed through topics such as economy, history, family and kinship, and sociopolitical organization. The ability to research cultural phenomena across cultures has become increasingly easier with the advent of the online database. HRAF analysts code all entries into the database, using Outlines of Cultural Materials (OCM) 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.

We cross-checked our Atlas.ti coding with the HRAF, and in the main our codes corresponded very well with the topics in the Outline of Cultural Materials. One area where we found little to no correspondence, however, was in the realm of technology, with the HRAF/OCM having little or dated entries. For example (Figure 1), there was nothing in the Outline of Cultural Materials for 'apps,' 'Bluetooth,' 'chargers,' or 'cloud [storage]' all of which figured prominently in our conversations with participants.

3.2 Statistical Tests

Below are a series of statistical tests we conducted for the project. Specifically, we performed hypothesis testing and exact goodness of fit tests on our data. We were looking for correlations (or lack thereof) between cybersensitives and cyberawares and variables we felt would demonstrate the uniqueness of the segment.

3.2.1 Hypothesis Testing

We used statistical methods to test hypotheses on the relationship between various question responses and cybersensitivity. We explore whether there is a significant difference between cybersensititives and cyberawares and the rest of the population with respect to their answers to the survey questions, demographic questions, and in-depth interview questions.

Most of the data in the survey are categorical. Chi-squared tests are a logical choice for such a scenario, but they tend to not be as accurate when dealing with small sample sizes whereas Exact Goodness of Fit is. This test calculates the exact probability instead of using a model (like the chi-squared model or another model) to approximate the probability. When the data is binary, Fisher's Exact Goodness of Fit test was used, and when the data is not binary, a Multinomial Exact Goodness of Fit test was used. Multinomial Exact Goodness of Fit tests test the probability of each column (cybersensitives, cyberawares, mainstream, low mainstream, and nulls) possessing its current distribution if the variable in question is independent of cybersensitivity. As such, it conducts a unique probability (p value) for each column. For this report, we will use an alpha level of 0.05 to designate significance.

4 Results

4.1 Psych Codes, Energy Codes, and Device Codes

We analyzed the sets of Psych codes, Energy codes, and Device codes. For each, signals of propensity were tallied and recorded during each interview. Psych Total, Energy Total, and Device Total represents the total numbers of recorded codes for each interviewee. These totals will be primarily used to represent each category as a single metric.

This report will primarily analyze each code total to determine there is any of these codes are correlated with cybersensitivity or particular survey answers. Before these tests occur, however, preliminary tests on the potential relationship between psych codes, energy codes, and device codes are needed to understand their interconnectedness.

4.1.1 Codes Compared with Each Other

This section will test the potential correlations for psych codes, energy codes, and device codes and each other.

Psych Codes vs Energy Codes

Below is a correlation test between psych codes and energy codes. This establishes that these two are pretty likely to be correlated with each other (assessed as total values). This connection needs to be taken into consideration when each variable is tested against question responses. Many people assume that variables are probabilistically independent, but in this case these categories are likely dependent upon one another, and they influence one another. That is, if someone answers a question about devices, the answer they give may also influence the answer they give on another topic. Our findings were that the categories of Energy, Device, and Psych were correlated, though with different levels of significance. This is important context for the findings about cybersensitives and their responses to questions within the categories, because there is a transitive association of correlation (if a is correlated to b, and b is correlated to c, then c is correlated to a).

- Null Hypothesis: Psych codes and energy codes are independent.
- Alternative Hypothesis: Psych codes and energy codes are correlated.

With an extremely low p value of about 0.000155, these two variables have an extremely high likeliness of being correlated. The moderately high R-value of about 0.628 confirms a strong correlation.

Energy Codes vs Device Codes

Below is a correlation test between energy codes and device codes (assessed as total values). This establishes that these two are pretty likely to be correlated with each other (assessed as total values), an important connection to note when each variable is tested against question responses.

- Null Hypothesis: Energy codes and device codes are independent.
- Alternative Hypothesis: Energy codes and device codes are correlated.

With an extremely low p value of about 0.00039, these two variables have an extremely high likeliness of being correlated. The moderately high R-value of about 0.597 confirms a strong correlation.

Psych Codes vs Device Codes

Below is a correlation test between psych codes and device codes. These variables are pretty likely correlated as well.

- Null Hypothesis: Psych codes and device codes are independent.
- Alternative Hypothesis: Psych codes and device codes are correlated.

The p-value is 0.031, meaning the best conclusion is that these variables are correlated. With an R-value of about 0.39, the correlation is likely moderate. Of the tested connections between the three codes in this section, this appears the weakest, but it is still a statistically significant and moderately strong connection.

4.1.2 Codes Compared with Cybersensitivity

This section will compare each code with grouping (cybersensitive, mainstream, null) for a correlation. An F-test is conducted to determine a statistically significant difference in mean for each group.

Energy Codes vs Cyber Status

An F-test is used to test for a correlation between Energy Codes and cyber status group. Specifically, this tests for a statistically significant variation in the mean Energy Code Totals among cyber status groups.

- Null Hypothesis: Energy Codes have the same means across the various levels of cybersensitivity.
- Alternative Hypothesis: Energy codes are different across cyber statuses

With such a small p-value of 0.0003, Energy Codes and cybersensitivity are likely correlated with each other.

Device Codes vs Cyber Status

An F-test is used to test for a correlation between Device Codes and cyber status group. Specifically, this tests for a statistically significant variation in the mean Device Code Totals among cyber status groups.

- Null Hypothesis: Device Codes have the same means across the various levels of cybersensitivity.
- Alternative Hypothesis: Device codes are different across cyber statuses.

With such a small p-value of p = 3.97e-05, Device Codes and cyber status are likely correlated with each other.

Psych Codes vs Cyber Status

An F-test is used to test for a correlation between Psych Codes and cyber status group. Specifically, this tests for a statistically significant variation in the mean Psych Code Totals among cyber status groups.

- Null Hypothesis: Psych Codes have the same means across the various levels of cybersensitivity.
- Alternative Hypothesis: Psych codes are different across cyber statuses.

Given an alpha of 0.05, this shows that psych codes are not correlated with cyber status. With a p-value of 0.103, lower than normal for this dataset, it should be noted that there may be a proclivity for relationship, although not statistically significant. However, as mentioned above, due to the transitive property of correlation among the three categories, the likelihood that cybersensitivity is related is boosted. So why do we think this was weakly supported? At this point we can only surmise, but our working hypothesis concerns the number of codes in the Psych category: with many more codes than the other two categories, and the codes referring to more subjective themes, we think it is likely that a statistical relationship is harder to establish. By way of illustration, if someone is talking about a phone, there is very little subjectivity involved in determining how to code this portion of the interview. However, when someone is talking about their feelings, which can be complex and multi-layered, the ethnographer doing the coding has to make a subjective call in how to reduce the theme to a one-dimensional code.

4.2 Demographic Variables

First, we tested key demographic variables to see whether they may be confounding variables in the process: gender, age, and income. For every group in each test, age, gender, income was not significant. Overall, we can conclude with a pretty high likeliness that cybersensitivity is independent of gender, income level, and age. This supports our assertion in both the *Preliminary Ethnographic Report on Cybersensitives and Technology Detailing the Fieldwork and Early Findings* as well as in *Psychosocial Drivers of Technology Engagement* that neither the distribution of the characteristics of the population, nor our sample selection process is biased.

4.2.1 Gender

Below we conduct hypothesis testing on gender.

- Null Hypothesis: Cybersensitivity and gender are independent in the population.
- Alternative Hypothesis: They are dependent of each other in the population.

	Female	Male
Cybersensitive	7	2
Non Cybersensitive	13	11

Chi = 2.96 and p = 0.26. We fail to the reject the null. Thus, if cybersensitivity and gender were independent, this distribution of gender and cybersensitivity would be likely. We can conclude that gender and cybersensitivity are independent.

4.2.2 Income

Below we conducted two Exact Goodness of Fit tests to test for connections between income and cybersensitivity: the first on all income groups and cybersensitivity groups, and the second on just cybers as a binary.

- Hypothesis: Cybersensitivity and income are independent in the population.
- Alternative Hypothesis: They are dependent of each other in the population.

Test 1

	Household Income ($USD)					
	20,000 to 49,999	**50,000 to 99,999**	**100,000 to 149,999**	**150,000 to 199,999**	**$200,000+**	**Prefer not to answer**
Cyberaware	1	1	0	0	1	0
Cybersensitive	1	1	0	1	1	2
Low Mainstream	2	3	2	1	0	1
Mainstream	3	3	1	2	2	0
Null	0	2	1	1	0	0

	P Values by Row
Cyberaware	0.84
Cybersensitive	0.35
Low Mainstream	0.88
Mainstream	0.93
Null	0.69

Test 2

	Household Income ($USD)					
	20,000 to 49,999	**50,000 to 99,999**	**100,000 to 149,999**	**150,000 to 199,999**	**$200,000+**	**Prefer not to answer**
Cybersensitive	2	2	0	1	2	2
Non Cybersensitive	5	8	4	4	2	1

	P Values by Row
Cybersensitive	0.50
Non Cybersensitive	0.95

For every income column in each test, income is not significant. We safely conclude that cybersensitivity is independent of income.

4.2.3 Age

Below we conducted two Exact Goodness of Fit tests to test for connections between age and cybersensitivity: the first on all income groups and cybersensitivity groups and the second on just cybers as a binary. This will test the full range of possibilities.

- Hypothesis: Cybersensitivity and age are independent in the population.
- Alternative Hypothesis: They are dependent of each other in the population.

Test 1

	Age				
	25-34	**35-44**	**45-54**	**55-64**	**65-74**
Cyberaware	1	0	1	1	0
Cybersensitive	0	1	4	0	1
Low Mainstream	2	2	2	2	1
Mainstream	0	1	5	3	2

	P Values by Row
Cyberaware	0.63
Cybersensitive	0.56
Low Mainstream	0.49

	P Values by Row
Mainstream	0.86
Null	0.67

Test 2

	Age				
	25-34	**35-44**	**45-54**	**55-64**	**65-74**
Cybersensitive	1	1	5	1	1
Non Cybersensitives	3	3	8	6	4

	P Values by Row
Cybersensitive	0.97
Non Cybersensitive	0.96

For every age group in each test, the age is not significant. We can pretty safely conclude that cybersensitivity is independent of one's age group.

4.2.4 Region

We conducted an Exact Goodness of Fit test to examine connections between region (Northern or Southern California) and cybersensitivity.

- Null Hypothesis: Cybersensitivity and region are independent in the population.
- Alternative Hypothesis: They are dependent of each other in the population.

	Northern California	Southern California
Cyberaware	1	2
Cybersensitive	3	3
Low Mainstream	3	6
Mainstream	4	7
Null	4	0

	P Values by Row
Cyberaware	1.00
Cybersensitive	1.00
Low Mainstream	0.52

	P Values by Row
Mainstream	0.76
Null	0.04

With such a high p-values, we can pretty safely conclude that cybersensitivity and region are independent in the population. However, Nulls, or people who lack cybersensitivity, appear to correlate with Northern California.

Overall, we can conclude with a pretty high likeliness that cybersensitivity is independent of gender, income level, age, and region.

4.3 Survey Question Responses

This section analyzes whether cybersensitives and/or cyberawares answered specific questions significantly differently than other groups. For each question, a series of hypothesis tests was conducted to analyze the likeliness of significant difference in the response. Given that most of the questions are categorical with a sample size not conducive to chi-square analysis, an exact goodness of fit test was conducted.

4.3.1 Cell Phone Data Usage

In "Psychosocial Drivers of Technology," our 'eyeballing' of the data made us think there might be a statistically significant relationship between cybersensitive status and data plan purchases. Below are several tests to determine whether that is the case; the overall conclusion is that there is not a significant difference.

- Null hypothesis: Data plan type is independent of cybersensitive status.
- Alternative hypothesis: Cybersensitive groups have distinct data plan distributions

Two tests were conducted:

- Test 1) On all groups
- Test 2) Just on cybersensitives vs. others

Test 1

Data Plan	Cyberaware	Cybersensitive	Low Mainstream	Mainstream	Null
1-5 GB per month	0	2	1	2	1
I do not have a data plan	0	1	0	1	0
More than 5 GB per month	3	2	4	2	1
Unlimited data plan	0	1	3	6	1

Data Plan	P Values by Row
1-5 GB per month	0.71
I do not have a data plan	0.82
More than 5 GB per month	0.28
Unlimited data plan	0.74

Test 2

Data Plan	Cybersensitive	Non Cybersensitive
Greater than 5 GB per month	6	17
Less than 5 GB	3	7

Data Plan	P Values by Row
Greater than 5 GB per month	1.00
Less than 5 GB	0.74

The high p-values conclude that 'data plan size' does not vary by cyber status and that cybersensitives possess the same basic data plan distribution as the rest of the population.

4.3.2 Energy Awareness

This question asked them to rank their self-awareness of their own energy consumption based on a set of potential answers. Below are several tests to determine whether that is the case.

- Null hypothesis: Energy awareness is independent of cybersensitivity
- Alternative hypothesis: Cybersensitive groups have distinct patterns in energy awareness

We conducted three tests:

- Test 1) On all groups and all answer responses
- Test 2) Just on cybersensitives vs. others
- Test 3) On cybersensitives vs others compared with just the first energy awareness question

Test 1

Energy Awareness	Cyberaware	Cybersensitive	Low Mainstream	Mainstream	Null
I am fully aware of, and monitor the level of energy consumption in my household. I have made and continue to make many changes	1	2	3	3	1

Energy Awareness	Cyberaware	Cybersensitive	Low Mainstream	Mainstream	Null
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.	2	3	4	8	3
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.	0	1	2	0	0

Energy Awareness	P Values by Row
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.	1.00
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.	0.90
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.	0.51

Test 2

Energy Awareness	Cybersensitive	Non Cybersensitive
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.	3	7
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	5	15

Energy Awareness	Cybersensitive	Non Cybersensitive
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.	1	2

Energy Awareness	P Values by Row
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.	0.74
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.	1.00
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.	1.00

Test 3

Energy Awareness	Cybersensitive	Non Cybersensitive
Fully Energy Aware	3	7
Partially or Not at All Energy Aware	6	17

Energy Awareness	P Values by Row
Fully Energy Aware	0.74
Partially or Not at All Energy Aware	1.00

The high p-values indicate that we can conclude that reported energy awareness does not vary by cybersensitive status. The overall conclusion is that there is not a significant difference between cybersensitives and non-cybersensitives with respect to self-reported energy awareness.

4.3.3 Codes Compared with Emotional Responses

This section analyzes how each code compares to reported emotional responses when asked to think about a time without technology. We tested whether there is a relationship between Psych

codes with the response to a specific question. In other words, 'did how people answer any given question correlate with their Psych code scoring?'

These tests address the question: Did people with larger Psych (or Energy, or Device) code scores tend to answer any given question the same way? We wanted to test whether patterns in these codes could connect with how people answer the questions. Since the specific cybersensitive status of an individual did not appear to relate to how people answered that question, maybe these codes still did, which would help explain and statistically confirm the pattern we had elicited via the ethnographic data in "Psychosocial Drivers of Technology." The basic answer we found was that, "Yes, in some cases (but not all), these were related."

For each code and for each emotion, these tests were conducted:

- Test 1) Correlation test between the given code and responses to the given agree/disagree question
- Test 2) F-test to determine whether there is a significant different in mean code totals for each answer response

For any specific test where we report that it an answer correlated with one set of codes (i.e. Psych) but not with the other two (i.e., Device or Energy) it means that the overall set of Psych codes does statistically correlate with how people answered that question (although it is not correlated with Energy codes or Device codes). That means that that question could be a potential variable to look for to in connection with cybersensitive status.

- Reports of 'feeling happy' is likely correlated with Psych Codes, but not likely correlated with Energy or Device Codes.
- Reports of 'feeling relieved' is likely correlated with Psych Codes, but not likely correlated with Energy or Device Codes.
- The emotional response of 'feeling free' is likely correlated to Psych and Device codes, but not Energy codes.
- Reports of 'feeling concerned' is likely correlated with Device Codes, but not likely correlated with Psych or Energy codes.

This series of tests underscores the probabilistic inter-relatedness of the three sets of codes overall. Referring back to the transitive property, since we have established correlation between Device and Energy codes and cybersensitive status, but correlation between Psych codes and cybersensitive status was not apparent (though not ruled out) the correlation between *ranges* of code frequencies in the Psych category, and survey answers, strengthens our case.

4.4 Codes Compared with Agree/Disagree Questions

This section analyzes how each code compares to agree/disagree questions from the survey. For each code and for each agree/disagree question, these tests were conducted:

- Test 1) Correlation test between the given code and responses to the given agree/disagree question
- Test 2) F-test to determine whether there is a significant different in mean code totals for each answer response

4.4.1 Technology Breadth

This question asked them to what extent they agreed or disagreed with the following statement:

"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."

The overall conclusion is that there is not a significant difference, however, as discussed in "Psychosocial Drivers of Technology," cybersensitives were the only group that strongly disagreed. The p-values associated with the Strongly Disagree response in each exact-goodness-of-fit test are smaller than normal, seeming to indicate a probabilistic significance to this. This factor is also likely the reason the F and T tests report smaller than normal percent p-values in the teens. Although this does not cross our alpha threshold for "statistical significance" of 0.05, this is potentially important and further analysis should be conducted to determine its implications.

4.4.2 Advice

This question asked them to what extent they agreed or disagreed with the following statement:

"Friends often ask for my advice before buying new devices."

This question is compared with Psych Codes, Energy Codes, and Device Codes. Responses to this question on advice are not likely correlated with Psych or Device Codes, but are potentially correlated with Energy Codes.

4.4.3 Easy

This question asked them to what extent they agreed or disagreed with the following statement:

"Technology is easy."

This question is compared with Psych Codes, Energy Codes, and Device Codes. Responses to this question are not likely correlated with Energy or Device Codes, but are potentially correlated with Psych Codes.

5 Findings

5.1 Cybersensitivity as 'X' Factor

We set out to find the traits that associate with the cybersensitive persona. Our review of energy efficiency literature had provided us with supporting evidence that typical demographic variables would not be explanatory of differences in behavior and lifestyles. That there was an 'X' factor at play, responsible for the different outcomes when exposed to similar treatments. We came to believe that this X factor was the depth of emotional attachment to personal technology that someone experiences. The level of intensity of that attachment, i.e. the valency, would be reflective of the level of cybersensitivity in someone's behavior.

In our last deliverable, "Psychosocial Drivers of Technology," we used ethnographic analysis and looked at the sorting of code in the categories of Psych, Energy, and Device. We asserted that, by eliciting the rules that produced the sorts, we could establish qualitatively that there was a consistent relationship between the frequency of codes appearing in an interview and the intensity

of someone's cybersensitive characteristics. Our conclusions based on the code frequency sorts were supported by the in-home observations made by three different ethnographers. In this paper, we have shown that, with respect to Device and Energy codes, our conclusions are statistically robust. We have weaker evidence for Psych codes, but the probabilistically inter-related nature of the three categories means it is likelier to be true than not. We also believe that our difficulty in establishing a straightforward correlation for Psych codes is due to 'noise' introduced by both the variety of codes found in that set, and the greater subjectivity of topics related to emotions.

5.2 Cybersensitives and their characteristics

Our research aim has been to assess if cybersensitives as a behavioral profile exist, and what characteristics might differentiate them from other members of their cohort. In our second deliverable for this topic, "Psychosocial Drivers of Technology Engagement among Cybersensitives," we presented the results of our analysis of the ethnographic data collected through in-depth interviews and in-home observations. In that paper, we outlined several traits we felt were common to cybersensitives (and the closely aligned segment, cyberawares). Traits we observed among cybersensitives include that they tend to be meticulous with their homes and other possessions. They tend to be highly active and aware individuals, with multiple revenue streams, extensive hobbies, and a passion for life-long learning.

We have hypothesized that a cybersensitive not only may not be an early adopter, but that they may even hang on to a device longer than the average consumer. This would be due to their emotional relationship with their device; parting with an old phone would be like parting with an old friend. Because of the length of this relationship, we believe cybersensitives spend more time learning the intricacies of their device than do their non-cybersensitive peers. Cybersensitives will tend to patch their devices, or extend their lifecycle and/or functionality using add-ons. They were generally what we might call 'device-heavy' as in they tend to use multiple computers or devices, often simultaneously. They were more likely to have multiple screens, and more likely to report switching from a work computer that was a PC to a personal computer that was a Mac.

5.3 Key Takeaways

One of the most important takeaways from the statistical analysis is that our assignment of participants to the group 'cybersensitives/cyberawares' was not the product of researcher bias nor an accidental gloss on a pre-existing demographic segment such as age, gender, or income. This supports our hypothesis that this propensity will be a unique attribute, not associated with membership in any particular demographic, e.g., age, gender, socio-economic status. We believe that establishing cybersensitivity as its own segment will help address common stereotypes about age, gender, and technology usage, that persist despite evidence to the contrary. We also believe that distinguishing cybersensitivity from income brackets and purchasing power will help unlock potential future engagement with low-income consumers.

Thanks to our statistical analysis, showing the independence of cybersensitivity from geography, we feel confident that the distribution of cybersensitives as shown in our sample will hold up for a larger sample. Our combined segment of cybersensitives and cyberawares is about 30% of our sample. This has enormous implications regarding the use of feedback via electronic devices to inform a population, regardless of the topic or goal (e.g., energy efficiency, carbon reduction, reducing water usage). If 30% of your audience is five, ten, or even fifteen times more receptive to

your message via device than their peers, it makes sense to target this population for a greater return on investment of program dollars.

5.4 Future Research

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. We are skeptical that correlations would be found, given that we did not find them 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 been fully examined in the past.

An interesting note, the cyber status group of Nulls do appear to correlate with Northern California. This supports our belief, discussed in "Psychosocial Drivers of Technology" that people who are technically oriented, or work with technology in an intimate fashion, tend to be less emotionally engaged by it. Our hypothesis, purely speculative at this point, is that they view technology exclusively as tools and do not tend to engage with it as a 'friend' or 'pet' or other emotional relationship. More research on this is needed.

6 Conclusions

In conclusion, we have defined cybersensitivity: it is a propensity to have a greater emotional engagement with one's personal (mostly handheld) technology, whether smartphone, tablet, or laptop. We discussed our overall hypothesis, which is that, the more positive emotion is expressed with respect to a device, the higher the likelihood is that someone has the trait of being a cybersensitive. Using the combined survey/interview data set, we statistically validated our hypothesis that cybersensitivity does not correlate with the demographic variables of age, gender, or income. Nor does cybersensitivity correlate with a specific geography in our sample.

From data collected in earlier stages of the project[2], we identified cybersensitives and cyberawares through their differing responses to questions posed by the ethnographers during the in-depth interviews. This distinction, which first manifested itself as a clustering of code frequencies in the Atlas.ti output, was statistically validated with respect to the device and energy categories. The evidence with respect to psych codes is less conclusive, but we have reason to believe that the relationship would become clearer with further analysis.

We established the probabilistic interdependence of our sets of code categories. We also showed that, in several cases, there was a correlation between the answers given on our surveys and the clusters of cybersensitives in the code categories – even though we could not establish a direct one to one relationship between individuals, their specific ranks, and their answers on particular questions. Given our small sample size, the pattern of correspondence is likely sufficient, when combined with the rules we elicited from ethnographic analysis, to enable us to model cybersensitive behavior on a larger scale.

[2] We have surveyed approximately 400 individuals and interviewed 45 households.

References

Caulkins DD, Andelson JG, Bentley-Condit V, Kamp KA. 1999. Discovery-Mode Teaching Using the Electronic Human Relations Area Files for Cross-Cultural Comparison. *Cross-Cultural Research* 33(3): 278-297.

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

Colombetti G. 2005. Appraising Valence. *Journal of Consciousness Studies*, 12(8–10): 103–26.

Foster B, Mazur-Stommen S. 2012. Results from Recent Real-Time Feedback Studies. ACEEE research report B122. Available at http://aceee.org/research-report/b122

Frijda NH. 1986. The Emotions. Cambridge: Cambridge University Press.

Grønhøj A, Thøgersen J. 2011. Feedback on household electricity consumption: learning and social influence processes. *International Journal of Consumer Studies* 35(2): 138-145.

HRAF. Human Relations Area Files - Cultural information for education and research. Accessed June 11, 2017 at http://hraf.yale.edu/

Kottak CP. 2010. Melvin Ember and HRAF, Anthropology's Archive. *Cross-Cultural Research* 45(1): 11-15.

Pietri SE, Fazio RH, Shook NJ. 2013. Weighting Positive Versus Negative: The Fundamental Nature of Valence Asymmetry. *Journal of Personality* 81(2):196-208.

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

Schneirla TC. 1959. An evolutionary and developmental theory of bi-phasic processes underlying approach and withdrawal. In "Nebraska Symposium on Motivation", ed. M.R. Jones Lincoln, University of Nebraska Press.

Shuman V, Sander D, Scherer KR. 2013. Levels of Valence. *Frontiers in Psychology* 4(261): 17 pp.

Sutton J, Austin Z. 2015. Qualitative Research: Data Collection, Analysis, and Management. *Canadian Journal of Hospital Pharmacy* 68(3): 226–231.