Building Eco-Informatics: Examining the Dynamics of Eco-Feedback Design and Peer Networks to Achieve Sustainable Reductions in Energy Consumption

Rishee K. Jain

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ABSTRACT

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Rishee K. Jain

The built environment accounts for a substantial portion of energy consumption in the United States and in many parts of the world. Due to concerns over rising energy costs and climate change, researchers and practitioners have started exploring the area of eco-informatics to link information from the human, natural and built environments. Specifically, they have begun exploring the use of normative eco-feedback systems to encourage energy efficient behavior and reduce building energy consumption. A normative eco-feedback system provides building occupants with information regarding their own energy consumption and the energy consumption of others in their peer network. While such eco-feedback systems have been observed to drive significant reductions in energy consumption, little is known about the specific system and peer network dynamics that are driving observed reductions. Without this deeper understanding, researchers run the risk of designing eco-feedback systems with low efficacy and may therefore fail to capitalize on potential energy savings. The central aim of this dissertation is to investigate the impact eco-feedback system design and peer network dynamics have on occupant energy consumption behavior.

To enable both energy consumption and network data collection, I developed a web-based of an eco-feedback system prototype for an 69 unit residential building in New York City and utilized the system in three empirical experiments. The first experiment was designed to ascertain the
effect eco-feedback interface design components have on energy consumption behavior. Analysis of time stamped interface usage and energy consumption data revealed evidence that providing users with incentives and information on their historical consumption levels encourages conservation behavior. Results also suggested that penalizing users for using more energy is not effective in driving energy reductions and instead discourages user engagement.

To further understand the effect eco-feedback system design has on energy consumption behavior, a second experiment was conducted using an email-based eco-feedback system. The aim of this study was to examine the role feedback representation plays in encouraging reductions in energy consumption. Participants were broken into two different study groups; one group was provided with feedback in kWh, while a second group was provided with feedback in the equivalent trees required to offset emissions associated with their kWh energy usage. Results revealed that users who received feedback in the form of equivalent trees were more likely to reduce their consumption and had a less dramatic response-relapse effect to feedback emails than their counterparts who received feedback in kWh.

The third experiment aimed to characterize the impact peer networks have on modifying energy consumption behavior. Specifically, the experiment was designed to determine if social influence drives energy savings in eco-feedback systems. Analysis of user interaction and energy consumption data was conducted by developing an algorithmic approach based on stochastic and social network test procedures. Social influence was found to impact energy consumption behavior and results indicated the potential of utilizing social influence and peer networks as a means to encourage energy conservation.
Overall, the research in this dissertation provides insight into what design elements of an eco-feedback system encourage energy conservation and the impact social influence has on consumption behavior. Results from this research have widespread implications for researchers and policy makers as they strive to design effective policies and systems that will result in sustained energy savings and pave our transition to a less carbon intensive society.
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Chapter 1

INTRODUCTION

“Electricity connects people with each other in many ways, but its way of doing this usually remains hidden and conceptualized.”

– Turo-Kimmo Lehtonen (Lehtonen, 2009)

Electricity is a powerful tool that is often credited with revolutionizing the way we generate, transmit and consume energy. It has allowed us to connect with each other in previously unimaginable ways, both physically (e.g., electric transport) and virtually (e.g., telecommunication networks). However, as the consequences of global climate change are becoming more apparent, there is a renewed effort to curb our unbridled consumption of electricity. Two major culprits of excessive consumption are commercial and residential buildings, which account for over 40% of all energy consumption in the United States (Energy, 2011). As a result, researchers and practitioners have begun exploring innovative energy efficiency and conservation mechanisms for these two types of buildings that utilize two new technologies: smart sensors and online social networking.

Advancements in sensor technology have led to the development of smart sensors that are able to capture large amounts of energy consumption data cost-effectively and less intrusively. Simultaneously, online social networking tools such as Facebook, LinkedIn and Twitter have become increasingly pervasive in our society, allowing for the previously hidden virtual connections enabled by electricity to now be quantified and studied. These two new technologies converge into a broad discipline known as eco-informatics that aims to link
information from the human, natural and built environments. Within the discipline of eco-informatics, researchers have developed normative eco-feedback systems that utilize energy consumption data from smart meters to provide building occupants with information regarding their own historical energy consumption and the energy consumption of others in their peer or social network.

Normative eco-feedback systems have been successfully deployed by both academia and industry. OPower, an energy data analytics and software company, recently launched a normative eco-feedback system in conjunction with National Resource Defense Council that allows utility customers to view the energy consumption of their Facebook friends (Proatalinkski, 2012). Academia has extensively examined the use of eco-feedback systems with a meta-analytical study by Fischer concluding that eco-feedback is an effective mechanism to motivate energy conservation (Fischer, 2008). Additionally, several empirical eco-feedback experiments have observed savings ranging from 2% to 55% (Allcott, 2011; Brandon, 1999; Peschiera et al., 2010; Petersen et al., 2007; Siero et al., 1996). This large variability in observed savings from past empirical study points to the need for a deeper more nuanced examination of what is driving observed reductions in energy consumption from such systems. In this dissertation, I aim to fill this need by exploring two key aspects of normative eco-feedback systems – system design/data representation and peer network dynamics – extensively through empirical experimentation.
1.1. Background

1.1.1 Eco-Feedback System Design and Data Representation

In eco-feedback systems, user interface design has been shown to play a large role in driving energy savings from participants (Jacucci et al., 2009). The large variability in observed savings (2-55%) from previous experiments has been accompanied by a large variability in the design and components of interfaces (Allcott, 2011; Brandon, 1999; Peschiera et al., 2010; Petersen et al., 2007; Siero et al., 1996). While some key design components have been established for eco-feedback systems by previous work (Jacucci et al., 2009; Karjalainen, 2011), they are derived from user surveys and not substantiated by empirical experimentation and energy consumption data. Additionally, previous work (Peschiera et al., 2010; Petersen et al., 2007) has implied a correlation exists between interface user engagement and reductions in energy consumption but no empirical evidence currently exists to back up this assertion. For this reason, I ask the question – what design components of user interfaces drive actual energy savings from building occupants?

Data representation within an eco-feedback system has also been shown to have a significant impact on the effectiveness of such a system to engender energy savings (Wood and Newborough, 2007). While the research community has explored this area extensively through user surveys, uncertainty remains as to what is the most effect means of communicating eco-feedback and no empirical evidence exists supporting a specific form of data representation. Several studies have utilized direct energy units, such as kWh or kW (Grønhøj and Thøgersen, 2011; Jain et al., 2012; Peschiera et al., 2010; Peschiera and Taylor, 2012; Petersen et al., 2007; Wilhite and Ling, 1995); others have utilized environmental externalities, such as associated CO₂
emissions, (Grevet et al., 2010; Holmes, 2007; Mankoff et al., 2010; Petkov et al., 2011) while a third community has utilized monetary units, such as US dollars, to convey feedback (Faruqui et al., 2010; Fitzpatrick and Smith, 2009; Grevet et al., 2010; Wilhite and Ling, 1995). This tension in the literature regarding data representation has prompted me to ask the question – *how does data representation in eco-feedback systems impact the actual energy consumption patterns of users?*

1.1.2. Peer Network Dynamics in Eco-Feedback Systems

The concept of utilizing social or peer network dynamics in conjunction with an eco-feedback system was first introduced in the Human-Computer Interaction research community where researchers developed *Stepgreen.org*, a website focused on encouraging energy efficient behavior through the use of self-reported feedback and social networks (Mankoff et al., 2010). Pilot results were promising and spawned the development of fully automated normative eco-feedback systems, one of which is *Watt’s Watts*, a system I co-developed to enable data collection for the three experiments reported in this dissertation (Gulbinas et al., 2013). Prior empirical studies revealed that users who were presented with socially contextualized feedback (i.e., feedback with comparisons to others in their peer network) used a lower amount of energy than users presented with feedback solely on their own usage (Foster et al., 2010; Peschiera et al., 2010). A follow-on study by Peschiera & Taylor revealed that a statistically significant correlation existed between how connected a user was to his/her peer network and how much a user reduced his/her consumption (Peschiera and Taylor, 2012). In other words, the more connected a user was, the less energy he/she consumed. While these studies suggest that users were influenced to change their energy consumption behavior, the observed correlation could be
the result of other network effects (i.e., homophily, confounding factors) and not social influence. The data acquisition and analysis techniques employed by Peschiera & Taylor were unable to clearly decipher between the network effects. For this reason, I ask the question – can social influence drive energy savings?

1.2. Research Questions and Structure of Dissertation

This dissertation follows a three-paper format. The structure of this dissertation, the overarching research question that served as the basis for my general academic exploration and the sub-questions that correspond to specific chapters in this dissertation are outlined in Figure 1.

Figure 1: Research Questions and Structure of Dissertation
In Chapter 2, I examine the impact design components of eco-feedback systems have on the observed energy savings of building occupants. Chapter 3 expands the discussion of eco-feedback system design to explore the effect data representation has on the consumption patterns of users. Chapter 4 addresses the theme of peer network dynamics in eco-feedback systems by developing an algorithmic approach based on stochastic and social network test procedures to determine if social influence can engender savings. In Chapter 5, I outline the theoretical and practical contributions of this research and in Chapter 6, I discuss potential avenues for future research that build upon the work presented in this dissertation. Lastly, a references section provides an alphabetized list of publications cited in this dissertation.
Chapter 2

ASSESSING ECO-FEEDBACK INTERFACE USAGE AND DESIGN TO DRIVE ENERGY EFFICIENCY IN BUILDINGS

Abstract

In response to growing concerns over climate change and rising energy costs, a number of eco-feedback systems are being tested by researchers. Yet, the interface design aspect of these systems has largely been ignored. Therefore, the role that interface design plays at the component level in driving actual energy savings from users is unclear. In this paper, we evaluate the impact interface design has on eco-feedback performance by investigating five established design components. We conducted a six week empirical study with 43 participants using a prototype eco-feedback interface. Analysis of usage data affirmed a statistically significant inverse correlation between user engagement (measured as logins) and energy consumption. Utilizing this relationship as a basis for performance, we expanded our analysis to evaluate the five design components. The study revealed statistically significant evidence corroborating that historical comparison and incentives are design components that drive higher engagement and thus reductions in energy consumption. Results for the normative comparison and disaggregation components were inconclusive, while results for the rewards and penalization component suggest that a revision to the penalization aspect of the component maybe necessary.
This study raises pertinent questions regarding the efficacy of various eco-feedback components in eliciting energy savings.

2.1. Introduction

Advancements in sensor technology and computing have allowed for rapid access to a multitude of information about the infrastructure we utilize and occupy. Drivers can view real-time traffic conditions on their mobile device (Traffic.com, 2011), utility companies can evaluate operational failures without leaving the office (Moore and Gazette, 2011) and occupants can understand how they interact with their building. In response to rising energy costs and the effects of climate change, citizens and governments are searching for innovative ways to increase energy efficiency. In most countries around the world, the built environment accounts for a substantial proportion of energy consumption. In the United States the built environment accounts for about 40% of all energy consumption (Energy, 2011) and consumes more energy than any other sector. To reduce building energy consumption, researchers have responded by integrating sensors and information systems to create eco-feedback systems. These eco-feedback systems provide building occupants with information regarding their consumption behavior with the goal of encouraging energy efficient behavior.

Eco-feedback systems operate on the premise that building occupants are largely unaware of how much energy they consume on a day-to-day basis (Attari et al., 2010), and once occupants become aware of their actual consumption, they will take steps to decrease energy consumption (Abrahamse et al., 2007; Darby, 2006; Hutton et al., 1986; Wever et al., 2008; Wilson and Dowlatabadi, 2007). Researchers have concluded that behavioral interventions alone offer the potential to reduce household direct CO2 emissions by 20% over the next 10 years (Dietz et al.,
Recent research has shown computerized consumption feedback to be the most effective delivery mechanism for an eco-feedback system (Fischer, 2008). Computerized systems require the development of a user interface that serves as a connection between building occupants and their usage data which may induce energy savings. While numerous factors can be attributed to the variability in savings associated with eco-feedback studies, the design of the user interface is a key factor to achieve a sustained impact on energy consumption behavior (Jacucci et al., 2009). Therefore, a deeper understanding of the design components of eco-feedback interfaces is crucial to develop interfaces that achieve substantial and sustainable energy use reductions in the built environment. In this paper, we utilize one particular eco-feedback interface to examine how the various components of the interface contribute to user engagement and a reduction in overall consumption.

2.2. Background

2.2.1 Eco-Feedback System Design

Early eco-feedback research relied on static physical interfaces (Becker, 1978; Seligman et al., 1978) and transitioned to electronic displays (Van Houwelingen and Van Raaij, 1989) as personal computers came into use. More recent studies (Abrahamse et al., 2007; Foster et al., 2010; Peschiera et al., 2010; Petersen et al.; Petersen et al., 2007; Spagnolli et al., 2011) relied on internet connectivity to deliver consumption information via web-based interfaces. An examination of past eco-feedback studies (Abrahamse et al., 2007; Becker, 1978; Foster et al., 2010; Grevet et al., 2010; Grønhøj and Thøgersen, 2011; McCalley, 2002; Peschiera et al., 2010; Petersen et al., 2007; Seligman et al., 1978; Siero et al., 1996; Spagnolli et al., 2011; Ueno et al., 2006; Van Houwelingen and Van Raaij, 1989; Wilhite and Ling, 1995; Wood and Newborough,
revealed a lack of consistency between components of eco-feedback interfaces and observed savings. Observed savings ranged from 5% to 55% and system features ranged from simple feedback with graphic visualizations (Foster et al., 2010; Grevet et al., 2010; Petersen and Svendsen, 2010) to complex tools (Abrahamse et al., 2007; Grønhøj and Thøgersen, 2011; Jacucci et al., 2009) that allow users to further understand their energy usage and conservation options. One residential eco-feedback study (Ueno et al., 2006) was able to reduce energy consumption by 10% by providing users with historical consumption information while another residential study (Peschiera et al., 2010) observed savings up to 26% by providing both historical and normative consumption information to users. A third residential study (Abrahamse et al., 2007) provided users with historical and detailed appliance-specific consumption information and yielded savings of 5.8%. These three studies illustrate the variability in observed savings and constituting interface components across eco-feedback studies. Some of this variability is likely due to idiosyncratic differences in the interfaces studied. However, given the range of components employed and the widely varying observed energy consumption reductions across studies, the question of if and how the components that make up an eco-feedback system drive energy savings from users deserves attention.

Several recent studies have begun to address the impact of eco-feedback system design. Wood and Newborough (Wood and Newborough, 2007) concluded that optimal design of an eco-feedback system will facilitate the greatest amount of energy savings for the maximum amount of users. These conclusions were derived from literature in adjacent fields such as human computer interaction (HCI) and not examined using empirical results from eco-feedback systems. Eco-feedback empirical studies addressing design have been limited to qualitative user surveys (Jacucci et al., 2009; Mankoff et al., 2010; Wever et al., 2008) and focus groups (Foster
et al., 2010; Petersen et al.). Karjalainen (Karjalainen, 2011) expanded on these qualitative studies by examining key features of prototype eco-feedback interfaces in interviews with users. This study provided insight regarding eco-feedback system user preferences, but the relationship between system components and the intended or actual performance of an eco-feedback system has not been empirically established. Therefore, research that establishes whether a relationship exists between eco-feedback design components and performance is needed.

2.2.2 Design Components of Eco-Feedback

A study of user interfaces (Karjalainen, 2011) introduced the following key design components into the eco-feedback literature: historical comparison, normative comparison, incentives and disaggregation. These four design components were augmented by the findings of Jaccuci et al. (Jacucci et al., 2009) to add an additional design component, rewards and penalization. In the following paragraphs, we explore each of these five design components in detail.

*Historical comparison* is defined as the ability of users to view their current consumption relative to past consumption. For example, an eco-feedback system with a *historical comparison* component could provide users with a graph that displays their energy consumption over the last 24 hrs, week or month. From observing these graphs and recalling their activities, users can begin to deduce the reasons for higher energy consumption and develop strategies to change their energy consumption patterns. In a review of eco-feedback studies, Darby (Darby, 2006) concluded that the most useful eco-feedback to be provided to users was *historical comparison*. This conclusion is further corroborated by the success of several eco-feedback interfaces that have incorporated *historical comparison* into their design (Abrahamse et al., 2007; Becker, 1978; Brandon, 1999; Grønhøj and Thøgersen, 2011; Peschiera et al., 2010; Petersen et al., 2007;
Seligman et al., 1978; Siero et al., 1996; Ueno et al., 2006; Van Houwelingen and Van Raaij, 1989; Wilhite and Ling, 1995). A meta-analytical study of eco-feedback systems also revealed that *historical comparison* is a primary tool necessary to achieve energy savings (Fischer, 2008). In addition to Karjalainen, other interface studies (Jacucci et al., 2009; Wood and Newborough, 2007) have introduced *historical comparison* as a key design component for eco-feedback interfaces. The *normative comparison* design component operates in conjunction with *historical comparison* by contextualizing both current and historical consumption in relation to a user’s peers. By allowing users to compare their own consumption information with their peers, *normative comparison* has been shown to persuade users to modify their behavior to conform to social norms (Fischer, 2008; Schultz et al., 2007) and thereby reduce energy consumption. In other words, users have been shown to curb usage to match the consumption patterns of their peers. Several studies (Iyer et al., 2006; Peschiera et al., 2010; Siero et al., 1996) that deployed eco-feedback systems with a *normative comparison* component have been observed to drive substantial energy savings from users. Other studies (Karjalainen, 2011; Wood and Newborough, 2007) have highlighted that *normative comparison* is a key component of eco-feedback interface design and researchers in the HCI community have also demonstrated the potential of *normative comparison* in motivating energy efficient behavior through competition and public perception (Grevet et al., 2010; Mankoff et al., 2010).

The *rewards and penalization* design component provides users with the ability to earn rewards for saving energy and be penalized for wasting energy. Current literature advocates the use of *rewards and penalization* to encourage both conservation behavior and discourage wasteful behavior (Jacucci et al., 2009). Additionally, a study in the field of psychology (Kluger and DeNisi, 1996) concluded that the use of both positive and negative feedback can likely yield
gains in human performance, which would translate into additional energy savings for eco-feedback interfaces. The importance of the *rewards and penalization* component is further supported by its use in real-time electricity pricing, in which users are rewarded for electricity use during off-peak hours and penalized for electricity use during peak hours (Holland and Mansur, 2008). The *rewards and penalization* design component addresses only those activities which result in rewards or penalties, so a separate design component, *incentives*, is necessary to address the types of awards users will receive for reducing consumption. The *incentives* design component can provide users with both financial and non-financial awards. For instance, if users accumulated points for saving energy through the *rewards and penalization* component, the *incentives* design component would enable them to redeem the points for a credit on their electricity bill (financial) or a new energy efficient lamp (non-financial). *Incentives* have been shown (Spagnolli et al., 2011) to support sustained interaction and consumption reduction from users in long term studies. Wood and Newborough (Wood and Newborough, 2007) also included *incentives* as a key design component of eco-feedback systems, but concluded that only financial *incentives* are effective at driving energy use reductions. Others have concluded that financial *incentives* do not provide sufficient motivation for users to become engaged and adopt energy conservation measures (Dietz et al., 2009; Pierce et al., 2008). Successful eco-feedback interfaces have introduced non-financial *incentives* such as prizes (Jacucci et al., 2009; Petersen et al., 2007) or game-like levels (Froehlich et al., 2010) as a means to motivate behavior change. These conflicting conclusions demonstrate the need for further research on the *incentives* design component.

The *disaggregation* design component allows users to disaggregate energy consumption data to the appliance level. Fischer’s review (Fischer, 2008) of eco-feedback studies affirmed the need
for interface tools that draw a direct link between specific actions or appliances and consumption. Providing such granularity allows users to increase self-efficacy associated with consumption behavior modifications (Wilson and Dowlatabadi, 2007). The need for such disaggregation tools is further bolstered by survey responses of eco-feedback users, which indicated a strong desire to know usage relative to individual appliances (Fitzpatrick and Smith, 2009). Karjalainen (Karjalainen, 2011) introduced disaggregation as a design component for interfaces but provided little guidance as to how eco-feedback systems can achieve disaggregation. Researchers have achieved disaggregation by either installing individual sensors on appliances (Grønhøj and Thøgersen, 2011; Jacucci et al., 2009) or using eco-analytic tools that parse data to provide information regarding the impact of a specific behavior or appliance (Abrahamse et al., 2007). Because installing and maintaining individual sensors has proven to be logistically difficult in residential settings, researchers have begun to turn their attention toward further developing and studying eco-analytic tools.

2.2.3 Quantitative Examination of Eco-Feedback System Design Components

Our study aims to collect clickstream data for an eco-feedback user interface to investigate how the five identified design components impact performance. In the HCI literature, modern web tracking technology in the form of clickstream data has been shown to be an effective means of measuring user behavior quantitatively and assessing the performance impact that design components have on a web based application (Benevenuto et al., 2009; Das and Turkoglu, 2009; Srivastava et al., 2005). Fischer (Fischer, 2008) defined performance of an eco-feedback system as its ability to generate a reduction in energy consumption of its users. Consistent with Fischer’s definition, this study seeks to link the efficacy of design components to energy savings.
Previous eco-feedback studies (Peschiera et al., 2010; Petersen et al., 2007) have implied that energy savings are related to overall interface engagement (i.e., user logins) and research in other fields has established that user engagement is correlated with improved performance (Leslie et al., 2005; Strecher et al., 2008). This relationship has yet to be empirically ascertained for eco-feedback web interfaces. Thus, the first objective of this study is to confirm that an inverse correlation between user engagement and energy consumption (i.e., as engagement increases, energy consumption decreases) applies. If we can establish this to be the case, our second objective is to evaluate the key components of an interface in terms of engagement. Overall, this study aims to fill a gap in the existing literature as to what key design components of an eco-feedback system correlate with reductions in energy use.

2.3. Research Methodology

2.3.1 Eco-Feedback System Studied

The five key design components identified in the literature were included as distinct features in a prototype eco-feedback web interface. This prototype eco-feedback web interface was developed by the authors in collaboration with a professional information system design firm. It served as the primary research instrument for data collection. A summary of each design component and the corresponding functionality in the prototype interface is provided in Table 1.
Table 1: Summary of Design Components and Prototype Interface Functionality

<table>
<thead>
<tr>
<th>Design Component</th>
<th>Corresponding Functionality in Prototype Eco-Feedback Web Interface</th>
<th>Functionality Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Historical comparison</td>
<td>Ability to view three historical electricity utilization graphic modes (24 hour, To date, Last week)</td>
<td>Users have the ability to view their consumption on three different historical graphs: line graphs showing 24 hr and To date consumption and a bar graph showing the Last week consumption snapshot.</td>
</tr>
<tr>
<td>Normative comparison</td>
<td>Ability to view friends’ average electricity utilization and building average electricity utilization</td>
<td>Users can add or remove designated friends from their peer network on their consumption graphs and their network consumption average.</td>
</tr>
<tr>
<td>Rewards and penalization</td>
<td>Ability to earn positive and negative reward points based on consumption</td>
<td>Users are credited with points for reducing consumption from their baseline (pre-study level), completing audits, or answering surveys. However, users are deducted points for increasing consumption and are shown if they have negative points to reinforce penalization.</td>
</tr>
<tr>
<td>Incentives</td>
<td>Ability to redeem reward points for prizes</td>
<td>Rewards points can be redeemed for prizes (i.e. gift certificates to local restaurants, energy efficient power strips) on the redemption page of the interface.</td>
</tr>
<tr>
<td>Disaggregation</td>
<td>Ability to audit the consumption of specific appliances and devices by using an energy audit tool</td>
<td>Users receive an approximation of the energy usage of a given appliance by designating a time that the appliance was on and a time that it was off. Users are asked to minimize the change in other electrical devices to achieve maximum accuracy.</td>
</tr>
</tbody>
</table>

The prototype interface was designed to allow users to quickly access key features from a single view. The features of the prototype interface studied are detailed in the Figure 2 screenshot.
Users utilized the historical comparison component by employing one of three views: 24 hour, Last week and To date. In the 24 hour view, users viewed their average power draw over 10-minute intervals for the previous 24 hours and hourly power readings on a cumulative basis during the study period. The Last week view provided users with information in the form of a bar graph with the color of the bar (green, yellow, red) indicating their consumption relative to the building average. A green bar indicated that the user’s consumption was at least 20% below the building average whereas a red bar indicated that their consumption was at least 20% above the building average. A yellow bar indicated that their consumption was within 20% of the
building average. Collectively, these features of the prototype interface enabled users to assess their historical consumption patterns.

Users made use of the normative comparison component by adding the usage of peers in their network to the historical comparison graphs. By clicking on the add/remove drop down menu in the top right of the graph, additional consumption plots are added to the graph. For example, in the To date view, users viewed their daily consumption through the previous day. This view also allowed users to add/remove friends to the historical comparison plot using the same tool as the Last week view. By default, historical comparison graphs do not provide users with normative comparison information (i.e., a friend’s usage) without it being enabled by the user. Further normative comparison functionality was provided in the friend feed functionality of the interface. The friend feed informed users when their friends conducted an energy audit or redeemed reward points for a prize and was designed to supplement the normative comparison feedback presented in the graph portion of the interface. Therefore, text in the friend feed was limited to instant consumption values for appliances to avoid redundancy. A screenshot of the three graphical views available for the historical comparison and normative comparison design components is provided in Figure 3.
Figure 3: Historical Comparison and Normative Comparison Views of the Prototype Interface
Users utilized the *incentives* and *rewards and penalization* components through the current reward points balance section on the start page of the user interface. Points for each user were computed and updated daily. A hyperlink to the prize redemption web page was provided below the points balance in the eco-feedback web interface. The redemption page consisted of a list of all prizes available to users and the number of required points to redeem each prize. In order to redeem a prize, users clicked the “buy with points” button and then confirmed their purchase.

The start page of the prototype interface also allowed for utilization of the *disaggregation* design component via the energy audit tool. Users were required to enter the name of the appliance and designate times that the appliance was on and off using the drop down boxes. This type of input format was selected to allow users the maximum amount of flexibility when choosing the test appliance and test period. To complete the audit, users then clicked the submit button and the tool parsed through consumption data to determine the approximate amount of power that the appliance drew during the designated period. The energy audit tool (*disaggregation*) of the prototype interface is highlighted in Figure 2.

The code for the prototype interface was written in Ruby using the Rails framework and hosted on Heroku, a widely used Ruby platform. Comprehensive data on logins, views of the incentives page, changes to the historical view options, addition or removal of peers to the historical graphs and energy audit submissions were stored in an online SQL database. The empirical study resulted in 1,410 points of clickstream usage data being captured.
2.3.2 Test-bed Building

Monitoring of the test-bed building was conducted using Onset Computing HOBO U30 Data loggers connected to 0-20 A Continental Control Systems current transducers. Six data loggers were installed in the basement of the building on the electrical sub panels for each room with each logger reporting electric current usage for approximately 15 rooms. The data loggers connected to the Onset server every 10 minutes to download current readings in minute intervals by routing through a single wireless router located in the basement. Code was written to use curl—a command line function for transferring data via URL syntax—to pass authentication information to the Hobolink website (Onset hosting website for sensor data), retrieve the cookie produced upon successful login and use that cookie to download the CSV file with the most up to date readings for each data logger. All current values were converted to watts by multiplying by 110 volts and adjusted for room occupancy to obtain per capita power consumption.

The test-bed building was a residential multistory building on the campus of Columbia University in New York City. We had continuous wireless radio access to electricity consumption data for 72 rooms in the test-bed building. The test-bed building contains both double occupancy and single occupancy rooms. The Control Group consisted of 33 double occupancy rooms and 6 single rooms. Only electricity was monitored, therefore adjustments made to the gas radiator based heating were not captured. The six-story building was built prior to World War II and has high ceilings and thick plaster walls. The building has two central courtyards and thus allows for all rooms to receive natural light.
2.3.3 Study Design and Recruitment

Participants were divided into the following two study groups and non-participants made up the control group:

- **Study Group A** – Access to room-level electricity utilization data via the prototype interface adjusted for occupancy and electricity consumption information for participants in their peer network (*normative comparison*).

- **Study Group B** – Access to room-level electricity utilization data via the prototype interface adjusted for occupancy.

- **Control Group** – No access to the prototype interface.

Recruitment resulted in a Study Group A of 38 participants with 23 of these participants logging in to the interface site at least once. Study Group B consisted of 16 participants with all participants logging in to the prototype interface at least once. Only users who logged in at least once to the prototype interface in study group A and B were included in the analysis. The Control Group consisted of 72 residents.

Before recruiting participants, we obtained approval from Columbia University’s Institutional Review Board for the human subjects experiment and all recruitment materials. A recruitment e-mail was sent to users that provided an overview of the experiment. This e-mail emphasized that participating students would have access to their own electricity consumption data and be eligible to redeem reward points for prizes. The potential environmental benefits associated with reducing energy consumption were explicitly omitted from all recruitment materials and in-
person recruitment discussions in order to limit a study group bias towards environmentally conscious residents. Points were earned by reducing electricity consumption and conducting energy audits. If users elected to sign up, a link was provided to a recruitment web site that provided the full consent form detailing the risks and benefits associated with the study. The recruitment web site enabled users to digitally consent to participating in the study and provided a form for participants to nominate friends in the building to participate. Digital recruitment was supplemented with face-to-face recruitment at the test-bed building.

2.3.4 Hypotheses

Our first objective was to establish whether engagement, measured by the number of logins to the prototype interface, was correlated with a reduction in energy usage. The following hypothesis was tested:

*Hypothesis 1: Participants (Study Group A and B) who reduced their electricity consumption relative to the Control Group will have visited the prototype interface more often than participants who increased or maintained their electricity consumption relative to the Control Group.*

If we disconfirm the null hypothesis for Hypothesis 1, then our second objective was to test whether utilization of a feature associated with a design component was correlated with an increase in user logins.

*Hypothesis 2: Participants who utilize; (a) Historical comparison (Study Group A and B), (b) Normative comparison (Study Group A), (c) Incentives (Study Group A and B) or (d)*
Disaggregation (Study Group A and B) will login more than participants who did not utilize the feature.

On their first login, users viewed either positive or negative point balances based on their energy consumption up to that point. The *rewards and penalization* design component was tested by using the point balance at initial login as a proxy to understand the effect that rewards (positive points) and penalization (negative points) had on overall login behavior.

**Hypothesis 3:** The sign (positive or negative) of reward points a participant (Study Group A and B) views upon logging in for the first time will correlate with the number of times a participant logs in to the prototype interface.

### 2.3.5 Study Procedure

Upon signing up for the experiment via face-to-face or electronic recruitment, participants were asked to identify whether other participants within the building were acquaintances, friends, or close friends. This information was used to construct a peer network for each of the participants in Study Group A. The friendship nomination had to be reciprocated in order for a peer to be added to a participant’s network. The study was launched on March 31, 2011, when participants received an e-mail with their username and an initial password. Emails were sent approximately once a week over the study period to encourage users to check their energy use profiles and to redeem accumulated points for non-financial prizes. Additional emails were sent to participants when a member of their peer network redeemed their reward points or conducted an energy audit. Prizes (e.g. gift certificates to local restaurants, energy efficient power strips) ranged in price from 2,000 to 20,000 reward points. Users accumulated or lost 500 points for every kWh
above or below their pre-study consumption levels. The study was concluded on May 12, 2011 with a total study period of 6 weeks.

2.3.6 Data Analysis

The performance of each user was evaluated in terms of the change in consumption relative to the control group for both pre-study and study periods. The pre-study electricity use was then compared to the electricity use during the study period. This was calculated using the following formulas:

$$\Delta_{consumption} = \delta_{study} - \delta_{pre-study}$$

$$\delta_{x} = \frac{\sum_{i=1}^{n} \left[ \frac{P - C}{C} \right]}{n}$$

$\Delta_{consumption} =$ the change in consumption relative to the control group between the pre-study period and the study period

$\delta_{x} =$ the average percent difference between participant consumption ($P$) and control group consumption ($C$) for the study period and the pre-study period ($x$).

$n =$ number of days in time the study period or pre-study period ($x$)

$P =$ average daily power draw per participant in a given room

$C =$ average per capita daily power draw of the control group

The pre-study baseline period consisted of 28 days from February 1, 2011 to February 28, 2011. This pre-study baseline period was chosen so that recruitment (which commenced in early...
March) would have no effect on the captured baseline energy usage. The difference in pre-study and study period values yielded the change in consumption relative to the control group ($\Delta_{\text{consumption}}$).

To evaluate Hypothesis 1, participants in both Study Group A and B were divided into two sub-groups based on their change in consumption. Sub-group 1 contained participants who reduced their consumption and sub-group 2 contained users who increased their consumption over the study period. The number of logins for both groups was compared using the Welch two sample t-test. A p-value below .05 indicated statistical significance in all tests.

Hypothesis 2 was evaluated by dividing participants into two sub-groups based on whether they used a given feature or not. Login values were compared using the Welch two sample t-test to determine if users who used a feature logged in more than users who did not use a feature.

Hypothesis 3 was evaluated using a similar method as Hypothesis 1 and 2, with participants split into two sub-groups based on whether they viewed a positive or negative point total when they logged in for the first time.

Four participants (2 rooms) signed up for the study after the launch date of March 31, 2011 and were allowed to participate, but excluded from all usage data analysis to maintain a consistent time period for all data collected and analyzed during the study. Additionally, any users that logged in for the first time on the final day of the study were excluded from analysis because they could no longer utilize the functionality of the site to make changes in consumption behavior. Login data was parsed to identify logins that occurred within a 30 minute interval so that they could be counted as a single login. This adjustment was made so that logins represented unique visits to the site and did not include repeat logins due to loss of connectivity.
and/or accidental Internet browser closing. It should be noted that the prototype interface was unavailable to users from April 21, 2011 to April 24, 2011 due to an unexpected server failure from the host site Heroku. The server outage affected all participants of the study with no users being able to login during the downtime. Participants were notified via e-mail once the site was operational and encouraged to login and redeem accumulated reward points.

2.4. Results

2.4.1 Hypothesis 1

Results for Hypothesis 1 are provided in Table 2. Users who decreased consumption (i.e., $\delta_x$ values were lower during the study period than the pre-study period) on average logged in to the prototype interface nearly twice the number of times as users who increased their consumption (i.e., $\delta_x$ values were higher during the study period than the pre-study period). A significance value of $p=.028$ provides statistical evidence to reject the null hypothesis of Hypothesis 1 enabling us to compare mean user logins across the two groups.

<table>
<thead>
<tr>
<th></th>
<th>Participants Who</th>
<th>Participants Who</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Reduced Consumption</td>
<td>Increased Consumption</td>
<td></td>
</tr>
<tr>
<td><strong>Mean User Logins</strong></td>
<td>5.13</td>
<td>2.60</td>
<td>.028*</td>
</tr>
</tbody>
</table>

* p<0.05, ** p<0.01, *** p<0.001
2.4.2 Hypothesis 2

Having found statistical support that users reducing consumption visited the prototype interface roughly twice as much as users that increased consumption, we turned to our second objective and examined whether user logins correlated with the use of specific design components. Results of the average number of user logins for Hypothesis 2 are provided in Table 3. Users who utilized historical comparison views visited the site on average nearly 3 times more than users who did not use this component. Additionally, users who utilized the incentives component by visiting the prizes page logged in on average over 3 times more than users that did not utilize this component. Analyses of both of these components carry p-values well below the threshold of p<.05 and therefore, strong evidence exists to reject the null Hypotheses of 2a and 2c. While the analysis of the normative comparison component yielded on average twice the number of logins for users that utilized it, the p-value for this analysis was above the significance threshold of .05. As a result, there is not significant evidence to reject the null Hypothesis of 2b and further research is needed regarding the normative comparison component. Analysis regarding disaggregation revealed that users showed little improvement in the average number of logins if they utilized the component. Therefore, we cannot reject the null hypothesis of 2d.

Table 3: Results of Hypothesis 2

<table>
<thead>
<tr>
<th>Mean User Logins by Utilized Component</th>
<th>Participants Who Used Feature</th>
<th>Participants Who Did Not Use Feature</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Historical Comparison</td>
<td>4.61</td>
<td>1.67</td>
<td>.0009***</td>
</tr>
<tr>
<td>(b) Normative Comparison</td>
<td>5.00</td>
<td>2.40</td>
<td>.12</td>
</tr>
</tbody>
</table>
2.4.3 Hypothesis 3

Results for Hypothesis 3 are provided in Table 4. On average users who viewed positive points during their first login to the interface site visited roughly 2.5 times more than users who viewed negative points. This analysis resulted in a p-value of .0059 and therefore enables us to reject the null hypothesis of 3.

Table 4: Results of Hypothesis 3

<table>
<thead>
<tr>
<th></th>
<th>Participants Who Viewed Positive Points</th>
<th>Participants Who Viewed Negative Points</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean User Logins</td>
<td>4.79</td>
<td>2.10</td>
<td>.0059**</td>
</tr>
</tbody>
</table>

2.5. Discussion

Disconfirming the null hypothesis for Hypothesis 1 allows us to conclude that the correlation between engagement and performance observed in other research fields extends to eco-feedback interfaces. While causation is difficult to prove with purely quantitative data, a statistically significant correlation between reducing one’s consumption and number of site logins was clearly observed. This conclusion establishes logins as a possible metric for measuring the performance of an eco-feedback interface. Current research on the topic of eco-feedback interfaces has been largely limited to non-empirical studies (Jacucci et al., 2009; Wood and
Newborough, 2007) or user surveys (Karjalainen, 2011). The approach taken in this study provides a quantitative alternative by establishing an approach for assessing the efficacy of the design components of eco-feedback interfaces systems in encouraging energy savings through the use of clickstream data.

Using mean user logins as a dependent variable, historical comparison and incentives were supported as key design components of eco-feedback interfaces. The statistically significant result that users who utilized the historical comparison component visited the site nearly 3 times more than their non-utilizing counterparts further corroborates prior conclusions that historical comparison is a key design component of an eco-feedback system’s performance (Fischer, 2008). While the statistically significant results regarding the historical comparison and incentives components could have been a function of their design, the results provide empirical evidence that these components can be used to drive reductions in energy consumption. Moreover, the results of the incentives component corroborate prior research that employed the use of non-financial incentives in eco-feedback systems to illicit a reduction in energy consumption (Jacucci et al., 2009; Petersen et al., 2007). These findings are in contrast to Wood and Newborough (Wood and Newborough, 2007) who concluded that only financial incentives should be included in eco-feedback interfaces. The empirical results of this study provide quantitative justification for the inclusion of both financial and non-financial incentives in future eco-feedback research and eco-feedback interface development.

Past research on normative comparison feedback has shown the potential of this design component to motivate behavior changes and, in turn, reduce consumption (Iyer et al., 2006; Peschiera et al., 2010; Siero et al., 1996). In the context of our study, participants who utilized
normative comparison would have visited the prototype interface more than their counterparts. While our results indicated that users who utilized normative comparison visited the site nearly twice as many times as their non-utilizing counterparts, the usage data did not provide statistically significant evidence to reject the null hypothesis of Hypothesis 2b. Therefore, results are inconclusive regarding normative comparison and further research is required to validate the current literature regarding the importance of normative comparison feedback and substantiate it as a key design component for eco-feedback interfaces.

Our study revealed almost no change in the mean number of logins for users who utilized the disaggregation component of the prototype interface versus for users who did not (Hypothesis 2d). Therefore, results regarding the disaggregation component are inconclusive. A lack of support for the disaggregation component is incongruent with recent research (Abrahamse et al., 2007; Fischer, 2008) that suggested users who have a deeper understanding of appliance specific consumption would reduce consumption and login to the interface more often. This deviation from prior research could be explained by the fact that eco-analytics tools, like the one used in testing disaggregation, require more time investment by users to provide inputs. The large number of inputs required could be viewed by users as being tedious to operate. This assertion is consistent with previous research that indicates users require easy access to information for it to impact their behavior (Attari et al., 2010). Furthermore, this assertion is supported by usage patterns of the eco-analytics tool which revealed that of the 23 times the tool was used correctly, 20 were by users who utilized the tool more than once. This finding extends the current literature (Fitzpatrick and Smith, 2009) by identifying a potential limitation in the implementation of the disaggregation component in eco-feedback systems. Future research on the disaggregation component should focus on whether this component drives reductions in
energy use, methods to streamline interactions with users and the implications such methods would have on user engagement and performance.

The rejection of the null hypothesis of Hypothesis 3 provides statistically significant evidence that the reward points balance presented to a user at first login has a significant impact on the number of times a user returns to the site. Users who viewed positive points on first login were found to visit the site on average about 2.5 times more than their counterparts who viewed negative points on first login. This finding is inconsistent with current literature regarding the rewards and penalization design component that both positive and negative points motivate users to reduce consumption (Jacucci et al., 2009), and therefore, initial point values should have little bearing on login behavior. While Jacucci et al. (Jacucci et al., 2009) advocated the use of penalization as a mechanism to reduce wasteful behavior, they did not address the discouraging factors associated with viewing negative points. Current support in the literature for penalization in real-time electricity markets (Holland and Mansur, 2008) relied on time of day consumption, not necessarily a reduction in overall consumption. Time of use costs may not be viewed by users as a penalty, but more as variable pricing. A lack of support from usage data for the rewards and penalization design component suggests a modification may be necessary.

Drawing from consumer marketing literature in which strictly rewards based loyalty programs (e.g. airline frequent flier miles, grocery loyalty points) have been successful in motivating behavior change in consumers (Gómez et al., 2006; Kivetz and Simonson, 2002), our research suggests that a revision of the rewards and penalization design component may be needed to deemphasize the penalization aspect of the program. The revision could be accomplished by eliminating the ability of users to accumulate negative points so that only positive rewards credit
growth is available. Once users accumulate positive points, then the deduction of points for over consumption could be reintroduced, but at a fraction of the point earning ratio. For example, if a user saves 1 kWh of electricity, the user would earn 1,000 reward points. However, if on a later date the user consumes 1 kWh more of electricity, the user would only lose 500 to 1,000 points and not drop below a zero balance. Determination of the optimal point earning to point losing ratio requires further investigation in future studies.

2.6. Limitations

Our study could have benefited from a larger sample size. However, this would have required outfitting an entire new building with monitoring equipment which was cost prohibitive. Moreover, the sample size was adequate to arrive at statistical significant results for the testing of design component utilization. This study only accounted for electricity usage and failed to capture heating use which is a large part of energy consumption during winter months in the northeast United States. However, gas heat was provided centrally by the building so users would have had a minimum ability to modify their behavior and conserve energy relating to heat. Other limitations of the eco-feedback interface included the accuracy of energy usage monitoring devices. Monitoring devices used in this study did not capture real power or voltage and therefore, energy usage (kWh) was obtained using apparent power and an average voltage of 110 volts. Because residential buildings have largely negligible reactive loads, installing high cost real power monitoring devices would have provided only incremental accuracy improvements. Additionally, manual meter checks showed that our system was generally within 10% accuracy of the utility meters for each room, which was adequate for the purpose of our study.
A limitation regarding studying individual components on the prototype interface was that a minor overlap in functionality between the components did exist (e.g., “network average” on historical comparison graphs). Nevertheless, the component functionalities were independent enough to facilitate conclusive data analysis. Furthermore, results for components that were not supported must be taken as inconclusive because usage data could have been impacted by the idiosyncratic design of these components in the eco-feedback interface studied. In other words, if a lack of support is found for a design component it cannot be concluded that the component does not drive energy savings but that further research is required to make a conclusive argument. While a positive result could also be a function of the design of the studied interface, the result allows for a conclusion that the component has been shown empirically to drive engagement and energy use reductions regardless of idiosyncrasies in design.

A limitation regarding measuring user logins was that roommates could have logged-in together to the prototype interface under one user id and password. Joint logins would have resulted in a lower number of logins being captured as compared to independent users. Because users were individually assigned a secure password and earned and redeemed reward points independently, it is unlikely users shared password information with each other and then participated in joint use. A limitation of conducting usage analysis with clickstream data is that the duration of use for each login is not captured because users do not necessarily logout when they are finished viewing their profile. However, in the context of this study, our analysis was sufficient to establish overall interface engagement. Furthermore, we guarded against the data being skewed as a result of repeated short user logins by treating logins that occurred within 30 minutes of each other as a single visit.
2.7. Conclusion and Implications

The results of this study allowed us to confirm the link between interface engagement and reductions in energy consumption and to add user logins as a metric for assessing the performance of eco-feedback interfaces and associated interface components. Usage data gathered from the prototype interface served as the primary mechanism for assessing key design components of eco-feedback interfaces. The results of a Welch two sample t-test indicated statistical support for hypotheses associated with the *historical comparison* and *incentives* design components. Statistically significant results for the *rewards and penalization* component suggest that a modification to emphasize rewards over penalization may drive further reductions in energy use and requires further attention from researchers. Usage data did not statistically support the *normative comparison* or *disaggregation* design components and therefore results were inconclusive. The *normative comparison* results showed that participants who used this component logged in over twice as frequently as participants who did not; however, the p-value for this finding was not statistically significant. The result was inconclusive and future research is needed to assess whether a statistically significant correlation exists. Participants who used the *disaggregation* component logged in about as frequently as those that did not. Therefore, the results of this component were inconclusive. The tools associated with *disaggregation* design components may benefit from efforts to decrease the number of steps required to receive appliance level energy consumption. However, future research is required to determine whether *disaggregation* in other interfaces drives reductions in energy usage and/or whether streamlining *disaggregation* tools will impact eco-feedback performance.
This study established an approach for utilizing clickstream data to analyze eco-feedback system-level and component-level performance and use. Though results of this experiment cannot be directly applied to other interfaces and further work is needed to better understand user behavioral patterns and incorporate them into eco-feedback interface design, these findings provide an initial view of how interface design can be understood and ultimately improved through the use of web analytics. With governments around the world under fiscal strain, investment in energy efficient building improvements may decrease over the next several years. Because buildings account for the majority of energy use and associated greenhouse gas emissions in the United States and many other countries, eco-feedback systems offer the potential to deliver substantial and predictable long term energy savings at costs considerably cheaper than physical efficiency measures. However, without further research on eco-feedback interface design we run the risk of not maximizing the potential savings from these systems. An improved understanding of how users interact with eco-feedback interfaces to save energy may enable us to reduce energy consumption and help meet the ambitious greenhouse gas emission reduction targets being set by our local and national governments.
Chapter 3

INVESTIGATING THE IMPACT ECO-FEEDBACK INFORMATION REPRESENTATION HAS ON BUILDING OCCUPANT ENERGY CONSUMPTION BEHAVIOR AND SAVINGS

Abstract

In response to rising energy costs and concerns over environmental emissions, researchers and practitioners have developed eco-feedback systems to provide building occupants with information on their energy consumption. While such eco-feedback systems have been observed to drive significant reductions in energy consumption, little is known as to what specific design features of these systems are most motivational. One common feature of eco-feedback systems is the way in which energy consumption is represented to users. In this study, we empirically examine the impact that information representation has on energy consumption behavior by comparing the effectiveness of direct energy feedback versus feedback represented as an environmental externality. A one month empirical study with 39 participants in an urban residential building was conducted. Participants were divided into two different study groups; one group was provided with feedback in direct energy units and a second group was provided feedback in environmental externality units. Results revealed that information representation has a statistically significant impact on the energy consumption behavior of users, and that users receiving eco-feedback as an environmental externality reduced their consumption more than their counterparts who received feedback in direct energy units. This study represents a crucial
first step towards gaining a deeper understanding of how information representation can be leveraged to maximize energy savings.

3.1. Introduction

The built environment is responsible for over 40% of energy consumption in the United States (Energy, 2011) making it a prime target for the application of energy efficiency measures. Pressure is rising to reduce energy consumption in buildings amid increasing energy costs and concerns over environmental emissions. Most efforts to improve energy efficiency in buildings focus on physical “green” retrofits and other energy saving technologies (e.g. energy efficient appliances, upgrades to HVAC systems, energy-efficient lighting). While such physical measures and upgrades can boost energy efficiency substantially, concerns over the long-term effectiveness of such capital intensive retrofits exist due to the “take back effect” (Haas et al., 1998). The “take back effect” occurs when a building occupant adopts inefficient consumption behavior that could reduce or nullify the efficiency gains associated with a retrofit. The installation of energy saving technologies must be accompanied by energy efficient occupant behavior to ensure sustained reductions in energy consumption. Several studies (Azar and Menassa, 2012b; Chen et al., 2012; Yu et al., 2011) have concluded that occupant behavior can have a substantial impact on building energy consumption, and that occupant energy savings have the potential to reduce US emissions by 7.4% with little or no impact on household well-being (Dietz et al., 2009). Moreover, behavior-based efficiency programs have been proven to be among the most cost effective energy efficiency strategies on the market (Allcott, 2010).

Simultaneously, breakthroughs in the fields of information technology and sensor systems have led to the development of devices that allow for energy consumption data to be acquired cost
effectively and less intrusively (e.g., (Berges et al., 2011)). To harness this growing amount of consumption data into efficiency gains, the research community has begun to explore the use of eco-feedback systems. An eco-feedback system provides building occupants with information regarding their historical and current energy consumption. Meta-analytical studies (Abrahamse et al., 2005; Fischer, 2008) of empirical eco-feedback experiments concluded that eco-feedback systems are an effective tool for reducing energy consumption. While several eco-feedback studies (Abrahamse et al., 2007; Allcott, 2010; Brandon, 1999; Grønhøj and Thøgersen, 2011; Peschiera et al., 2010; Peschiera and Taylor, 2012; Petersen et al., 2007; Seligman et al., 1978; Siero et al., 1996; Ueno et al., 2006;; Vassileva et al., 2012; Wilhite and Ling, 1995) have observed eco-feedback systems to drive significant reductions in consumption, there is a paucity of research regarding what specific system design features are steering these reductions. Without this deeper understanding, researchers and practitioners run the risk of designing and implementing eco-feedback systems that fail to maximize energy savings. In this study, we examine a key design aspect of eco-feedback systems, the representation of energy consumption information to occupants, and its impact on observed energy savings.

3.2. Background

Results have been promising for eco-feedback systems implemented in academia and industry with observed energy savings ranging from 2.7%-55% (Abrahamse et al., 2007; Allcott, 2010; Brandon, 1999; Grønhøj and Thøgersen, 2011; Peschiera et al., 2010; Peschiera and Taylor, 2012; Petersen et al., 2007; Seligman et al., 1978; Siero et al., 1996; Ueno et al., 2006;; Vassileva et al., 2012; Wilhite and Ling, 1995). However, this wide range in savings across studies highlights a lack of understanding among researchers and practitioners as to what specific components drive significant savings and why some eco-feedback systems are more successful,
while other are not. Pierce et al. (Pierce et al., 2010) underscore the need for future research that investigates why some systems motivate conservation behavior and others do not. In response, researchers have begun to examine the design of eco-feedback systems in greater detail.

3.2.1 Eco-Feedback System Design

Previous research regarding the design of eco-feedback systems has largely been based on meta-analysis and user surveys. A meta-analytical study by Froehlich et al. (Froehlich et al., 2010) examined over 100 eco-feedback systems and established design guidelines and heuristics for eco-feedback systems in the areas of interface design, feedback frequency and information visualization. Karjalainen (Karjalainen, 2011) extended this work by utilizing a rapid prototyping methodology and user surveys to understand preferences regarding eco-feedback design and found that users valued features such as appliance-specific breakdowns and historical comparison. Other research (Bonino et al., 2012; Strengers, 2011) supplemented previous work by qualitatively examining the preferences of eco-feedback users through surveying methods. A more recent study (Chiang et al., 2012) conducted a laboratory experiment to understand user comprehension of various eco-feedback interface designs. Spot-the-difference task analysis was undertaken to measure accuracy rates and response times for several eco-feedback interface designs. While previous work has provided insight into the design of eco-feedback systems, conclusions from this work have yet to be validated through observed reductions in energy consumption. Thus, a natural extension of eco-feedback design research is to integrate empirical energy consumption data that will allow researchers to analyze and validate established design guidelines and heuristics.
A recent study (Jain et al., 2012) incorporated empirical energy consumption data into the analysis of eco-feedback interface design by assessing the effectiveness of specific interface components in terms of empirically observed savings. This study found that providing occupants with historical comparison visualizations and an incentives feature correlated with reductions in energy consumption. The focus of this study was to correlate interface components to energy savings on the meta-interface level and, as a result, specific design details of the individual components were not analyzed. Subsequently, little is known on how specific design details of eco-feedback systems might impact actual energy consumption behavior. In this study, we aim to explicitly examine a specific design detail – information representation – by conducting an experiment and analyzing comparative differences in real energy consumption data.

3.2.2 Information Representation in Eco-Feedback Systems

Previous work regarding information representation has been limited to survey-based studies or secondary analysis within empirical eco-feedback experiments. Major, eco-feedback studies have utilized one of the following three representative units:

- Direct energy units such as kWh or kW (Grønhøj and Thøgersen, 2011; Jain et al., 2012; Peschiera et al., 2010; Peschiera and Taylor, 2012; Petersen et al., 2007; Wilhite and Ling, 1995)

- Environmental externalities such as associated CO₂ emissions (Grevet et al., 2010; Holmes, 2007; Mankoff et al., 2010; Petkov et al., 2011)

- Monetary units such as US Dollars (Faruqui et al., 2010; Fitzpatrick and Smith, 2009; Grevet et al., 2010; Wilhite and Ling, 1995)
The literature in the area of eco-feedback information representation has not come to agreement on what representative unit is the most effective in driving reductions in energy consumption. Meta-analysis by Wood & Newborough (Wood and Newborough, 2007) found direct energy units to be the most effective, citing that environmental indicators and monetary units are ineffective in encouraging conservation behavior. While direct energy units have been the most popular among eco-feedback studies, pre-trial user interviews conducted by Fitzpatrick (Fitzpatrick and Smith, 2009) indicated that users prefer monetary units over direct energy units and is contradictory to the findings of Wood & Newborough (Wood and Newborough, 2007). Additionally, a survey study (Bonino et al., 2012) found that users have a limited understanding of the kilowatt-hours (kWh) unit. Environmental externalities such as CO₂ emissions have been utilized in some eco-feedback studies, (Grevet et al., 2010; Mankoff et al., 2010) but this unit has been difficult to understand by some users (Fitzpatrick and Smith, 2009; Vassileva et al., 2012). In order to increase comprehension of environmental units, representing energy usage in terms of the “number of trees needed to mitigate CO₂ emissions associated with consumption” was introduced as an alternative by (Holmes, 2007; Petkov et al., 2011; Wood and Newborough, 2007).

The inconsistency and discord within the eco-feedback literature regarding information representation highlights the need for research that explicitly and empirically tests the impact representation has on energy consumption behavior. Previous work identifies that “*the units of display can have a powerful influence on the consumer as they effectively dictate the comprehension, importance and relevance of energy use to associated environmental problems*” ((Wood and Newborough, 2007), p.499). Industry (e.g., Lucid Design Group, C3 Energy) has also begun to implement various forms of information representation in their eco-feedback
products. Yet, neither industry nor academia has explicitly and empirically tested the impact information representation has on the effectiveness of eco-feedback systems. Doing so, would provide a foundation for the effective design of eco-feedback systems and maximize energy savings. Thus, the first objective of this study is to empirically ascertain whether information representation in eco-feedback systems can impact energy consumption behavior of building occupants. The second objective of this study is to characterize the impact two different types of information representation (i.e., environmental units, direct energy units) have on eco-feedback system performance.

3.3. Methodology

3.3.1 Experimental Design and Procedure

In order to empirically examine the impact information representation has on eco-feedback system performance, an experiment was designed with two study groups and a control group. Direct energy units and environmental externality units were tested as part of the study. Residents of the instrumented test-bed building we utilized in the experiment (described in detail in section 3.3.3) do not pay directly for electricity and therefore monetary units were not included in experimental design. This experimental set-up allowed for us to examine the impact eco-feedback had on energy consumption behavior independent of the external motivation to save money. The study groups were designed as follows:

- Study Group A – provided with eco-feedback in direct energy units (kWh)
• Study Group B – provided with eco-feedback in environmental externality units
  (equivalent number of trees required to offset CO₂ emissions associated with their electricity consumption)

• Control Group – not provided with eco-feedback

The study has conducted over 32 days (March 30, 2012 through April 30, 2012). During the study period, an eco-feedback email was sent each Friday to participants in Study Group A and Study Group B (total of 5 emails sent over study period). A more detailed description of the content contained in the eco-feedback emails sent to participants is provided in section 3.3.3.

Recruitment resulted in 21 participants in Study Group A and 18 participants in Study Group B. The Control Group consisted of 39 building residents. Both study groups consisted of college students between the ages of 19-22 years old with an approximately equal proportion of males and females. Prior to recruiting participants, the research team obtained approval from Columbia University’s Institutional Review Board for the human subjects experiment and all recruitment materials. All recruitment materials emphasized participating students would be sent an email once a week detailing their electricity consumption and would be entered in a random drawing to win eco-powerstrips or gift certificates to local restaurants. Any potential environmental benefits associated with participating were omitted from recruitment materials and other communication to avoid a recruitment bias towards environmentally conscious residents. Recruitment was done both electronically and in-person at the test-bed building. Emails were sent to all residents with a link to a recruitment website that allowed potential participants to view the digital consent form and sign-up for the study. In-person recruitment consisted of presenting building residents with a printout of the consent form and having them fill out a short printed form to sign-up. Residents
who opted to participate in the study were randomly placed into either Study Group A or Study Group B.

3.3.2 Hypotheses

In order to ascertain if representation units in an eco-feedback system impacts energy consumption behavior, we tested the following hypothesis:

**Hypothesis 1:** The units in which eco-feedback information is represented will cause participants in Study Group A (direct energy units) and Study Group B (environmental externality) to have statistically distinct changes in energy consumption relative to the Control Group.

If we disconfirm the null hypothesis for Hypothesis 1, then our second objective is to characterize the performance (i.e., energy savings) of the eco-feedback system relative to each type of representation unit. Previous research has indicated that direct energy units are difficult to comprehend by users (Fitzpatrick and Smith, 2009; Vassileva et al., 2012) and that providing feedback in terms of tangible units, such as “trees,” may increase user comprehension and energy savings (Holmes, 2007; Petkov et al., 2011). Therefore, we tested the following hypothesis:

**Hypothesis 2:** Participants in Study Group B (environmental externality) will conserve more energy on average than participants in Study Group A (direct energy units) relative to the Control Group.
Response-relapse patterns\(^1\) have been observed in a previous eco-feedback study (Peschiera et al., 2010) that utilized emails as a method to convey feedback information. Since we utilized a similar email based eco-feedback system, we expected similar response-relapse effects to be present in our own study. In order to more clearly delineate performance (i.e., energy savings) of each type of representation unit from expected response-relapse patterns, cumulative savings were calculated and the following hypothesis was tested:

**Hypothesis 3:** Participants in Study Group B (environmental externality) will cumulatively conserve more energy than participants in Study Group A (direct energy units) relative to the Control Group.

### 3.3.3 Test-bed Building and Eco-Feedback System Utilized

The instrumented test-bed building is a six story, 69 unit residential building on Columbia University’s campus in New York City. Monitoring instruments captured the energy consumption of each residential unit in the test-bed building continuously from September 2011 until June 2012. The building has approximately 150 residents with a living density of about 18 m\(^2\) per resident. Residential units in the building are either single or double occupancy and have access to natural light via a central courtyard, alleyways or the street. Each unit is comprised of a kitchen, bathroom, living area and bedroom area and is representative of a typical apartment unit in the New York City urban area. The building is over 100 years old and has high ceilings and thick plaster walls.

\(^1\) We define a response-relapse pattern to be when a user decreases energy consumption in response to an eco-feedback email but relapses back to previous consumption levels in the subsequent days after the email.
For the execution of this study, an email based eco-feedback system was designed, built and utilized. The eco-feedback system consisted of three main components: data capture, data processing and data delivery. Each of these components and how energy consumption data flows between them is depicted in Figure 4.

Figure 4: Schematic of Eco-Feedback System Utilized in Study

Data capture was achieved using Onset Computing HOBO U30 data loggers connected to Continental Control Systems current transducers (range: 0-20 amps). Current transducers captured current data from electricity meters corresponding to each individual unit in 5 minute intervals and transferred this data to one of six data loggers. Data loggers wirelessly pushed amperage data from all electricity meters to a web server every hour. Custom SQL code was written to process and parse amperage values for each unit by first multiplying by 110 volts to calculate apparent power and then taking a Riemann sum of apparent power values over each
day to obtain energy consumption values (kWh). Energy consumption values for each unit were then adjusted for occupancy to obtain consumption values for a single participant. For participants in Study Group B, values were converted to the “number of trees required to offset emissions associated with their electricity consumption in one year” by multiplying by a factor of .151 for each kWh consumed. This factor was derived from values published by the U.S. Environmental Protection Agency on the average metric tons of carbon sequestered by an urban tree in one year (.0039 metric tons of CO$_2$ per tree each year) and the average emissions of home electricity consumption in the United States (1,301.31 lbs or 590.26 kg of CO$_2$ per MWh consumed) (U. S. Environmental Protection Agency, 2011). Final electricity consumption values and environmental externality values were exported to a comma-separated value (CSV) file and imported into an email distribution server (Mail Chimp). The email server populated the custom fields in HTML based eco-feedback emails (i.e., first name, consumption values) and sent personalized eco-feedback emails to all participants on each of the five Fridays in the study period.

Each eco-feedback email contained information on a participant’s energy consumption in the preceding week and their to-date total consumption from the start of the school year (September 1). The to-date total consumption was provided so that participants could comprehend how their study period usage factored into their cumulative school year consumption. Participants in Study Group A only received feedback in kWh and participants in Study Group B only received feedback in the number “trees needed to offset emissions”. Each email contained two energy saving tips for reducing energy consumption that were chosen to reflect realistic efficiency opportunities (e.g., reducing standby power, turning off lights, adjusting refrigerator cooling
settings) available to residents of the test-bed building. Participants in study groups A and B received the same energy saving tips each week to maintain consistency.

3.3.4 Data Analysis

Energy savings was evaluated for each user by determining the change in energy consumption relative to the control group between the study ($\delta_{\text{study}}$) and pre-study ($\delta_{\text{pre-study}}$) periods. The pre-study period was taken as the month of February (29 days) to ensure that recruiting efforts which commenced in March did not influence the energy consumption of building residents during the pre-study period. Energy savings were evaluated relative to the control group to normalize consumption data for external factors, such as weather, daylight hours and the day of the week on which eco-feedback emails were sent. Overall, Equation 1 calculates the change in consumption ($\Delta_{\text{consumption}}$) between the study and pre-study periods as a percent difference. Equation 2 calculates the cumulative change in consumption ($\Delta_{\text{consumption,cum}}$) between the study and pre-study period in terms of absolute kilowatt-hours (kWh). Both Equation 1 and Equation 2 control for the day of the week (i.e., Monday) by evaluating consumption for a day in the study period to the corresponding day of the week in the pre-study period (see Equation 5 and Equation 6). Equation 3 and Equation 4 evaluate the energy consumption relative to the control group for the study period and Equations 3a and 3b evaluate energy consumption relative to the control group for the pre-study period.

**Equation 1**

$$\Delta_{\text{consumption}}(\%) = \delta_{\text{study}} - \delta_{\text{pre-study}}$$
Equation 2

\[ \Delta_{\text{consumption,cum}} \text{(kWh)} = \delta_{\text{study,cum}} - \delta_{\text{pre-study,cum}} \]

\( \delta_{\text{study}} \) is the percent difference in consumption for a given day in the study period calculated using Equation 3. \( \delta_{\text{study,cum}} \) is the absolute (kWh) difference in consumption for a given day in the study period calculated using Equation 4. \( \delta_{\text{pre-study}} \) is the average percent difference in consumption for a day of the week in the pre-study period calculated using Equation 5. \( \delta_{\text{pre-study,cum}} \) is the average absolute (kWh) difference consumption for a day of the week in the pre-study period calculated using Equation 6.

Equation 3

\[ \delta_{\text{study}} = \frac{P-C}{C} \]

Equation 4

\[ \delta_{\text{study,cum}} = P - C \]

Equation 5

\[ \delta_{\text{pre-study}} = \frac{\sum_{i=1}^{n} \left( \frac{P-C}{C} \right)}{n} \]

Equation 6

\[ \delta_{\text{pre-study,cum}} = \frac{\sum_{i=1}^{n} (P-C)}{n} \]

\( P \) is a participant’s consumption adjusted for occupancy. \( C \) is the average consumption of the control group. \( n \) corresponds to the number of each day of the week in the pre-study period.
(n=4). The cumulative energy savings in kWh (Δ_cumulative) for each participant was calculated using Equation 7.

**Equation 7**

\[ \Delta_{\text{cumulative}} = \sum_{i=1}^{d} \Delta_{\text{consumption, cum}} \]

\(\Delta_{\text{consumption}}\) is as described above in Equation 1 and is calculated in terms of kWh using Equation 3 and Equation 5. \(d\) corresponds to a given day in the study period (i.e. March 30 = 1, April 30 = 32).

The change in consumption (\(\Delta_{\text{consumption}}/\Delta_{\text{consumption, cum}}\)) for Study Group A and Study Group B were found to be homoscedastic (having equal variances); hence, a statistical comparison of the two groups was performed using the Student’s t-test to test all hypotheses. The Student’s t-test is a variant of the Welch’s t-test and accounts for the homoscedastic properties observed in the data. This procedure is based on a method established by Peschiera et al. (Peschiera et al., 2010) and utilized by several empirical studies thereafter. A p-value below .05 indicated statistical significance in all tests.

**3.4. Results**

**3.4.1 Hypotheses 1 and 2**

A plot of the change in consumption relative to the Control Group (\(\Delta_{\text{consumption}}\)) by day for Study Group A and Study Group B is provided in Figure 5. Results of the statistical analysis are provided in Table 5. The average change in consumption of Study Group A and Study Group B during the study period are shown to be statistically distinct from each other (\(p\text{-value} = .013\))
allowing us to reject the null hypothesis for Hypothesis 1. Moreover, the analysis shows that on average Study Group B reduced consumption by 10% while Study Group A increased consumption by 18% over the study period allowing us to reject the null hypothesis for Hypothesis 2.

**Figure 5: Plot of Change in Consumption ($\Delta_{\text{consumption}}$) by day for Study Group A and Study Group B**

**Table 5: Results of Hypothesis 1 and 2**

<table>
<thead>
<tr>
<th></th>
<th>Study Group A</th>
<th>Study Group B</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Change in Consumption ($\Delta_{\text{consumption}}$) Over Study Period</td>
<td>18%</td>
<td>-10%</td>
<td>.013</td>
</tr>
</tbody>
</table>
3.4.2. Hypothesis 3

A plot of the cumulative energy consumption relative to the Control Group ($\Delta_{cumulative\_cum}$) for Study Group A and Study Group B is provided in Figure 6. Results of the statistical analysis are provided in Table 6. Results indicate that each person on average in Study Group B reduced consumption by 1.84 kWh while Study Group A increased consumption by 5.79 kWh ($p$-value of .017) allowing us to reject the null hypothesis for Hypothesis 3.

![Figure 6: Plot of Cumulative Energy Consumption Relative to the Control Group ($\Delta_{cumulative}$) by day for Study Group A and Study Group B](image-url)
Table 6: Results of Hypothesis 3

<table>
<thead>
<tr>
<th></th>
<th>Study Group A</th>
<th>Study Group B</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Energy Consumption (Δ_{cumulative}) Over Study Period</td>
<td>+5.79 kWh</td>
<td>-1.84 kWh</td>
<td>.017</td>
</tr>
</tbody>
</table>

3.5. Discussion

The results of this study indicate that information representation in eco-feedback systems can have a significant impact on the energy consumption behavior of users utilizing such systems. In our experimental set-up, we controlled for the most common external motivational factor to save energy (i.e., monetary savings); thus, our results are highly indicative of the internal motivation to reduce consumption from eco-feedback information. Disconfirming the null hypothesis for Hypothesis 1 provides empirical evidence to validate the literature based arguments made by Wood & Newborough (Wood and Newborough, 2007) regarding the impact information representation has on the effectiveness of eco-feedback systems. By linking information representation to actual changes in energy consumption, results from this experiment also extend the findings of previous studies (Bonino et al., 2012; Chiang et al., 2012; Karjalainen, 2011; Petkov et al., 2011) beyond the examination of user preferences and into the impact information representation has on actual eco-feedback effectiveness. Moreover, this experiment contributes to the growing body of knowledge regarding eco-feedback design (Froehlich et al., 2010; Bonino et al., 2012; Chiang et al., 2012; Karjalainen, 2011) by incorporating the analysis of empirical energy consumption and by deepening our understanding of a specific design detail (i.e., information representation) as called for by Pierce et al. (Pierce et al., 2010).
Rejecting the null hypothesis for Hypothesis 2 allows us to conclude that users who received eco-feedback in terms of the environmental externality “trees needed to offset emissions” (Study Group B) on average conserved more energy than their counterparts (Study Group A) who received eco-feedback in the direct energy units of kWh. Kilowatt-hours (kWh) has been the default and most commonly utilized representation unit in eco-feedback studies (Grønhøj and Thøgersen, 2011; Jain et al., 2012; Peschiera et al., 2010; Peschiera and Taylor, 2012; Petersen et al., 2007; Wilhite and Ling, 1995). Yet, in our empirical experiment participants who received feedback in kWh (Study Group A) on average increased consumption by 18% while those who received feedback in the more relatable units of an environmental externality decreased consumption by 10%. Our results corroborate previous research (Bonino et al., 2012; Fitzpatrick and Smith, 2009) that indicated users have a limited understanding of kWh due to its scientific origin and abstract qualities (i.e., users can not visualize a kWh). This results also reinforces the findings of previous research (Fitzpatrick and Smith, 2009; Vassileva et al., 2012) that building occupants have limited comprehension of CO₂ emissions as a representation unit by users due to its own abstract qualities. Therefore, based on our results we postulate that representing eco-feedback through the proxy “trees needed to offset emissions” as introduced by Holmes, 2007; Petkov et al., 2011; Wood and Newborough, 2007) is a viable alternative to the abstract scientific units of kWh or CO₂ emissions. The metric of “trees” is a commonly known object that can be easily visualized by users to get a tangible representation of their changes in energy consumption. Previous work (Wood and Newborough, 2007) has raised concerns that conversion factors to environmental metrics, such as “trees”, are often based on arbitrary conversions and therefore users may question their accuracy. However, our results indicate that this issue can be mitigated by utilizing published conversion factors from reputable sources (e.g.,
U.S. Environmental Protection Agency) and by maintaining a consistent conversion factor throughout the execution of a study. Historical comparison has been shown to be one of the most effective tools in driving energy reductions (Jain et al., 2012) and maintaining a consistent conversion factor allows users to make accurate historical comparisons independent of potential issues surrounding conversion factor accuracy.

Surprisingly, results revealed that on average Study Group A increased its consumption during the study despite receiving eco-feedback emails and the same energy saving tips as Study Group B. This unexpected result led us to take a closer examination of the energy consumption plot in Figure 5. We found response-relapse effects to eco-feedback emails (similar to those observed in (Peschiera et al., 2010)) had occurred in both study groups. Eco-feedback emails were sent on the following five dates: 3/30, 4/6, 4/13, 4/20, 4/27 and are indicated in Figure 5 and Figure 6 by solid point markers in each line plot. The plots in Figure 5 generally follow the following pattern: energy consumption drops in the three days after an eco-feedback email is sent and then subsequently rises over the next four days. Study Group B can be seen to more tightly follow such response-relapse patterns but patterns are also visible in Study Group A. Study Group A can be observed to respond to the eco-feedback emails and reduce consumption enough to start saving energy (i.e., 4/6 to 4/10) but unable to sustain this level of conservation beyond a few days. We postulate that this result was due to the fact that the abstract unit of kWh may have lacked sufficient meaning to the participants in Study Group A to engender long-term engagement. Previous research (Peschiera et al., 2010) has raised concerns regarding the long-term effectiveness of eco-feedback systems due response-relapse patterns. Because savings are experienced for short periods when response-relapse patterns are present, it is unclear whether any cumulative savings occur over the study period.
The cumulative usage for each study group ($\Delta_{\text{cumulative}}$) in Figure 6 clearly indicates that Study Group B maintains a net savings through the entire study period. Specifically, Study Group B cumulatively used 7.63 kWh less per capita than Study Group A over the study period. By disconfirming the null hypothesis for Hypothesis 3, we can conclude that Study Group B cumulatively outperformed Study Group A despite observations of short term response-relapse patterns. More importantly, results indicate that Study Group B saved energy overall and the representation unit of “trees needed to offset emissions” was more effective in eliciting cumulative savings than the unit kWh provided to Study Group A. This conclusion extends the research on response-relapse patterns by analyzing the impact of information representation on cumulative eco-feedback system performance in relation to response-relapse patterns. Previous work (Pierce et al., 2010) has questioned the long-term effectiveness of eco-feedback to drive savings. The results of this study provide empirical evidence to illustrate that savings are not diminished due to patterns such as response-relapse when the environmental proxy “trees” is used to convey eco-feedback to participants. Furthermore, the results of Hypothesis 3 support our postulation that the environmental externality unit of “trees” is a viable proxy for the default representation unit of kWh currently being utilized in most eco-feedback systems and can drive long-term energy savings.

3.6. Limitations

We acknowledge that our study could have benefited from a larger sample size. However, the sample size utilized was adequate to obtain statistically significant results and expanding our study’s sample size would have required outfitting a new building with energy monitoring devices that were cost prohibitive. A limitation regarding the email based eco-feedback system
was that user engagement among participants was difficult to gauge. While it is possible that one study group could have had a higher user engagement than the other, analysis of the limited engagement data (i.e., the number of email “opens”) captured by our email distribution server indicated that engagement was comparable across the randomly chosen study groups.

3.7. Conclusions and Future Research

Overall, this work empirically establishes that information representation in eco-feedback systems can have a significant impact on energy consumption behavior and establishes the environmental proxy of “trees needed to offset emissions” as a viable alternative to current units (e.g., kWh, CO₂ emissions) utilized in eco-feedback systems. This study represents a crucial first step to settle the current discord in the eco-feedback literature regarding information representation by analyzing empirical energy consumption data. The methodology established in this paper provides a first pathway toward a more holistic analysis of eco-feedback system design by incorporating empirical energy consumption data. It also allowed for the validation of conclusions from previous user surveys and laboratory experiments.

The results of this study have important implications for how we approach eco-feedback system design and the use of information representation in eco-feedback systems. Information representation has been acknowledged to be an important aspect of eco-feedback systems, yet little research exists that empirically and explicitly tests it. The authors hope that the findings from this paper will spark dialogue among researchers and practitioners regarding information representation leading to future studies that will extend and expand the results and methodology presented in this paper. Future research should aim to simultaneously employ user surveying techniques, empirical experimentation and real energy consumption data to analyze not only
information representation but other aspects of eco-feedback system design. Through the use of empirical experimentation and observed energy savings data we can validate currently established design heuristics and begin to resolve the current discord in the eco-feedback design literature.

The results of this work also have implications for the extension of eco-feedback systems to commercial buildings. Our experimental set-up controlled for monetary incentives of participants to reduce consumption. Analogously, occupants of commercial and institutional buildings most often do not pay directly for their own electricity usage. Providing eco-feedback to commercial building occupants could be a valuable tool for building managers and owners to intrinsically motivate workers to decrease energy consumption and should be explored in future studies. Eco-feedback systems have the potential to make a substantial impact on the energy consumption of buildings, but maximizing their potential will require continued empirical research and analysis. If designed effectively, eco-feedback systems combined with other energy efficiency measures could prove to be the mechanism of change required to foster our transition to a more sustainable energy society.
Chapter 4

CAN SOCIAL INFLUENCE DRIVE ENERGY SAVINGS? DETECTING THE IMPACT OF SOCIAL INFLUENCE ON THE ENERGY CONSUMPTION BEHAVIOR OF NETWORKED USERS EXPOSED TO NORMATIVE ECO-FEEDBACK

Abstract

Eco-feedback systems provide a significant opportunity to reduce energy consumption. Previous studies have demonstrated a link between providing users with socially contextualized feedback on their energy consumption and reductions in energy use. Yet, the question—can social influence drive energy savings—remains unanswered. In this paper, we develop an algorithmic approach based on stochastic and social network test procedures to assess whether social influence impacts energy consumption behavior and apply the approach to an empirical data set of users exposed to unit-level socially contextualized feedback. We conducted a 47-day empirical experiment in a New York City midrise residential building occupied by students to capture energy consumption and user interaction data for participants in self-identified social networks. Social influence effects on peer network energy consumption were successfully characterized and isolated using adapted social network tests. These results indicate that future research should focus on how social influence and social networks can be leveraged to maximize savings in energy conservation programs.
4.1. Introduction

Rising energy costs and increased pressure to reduce carbon emissions have made energy efficiency a centerpiece of global policy debate. Because building energy usage accounts for over 40% of total consumption in the United States (Energy, 2011) and a significant portion of consumption in other countries, the built environment will play an important role in maximizing savings from efficiency measures. Efficiency measures in buildings have traditionally concentrated on physical improvements, but researchers have observed a phenomenon known as the “take back” effect where energy savings realized through physical improvements may be severely diminished by a corresponding increase in inefficient behavior by the consumer (Haas et al., 1998). For example, if a consumer installs an energy efficient compact fluorescent light bulb but then leaves the bulb on longer than before, then the energy savings associated with the new light bulb may be diminished. Therefore, effective realization of sustained energy savings may require a coupling of infrastructural modifications with behavioral interventions.

Behavioral interventions that promote energy efficiency provide significant opportunities to reduce consumption and associated carbon emissions. Recent work has shown that behavioral interventions have the potential to reduce carbon emissions by 7.4% in the United States (Dietz et al., 2009). Accordingly, a recent article in Science calls for increased effort to understand the dynamics behind such behavior-based energy efficiency programs (Allcott and Mullainathan, 2010). Past research has also demonstrated that providing users with eco-feedback—information regarding their current and historical energy consumption levels—can effectively motivate energy efficient behavior (Fischer, 2008; Kang et al., 2012; Wilhite and Ling, 1995). Several studies (Iyer et al., 2006; Mankoff et al., 2010; Peschiera and Taylor, 2012; Peschiera et al.,
2010; Siero et al., 1996) have incorporated a normative comparison component within an eco-feedback system that allows users to compare their energy usage with their peers and neighbors. The success of normative eco-feedback relies on the premise that a user is influenced by actions of others in his/her social network.

While prior studies have found correlations between energy savings and normative comparisons, the inherent drivers motivating the observed energy conservation behaviors of eco-feedback system users are still unknown. To provide a foundation for better understanding motivational drivers, it is thus necessary to investigate beyond correlative statistics and explore if social influence has a direct impact on energy conservation. In this paper, we establish a technique based on stochastic and social network test procedures to detect social influence in social networks of users exposed to eco-feedback and apply the technique to energy consumption and user interaction data collected from a 47 day empirical eco-feedback experiment.

4.2. Background

Thus far, studies (Bonino et al., 2011; Mahapatra and Gustavsson, 2009) that have examined the impact of social influence on energy conservation have relied on user surveys as the primary data source. However, a recent field experiment (Nolan et al., 2008) revealed that user surveys can be unreliable in determining the extent to which influence plays a role in conservation. The field experiment found that social effects engendered the greatest conservation behavior change despite respondents rating normative information as the least motivating factor for their conservation behavior. Therefore, research studying the role of influence needs to expand beyond user surveys and incorporate real energy consumption data in order to understand the underlying mechanisms driving conservation efforts. Eco-feedback provides a platform to
capture such energy consumption data, but new innovative methods to analyze these data are required to gain a deeper understanding of the role of social influence in engendering energy conservation.

4.2.1. The Impact of Eco-Feedback and Normative Comparison on Energy Consumption Behavior

An early empirical residential eco-feedback study (Seligman et al., 1978) was among the first to highlight the role that user behavior can play in energy consumption. Savings in this study were significant, ranging from 10.5% to 15.7%, and demonstrated that behavior change can play a major role in reducing consumption. Later empirical experiments (Ellegård and Palm, 2011; Fawkes, 1989; Ueno et al., 2006; Van Houwelingen and Van Raaij, 1989) reinforced the observations of Seligman et al. (Seligman et al., 1978) and provided insight into the effects that goal-setting and tailored eco-feedback have on energy use behavior. More recently, a large scale study (Vassileva et al., 2012) of 2,000 households and a meta-analytical study (Faruqui et al., 2010) of utility eco-feedback programs concluded that users respond well to eco-feedback with reported energy savings of 15% and 7%, respectively.

Numerous studies (Brandon, 1999; Petersen et al., 2007; Siero et al., 1996) have expanded eco-feedback to include a normative comparison component that provides users with information regarding the energy consumption of their peers. The savings observed from these expanded studies have been as high as 55%. It should be noted that savings observed in this study’s data-set are consistent with previous findings (users who utilized normative comparison reduced consumption by 5% from pre-study levels). A study (Jain et al., 2012) regarding user interface design of eco-feedback systems also suggests that normative comparison is an effective
component in driving energy use reductions. Although these studies provide further evidence to support normative comparison as an eco-feedback tool for reducing consumption, they fall short of defining the impact of normative comparison on a per user level. Without this level of granularity, it is difficult to ascertain what specific factors are driving the success of normative eco-feedback systems in modifying user behavior.

The emergence and widespread use of online social networking provides researchers with new tools to explore the effects of normative comparison on an individual basis. Several studies (Grevet et al., 2010; Mankoff et al., 2010; Mankoff et al., 2007) have successfully elicited energy savings by integrating online social networking tools with eco-feedback systems. In particular, a study by Peschiera et al. (Peschiera et al., 2010) combined social networking tools and eco-feedback into a single web interface. This interface allowed users to directly compare their energy consumption with others in their social network. The study revealed that normative feedback is more effective than purely historical feedback in yielding energy savings. A more recent study (Peschiera and Taylor, 2012) expanded on this result by analyzing the network position of users in a social network relative to their energy consumption. The authors observed a correlation between the social position of a user in the network and the amount of energy they conserved, finding that the number of social connections of a user is positively correlated to the amount of energy the user conserves. While this correlation allows for the conclusion that social network effects impact consumption, it does not isolate the role of social influence (defined in Table 1) from other network effects. Observed correlations between energy use reductions and network position could be the result of other social network-related effects, such as homophily, that are described in detail in the next section of this paper. For this reason, this study expands upon previous work by investigating the time dependency of energy consumption on the level of
an individual action to allow for the differentiation of social influence from other social network-related effects.

Additionally, recent building energy simulations (Anderson et al., 2012; Azar and Menassa, 2012a; Chen et al., 2012) have been built based on these observed correlations and assume that when users interact they will inherently influence each other to change their consumption behavior. Yet, empirical evidence validating that users can influence each other’s consumption behavior has not been clearly observed by researchers. New methods are therefore required to analyze energy consumption data to determine if social influence actually plays a role in the energy consumption of users. Without this deeper understanding of what is motivating users to conserve energy, researchers and policy makers will be limited in their ability to effectively optimize energy policies and eco-feedback systems to reduce consumption.

4.2.2. Social Network Effects

Social network effects have been studied by researchers in computer science and social science extensively. The three main types of network effects—homophily, confounding factors, and social influence—and an example of how each effect could impact energy consumption are described in Table 7 (adapted from (Anagnostopoulos et al., 2008; Sun and Tang, 2011)).
Table 7: Types of Network Effects, adapted from (Anagnostopoulos et al., 2008; Sun and Tang, 2011)

<table>
<thead>
<tr>
<th>Network Effect</th>
<th>Definition</th>
<th>Energy Consumption Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homophily</td>
<td>A user tends to create relationships with other users who share similar characteristics</td>
<td>A user creates a relationship with a user who also enjoys computer gaming causing them to use their computer the same amount and have similar energy consumption</td>
</tr>
<tr>
<td>Confounding Factors</td>
<td>A user is exposed to similar external factors or stimuli as others in their social network</td>
<td>Two users in the same social network have the same work schedule causing them to adopt similar patterns of energy use and, as a result, to use similar amounts of energy</td>
</tr>
<tr>
<td>Social Influence</td>
<td>A user’s actions are triggered by the actions of another user in their social network</td>
<td>A user uses less energy because they observe his/her friend to be using less energy</td>
</tr>
</tbody>
</table>

By definition, the network effects of homophily and confounding factors are governed by users’ characteristics and external influences, rather than peer-to-peer interactions. User characteristics and external influences can change at any time and are independent of peer interactions in a network. Therefore, network effects attributed to homophily and confounding factors do not depend on when a peer interaction takes place. On the contrary, social influence is driven by peer-to-peer interactions and therefore is time dependent on these interactions. Because user characteristics and external influences are extremely difficult to modify and optimize, researchers have concentrated their efforts on optimizing social influence to facilitate the spreading of information (Bharathi and Kempe, 2007; Kempe et al., 2003; Wang et al., 2012). In the case of an eco-feedback system, we aim to maximize the spread of information about conservation measures users can take to reduce energy consumption across everyone in the system.

By leveraging social influence, researchers can substantially increase the efficacy of eco-feedback systems leading to long-term sustained reductions in energy consumption. For this
reason, this study aims to take the first step in gaining a deeper understanding of the impact that social influence has on driving energy consumption reductions in users exposed to normative eco-feedback.

4.3. Methodology

4.3.1. Tests for Social Influence

In order to determine if social influence impacts the energy use of users exposed to eco-feedback, we adapted two social network data tests for longitudinal energy consumption data: the shuffle test and edge-reversal test. While both the shuffle test (Anagnostopoulos and Brova, 2011; Anagnostopoulos et al., 2008; Sun and Tang, 2011) and the edge-reversal test (Anagnostopoulos et al., 2008; Christakis and Fowler, 2007) have been utilized by previous studies to establish social influence, the shuffle test has been shown to overestimate the presence of social influence when the social ties between users are symmetric\(^2\) (Aral et al., 2009) and the edge-reversal test has been shown to overestimate when significant friendship attrition\(^3\) occurs in the network (Noel and Nyhan, 2011). Analysis of the network data revealed that users formed ties with users in other friendship clusters and that social tie formation did not follow any particular pattern that would lead to symmetry. It was unlikely that significant friendship attrition occurred in our data set since the duration of the study provided a limited period for friendships to be dissolved. Nonetheless, to mitigate any potential overestimation errors and to further validate our results, we apply both tests independently to our energy consumption and user interaction data set.

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\(^2\) Symmetric social ties occur when users form friendships in a symmetrical pattern. The most common form of symmetric social ties occurs when users form an insular cluster in which users are all connected.

\(^3\) Friendship attrition occurs when friendships between users are not maintained over time.
4.3.2. Hypotheses

Hypothesis 1a: Social influence impacts the energy consumption behavior of users exposed to normative eco-feedback (utilizing the Shuffle Test).

Hypothesis 1b: Social influence impacts the energy consumption behavior of users exposed to normative eco-feedback (utilizing the Edge-Reversal Test).

4.3.3. Shuffle Test

The shuffle test relies on the time dependence characteristic of social influence to distinguish it from other effects. Previous studies (Anagnostopoulos and Brova, 2011; Anagnostopoulos et al., 2008; Sun and Tang, 2011) make the assumption that once a user is exposed to normative information, a permanent behavior change is made (i.e. adopting a photo tag on Flickr). However, users exposed to eco-feedback have been observed to exhibit response-relapse patterns (Peschiera et al., 2010) in regards to energy behavior change and therefore this assumption must be modified. For eco-feedback experiments, social influence is more accurately modeled as being event dependent, with each event representing when a user views peer consumption information. An example of this adapted shuffle test is provided in Figure 7.
In the figure, for simplification we define set $D$ as five sequential days and $t_e$ as the day on which a user $i$ utilizes the normative eco-feedback feature ($e$). $C_i(t)$ is defined as the consumption of user $i$ on day $t$ and $\Delta_i(t)$ is defined as the change in consumption between days ($t-1$) and ($t+1$). If the energy consumption patterns are event independent and influence has no effect on consumption, then there would not be a difference between the probability of an observed peer interaction yielding a change in energy consumption and the probability of observing a change in energy consumption over a randomly selected day ($t_r$) in the set $D$. By testing the consumption changes at times when normative treatment occurred ($t_e$) against a randomized set of event times in the consumption data set, we can determine if a user’s consumption change is dependent on normative feedback events. If consumption changes were dependent on a normative feedback event, it would indicate that social influence plays a role in the energy consumption behavior of users.

4.3.4. Edge-Reversal Test

The edge-reversal test is premised on the assumption that social influence only travels in the direction of information flow, while homophilic and confounding effects can travel in both
directions (Anagnostopoulos et al., 2008; Christakis and Fowler, 2007). In Figure 2, user A views the consumption information of users B and C.

![Diagram](image)

If: \( P_{\text{norm}}(A \text{ increases}) = P_{\text{reversed}}(B \text{ and } C \text{ increases}) \)

Then: social influence would not have an effect on the energy consumption behavior

**Figure 8: Adapted Edge-Reversal Test**

This information flow is modeled by two directional edges pointing from users B and C to user A, as shown on the left in Figure 8. If the edges were hypothetically reversed as on the right in Figure 8, then influence has no effect on consumption if the probability that user A would increase consumption would be equal to the probability that user B and C would increase consumption. This probability equivalence would also hold for a decrease in consumption. By comparing the cumulative distribution functions of consumption patterns for a normal and edge-reversed data set we can establish if probabilities are modified as a result of edge-reversal. A result showing that the probabilities have changed would indicate that directional effects are present and therefore social influence plays a role in the energy consumption patterns of users.

4.3.5. Recruitment and Study Design

Before recruitment of participants commenced, approval for a human subjects experiment was obtained from Columbia University’s Institutional Review Board. Recruitment was conducted
via email and face-to-face communication and resulted in a total of 38 participants. The sample from which recruitment took place was comprised of adults between the ages of 18-23 years old with a relatively even ratio of males to female. Students from all backgrounds and fields of study were represented in the sample due to the university’s effort to diversify each residential building. Participants were provided with an overview of the experiment and given an opportunity to sign-up for the study. All recruitment material emphasized that participating in the experiment was optional and that students would have access to their own electricity consumption data. Any potential environmental or social benefits associated with reducing and sharing energy consumption were omitted from all recruitment materials. Full consent forms were provided in either paper or digital format to all users who elected to sign-up for the study. During the sign-up process, participants were asked to identify friends and acquaintances in the building. Relationships were confirmed by both participants in order to ensure reciprocity among the users. This information was used to enable the normative feedback components of the online user interface. An e-mail was sent to each user at the start of the study with log-in information and a weekly reminder e-mail was sent encouraging them to visit the eco-feedback interface. It should be noted that residents who did not participate in the study remained in the building during the data collection period.

All 38 participants in the study were given access to an online web interface where they could view both individual and normative energy consumption eco-feedback. A total of 17 users logged into the interface and utilized the normative eco-feedback feature resulting in an uptake rate of 44.7% for the normative feature (i.e., 21 users did not utilized the normative eco-feedback feature). Within the web interface, users could view their historical energy usage graphically in kWh for the previous 24 hours (by hour), the last week (by day), or for all days to date. In each
of these historical views, users had the option to enable the normative eco-feedback feature by clicking to overlay a peer’s consumption information over their own in the selected view. Clicking to add a peer’s consumption and subsequent interaction between participants was initiated by each user and not controlled by study administrators. Additionally, a line indicated the “building average” in the graph presented to users. Figure 9 illustrates the type of historical and normative feedback provided to users. For a more detailed description and additional screenshots of the online eco-feedback interface see Jain et al. (Jain et al., 2012) and Gulbinas et al. (Gulbinas et al.). Only users who utilized the normative feedback feature were included in this analysis, since only these users were subject to social influence effects from peers.

Figure 9: Screenshot of Historical and Normative Feedback Provided to Users
4.3.6. Test-Bed Building

Electricity consumption (i.e., plug-loads, lighting) was monitored and collected in the test-bed building using Onset Computing HOBO U30 data loggers connected to 0-20 A Continental Control Systems current transducers. Six data loggers were installed in the basement of the test-bed building with each data logger tracking usage for approximately 15 rooms. The data loggers connected to the Onset server every 10 minutes to transfer RMS current readings in minute intervals. The online web interface downloaded CSV files from the Onset server and stored them in an SQL database. Apparent power was calculated from RMS current values by multiplying by 110 volts and converted to daily energy consumption values by summing all power values for a 24 hour period. Consumption values were then adjusted for room occupancy to determine per capita power consumption and provided to users via the online interface.

The test-bed building itself is a residential six-story building on the campus of Columbia University in New York City that contains 58 double and 11 single occupancy flats. Residents occupied the flats continuously before, during and after the study period. Each flat is comprised of a kitchen, living area and bedroom area allowing for the capture of electricity consumption for a variety of daily activities (e.g., turning on lights, cooking, watching TV, computer usage). Only electricity consumption was monitored, since the centrally controlled heating system could not be controlled by individuals and thus was not relevant to the study. The building was built prior to World War II and has high ceilings and thick plaster walls. All flats receive natural light via one of the two central courtyards or the street.
4.3.7. Data Collection

The study period lasted 47 days (March 23 thru May 8) and resulted in the capture of 1,095 daily electrical energy consumption data points. User interaction data points were captured from the web interface using clickstream capture technology. Each user interaction data point contained three pieces of information: the time-stamp of when the normative comparison feature was utilized (click to add peer’s consumption), the user who utilized the feature and the peer whose consumption was being viewed. A total of 86 of these user interaction data points were captured during the study period with a fairly even distribution across the users. Due to an unexpected server failure, energy consumption data was unavailable for 3 rooms from April 7 to April 11 and for another room from April 12 to May 12. Therefore, 11 interaction data points corresponding to these dates and rooms were removed from the analysis, resulting in 75 valid user interaction data points.

4.3.8. Data Analysis

4.3.8.1 Hypothesis 1a

For hypothesis 1a, our analysis sought to determine if energy consumption patterns were event dependent on a user’s exposure to normative feedback. To accomplish this, we developed an algorithm based on the Monte Carlo Permutation Procedure. To analyze the stochastic nature of energy consumption, the observed system response around discrete normative query events (empirical state change ratio) was compared to a simulated uniform distribution of random times to ensure validity. A flow diagram of the algorithm is provided in Figure 10.
$T = \{t_1, t_2, ..., t_{47}\}$, where $T$ is the set of days in the study period

$S = \{(i_1, j_1), (i_2, j_2), ..., (i_{75}, j_{75})\}$, where $S$ is the set of interaction data points representing an instance of user $i$ viewing a peer $j$’s energy consumption

$C_i(t)$ is the energy consumption of user $i$ on day $t$
We define set $T$ as a set of all days in the study period and set $S$ as containing elements corresponding to discrete events when user $i$ viewed the consumption information of peer $j$ (i.e., the 75 valid user interaction data points). Each interaction data point in set $S$ is independent of user and peer, and as such multiple instances of each can appear within set $S$. $C_i(t)$ is the consumption of user $i$ on day $t$. The algorithm begins by initializing counter variables $p$, $k$ to zero and uniformly choosing a random day ($t_r$) from the set $T$. Next, for each user ($i$) in set $S$ we determine $\Delta_i(t_r)$, the change in energy consumption of user $i$ between days $t_r + 1$ and $t_r - 1$.

Variable $k$ represents the number of instances that users increased consumption $(\Delta_i(t_r) > 0)$ and variable $p$ represents the number of instances that users decreased or maintained the same consumption $(\Delta_i(t_r) \leq 0)$. $W_r$ represents the ratio of the number of instances when consumption decreased to the number of instances when consumption increased across the randomly chosen day $t_r$. We repeated this procedure one million times ($n$) to obtain an adequate estimate of the distribution of the ratio ($W_r$) for the 17 users who utilized normative comparison at random times (uniform distribution) during the experiment.

The empirical state change ratio is the observed ratio of users (sample is the 17 users that utilized normative comparison) who decreased or maintained consumption $(\Delta_i(t_e) \leq 0)$ to the number of users who increased consumption $(\Delta_i(t_e) > 0)$ where $t_e$ is the day on which a user $i$ viewed normative comparison information. To determine if the empirical state change ratio differs from random changes in electricity consumption of the 17 users that utilized normative comparison, the empirical ratio is compared to the distribution of the simulated ratio ($W_r$). A p-value for this comparison is obtained by dividing the total number of $W_r$ that are greater than the empirical value by the total number of simulation runs ($n = 1$ million). A p-value of below .05 indicates statistical significance.
4.3.8.2. Hypothesis 1b

To test hypothesis 1b, our analysis aimed to determine if observed patterns of energy consumption behavior of users change when the direction of the edges of information flow are hypothetically reversed. To achieve this, we modified our previous algorithm for the edge reversal test. A flow diagram for the new algorithm is provided in Figure 11.
Figure 11: Algorithm for Edge-Reversal Test

The definitions remain the same from the shuffle test algorithm and we define $C_j(t)$ as the consumption of peer $j$ on day $t$. The algorithm begins by initializing counter variables $p, k, q, z$. 

\[
T = \{t_1, t_2, \ldots, t_{47}\}, \text{ where } T \text{ is the set of days in the study period}
\]

\[
S = \{(i_1, j_1), (i_2, j_2), \ldots, (i_{75}, j_{75})\}, \text{ where } S \text{ is the set of interaction data points representing an instance of user } i \text{ viewing a peer } j \text{'s energy consumption}
\]

$C_i(t)$ is the energy consumption of user $i$ on day $t$

$C_j(t)$ is the energy consumption of peer $j$ on day $t$
to zero and uniformly choosing a random day \((t_r)\) from the set \(T\). Similar to the shuffle test algorithm for each user \(i\) in set \(S\), we determine \(\Delta_i(t_r)\). In addition to account for edge-reversal, we also determine \(\Delta_j(t_r)\) for each peer \((j)\) in set \(S\). \(W_r\) and \(W'_r\) represent the ratios of users who decreased or maintained their consumption \((p\) and \(z\)) to the number of users who increased their consumption \((k\) and \(q\)). The procedure is repeated one million times \((n)\) to obtain an adequate estimate of \(W_r\) and \(W'_r\) and the cumulative distribution functions for each are plotted on a single graph. The cumulative distribution functions were compared using a two-sample Kolmogorov-Smirnov test to determine if the probability distribution for \(W_r\) was greatly modified due to edge-reversal \((W'_r)\). A p-value below 0.05 for the Kolmogorov-Smirnov test provides statistically significant evidence that the distribution for \(W_r\) differed from \(W'_r\) and therefore edge-reversal had an impact on the distribution of the energy consumption ratios.

4.4. Results

4.4.1 Hypothesis 1a

A histogram of the results for Hypothesis 1a is provided in Figure 12. For all users exposed to normative feedback, the empirical ratio value of 1.5 can be seen to differ substantially from the distribution of random time generated ratios \((W_r)\) with a resulting p-value of 0.0327. This value is below the statistical significance threshold and provides evidence to reject the null hypothesis of Hypothesis 1a that social influence does not impact the energy consumption behavior of users exposed to normative eco-feedback.
**Figure 12: Results of the Shuffle Test Indicating the Presence of Social Influence**  
(p-value = 0.0327)

### 4.4.2. Hypothesis 1b

Results comparing the cumulative distribution functions (CDF) for Hypothesis 1b are provided in Figure 13. For users exposed to normative eco-feedback, the Kolmogorov-Smirnov test yields a p-value of $2 \times 10^{-16}$ indicating that the probability distribution was modified due to edge-reversal of the data set. This modification is visible in Figure 13 with the original cumulative distribution function shown to clearly shift to the right due to edge-reversal. In addition to visual evidence, the resulting p-value of the Kolmogorov-Smirnov test provides strong statistical evidence to reject the null hypothesis of Hypothesis 1b that social influence does not impact the energy consumption behavior of users exposed to normative eco-feedback.
4.5. Discussion

This study aimed to determine if social influence played a role in the energy consumption behavior of users exposed to normative eco-feedback. By demonstrating the event dependency of energy consumption patterns in our data set using the shuffle test, we were able to reject the null hypothesis for Hypothesis 1a and conclude that social influence impacted the energy consumption behavior of users. Furthermore, by demonstrating that the probability distribution of energy consumption ratios changed as a result of edge-reversal, we were able to reject the null hypothesis for Hypothesis 1b. This result corroborated the results of Hypothesis 1a and provided further validation to the conclusion that social influence played a substantial role in the energy consumption behavior of users exposed to normative eco-feedback.
Further examination of the results for Hypothesis 1a revealed that there were 50% more instances that a user viewed normative eco-feedback and reduced consumption than increased consumption (state change empirical ratio value of 1.5). Therefore, the results not only demonstrate the presence of social influence but also indicate that users were influenced towards reducing their consumption rather than increasing it. While previous normative eco-feedback studies (Brandon, 1999; Petersen et al., 2007; Siero et al., 1996) were limited in their ability to characterize the user dynamics responsible for driving savings, this result is directionally consistent with the energy savings observed by those studies. We postulate that because users in our dataset were influenced by other users, a competitive drive as observed in Petersen et al. (Petersen et al., 2007) and Siero et al. (Siero et al., 1996) could have motivated the resulting energy savings. Overall, this study takes an initial step to understand what factors could be driving energy savings in normative eco-feedback studies, but further research is necessary to understand specific dynamics such as the interplay between social influence and competition in conservation.

Results of this study also build on previous work (Peschiera and Taylor, 2012; Peschiera et al., 2010) that applied social network analysis to subjects exposed to eco-feedback systems and established a correlation between social network position and energy consumption reduction. While this previously identified correlation suggests that social influence may have impacted consumption, limitations in data collection methods did not provide sufficient evidence for a concrete conclusion. The study presented in this paper aimed to extend the literature beyond conjecturing that social influence plays a role in the consumption of users by providing empirical evidence of such an effect. By empirically demonstrating the existence of a social influence effect on energy consumption behavior, this study establishes social influence as a tool that could
be used to reduce energy consumption. Furthermore, the results validate building energy simulations (Azar and Menassa, 2012a; Chen et al., 2012) built on the assumption that occupants are influenced to change their energy consumption. Future simulations could incorporate the results and direct data of this study to construct more accurate simulations of energy consumption behavior. By demonstrating the presence of social influence, we can characterize energy conservation information as a flow between users and, in turn, can utilize modeling methods introduced in the social and computer sciences (Bharathi and Kempe, 2007; Kempe et al., 2003; Wang et al., 2012) to optimize such a flow. Researchers have observed several challenges to sustaining long-term reductions in energy consumption, such as response-relapse patterns (Peschiera et al., 2010) and the “energy efficiency gap” (Jaffe and Stavins, 1994). Further expansion of energy efficiency and eco-feedback research that harmonizes existing adoption models such as the Diffusions of Innovations (Rogers, 2003) and energy information flow research could provide the necessary tools to overcome these barriers and maximize potential long-term energy savings.

A secondary contribution of this study was the development of a quantitative method that integrates empirical energy consumption and user interaction data to determine if social influence impacts energy consumption behavior. Two established social influence tests—the shuffle test and the edge-reversal test—were adapted and application algorithms that take into account the stochastic nature of energy consumption and the discrete event dependency characteristics of users in eco-feedback systems were developed. Previous data analysis methods (Azar and Menassa, 2012b; Yu et al., 2011; Yu et al., 2011) for energy consumption data are focused on characterizing and identifying energy inefficient occupant behavior. While these techniques are valuable to quantify the maximum potential energy savings, they are limited in
their ability to identify mechanisms that will drive behavior changes and subsequent savings.

Our method extends the literature by integrating user interaction data with energy consumption data to establish social influence as a mechanism to drive conservation. Additionally, our method introduces a probabilistic data analysis technique to account for the stochastic nature of energy consumption and compares the results of experimental data with a simulated distribution.

Prior to this study, researchers relied on indirectly observing and analyzing the underlying mechanisms driving energy conservation efforts through user surveys (Bonino et al., 2011; Mahapatra and Gustavsson, 2009). The quantitative method and algorithms introduced in this study offer an alternative to survey based research, which has been shown in some cases to be unreliable in isolating the driving forces behind conservation behavior (Nolan et al., 2008).

Future studies could extend this method to evaluate the social influence tests on different time scales to understand how social influence changes over time. Researchers could also apply this method to more heterogeneous populations of users to identify what types of users are influenced the most by their peers to conserve. Such research efforts could lead to valuable insights that will have important implications for the design of eco-feedback systems and other behavior based energy efficiency programs.

4.6. Limitations

The authors acknowledge that our study could have benefited from a larger sample size. However, the sample size was adequate to obtain statistically significant results by applying the methodology introduced in this paper. We also acknowledge the sample population utilized in this study was homogenous. Future studies should aim to extend this work by applying our methodology to larger heterogeneous data sets as they become available (to the authors’
knowledge a larger data set adequate for testing social influence in energy consumption currently does not exist). Nonetheless, this work represents an important first step in understanding the social dynamics of energy consumption behavior by establishing and testing a methodology that can empirically ascertain the presence of social influence in users exposed to eco-feedback. A limitation of the monitoring equipment used in the study included calculation of the energy usage (kWh) on an average voltage of 110V rather than measuring voltage in real time. However, manual meter checks demonstrated that energy measurements were consistent across the study period for each unit. Thus, our system allowed us to compare consumption values between dates. Additionally, a limitation of our monitoring equipment is that energy consumption data was captured on a unit level and thus, participants in double rooms were unable to act completely independent of each other. It should also be noted that we did not monitor centrally controlled steam based heating in the test-bed building and therefore limited consumption associated with the heating system (study was conducted in the spring and summer months) was outside the scope of this study. We acknowledge that seasonal external factors (e.g. variation in daylight hours, variation in outdoor temperature) could have impacted the energy consumption patterns of users exposed to normative eco-feedback, but examination of energy consumption data of users without access to the eco-feedback system revealed no evidence of temporal patterns over the study period (consumption stayed within a 10% band of the average consumption). Additionally, because our analysis techniques examined a time lagged dependent variable $\Delta_i(t_e)$ over a two day window, we found it unlikely that such external factors would have impacted energy consumption one day after each normative feedback event. We also acknowledge the limitation that the observations in this study are dependent on the subset of users who participated. However, the aim of this study was not to reach the conclusion that social influence
impacts everyone’s energy consumption behavior but rather to empirically demonstrate that
social influence can impact energy consumption behavior and that this requires the attention of
the research community. Furthermore, methods to test for social influence were established to
test for social influence that can be easily applied in future research to determine if social
influence plays a role in the energy consumption of other sets of users.

4.7. Conclusion and Implications

The results of this study allowed us to infer that social influence can drive energy savings in
users exposed to energy consumption feedback. Two tests—the shuffle and edge-reversal—were
adapted and utilized to determine if social influence played a role in the energy consumption of
users in an empirical eco-feedback experiment. Analysis of time stamped user interaction and
consumption data using a modified Monte Carlo Permutation Procedure revealed statistical
support that social influence impacted energy consumption behavior. A more in depth analysis
of the empirical state change ratio indicated that users were influenced to use less energy when
exposed to normative feedback.

Overall, this study provides an important initial step in gaining an overall understanding of the
dynamics of energy efficient behavior in social networks and extends the literature by
demonstrating the presence of social influence in users who were willingly exposed to eco-
feedback. Additionally, this study establishes a method to test social influence in energy
consumption data that can be readily applied to other experimental data sets. Future research
can build on the results of this study by investigating the impact of social influence on different
time scales and discern how to leverage social influence to further reduce energy consumption of
buildings. Expansion of this research effort will also be necessary to incorporate this work into a
mechanism that will guide the design of behavior based energy efficiency programs and broader energy efficiency policies. Coupling behavior based energy efficiency programs with social network research could provide a synergistic combination that substantially and sustainably reduces building energy consumption and helps facilitate our transition to a less carbon intensive society.
Chapter 5

CONTRIBUTIONS

The research presented in this dissertation makes significant theoretical and practical contributions to the areas of energy efficiency in the built environment, human-computer interaction, computational civil engineering and infrastructure management, eco-feedback systems and the broad interdisciplinary field of eco-informatics. Overall, this body of work aims to provide the research community a deeper understanding of how system design and peer network dynamics can be utilized to maximize the efficacy of eco-feedback systems and encourage significant and sustained reductions in building energy consumption. The specific theoretical and academic contributions of each empirical experiment and corresponding chapter are highlighted in the following subsections.

5.1. Theoretical and Academic Contributions

Chapter 2: Assessing Eco-Feedback Interface Usage and Design to Drive Energy Efficiency in Buildings

Prior research on the topic of eco-feedback interface design has been limited to non-empirical studies (Jacucci et al., 2009; Wood and Newborough, 2007) or user surveys (Karjalainen, 2011). The research I presented in Chapter 2 contributes to the existing body of literature on eco-feedback interface design by: introducing an alternative data-driven methodology to assessing the efficacy of components in encouraging energy efficient behavior; and empirically ascertaining the impact user engagement and, in turn, specific interface components have on
observed energy savings. The data-driven methodology allowed for empirically collected clickstream (usage) and energy consumption data to be analyzed in tandem. I was able to assess the effectiveness of different eco-feedback interface components that were previously studied only through the use of surveying (Karjalainen, 2011) and literature-based analysis (Jacucci et al., 2009; Wood and Newborough, 2007).

The results of my controlled experiment empirically verified that a statistically significant correlation exists between engagement with an eco-feedback interface and reducing one’s consumption. This conclusion extends previous work (Peschiera et al., 2010; Petersen et al., 2010) that suggested such a correlation exists but had not quantitatively ascertained it through experimentation. Moreover, I also deepened my analysis to examine the effectiveness of specific design components of eco-feedback interfaces by employing mean user logins as a dependent variable. Users who utilized the historical comparison component engaged with the interface more than their non-utilizing counterparts (statistically significant), which corroborated prior conclusions that historical comparison is a key design component of an eco-feedback system (Fischer, 2008). Moreover, the empirical results of the incentives component confirmed prior work that utilized non-financial incentives as a means to illicit a reduction in energy consumption (Jacucci et al., 2009; Petersen et al., 2007). The empirical results of this study also provided quantitative justification for the inclusion of incentives in eco-feedback interface development and built on the literature-based analysis of Wood and Newborough (Wood and Newborough, 2007). A weak correlation was found between normative comparison and user engagement and provided some empirical evidence to support prior work that employed normative comparison (Iyer et al., 2006; Peschiera et al., 2010; Siero et al., 1996).
The results of this experiment also make important contributions surrounding the use of *disaggregation* and *rewards and penalization* tools in eco-feedback systems. Prior research has advocated for the use of *disaggregation* tools as a means to provide more detailed information to users (Fitzpatrick and Smith, 2009). However, results of this experiment identified a potential limitation in this approach and suggest that future *disaggregation* tools should be streamlined to reduce the number of required user interactions. Lastly, this experiment provided empirical evidence that contradicts the previously held notion that both *rewards and penalization* motivate a user to reduce consumption. While Jacucci et al. (Jacucci et al., 2009) advocates for the use of penalization as a mechanism to reduce wasteful behavior, the results of this experiment indicated that viewing negative points can have a discouraging effect on users and that a modification to this design component may be necessary. In the end, Chapter 2 of this dissertation contributes to the growing body of literature regarding eco-feedback interface design by introducing a data-driven methodology for studying interface usage and effectiveness and conducting a controlled empirical experiment.

*Chapter 3: Investigating the Impact Eco-Feedback Information Representation has on Building Occupant Energy Consumption Behavior and Savings*

Prior research (Wood and Newborough, 2007) has highlighted the importance of data representation in eco-feedback systems but little empirical evidence exists supporting this assertion. The research presented in Chapter 3 contributes to the existing literature by: empirically verifying that information representation in eco-feedback systems has a statistically significant impact on the energy consumption behavior of users; and experimentally demonstrating that alternative environmental externality units are more effective in encouraging
long-term energy savings. The establishment of a relationship between eco-feedback data representation and actual changes in energy consumption extended the findings of previous studies (Bonino et al., 2012; Chiang et al., 2012; Karjalainen, 2011; Petkov et al., 2011) beyond the analysis of high-level user preferences and into the impact information representation has on the effectiveness of eco-feedback systems. The methodology presented in Chapter 3 also contributes to the growing body of knowledge regarding eco-feedback design (Bonino et al., 2012; Chiang et al., 2012; Froehlich et al., 2010; Karjalainen, 2011) by integrating the analysis of empirical energy consumption data into the study of information representation. Additionally, as called for by previous work (Pierce et al., 2010) this research took the necessary step of deepening our understanding of eco-feedback systems through analysis of a specific design detail (i.e., information representation).

Kilowatt-hours (kWh) has been the default representation unit most commonly utilized in eco-feedback studies (Grønhøj and Thøgersen, 2011; Jain et al., 2012; Peschiera et al., 2010; Peschiera and Taylor, 2012; Petersen et al., 2007; Wilhite and Ling, 1995). Results of this experiment indicated that providing feedback in the more relatable units of an environmental externality is a viable alternative to the traditionally used kWh. This work built on previous research (Bonino et al., 2012; Fitzpatrick and Smith, 2009) that concluded users have a limited understanding of kWh due to its scientific origin and abstract qualities. User presented with eco-feedback in the proxy units of “trees needed to offset emissions” were shown to use 28% less energy (statistically significant) than their counterparts who received eco-feedback in the conventional kWh unit. Additionally, the work presented in Chapter 3 also contributes to the ongoing dialogue regarding response-relapse patterns in energy consumption behavior (Peschiera et al., 2010) through cumulative analysis of energy consumption data. Results indicated that in
spite of response-relapse patterns being observed, users who received feedback in the representation unit of “trees needed to offset emissions” still cumulatively saved 7.63 kWh more per capita than their counterparts who received feedback in kWh (statistically significant).

This experiment contributes to the literature by providing empirical evidence that illustrates the environmental externality unit of “trees” is a viable proxy for the default representation unit of kWh. A secondary contribution is the observation that savings are not diminished due to observed patterns of response-relapse when an alternative representation unit (i.e., “trees”) is used to convey eco-feedback to participants. In the end, the research presented in Chapter 3 represented a crucial first step in settling the current discord within the literature regarding information representation and establishes a clear methodology for the analysis of eco-feedback data representation.

*Chapter 4: Can Social Influence Drive Energy Savings? Detecting the Impact of Social Influence on the Energy Consumption Behavior of Networked Users Exposed to Normative Eco-Feedback*

Previous work in the area of normative eco-feedback systems (Brandon, 1999; Petersen et al., 2007; Siero et al., 1996) has been unable to characterize the user dynamics responsible for driving savings. While some previous work (Foster et al., 2010; Peschiera and Taylor, 2012) has asserted that social influence could be responsible for observed energy savings, the analytical methods employed in such studies do not isolate the impact of social influence from other network effects. The research I presented in Chapter 4 makes two concrete contributions to the literature: first, I proposed and applied a novel method based on stochastic and social network test procedures to isolate the impact of social influence; second, I conducted and analyzed
empirical data to ascertain that social influence can impact the energy consumption behavior of users exposed to normative eco-feedback.

The methodology presented in Chapter 4 integrated empirical energy consumption and user interaction data to determine if social influence impacts energy consumption behavior. Two established social influence tests—the shuffle test and the edge-reversal test—were adapted and implementation source code was created to test empirical data. These data tests account for the stochastic nature of energy consumption and the discrete event dependency characteristics of users in eco-feedback systems to successfully isolate the impact of social influence. This work extended previous analysis methods of energy consumption data (Azar and Menassa, 2012b; Yu et al., 2011) by moving beyond quantification of potential energy savings and into the identification of mechanisms that are driving behavior changes and subsequent savings. Moreover, this method extended the literature by integrating data streams of user interaction and social network data with energy consumption data to understand what encourages conservation behavior. Lastly, the quantitative method and algorithms introduced in this study offer a viable alternative to previous survey-based research methods (Bonino et al., 2011; Mahapatra and Gustavsson, 2009). While survey-based research is valuable, it has been shown in some cases to be unreliable in isolating the driving forces behind conservation behavior (Nolan et al., 2008). Therefore, the alternative approach proposed and validated in this chapter was warranted.

The results presented in Chapter 4 also make an important contribution by extending previous studies (Peschiera et al., 2010; Peschiera and Taylor, 2012) beyond conjecturing that social influence impacts the energy consumption of users. Results provided empirical evidence that social influence impacts energy consumption behavior and establishes social influence as an
effective tool to engender energy savings. Results also validated the assumption that occupants can be influenced to change their energy consumption by their peers, which had been made in previous agent-based building energy simulations (Azar and Menassa, 2012a; Chen et al., 2012). Future agent-based energy simulations should incorporate the results of this study to enable more accurate simulations of energy consumption behavior. Demonstrating the presence of social influence in energy consumption behavior allows for energy conservation information to be modeled as a flow process. Thus, this research also contributes to the body of knowledge in the social and computer sciences regarding information flow and optimization (Bharathi and Kempe, 2007; Kempe et al., 2003; Wang et al., 2012). Overall, the body of work presented in Chapter 4 contributes to the literature by proposing a new data-driven approach to quantifying peer network dynamics in eco-feedback systems and by empirically ascertaining that social influence can drive energy savings.

5.2. Practical Contributions

The research presented and discussed in this dissertation makes practical contributions to the fields of eco-informatics, eco-feedback systems and energy efficiency. Behavior-based energy efficiency programs have been shown to be among the most cost effective energy efficiency strategies on the market (Allcott and Mullainathan, 2010). With the success of energy efficiency software companies, such as OPower, Lucid Design Group and Efficiency 2.0, there is significant interest from both policy makers and industry representatives in translating findings of eco-feedback research into commercial products.

Specifically, energy efficiency software companies are constantly in the process of redesigning their user interfaces and dashboards to increase the effectiveness of their eco-feedback programs.
Conclusions from Chapter 2 and 3 have direct implications for what components companies should include in their interfaces, how to present complex energy consumption data to non-technical audiences and how to measure the effectiveness of interface changes in near real-time.

As mentioned earlier, OPower has successfully partnered with the National Resources Defense Council and Facebook to add a social network dimension to their eco-feedback program (Protalinski, 2012). Understanding what specific social network dynamics are driving actual reductions in energy consumption are crucial to the success of this new partnership. The research presented in Chapter 4 provides a data-driven approach that would allow OPower to determine if social influence is responsible for driving observed energy savings. Armed with this result, OPower could begin to analyze how energy conservation information flow was occurring in various social networks to provide individualized feedback and realize even greater savings from its customers.

The results of the work presented in this dissertation illustrate the merits of eco-feedback as a tool to cost-effectively reducing energy consumption and associated environmental emissions. In light of recent natural disasters, President Obama has renewed his pledge to tackle climate change on a national policy level. The President’s Climate Change Action Plan (2013) calls for an increased effort to reduce energy waste in buildings. A significant amount of energy wastage has been linked to inefficient occupant behavior (Emery and Kippenhan, 2006; Yu et al., 2011); therefore, reducing the energy wastage in buildings will require engaging occupants. Eco-feedback systems provide a proven and systematic way to engage occupants and encourage them to adopt more efficient energy consumption behaviors. The research described in this dissertation provides practical guidance on how eco-feedback systems could be designed to maximize energy efficiency and reduce wastage. Additionally, the methodologies presented also
provide a theoretical starting point for companies aiming to develop new systems based on a data-driven iterative design process. By connecting people with their energy consumption data through eco-feedback systems, we have the opportunity to dramatically decrease our energy consumption and help meet the Climate Change goals laid out by President Obama.
Chapter 6

PROPOSED AVENUES OF FUTURE RESEARCH

In this dissertation, I highlighted the importance of system design, data representation and peer network dynamics in eco-feedback systems and presented the results of three empirical experiments. The results provided insights into how we can design more effective eco-feedback systems and utilize peer network dynamics to maximize energy efficient behavior among building occupants. However, successfully and significantly reducing the energy consumption of the built environment will require additional research. Many open questions remain in the areas of eco-feedback systems and data-driven energy efficiency. In the following subsections, I outline four proposed avenues of future research that could build on the theoretical basis established in this dissertation.

Understanding the Sharing, Adoption and Diffusion of Energy Saving Practices

This dissertation established that social influence impacts energy consumption behavior. Thus, we can now characterize energy conservation information as a flow between two users and apply modeling methods dealing with information flow from the social and computer sciences (Bharathi and Kempe, 2007; Kempe et al., 2003; Wang et al., 2012). Future work could build upon this research by conducting experiments and developing simulations to understand how energy saving practices are shared, adopted and diffuse through communities and social networks using the seminal Diffusion of Innovations framework (Rogers, 2003). By analyzing energy saving practices in this manner, researchers could optimize the diffusion of energy saving
practices and possibly overcome the “energy efficiency gap” (Jaffe and Stavins, 1994) that has plagued conservation strategies in the past.

*Extending Eco-Feedback Systems to Commercial Buildings and Organizational Networks*

The research presented in this dissertation was primarily concerned with the implementation of eco-feedback systems in residential buildings. The conclusions in this dissertation regarding residential buildings could be translated to commercial buildings where similar systems could be developed to reduce energy consumption. The network characteristics of commercial building occupants are vastly different than those of residential occupants as employer-defined organizational networks are superimposed over existing social networks (Carley, 1999). Thus, future research is needed to determine the type of network dynamics that are the most effective in encouraging energy efficient behavior in the workplace. Additionally, implementing eco-feedback systems at the individual employee level would allow researchers to integrate systems with existing Building Energy Management Systems (BEMS) already in place in many commercial buildings. Previous work has shown the merits of optimizing BEMS systems (Klein et al., 2012); exploring the integration of eco-feedback and BEMS systems would extend the work in this dissertation and could reduce commercial building energy consumption while simultaneously improving occupant comfort.

*Utilizing Data from Eco-Feedback Systems to Predict Building Energy Consumption*

Accurately predicting building energy consumption is crucial to the implementation of numerous energy efficiency initiatives and the integration of intermittent renewable energy into the electricity grid. There is a growing interest among the research community to forgo traditional
engineering forecasting methods for “sensor based” approaches due to the large amount of input data required for such engineering methods (Edwards et al., 2012). Sensor-based forecasting employs machine learning techniques to infer the complex relationships between past consumption and other variables (e.g., weather, time of day). High resolution energy consumption and social interaction data being captured by eco-feedback systems could be fed into a machine learning algorithm to increase the predictive power of sensor based forecasting models. Additionally, researchers could examine the role normative eco-feedback and spatial and temporal granularity has on such sensor based forecasting models. This research would complement work presented in this dissertation and could have widespread implications for both energy efficiency and renewable energy initiatives.

*Tackling Heating Consumption and Local Environmental Conditions through Eco-Feedback*

In New York City, the annual black carbon emissions from building heating systems that burn heavy heating oil exceeds that of all cars and trucks on the road (The City of New York, 2012). Previous work (Spira-Cohen et al., 2011) has linked black carbon emissions with adverse health effects, making reducing heating consumption both an environmental and human health issue. An extension of this dissertation could explore the use of an eco-feedback system to encourage heating conservation and reduce heavy heating oil consumption. Building occupants could be presented with information on how their heating consumption and the consumption of others in their building directly impacts local environmental conditions (i.e., air quality) and the associated health implications. Providing occupants with more direct feedback on how their energy consumption impacts their local environment and health could provide the impetus necessary for the long-term adoption of energy efficient behavior.
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