Establishing the Need for Tailored Energy Feedback Programs in Buildings

Ardalan Khosrowpour

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Civil Engineering

John E. Taylor
Michael Garvin
Farrokh Jazizadeh Karimi
Rishee K. Jain

08/10/2016
Blacksburg, VA

Keywords: Occupant Behavior, Energy Feedback Program, Eco-Feedback Program, Energy Efficiency

Establishing the Need for Tailored Energy Feedback Programs in Buildings

Ardalan Khosrowpour

ABSTRACT

Buildings account for 40% of energy consumption in the US. Despite all improvements in buildings shell, equipment, and design, CO_2 emissions from buildings are increasing as a result of increased energy consumption. Since occupants spend more than 90% of their time indoors, they are inseparable and significant elements of building system dynamics. Hence, there is a great potential for energy efficiency in buildings using a wide range of programs such as education, intervention, energy feedback, etc. Due to advancement of technology and accessibility of high resolution energy consumption data, utility companies are enabled to focus on implementing energy feedback programs to induce energy efficiency and reduce the peak energy load in the commercial and residential sector. In order to better understand various aspects of energy feedback programs, in the first chapter of this dissertation, I conduct a comprehensive literature review on the state-of-the-art energy feedback study methods and identify gaps of knowledge and challenges faced by researchers in the field. Accordingly, the future research vision is laid out at the intersection of methods and gaps of knowledge used in energy feedback studies and future research opportunities and questions are provided. One of the major gaps of knowledge I identified in the literature review is the lack of quantitative analyses used to investigate the variability of occupant responses to commercial buildings energy feedback programs to evaluate the need for targeted and tailored energy feedback programs. In the second chapter, I conducted a comprehensive analysis on occupant energy-use responses under the influence of a uniform energy feedback program. Furthermore, I investigated the effectiveness of notifications on increasing the level of engagement of the occupants in these studies. The results supported the existence of a variability in responses and engagement level in a uniform energy feedback program which may be due to intra-class variability of occupant behavior. In the third chapter, based on the established need for a targeted energy feedback program, I investigate the predictability of occupant energy consumption behavior and its correlation with energy consumption. The results report that 46% of occupants may be good candidates for targeted energy feedback programs due to their combination of higher levels of energy-use and predictability of their energy consumption behavior.

ACKNOWLEDGEMENTS

I would like to express my sincerest gratitude to my Advisor, John Taylor, and my dissertation Defense Committee, Michael Garvin, Rishee Jain, and Farrokh Jazizadeh. I would like to thank JT for giving me the opportunity to pursue a research topic that I am passionate about. I would also like to thank him for giving me the flexibility to deviate from our group norm and encouraging me to set out on the entrepreneurship career path I have always dreamed of following. I am truly grateful for having such a patient and trusting advisor who let me start my own venture prior to graduation and helped me with the seed funding for my company. Even though I annoyed him from time to time when I did not attend the research group meetings or forgot to submit my *"Weekly Updates",* he always supported me. I would never have been able to finish my dissertation if it were not for his willingness to help with all contingencies. I would like to thank Mike Garvin for his constructive feedback on the structure and methodology of my work. Rishee's help was also very instrumental in offering thought provoking questions during the literature review phase of my research and pushing me to provide a more realistic and practical solution that can be implemented by both researchers and industry. Farrokh provided me with great technical feedback on the machine learning and occupant behavior side of my effort and helped me narrow the focus of my thesis effectively. Moreover, the Civil Engineering Network Dynamic lab members, especially Gabriel, Rimas, Ryan, Neda, and Yilong, were invaluable with the constructive feedback they offered throughout the development of this dissertation.

I would like to thank the funding agencies that supported my research during my PhD studies. I would like to thank the Via family for granting me a generous scholarship that enabled me to obtain my PhD without any financial concerns. Moreover, this effort was also supported by the Department of Energy Building Technologies Program and National Science Foundation Grant No. 1142379. Indeed, any opinions, findings, and conclusions or recommendations expressed in this dissertation are those of the authors and do not necessarily reflect the views of the DOE or the NSF. I also thank the Alliance for Sustainable Colorado for hosting the study that provided the building occupant data used here in the experimental data analysis.

I would especially like to thank my friend, Sina, for his help and feedback throughout all of the dissertation process. The day he also decided to come to Virginia Tech to get his PhD, was one of the best days of my life. Having a true friend by your side is one of the greatest gifts anyone can ask for in life.

Finally, I would like to thank my family for encouraging me to follow an extended intellectual pursuit when I was at a most difficult stage of my life. Their guidance, support, and endless love motivated me to pursue my dream, regardless of the many challenges I faced during the process of my PhD studies. My appreciation for their love and support cannot be expressed in words. I hope I will make them feel proud by achieving another milestone along the path that they inspired me to envision and start originally. I thus dedicate this dissertation to my mom, dad, and brother who have supported me beyond words all my life.

TABLE OF CONTENTS

1. INTRODUCTION

Buildings account for 40% of energy consumption in the U.S. and despite the many technological advancements, their energy use and its associated CO_2 emission are growing at an annual rate of 1% [1]. In the past decade, numerous researchers have tried to improve building energy efficiency through core, shell, and equipment improvements. Nevertheless, those efforts are not sufficient enough to reduce the amount of emitted CO_2 from the increases in building energy consumption. Hence, there is a clear need to leverage all available resources to induce greater energy savings in buildings.

Occupants are one of the major impacting factors on building energy consumption, as they spend more than 90% of their time indoors. Therefore, their presence in a building eco-system and their considerable impacts make them valuable assets to examine to induce energy efficiency through improvement in their energy-use behavior. These behaviors are known as environmentally significant behaviors [2]. More precisely, they are a subcategory of environmentally significant behaviors referred to as private-sphere environmentalism behavior. This subcategory is defined as a type of behavior in the private sphere that focuses on the purchase, use, and disposal of personal and household products and equipment with an environmental impact [2]. In this dissertation, the main focus, therefore, is on energy consumption usage behavior.

As technology enhances further and buildings become more efficient, the role of human behavior becomes more critical to help the built environment reach its full energy efficiency potential. The percentage of energy consumption that occupants have control over (e.g. plug loads) has increased over recent years and become even more important when put into highly efficient (e.g. net-zero) building contexts. For example, a study by Torcellini et al. [3] compared the actual performance of multiple net-zero buildings to their simulated energy models and revealed that underestimating occupants' behavioral impacts on building energy consumption was the main underlying cause of most estimated energy use deviations.

To improve occupant behavior, there has been a significant body of research conducted in the past few years on a variety of energy efficiency programs for occupants (e.g. education, intervention, workshops, energy feedback, demand-response, etc.). Of all these programs, energy feedback—a method to make energy consumption more visible and interpretable so occupants will learn and control their energy consumption—has been one of the most effective. These programs vary based on the elements they use to design, execute, and maintain them. Thus, I decided to conduct a comprehensive literature review to better understand the components and methods used in the studies. The first chapter of this dissertation, "*A Review on Occupant Energy Feedback Programs in Buildings: Methods, Challenges, and Opportunities*", focuses on delivering a literature review on energy feedback studies to identify gaps in knowledge and research opportunities in the field. The following chapters (i.e., 2 and 3) address one of the most important knowledge gaps in the literature, namely, targeted energy feedback systems.

The current state of the art energy feedback program treats all occupants uniformly and is designed by using the assumption that the responses of all individuals to a specific energy feedback program will be similar. In other words, current feedback systems provide the same feedback to all occupants, regardless of their differences.

Nevertheless, the most recent findings in this field do support the fact that *one size does not fit all* and there is definite need for a more targeted and tailored feedback program to improve occupants' energy-use behaviors based on their personal needs and characteristics.

In the second chapter of this dissertation, "*One Size Does Not Fit All: Establishing the Need for Targeted Eco-Feedback*", I take a quantitative analysis approach in order to study occupants' responses to an energy feedback program. I formulate and test various hypotheses to determine whether a targeted feedback program can help different stakeholders to maximize the induced energy efficiency in commercial buildings. Further, I provide a comprehensive analysis on the impact of notifications sent throughout a study on the engagement levels of the occupants in these programs.

Based on an analysis in the second chapter, one of the main knowledge gaps found in the literature is precisely how to determine the actual potential of executing a targeted energy feedback program based on predictability and the level of energy consumption of building occupants. In other words, occupants can be closely targeted if a meaningful and predictable behavioral pattern can be extracted from their energy consumption and it characteristics. Furthermore, providing feedback to occupants is most effective when they do have an inefficient energy-use behavior. However, providing feedback to energy efficient users might not be a cost-effective project. Thus, in the chapter titled, "*Occupant Workstation Level Energy-use Prediction in Commercial Buildings: Developing and Assessing a New Method to Enable Targeted Energy Efficiency Programs*", machine learning algorithms are used (i.e. Support Vector Machine) to determine individuals' energy consumption behaviors and assess the potential of a targeted energy feedback program at the intersection of energy-use behavior predictability and the ongoing level of energy consumption.

2. A REVIEW ON OCCUPANT'S ENERGY FEEDBACK PROGRAMS IN BUILDINGS: METHODS, CHALLENGES, AND GAP OF KNOWLEDGE

Ardalan Khosrowpour[1], Rishee K. Jain[2], John E. Taylor[1], Gabriel Peschiera[3]

[1]Charles E via Department of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA, 24061, United States
[2]Department of Civil and Environmental Engineering, Stanford University, Stanford, CA 94305, United States
[3]BuildSense.io, New York City, NY 10011, United States

1. ABSTRACT

Occupants are integral elements of a building ecosystem, and their behavior makes a significant difference in the energy consumption of buildings. A wide range of energy feedback programs has been developed to make energy consumption more visible and interpretable to occupants to help them learn how to control and save energy. Potential methodological issues exist in the literature that has led to a fragmented use of research methods and also inconsistency in reported results. Lack of a systematic research framework for energy feedback studies and an open data platform that allows researchers build off of each other's work may be preventing a more coordinated collaborative effort. In this study, we review state- of- the- art energy feedback literature using a methodological perspective to determine four major types of research methods used for energy feedback: (1) survey, (2) analytics, (3) experiment, and (4) simulation. We categorize these studies based on their methods and discuss the advantages of information fusion where these four methods intersect. We identify the challenges and gaps in the literature, and propose a comprehensive vision for more precise targeted energy feedback studies. The proposed a vision providing a clear roadmap for the design, execution, and maintenance of future targeted energy feedback studies. Further, this paper delivers the necessary considerations and challenges for the different aspects of energy feedback studies (e.g., data collection, length of study, sample population, cross cultural and climatic differences, response relapse in occupant behaviors).

Keywords: Energy feedback program, Energy efficiency, Occupant behavior, Research methods, Research framework

2. INTRODUCTION

Commercial and residential buildings account for more than 40% of U.S. energy consumption and its associated CO_2 emissions [1]. These buildings are homes and work environments for people who spend more than 90% of their time indoors [2]. This detail suggests a huge energy savings potential through greater promotion of energy efficient behavior by building occupants, using a combination of methods, such as education, energy feedback systems, demand response programs, etc. In fact, occupants can save on average 7.4% of their used energy through such energy conservation programs [3]. The behaviors targeted in these programs are known as environmentally significant behaviors [4]. More precisely, the sub-category of environmentally significant behaviors is called, private sphere environmentalism behavior. This subcategory is defined as a type of behavior in the private sphere that focuses on the purchase, use, and disposal of personal and household products and equipment that have an environmental impact [4].

Over the past decade, numerous researchers have conducted innovative research on building energy efficiency with a focus on occupant behavior. The effort has led to new venues to try and enhance occupant energy efficiency using a wide range of programs. Energy feedback programs – one of the most common and effective energy efficiency methods [5]- make energy consumption more visible and interpretable for occupants, so they can learn and better control their energy consumption [5]. The research conducted in the energy feedback area varies from short term [6-8] to long term [9-11] (i.e., the length of experiments varies from a few days to 2 years), psychological [12, 13] to technological [14] (i.e. experimenting on psychological factors like social norms and technological factors like web-based vs. paper-based feedback), and small scale [15, 16] to urban scale [17-21] (i.e. examining a sample data population).

From a methodological viewpoint, these energy feedback studies have been tackled from different points of view, including surveys [22-34], energy use analysis (i.e. analytics) [35-42], experiments [6, 7, 11, 13, 43-60], simulations [61-66], and in certain cases combinations of these methods. Each method, mutually exclusively, investigates an important aspect of occupant energy use behavior with the ultimate goal being to develop an effective occupant energy feedback program. However, inconsistency of methods and currently a rather fragmented body of research [3] suggests a potential methodological issue and the need for further review.

There has been a handful of energy feedback literature review papers published in recent years. In a recent work, Delmas et al. [3] conducted a meta-analysis on the existing literature to determine the most effective feedback strategies to use for influencing energy behaviors. In addition to reporting the effectiveness of real time feedback and individualized audits, including higher involvement interventions, their finding suggests there is a potentially fundamental methodological issue in the current literature. Their work is one of the first to point out the lack of consistency and unity in the methods used in energy feedback experiments. This lack of sophisticated research methods, diminish energy savings post study and produces a lack of clarity about the research process due to simultaneous implementation of various strategies. There is thus a need for further methodological investigation into energy feedback experiments. The scope of Delmas et al. [3]'s work is limited to field experiment meta-analysis, however, and does not include details related to the broader occupant energy feedback methodological issues.

Therefore, we use Delmas et al. [3] as the point of departure in this paper to conduct a comprehensive literature review on the methods currently used to design, analyze, and maintain energy feedback. Based on the methods seen in the literature, these studies fall into four main categories: (1) surveys (i.e., interviews and questionnaires); (2) analytics (i.e., load profiling and clustering, energy use disaggregation, occupancy detection, etc.); (3) experiments (i.e., conducting actual experiments to evaluate the hypothetical effect of feedback components); and (4) simulations (i.e., imitating real world energy feedback processes based on developed mathematical and stochastic models). Further, we identify and categorize those studies that have further exploited the data at the intersection of different methods (e.g. Analytics and Survey). Section 2 discusses the scholarly peer reviewed manuscripts in each category in detail based on their methodological differences and acquired information. Section 3 identities the gaps in knowledge and categorizes them based on the methodological approaches needed to fill these gaps. Section 4 discusses the challenges of occupant energy feedback research that have been either widely reported, or ignored in the literature. Finally, Section 5 proposes a vision to build to address the identified gaps of knowledge and recommends useful future venues for further research.

3. METHODS

This paper conducts a thorough literature review to identify the linkages between the numerous facets of occupant energy feedback programs. We utilized two complementary research strategies to find relevant studies for our analysis. First, we conducted a manual search for highly cited (e.g. [5, 10, 18, 21, 44, 67-72]) and literature review papers (e.g. [3, 14, 69, 73-84]) that focused on energy feedback research. Then, we traced the papers we cited to their aforementioned journal publications to build a comprehensive pool of 6,113 scholarly peer- reviewed publications. Due to significant advancements in technology and major improvements in energy monitoring and feedback resolutions, we decided to focus on analyzing the most recent approaches used to conduct energy feedback research. Therefore, we mainly concentrated on recent advanced feedback methods such as cell-phone based, web- based, in- home display, etc. (published in the past few years) in addition to highly cited other feedback studies and literature review papers so as to capture the state- of- the art methods used to conduct energy feedback research.

Secondly, we used the Google Scholar search engine to filter the papers based on the main keywords used in the field. Following Delams et al. [3], three categories of keywords were used to narrow down our publication pool.

1. Energy- related keywords, such as “energy efficiency”, “energy consumption”, energy saving”, “energy conservation”, “energy monitoring”, “building energy efficiency”.

2. Feedback- related keywords, such as “eco feedback”, “feedback”, “In home display”, “demand response”, “smart meter”.

3. Occupant- and building- related keywords. such as “occupant behavior”, “household energy consumption”, “residential building”, “commercial building”, “residential sector”, “commercial sector”, and “dormitory energy consumption”.

The 340 papers identified in this search were manually handpicked using a filter for publication abstracts. We manually filtered every paper and read its abstract to determine whether to read the paper fully in the next step. The measures taken into account to approve an abstract were the following:

1. It should focus on electricity consumption. Water- and gas- consumption- related papers were not considered for this meta-analysis.
2. It should target either residential, commercial, or university sectors (e.g., dormitories).
3. The paper should evaluate at least a single type of feedback method or human behavior that affected feedback studies

Implementing the aforementioned two- step data collection method resulted in 259 scholarly peer reviewed conference and journal papers. After reading these 259 journal and conference papers, we used the peer review process as a quality filter and thus removed the majority of the conference papers. A total of 115 peer- reviewed papers were then selected, and analyzed. For the sake of our methodology analysis, we selected only 62 peer- reviewed papers via a rigorous methodological review. The main criteria for selecting these papers were the sophistication of the methods used in the studies (e.g. a combination of different methods, inclusion of a control group in experiments), and the originality and contribution of their conclusions to the overall literature. We provide a list of the papers used in this study in Appendix 1-A, and the temporal combination of the methods used for each study in Appendix 2-B.

3.1. Surveys

Surveys consist of a sample population (e.g., occupants), a method of data collection (e.g., interviews and questionnaires), and questions that can be turned into data for statistical data analysis. There is a vast body of research that has focused on understanding occupants' behavioral characteristics, attitudes, and similar factors that are not fully interpretable using the quantitative data captured by the sensors (e.g., smart meters) deployed in buildings. Some of these characteristics are: occupants' behaviors [25-27, 29], perception of energy consumption and information [24, 30], understanding of feedback content [22, 31], knowledge of energy efficiency [30, 32], attitude [85], awareness of energy consumption [26, 33], literacy [26, 34], motivation [86], demographics [30, 87], social and economic information [29, 82, 86], eco feedback and in- home displays (IHD). and interface design preferences [21, 31, 34, 71, 86, 88], etc.

There are various approaches implemented in studies to collect the afore-mentioned information, which consider both sample size and the targeted information. Each approach is suitable for collecting a specific type of information, and that collected information ultimately affects the design, execution, and maintenance of these energy feedback studies. Interviews and questionnaires are two major survey categories. In-person interviews are one of the most comprehensive approaches that are suitable for targeting smaller sample sizes and collecting qualitative information. The majority of researches incorporating this method [15, 22, 23, 43, 71, 86, 88, 89] focus on understanding the underlying occupants' motivations, interpretations, and preferences, as they apply to energy feedback interface design. Feedback platform interface design is among the most important elements of such programs, which without a proper understanding of the environmental psychology of occupants can be only a redundant and ineffective effort [14]. Further, there are only limited studies on using interviews to investigate other influencing factors [86, 90].

To illustrate, Simcock et al. [24] used interviews to understand the human's perception of energy feedback information. These findings determined that the channel of communication, the information source, and the process of communication were the most important elements. To the contrary, the majority of the studies focused on capturing occupants' characteristic- related information (e.g. occupant behavior [25-28], lifestyle [29], perception of energy consumption and information [24, 30], understanding of feedback content [22, 31], knowledge of energy efficiency [30, 32], attitude [85], awareness of energy consumption [26, 33], literacy [26, 28, 34], social and economic information [28, 29, 82, 86]), incorporated online and paper- based questionnaires. Online and paper- based questionnaires facilitate access to a larger population of participants and provide the possibility of conducting more structured studies that potentially can be leveraged via cross comparisons, classifications, and factor analyses. Moreover, questionnaires have been found to provide better data quality and depth when compared to the information from personal interviews conducted [91].

Surveys are usually implemented as a stand-alone method in most energy feedback studies. Nevertheless, some studies have used a combination of survey and other methods (e.g. experiments and analytics) to validate self-reported information, capture deeper behavioral information through fusion of information, and further investigate the determinants of energy consumption in buildings. Table 1 represents a classification of those studies that have a survey component. Further details on each category are provided in Section 2.3. and 2.5 that follow.

Table 1. Studies that have a survey component. The arrows represent the sequence of implemented methods

Studies	**Methodological Approach**
[22-34]	Survey
[85, 87, 92-94]	Analytics Survey
[43, 71, 86, 95-97]	Experiment → Survey
[70, 72, 89, 98]	Survey → Experiment → Survey

3.2. Analytics

Analytics, a systematic computational analysis used to discover and interpret the meaningful patterns in data, has been another widely used method for expanding the energy feedback research boundaries over the past few years. In this paper, analytics mainly refers to those analyses carried out on energy consumption data at various resolutions (e.g., captured through energy feedback experiments or smart meters) to infer such information as occupancy patterns, energy use load shapes, and energy-use behavior similarities. The advancement of technology has facilitated capturing such high resolution data through smart meters. This advance provides a great opportunity for researchers to extract valuable information from occupants' energy consumption patterns and behaviors. The majority of studies that have leveraged analytics to induce energy savings or provide behavioral information to residential and commercial buildings utility companies have focused on one of the following areas: Load profiling and clustering [35-39, 41, 42, 92, 94, 99], occupancy detection [92, 100], and behavior analysis [87, 93, 101, 102]. It be also noted that the statistical methods used for hypotheses tests (e.g. a t-test) are not included in the analytics section of this paper and instead are expected to have been conducted as part of the experiments and surveys.

Each of the afore-mentioned categories addresses the occupant energy efficiency, energy feedback, and demand response programs, but from a different perspective. Analytics can help infer occupancy status from energy consumption loads, indeed a valuable piece of information to use for tailoring and timing the feedback provided to households, occupants, or building operators in residential and commercial buildings. Only a limited number of studies [42, 100] have focused on such analytics to induce occupant- based energy efficiency in buildings; nonetheless, if such technology soon reaches an acceptable level of reliability, it will potentially increase the efficacy of many energy efficiency programs. Furthermore, there is a large body of knowledge within the analytics category that has focused on occupants' energy consumption profiling and clustering. The ultimate goal of this category is to increase the efficacy of demand response and feedback programs by targeting households and using energy consumption, occupancy, energy disaggregation, and other forms of data. The research conducted in this area can be divided into two groups: (1) studies focused on improving the algorithms used to perform profiling and clustering analyses [35-40], and (2) studies concentrating on the application of load profiling and classification to discover the potential determinants and features that can enhance the task of targeting [41, 42, 48, 82, 92]. Targeted and tailored energy feedback approaches have theoretically [69] and empirically [52, 57, 70] been recommended as the most important steps to use for increasing the effectiveness of energy efficiency programs in the residential sector.

Although the analyses of building energy and smart meter data is a vast research realm with considerable valuable information to offer, researchers are advancing this body of knowledge by using a combination of analytics and other methods known in the field (e.g. Analytics-Experiments, Analytics-Surveys) to extract more valuable information. Thus, based on the reviewed literature, we categorize the studies that have an energy analysis component in Table 2 with arrows representing the sequence of those implemented methods. A detailed discussion on the advantages of these combinatory methods is provided in Sections 2.3. and 2.6.

Table 2. Studies that have an analytics component. The arrows represent the sequence of implemented methods.

Studies	Methodological Approach
[35-42]	Analytics
[85, 87, 92-94]	Analytics Survey
[9, 18, 44, 48, 103-105]	Experiment → Analytics

3.3. Analytics and Surveys

The “one size does not fit all” perspective (aka targeted and tailored energy feedback) stems from numerous human behavioral factors and characteristics that might not be able to be entirely captured by energy consumption analysis or survey data collection. The studies discussed in Sections 2.1 and 2.2 incorporated a uni-dimensional research method with a focus on surveys or analytics. However, the literature discussed below reports on the value of information that can be extracted using surveys and analytics as two complementary methods. The studies that combined survey and energy analysis information were conducted at various energy resolutions times. In a monthly resolution, Jones et al. [82] conducted a comprehensive literature review on the socio-economic factors’ affecting household electricity consumption. Despite all the inconsistencies in the research methods and the lack of a sufficient body of knowledge on specific socio-economic factors, the results found that 20 (4 socio-economic factors, 7 dwelling factors, and 9 appliance- related factors) out of 62 analyzed factors were positively correlated with household energy consumption, including the number of occupants, presence of young children and teenagers, and household income. It is worth noting as well that none of the socio-economic factors were reported to impact the level of energy consumption negatively (i.e., any reduction in energy consumption). Vassileva et al. [85] conducted one of the first attempts to evaluate occupants’ attitudes and knowledge toward environmentalism not only through the surveys, but also by evaluating their reflections on occupant actual energy consumption patterns. They reported that low energy consumers had less interest in filling out the questionnaires and the level of energy consumption of their households also correlated with their income levels. Likewise, Brounen et al. [87] carried out an analysis of 300,000 Dutch homes for energy consumption and the survey data collected on occupants’ demographics and dwelling characteristics to investigate the main determinants of occupant energy use. These results supported the importance of not only technical characteristics of a dwelling, but also the composition and background of the households that may shed light on underlying assumption of energy efficiency policies.

The afore-mentioned studies investigated the correlation between occupant and dwelling characteristics collected through surveys and collection of monthly energy consumption. The results hold promise for further informing the targeting and tailoring of energy feedback programs. Indeed, the advancement of technology and the higher penetration of smart meters have enabled a higher resolution data fusion and validation in this area. In a more advanced data analysis study, Albert and Rajagopal [92] investigated the existence of the potential correlations between occupants’ energy consumption patterns and their demographics, households, and appliance information. The validation of the study was conducted using an online survey. A Hidden Markov Model was implemented, which characterizes occupancy based on such features as the magnitude, duration, and variability of energy use. Their work aimed at household characteristics based on their energy consumption and provided major insight in tailoring the feedback and inferring certain user characteristics based on temporal energy consumption patterns.

Similarly, Beckel et al. [93] conducted an analytic-survey study in Ireland to cross-validate the information captured through surveys and infer households characteristics (e.g., employment status and number of occupants) from smart meter data. The accuracies achieved for occupant characteristics prediction varied between 30% and

80%, depending on the prediction target. However, the insights captured through a fusion of information between a survey and smart meter data analysis can increase the efficacy of energy feedback programs and further facilitate large scale targeted energy feedback programs for utility companies.

The afore-mentioned studies reported high resolution (i.e., daily, hourly, 30 minute) correlations between households' energy consumption and occupant/building characteristics that potentially are helpful for targeting and tailoring of energy feedback programs. Further, one of the main objectives of these studies is to replace the expensive and time-consuming process of survey data collection using energy-based characteristic inference. In one of the most recent studies, Viegas et al. [94] implemented a combination of survey and hourly energy consumption data to categorize residential customers using machine learning algorithms. Their study showed that incorporating survey data into energy consumption classification can improve the precision of customer categorization by 20%. This study reveals the potential of combining energy consumption data with occupant/building characteristics to further enhance the efficacy of targeted energy feedback programs and move one step closer to implementation of the "one size does not fit all" approach. Nevertheless, the practicality of conducting any large scale survey remains debatable.

3.4. Experiments

An experiment is a procedure carried out to verify, refute, or validate a hypothesis. In the context of energy feedback, experiments consist of a control group, at least one study group, baseline energy use data, and an energy feedback program. These studies validate a wide spectrum of hypotheses' targeting such factors as interface design, occupants' psychology, demographics, means of communication, and level of information. There are various studies that have analyzed the effectiveness of these factors [3, 14, 40, 69, 73, 76, 79, 80] and provided recommendations for increasing the efficacy of energy feedback programs. Despite all the recommendations, if a "one size does not fit all" vision is required as endorsed by many researchers [10, 18, 44, 52, 57, 69, 70], treating individuals by using a uniform approach will not produce the best outcomes. The experiments conducted in this field are designed differently, incorporate diverse combinations of methods, and collect different types of information regarding their contributions. However, there is still a limited body of experiments that has focused on targeted energy efficiency programs.

The majority of experiments focus on evaluating the components of energy feedback systems, In Home Displays (IHD), and demand response programs and their potential for inducing occupant based energy efficiency in buildings. These factors can be basically categorized as feedback frequency [18, 43], social norm effect [43-48, 60, 72, 95], feedback visualization [49-54], feedback information [6, 43, 50, 55, 56], communication channels [11, 13, 57], appliance level feedback [7, 56, 58, 95], cost effectiveness [44, 59], etc. The level of energy consumption in each group, before and after the baseline are the major pieces of information used in the hypotheses tests conducted in each study to validate the effectiveness of these components.

The importance of experimental field studies is undeniable, and the results reported in each experiment are important. However, more information has been captured at the intersection of experiments, surveys, and analytics. For example, using a simple post-study survey, researchers can gain insight into potential ineffective components of their platforms and the root causes of energy savings. In Table 3 we categorize those studies with an experimental component and in Sections 2.5 and 2.6, we provide a detailed description of the advantages of information fusion between experiments and other methods being used.

Table 3. Studies that have an experiment component. The arrows represent the sequence of implemented methods.

Studies	Methodological Approach
[6, 7, 11, 13, 43-60]	Experiment
[9, 18, 44, 48, 103, 104]	Experiment → Analytics
[43, 71, 86, 95, 97, 104]	Experiment → Survey
[58, 70, 72, 89, 98]	Survey → Experiment → Survey

3.5. Experiments and Surveys

Stand-alone experiment and survey studies provide valuable information to inform the design and execution of energy feedback programs, while also helping with better understanding of occupants' energy use behavior. Nevertheless, there are always questions that cannot be answered by the independent implementation of a single method. In the experiment-survey category [43, 70-72, 86, 89, 95-98, 104] researchers conducted pre- and post-study interviews and questionnaires to take into account the occupants' opinions of energy feedback interface design, and also to better understand the underlying causes of occupants' energy savings. Understanding and linking occupants' self-reported behavioral and demographic information to their actual energy consumption behavior is an invaluable piece of information that can potentially reveal the importance and redundancy of the various factors collected and analyzed in these survey and experiment studies. Furthermore, reliance on self-reported pro-environmental behavioral measures, rather than observing actual pro-environmental behaviors in field experiments is one of the shortcomings of environmental psychology studies (e.g. energy feedback studies) [106]. There is a potential for acquiring deeper knowledge of occupants' behaviors and the effectiveness of energy feedback program at the intersection of surveys and experiments as methods.

In the category of post-experiment surveys, Chen et al. [95] conducted a real time energy feedback study accompanied by a post-experiment survey to gather more information on the efficacy of the feedback interface design, the behavioral changes, and energy efficiency actions taken throughout the study. The results indicated that occupants' awareness of their energy consumption increased, and it also indicated there was a misperception of occupants regarding lighting and HVAC system energy consumption. Further, the authors reported that 78% of the participants felt encouraged enough to conserve energy after viewing the feedback dashboard. Similarly, Rettie et al.

[43] incorporated post-experiment survey data to enhance the design of the energy feedback program. Their survey revealed that users were more motivated to prevent waste of energy than they were in saving energy. They also reported that the social norm feedback increased interest in the program and developed competition between households. Alahmad et al [97] used the survey data captured during and at the end of an experiment to evaluate the efficacy of three types of in-home displays (IHD) in a long term study. These analytical results combined with follow- up surveys suggested that IHDs were more effective in the short term, and the level of engagement and interest of households did drop as time passed. The purpose of this survey was to collect data on user interface preferences, user involvement and engagement (e.g. the frequency of visits), motivation for energy savings, and behavioral changes.

A series of more sophisticated studies carried out pre- and post-experiment surveys to gather various information prior to and following the experiment and benchmark occupants' post-experiment responses against a pre-experiment survey. In this category, Peschiera et al [72] conducted a pre-experiment survey to capture the social bond information between occupants to design a normative comparison feedback experiment. They evaluated the impact of social bond strength on the level of the influence of peers on each other in a normative comparison feedback group. Further, they conducted a post-experiment survey to analyze the root causes of energy savings that were achieved during the experiment. Hargreaves et al [70] conducted a feedback study using IHDs along with a survey to understand the underlying causes of occupants' behavior changes and their assessment of IHDs and their efficacy. These results reported that the IHDs gradually became a background; nevertheless, the feedback system did increase occupants' awareness of their energy consumption, which unfortunately does not necessarily translate to a reduction in their energy use. Murtagh et al. [98] carried out an energy feedback experiment with both pre- and post-experiment surveys. These surveys were conducted to measure pro-environmental behaviors, attitudes, etc. The study reported a correlation between attitudes, energy conservation, and energy use. However, the surveys also revealed an absence of motivation when inducing energy savings among the occupants.

These afore-mentioned studies reported on the potential correlations between human behavior and their energy use responses when under energy feedback influences. Therefore, the effectiveness of pre- and post-experiment surveys do hold promise for informing researchers of various human energy use behavior determinants, while also providing additional information that can potentially enhance the efficacy of the targeting and tailoring process of these feedback programs.

3.6. Experiments and Analytics

There are studies that have indeed achieved a greater understanding of occupants' behavior and energy feedback efficacy at the intersection of experiments and analytics. For example, Taylor et al. [48] analyzed three demand response programs for their energy data (focusing on efficient heat pumps, attic insulation upgrade, and professional audit programs) to estimate their energy savings, compare cross groups of occupant performance, and investigate the potential changes that might lead to increases in the efficacy of such demand response programs by targeting their customers. The post-experiment analyses of the study reported a higher energy saving potential for less efficient households. Khosrowpour et al. [103] conducted a post-experiment analysis to investigate the effects of energy efficiency and predictability on the efficacy of targeted energy feedback programs. They learned and then predicted individual energy consumption patterns using a support vector machine algorithm for an hourly resolution. The occupants were categorized based on the accuracy of their energy-use prediction and level of efficiency. The results reported a potential for targeting almost 50% of inefficient occupants and 46% of all occupants in commercial buildings. At a daily energy resolution, Allcott [9, 18, 44, 104] conducted a multiple comprehensive post-experiment analysis on Opower's normative comparison feedback experiments. His analysis confirmed the persistence and durability of the normative comparison feedback effect, while identifying an action and backsliding pattern in the occupants' behavior for the first four months of the study.

The power of post-experiment analytics is obvious based on the depth of information captured in the afore-mentioned studies. Post-experiment analytics sheds light on *how* energy consumption has changed. This valuable piece of information can indeed contribute to a better understanding of the root causes of occupants' behavioral changes seen in these energy feedback studies.

3.7. Simulations

Simulations are used to imitate real world processes and operations based on developed mathematical and stochastic models [107]. This method is used to estimate the potential and cost-effectiveness of energy feedback programs for various scenarios prior to the launch of a program. Simulation research is an emerging field of study in the energy feedback area and has been gaining traction in recent years. In one of the most recent studies, Hong et al. [81] conducted a comprehensive literature review on the most recent efforts carried out in occupant behavior modeling and its impact on building energy use. A thorough vision is provided to define the occupant building interaction energy use behavior loop; however, the scope of Hong et al.'s [81] work does not take into account the effects of energy efficiency programs (i.e., energy feedback programs)on occupant behavior. Thus in this section, we review the literature on simulation studies, as they aim to imitate occupant behavior in energy feedback programs [61-66, 108, 109] and then discuss the advances of simulation studies being made in this field.

The application of agent- based simulation when modeling occupants' behaviors in commercial buildings under the influence of energy efficiency programs was recently introduced by Azar and Menassa [61]. In a later study [66] the authors built on the afore-mentioned work and increased the variability of occupants' behavior by allowing the occupants to have different energy use behaviors and influence each other's characteristics, while being enrolled in an energy efficiency program. The model used two variables to define occupants' behavioral states: (1) energy consumption intensity, and (2) the openness of an agent to adopt new energy consumption behaviors. The authors attempted to integrate the effect of energy efficiency intervention and occupants' behavior variation with social norm influence when building energy simulation. They reported that the results of energy predictions can vary up to 25% compared to conventional approaches. In the more advanced feedback scenarios, due to a rise of social norm- based approaches in feedback programs and a lack of information on the effect of social network types and structures on social norm behavioral interventions, Anderson et al. [64] conducted a grid- based change of the parameters to assess the sensitivity of those parameters (e.g. social network types, number of degrees, social network size) in social norm energy feedback simulation. The results reported that network type and structure can significantly impact the required time for intervention outcomes to reach a steady state.

These afore-mentioned studies have not been validated using real system data or a structure due to the lack of field experiment data in studies. However as illustrated in Table 4, there are studies in the field that do have access to energy feedback experiment data to use to develop more realistic and validated simulation models. In the following, we review these studies and discuss their advantages and contributions to the full body of knowledge.

Table 4. Studies that have a simulation component.

Studies	**Methodological Approach**
[61-66]	Simulation
[108-111]	Experiment → Simulation

3.8. Simulation and Experiment

There is a limited body of knowledge available that has tied the theoretical energy use behavioral models to empirical data collected in actual field experiments. In order to validate the simulation models, Zeigler [112] recommends three types of validation for the simulation models: (1) replicative validity (i.e., whether the model has the capability to replicate real field experiment data); (2) predictive validity (i.e., whether the model fits the data before that data are acquired from a real system); and (3) structural validity (i.e., whether the model completely reflects the way the real system operates). Real experiment data can facilitate Zeigler's three validation methods based on the availability of the data. In this section we review the papers that built and validated their simulation models based upon energy feedback field experiments.

In residential buildings, Chen et al. [108, 109] modeled the effect of network structure and type on occupant energy efficiency. These results reported that network degree and weights are more significant factors than the size of the network. In other words, the stronger the social bond, the higher the chance of the influence on peers. Anderson and Lee [110] took another leap by advancing occupant behavior models to simulate a normative comparison energy feedback. These results suggest that sending normative comparison feedback to above average energy consumers is the most successful scenario and yields 2.2% energy savings per person. In one of the others works, Yu et al. [111] conducted a Monte Carlo simulation derived from real experiment data to better understand the potential of enrolling customers in targeted and timely energy feedback programs.

The afore-mentioned studies [108-110, 113] are validated by replicating the real data collected from experiments that bring us one step closer to creating more accurate simulation models. Further, these simulation studies focus on important elements of energy feedback programs (e.g., social network structure, peer influence) to assess the potential energy savings and cost-effectiveness of these programs in various scenarios. Validated simulation models are also beneficial tools to use for potential estimation of energy feedback programs in the future.

4. RESEARCH GAPS

We have discussed the methods used in energy feedback research area and summarized the progress made in each methodological category. Despite all the major advancements in the energy feedback field, there is still room for improvement. In the following, we discuss the gaps of knowledge identified in each method or those found at the intersection of various methods.

4.1. Analytics and Surveys

As discussed in Sections 2.1, 2.3, and 2.5, there has been great progress made in energy feedback studies through the implementation of survey studies. The stand-alone survey study field is reaching a relative maturity that thus calls for shifting the focus to combinatory studies. However, one of the important gaps of knowledge identified in a majority of studies was lack of validation of acquired survey information on occupants' actual actions via energy use analytics. The value of such a validation step is a better understanding of inconsistencies and the correlations between occupants' perceptions and their actual energy consumption [95]. Furthermore, as reported by Viegas et al. [94], this fusion of information empowers the classification of participants to target feedback. Therefore, the knowledge gap that requires further investigation is:

A. *Knowledge Gap:* Further validating surveys with analytics to gain deeper knowledge of human behavior and the root causes of actions, while also enhancing the performance of classification algorithms used in any targeted energy feedback studies.

4.2. Experiments

The majority of studies reviewed in this paper focused on energy feedback field experiments. Regardless of the potential methodological issues reported in the literature [3], the progress made in recent years has significantly contributed to the entire body of knowledge. To take energy feedback experiments toward the highly recommended targeted and tailored approach, there is a need for more targeted and tailored energy feedback experiments. Tailoring feedback can be defined as simply providing individual appliance-level energy consumption information. However, the ultimate goal is to target individuals and tailor their feedback based on their energy use behaviors, characteristics, pro-environmental behaviors, psychological motivators, and energy savings opportunities. In other words, what type of feedback program (e.g., historical comparison, normative comparison, incentives), what type of information (e.g., KWh, environmental impact, health impact), and what other specific information should be sent to each individual? To the best of our knowledge, there are no studies that have automated and streamlined this process of targeting and tailoring feedback experiments to the level of complexity described here. There are very limited studies that have attempted to execute a personalized feedback experiment to better understand the impact of tailored feedback on occupants' behavior [114]. We thus recommend further investigation into this gap in the knowledge found in the literature as follows:

B. *Knowledge Gap:* Conducting more sophisticated targeted and tailored energy feedback studies to evaluate empirically the potential and the impact of tailored feedback vs. non-tailored and uniform feedback on customers.

4.3. Experiments and Surveys

As discussed in Section 2.5, pre- and post-experiment surveys can inform on experiment design and validate self-reported survey information. However, not all self-reported pro-environmental behaviors translate into energy savings or actions in field experiments [98]. The literature in this area does hold promise for informing energy feedback studies design and maintenance. Yet, there still is a need for further investigation to determine the links between occupants' self-reported behaviors and their actions in actual reality. The benefit of filling this aforesaid gap of knowledge is identifying the significant factors of participants' characteristics which can affect their performance in energy feedback programs as follows.

C. *Knowledge Gap:* Validating surveys with experiments so as to better understand the relationship between occupants' self-reported pro-environmental behaviors and the energy saving potential in field experiments.

4.4. Experiments and Analytics

As reported in previous studies [18, 48], occupant behavior is dynamic and can be changed through energy feedback programs; however, to our knowledge, there are very limited studies that have conducted prolonged energy load analysis to address *how* the behaviors of occupants have changed as a result of these energy feedback programs. Therefore, there is an opportunity to not only analyze occupants' energy consumption patterns in a baseline period, but also to monitor the change in these patterns during and after a study. The current body of research has conducted such studies with a focus on daily and average energy consumption of occupants. With the high resolution of information in hand gained through smart meter data, studies that report the variation of energy use patterns and shapes under the influence of energy feedback experiments still do not exist in the literature. Filling this gap of knowledge will provide more comprehensive information on where actual energy saving opportunities are and how energy use patterns have changed under the influence of feedback. This information can enhance the estimation and planning of energy load shifts when using energy feedback programs. Such studies exist in the demand response and pricing strategies [59, 83, 115, 116]; nevertheless, energy feedback programs have a distinct nature and do not necessarily follow the results obtained in these afore-mentioned studies.

D. *Knowledge Gap:* Performing energy analysis (e.g. load profiling) prior, during, and post any energy feedback experiments.

4.5. Experiments, Analytics, and Surveys

The advancement of technology for high resolution energy data collection through smart meters has enabled researchers to make great progress the in energy analytics domain. In a recent effort, Viegas et al. [94] reported that a combination of energy analysis and survey data can shape a better feature set and categorize occupants more accurately. Despite the importance of energy use classification for designing targeted energy feedback programs, the main question yet to be answered is how these analytically clustered behaviors can be related to effective energy feedback strategy that can then induce energy saving among each class. A recent study by Karatas et al. [117] proposes a conceptual framework to facilitate the process of treatment association by assessing occupants' motivation, opportunity, and ability. However, a single individual conceptual study might not provide the answers to all research questions in the field. Thus, further investigation is needed at the intersection of energy analysis, surveys, and experiments to further validate and improve this framework.

E. *Knowledge Gap:* Target various classes of customers that are categorized based on their energy consumption information (e.g., load pattern, occupancy patterns and energy use disaggregation) and survey information (e.g., pro-environmental attitude, literacy, demographics) using a proper feedback method to maximize the potential of energy feedback programs.

The targeted feedback methods already discussed in various papers focus on the stationary state behavior of occupants. Meaning that, once the occupants are targeted and the feedback is tailored, no changes will occur to the program for the rest of the period of that experiment. Nevertheless, occupant behavior does have a dynamic nature and varies over time. Thus, there is a need for programs that not only target occupants in a stationary station, but also consider the longitudinal dynamics of their behaviors. This gap in knowledge can be filled by combining experiments with a feedback loop and using the fusion of information captured through pre- and post-experiment surveys and analytics.

F. *Knowledge Gap:* Creating a feedback loop for energy feedback studies to update feedback based on the variation in individuals' energy use behavior over time.

4.6. Simulations

The field of simulation is the newest of the four methodologies discussed in this paper on energy feedback. Due to complexity, intra- class variability, and the uncertainty of occupants' behaviors, there are not many mathematical models available that can precisely emulate occupants' behaviors during the various energy feedback programs. Part of this problem is due to a lack of experimental open data in this field, and the remainder could be due to the complex nature of the challenges and limitations of the existing models. Therefore, there is still room for improving the underlying behavioral models used in such simulation and there is a gap in the knowledge when developing more precise simulation models in the field.

G. *Knowledge Gap:* Develop mathematical and statistical energy use behavioral models at the intersection of information captured through energy feedback experiments and the theory.

4.7. Simulations and Experiments

As discussed in Section 2.8, only a few studies have had the resources to validate their simulation models with real experimental data. Even though these studies [108-110, 113] have included a replicative validation step in their efforts to further improve the accuracy of their simulation models, their results have not been predictively validated with follow-up experiments. In order to conduct a predictive validation, there is a need for extensive real field experiment data to be able to create comprehensive and robust behavioral and structural models. Therefore, as reported in these studies, the results do not imply that simulation models built from individual experiments are powerful enough to estimate the energy savings and behavioral responses for all various scenarios (e.g. various demographics, weather, feedback).

This lack of a predictive and replicative validation step in simulation studies can be tied to the cost and the resources required to launch such field experiments. In other words, the majority of studies in this field are creating theoretical and hypothetical models for simulations, and thus, the studies suffer from a lack of validation using actual experiments. This situation calls for creating a stronger connection between simulations and the experiment methods in the community and opening up more experimental data to simulation experts so they can further enhance the efficacy of their models.

H. *Knowledge Gap:* Predictive, replicative, and structural validation of simulated energy use behaviors with field experiments can enhance the accuracy and reliability of simulations for the various energy feedback scenarios.

Creating reliable models to emulate occupants' behaviors and responses to different energy feedback programs will be in demand and can provide a significantly cost effective solution for energy feedback program assessment. Therefore, there is a need for a more comprehensive and coordinated effort to develop human energy use behavioral models and to conduct simulations prior to launching actual energy feedback programs. A large body of the research has focused on energy feedback experiments. However, due to privacy issues and IRB human subject protection regulations, researchers are not allowed to release the data collected in these studies. If these anonymized experimental data could be opened up to the energy feedback community, it would significantly increase the pace of and enhance the sophistication of simulation research.

5. RESEARCH CHALLENGES

Energy feedback studies are not free of challenges or obstacles. In order to shed light on the potential challenges that researchers may face during these studies, in this section we analyze and report on the necessary considerations and limitations of the studies found in the literature. These challenges are classified into four groups: (1) data collection and experiment methods; (2) human behavior complexity' (3) cross- cultural differences; and (4) a comfort- energy productivity trade- off. The following section informs researchers about the necessary considerations they need to take into account when carrying out energy feedback research.

5.1. Data Collection and Experiment Methods

All the complex interactions with human subjects inherent in energy feedback studies have several challenges related to data collection due to the high variability of human behaviors and privacy issues. One of the main shortcomings of experiments [10, 18, 44, 52, 57, 69, 70], surveys [118], and analytics [39, 100, 119] are the relatively small data samples used to conduct these studies. Unfortunately, due to the high intra- class variability of human characteristics and demographics, small sample data fails to cover a wide spectrum of the population if researchers do not consider any demographic controls in their studies. Acknowledging the difficulty of the recruitment process and data collection in energy feedback studies, the minimum sample data required to statistically validate the results obtained from such a study are usually suggested as a rule of thumb to be more than 30. However, based on the central limit theorem, there is also a need for a data normality check even if the sample population is greater than 30 [120]. This challenging process and this limitation are primarily more prevalent in experiments, and secondarily, in survey studies.

Even though Delmas et al. [3] reported that bias is probably not a significant issue in the field experiment literature, there remain instances in the literature that are biased toward students and young professionals [15, 51, 56, 60, 72, 121], pro-environmental communities [47, 71, 88], and in one instance, women [122]. Thus, encouraging researchers to disclose such information and consider that the results obtained from a biased population might not be fully generalizable is a recommended step.

Length of studies is another main important factor in the field of analytics and experiments. The longer the studies, the higher the chances of occupants' behaviors and responses to energy feedback programs being captured more reliably. Unfortunately, there is a large body of knowledge that was conducted in relatively short- term (i.e., from less than 1 month up to 3 months) studies to examine various energy feedback and occupants' behavior parameters [7, 16, 47, 60, 72, 118, 123]. The reported results of these studies may be significant in a short run, but nevertheless, due to the potential existence of the Hawthorne effect [10], response-relapse [72], and action and backsliding [104], there is no guarantee that this impact will be sustainable over a longer period of time. As reported by [104], after several months of feedback (4 months in this case), occupants most probably changed their capital stock of habits and physical technology. Thus, there is no guarantee that this length of study withstands the various types of feedback. We highly recommend that researchers continue their experiments for more than 4 months or whenever the level of energy consumption reaches a steady state, considering the potential impact of usual seasonal variations. Considering the lack of an absolute answer to use to determine the length of such experiments, conducting longer studies does increase the reliability of data, analysis, and obtained results.

Experiments are launched to evaluate the effectiveness of various psychological aspects, design, information, and other factors involved in energy feedback programs. The efficacy of such programs is commonly determined through a statistical analysis of variations in the level of energy savings induced through the program or the level of engagement. A variety of statistical tests, such as the student t-test, mixed effect regression models, analysis of variance, and multivariate analysis of the variance, can be implemented to evaluate these programs. Capturing two major components is necessary in order to measure the efficacy of energy feedback programs, namely, (1) collecting an appropriate baseline data, and (2) allocating a randomized study and control group (also known as a randomized control trail). Unfortunately, there are studies that have not considered the importance of having a control group included in their experiments [7, 8, 16, 52-54, 58] and as a result, they have limited their claims to merely reporting changes in the levels of energy consumption.

5.2. Survey Response Collection

Surveys are one of the most important methods by which to extract information for the further enhancement of targeted energy feedback programs. However, one of the greatest challenges of conducting survey studies is the process of data collection and the lack of complete response rates to questionnaires [23, 25-27, 32]. There have been studies with response rates of 7% to 32% [23, 25] while other studies have been receiving response rates of higher than 79% [26, 27, 32]. Perhaps one of the biggest differentiators of these response rates is the targeted sample population size or responders' incentives in responding to the surveys. Previously, we mentioned that survey data could be used as complementary information to reinforce customer classifications and clustering. Even so, the labor intensiveness of the process and lack of complete responses to questionnaires increase the difficulty of the process. There is a consequent need for further investigation in order to enhance the rates of occupant responses to survey questions. This can be done through incentivizing, simplifying the questions, decreasing the number of questions, and choosing the most convenient delivery method for responders.

5.3. Complexity of Human Behavior

Uncertainty, variability, and the complexity of human behavior is an established fact [101, 124, 125]. One of the major challenges that the energy feedback community faces is a high intra-class variability of human behavior [52, 101] which not only complicates the design and implementation of energy feedback systems [10, 18, 44, 52, 57, 69, 70], but also affects the interpretation of the underlying causes of human behaviors when under the influence of such programs [13, 90]. Furthermore, various reported phenomena, such as the Hawthorne effect [10, 33], action and backsliding [104], and the Nintendo effect [87] add to the complexity of any human behavior analysis. The Nintendo effect is defined as extensive use of television, personal computers, and gaming devices by older children, and it has a huge impact on the energy consumption of a household [87].

Excluding the effects of the Hawthorne effect and its action and backsliding is possible by increasing the length of the studies. However, disaggregating such effects from short-term results, or incorporating them as part of the statistical and mathematical models describing human behavior is a major challenge that is yet to be addressed.

Another major challenge reported by a substantial group of researchers is the response relapse in occupants' engagement in energy feedback studies. Most of the studies have reported the existence of such a problem [10, 70, 97, 98, 126, 127]. Peschiera et al. [72] particularly studied this phenomenon, and others have tried to numerically model the decaying rate of energy savings and engagement level in a study after treatment is discontinued [9, 58]. Despite extensive reports on such a phenomenon, there are studies that disagree with the majority of researchers and provide evidence that the response relapse can be controlled or eliminated from feedback programs if the treatment/feedback does not discontinue [11, 104, 128]. Gamberini et al. [128] designed and implemented a gamification- based feedback system which provided tailored feedback to users. The aim of the game is to increase the user awareness of their energy consumption, and the results do show significant savings in short term. In this study, the researchers reported that the effect of smart advice tips they sent throughout the study stayed stable across the study, which also contradicts the response relapse reported by other studies. Delmas and Lessem [11] conducted an energy feedback study and obtained marginally significant results' supporting the persistence of energy efficient actions after program termination. Further, Allcott and Rogers [104] confirmed the same findings by emphasizing that a continuous energy feedback program can maintain persistence and durability over the long term. Different lengths of experiments appear to be one of the underlying causes of this controversy in the literature; however, this calls for paying closer attention to detect any potential relapses in responses during experiments and also avoiding short- term experiments.

5.4. Cross-cultural and Climatic Differences

Cross- cultural difference is another major challenge, which has increased the complexity of data analysis and generalization of the results. A few researchers have already acknowledged the limitation of their studies due to cross- cultural differences [17, 129]. Likewise, the seasonal variation of weather and climatic diversity [48] are other impacting factors that need to be considered in the experiments [3]. There is no guarantee that an effective factor under a specific cultural and climatic condition, performs effectively in other cultures and climates. Despite the limited body of literature that has specifically acknowledged the existence of such challenges, the majority of studies merge this difference with the intra -class variability of occupants' behaviors from a more general perspective [10, 18, 44, 52, 57, 69, 70]. For example, an energy feedback study launched in Miami will not necessarily result in the same level of savings as one conducted in Michigan. To our knowledge, there are no mathematical models available to robustly transfer the findings obtained from one culture or climate to another in the field of occupant energy feedback. Developing these models can definitely facilitate a more collaborative effort on a national or international scale.

5.5. Trade-off between Comfort Energy and Productivity

Another challenge found based on a limited subset of studies analyzed here, points to the importance of existing trade-offs between energy-comfort-productivity [23]. Consideration of these factors is necessary, especially in commercial buildings, since occupant productivity comes before energy savings in the workplace [130]. In fact, there are studies [131] that support the importance and cost-effectiveness of productivity and indoor air quality in office buildings, even at the cost of higher energy consumption. In residential buildings, the socio- economic status of households including their incomes, positively affects their energy consumption [82]. An implication of such a finding can be linked to the different levels of comfort desired by various social classes. A recent study by Amasyali and El Gohary [23] reported the interdependence of energy consumption and comfort in buildings that put more emphasis on the importance of considering such a factor in energy feedback studies. The trade-off between energy, comfort, and productivity is yet to be investigated in residential and commercial buildings; however, it does suggest a great research opportunity is present in the field.

5.6. Data Sharing and Collaborative Research

Due to several privacy issues and IRB human subject protection regulations, researchers are not allowed to release the data collected in their studies. On the other hand, due to the length, scope, and intensive labor of processing the literature, we are witnessing a fragmented body of research and a lack of collaboration between various disciplines. If an anonymized experimental survey on energy used data which protected the occupants' privacy could be shared with the energy feedback community, it would significantly increase the pace and enhance the sophistication of all facets of research. For example, if we assume that there is a sequential process involved in energy feedback studies (starting with surveys, analytics, and experiments, and ending with simulations), the process of data collection is long, expensive, and labor-intensive. Therefore, to conduct a simulation study, one should carry out all or part of the sequence mentioned above to collect the experimental data [110]. In cases where a predictive validation is required, there is a need for multiple experiments with different settings to collect the sufficient data [108, 109]. One of the main challenges of the current body of research is the lack of a secured data-sharing platform among researchers which would make the experimental, analytics, and survey data available to simulation researchers while maintaining occupants' privacy. There is a lack of collaboration and standardized data-sharing approach among researchers to enhance the efficacy of simulation models to emulate occupants' behavioral responses to various energy feedback programs.

6. FUTURE RESEARCH VISION

We categorized these peer- reviewed papers based on four main research methods and their eight combinations: (1) surveys, (2) analytics, (3) survey-analytics, (4) experiments, (5) experiment-survey, (6) experiment-analytics, (7) simulations, and (8) experiment-simulation, Further, we laid out the knowledge gaps, challenges, and opportunities identified in the literature. The afore-mentioned analyses make a provision for proposing a the future research vision to provide a complete design and maintenance pipeline for targeted energy feedback studies. By leveraging available data and methods, the efficacy of such programs can potentially be improved through the implementation of a more systematic approach. In the following, we propose a research vision for the list of knowledge gaps to address in each step.

Knowledge Gaps:

A. Further validate surveys with analytics to gain deeper knowledge of human behavior and the root causes of their actions, while enhancing the performance of classification algorithms used in targeted energy feedback studies.
B. Conduct targeted and tailored energy feedback studies to empirically evaluate the potential and the impact of tailored feedback vs. non-tailored and uniform feedback on customers.
C. Validate surveys with experiments to better understand the relationship between occupants' self-reported pro-environmental behaviors and their energy saving potential in field experiments.
D. Perform energy analysis (e.g., load profiling) prior, during, and after energy feedback experiments.
E. Target various classes of customers and categorize them based on their energy consumption information (e.g., load pattern, occupancy patterns, and energy use disaggregation) and survey information (e.g., pro-environmental attitude, literacy, demographics) using a proper feedback method to maximize the potential of energy feedback programs.
F. Create a feedback loop in the energy feedback studies to update feedback based on individuals' energy use behavior variations over time.
G. Develop mathematical and statistical energy use behavioral models at the intersection of the information captured through energy feedback experiments and the theory.
H. Use predictive, replicative, and structural validation of simulated energy use behaviors with field experiments to enhance the accuracy and reliability of these simulations for various energy feedback scenarios.

We propose a vision that can facilitate filling the afore-mentioned 8 gaps of knowledge. The vision consists of two sections. The first is designed based on surveys, analytics, experiments and follows a 6- step process as illustrated in Fig 1: (1) An analysis should be conducted on all baseline energy data collected prior to the launch of any program to extract the information mentioned in Section 2.2. It should be noted that the longer the baseline period, the more reliable the benchmark will be. (2) the program should start with an initial survey to capture the important information discussed in Section 2.1. (3) A fusion of survey and energy analytics information should be performed to (a) validate the survey data using actual energy consumption data, and (b) provide a comprehensive input data for the sake of occupant classification and targeting. This step primarily addresses gap A and secondarily addresses gap E. (4) Based on the acquired information, energy feedback programs should be tailored specifically for each class of occupants. This step can help to address gap E. (5) Launching a targeted energy feedback experiment with necessary considerations is discussed in Section 4, a step is necessary to evaluate the hypotheses offered in previous sections here and validate the efficacy of the feedback system (addresses gap B). Finally, (6) require a design/maintenance feedback loop to repeat the afore-mentioned 5 steps; update the classifications and feedback design based on the change of behaviors observed after a couple rounds of treatment/feedback (addresses gaps D and F). Also, this loop will provide the necessary means to investigate the underlying causes of response relapse. This design and maintenance loop is recommended to be repeated to the point where occupants' capital stock of habits and physical technology is not only changed, but also then newly stabilized.

The second section of the vision build on the first section by combining a complete process consist of survey, analytics, and experiments with simulation. As depicted in Fig 1, Section 2 is demonstrated in yellow and consists of three steps (i.e., Steps 7 to 9): (7) Developing mathematical and statistical energy use behavior models is based on the information, process, and results obtained in the first segment of the vision. This step can help to address gap G. (8) Simulate various scenarios to choose or update a suitable targeted energy feedback program for each individual to provides a foundation for enabling replicative validation in simulation studies while partially addressing gap H. (9) Repeating steps (1) to (8) can validate simulation studies to the point that actual occupant responses to the suggested energy feedback program by simulation models will match the estimated energy use response. In other words, step (9) provides a replicative, predictive, and structural validation step to use to develop the simulation models needed to address gap H.

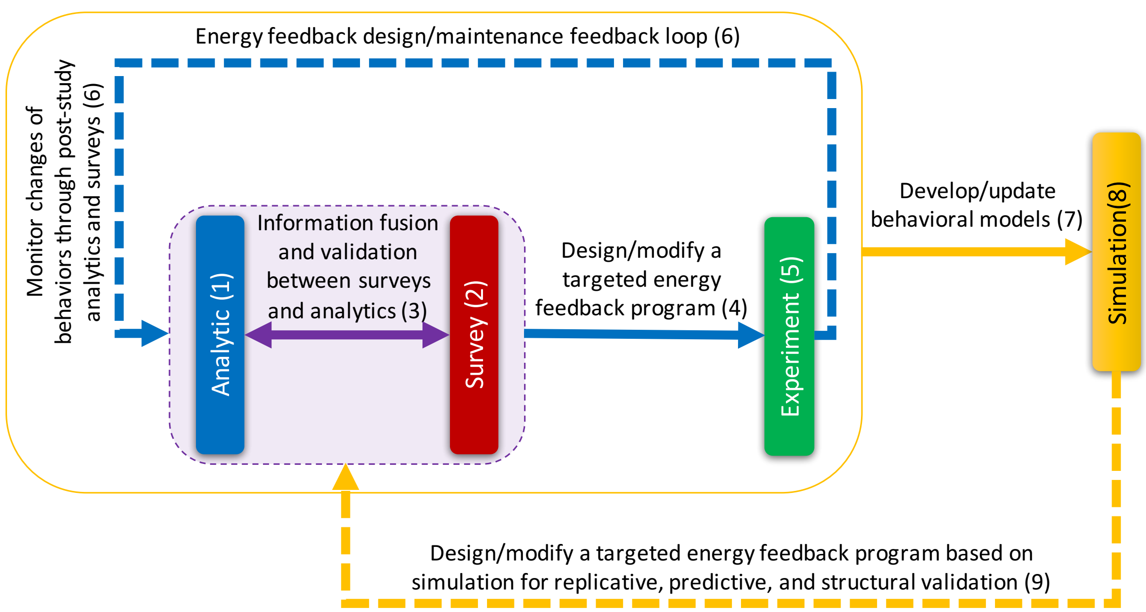


Figure 1. Energy feedback design and maintenance research vision (Section 1) and an energy feedback simulation framework vision here in yellow (Section 2). The precise steps (i.e. 1-9) are in brackets in front of each part of the framework.

The proposed vision offers a systematic approach for addressing the challenges and filling the 8 gaps in knowledge identified here in earlier sections. Moreover, it incorporates a design/maintenance feedback loop that enables the development of a dynamically targeted energy feedback program. The first section addresses opportunities related to the first three methods and their combinations: (1) surveys, (2) analytics, and (3) experiments. The second section covers (4) simulation research gaps. In practical terms, the proposed vision requires a multi-disciplinary coordinated effort due to the scope and length of the studies involved. Furthermore, such large scale study requires huge capital and other resources. To enable a collaborative effort in the community, we need to break down these studies while preventing the fragmentation of the entire body of research. The key to overcoming this fragmentation and the sparseness of research in the community is opening up properly documented empirical data (i.e. survey, experiment, analytics) to the public to enable researchers to build off each effort and then carry out a more coordinated effort to address the gaps of knowledge defined in this paper.

For example, environmental psychologists can be put in charge of conducting pre- and post-study surveys (Step 1). Electrical engineers can handle pre- and post-study energy analysis (Step 2). Data scientists can study the fusion of information between surveys and analytics and through collaboration with environmental psychologists, target each group of customers with a treatment/feedback method (Step 3). Researchers with human computer interaction expertise could be put in charge of the design and development of the feedback platform (Step 4). Field experiment researchers can launch the feedback experiment and monitor the entire process (Step 5). Step 6 allows the first two teams who conduct surveys and analytical studies to re-evaluate occupants' behaviors and their energy consumption patterns. This cycle can then continue. On the simulation side, if human building interaction researchers gain access to an open data platform, they can develop the more appropriate underlying behavioral models for simulation (Step 7). Based on publicly available data, various scenarios can be simulated and new models can be validated by replicating the data used to develop the simulation models (Step 8). Finally, Step 9 requires collaboration of all the aforementioned groups (or anyone with access to the data) to design and launch new experiments, surveys, and analytics using the most promising simulated scenarios. This step also facilitates the structural and predictive validation of any simulation models.

This example assigns various groups to each step to emphasize the inter-disciplinary nature of this challenging research area. Furthermore, it establishes the fact that there is no need for each and every group of researchers to collect their own data for analysis or simulation. The emphasis is on an open sourced and publicly accessible dataset, while still maintaining occupant privacy, which is the key to unleashing the potential research opportunities in energy feedback. It can provide a feasible and efficient solution for developing targeted and tailored feedback programs. Moreover, partnering up with utility companies [87, 92, 93] to leverage the existing infrastructure systems, give access to high resolution smart meter data and a larger sample population would suggestively expedite the research process by eliminating sensor deployments and the data collection phase. This latter option is not feasible in all types of buildings (e.g. commercial office buildings). The granularity of data needed to conduct occupant-based energy feedback studies in commercial office buildings must be at the plug load level [48], which is extremely expensive and labor-intensive to collect, another reason to move toward an open- source data platform to enhancing the research in this field.

Earlier, we discussed the challenges and barriers of occupant energy feedback research and provided both insights and recommendations for conducting more reliable studies. In the following text, we summarize the necessary considerations for more effective energy feedback studies and major consideration to implement the vision.

Major Considerations:

- Community members should consider the potential of anonymizing and releasing energy use, survey, and experimental data. Furthermore, they should take into account the necessary elements, in the IRB approval process, that could facilitate further collaborative research in the community.
- The interdisciplinary nature of energy feedback research requires collaborative research that improves the quality of interdisciplinary research and brings new perspectives to the research area.
- The vision proposed in this section recommends implementation of a closed-loop process to benchmark pre- and post-study behaviors, responses, and energy uses.
- Suggested behavioral determinants such as previous energy consumption level, socio-economic status, environmental attitude, dwelling size and type, and more should be considered when forming study groups. Research has reported the effect of these factors on occupant response to feedback programs.
- Studies need to consider the effects of comfort and productivity on occupants' energy consumption. While these are among the most significant constraints of occupants' energy efficiency, there have been, to date, limited efforts toward understanding them.

Necessary Considerations:

- The sample data used to conduct experiments and surveys should be unbiased and normally distributed based on demographics and other characteristics. However due to the difficulty of recruiting such a sample population, participants can be recruited from any specific demographic as long as necessary control measures are considered in the analysis and results are not generalized.
- Larger sample populations in surveys, analytics, and experiments can help researchers achieve more reliable and comprehensive results. The minimum sample data required to statistically validate the results obtained from such a study are usually suggested as a rule of thumb to be more than 30; however, based on the central limit theorem, there is a need for a data normality check even if the sample population is greater than 30 [120].
- Length of experiments should be stretched out enough to facilitate the elimination of temporary effects, such as the "Hawthorne" and "action and backsliding", while still providing information on potential response relapse patterns. Based on the literature, it takes several months (e.g. 4 months [104]) for occupants to change their capital stock of habits and physical technology; however, there is no guarantee that four months is long enough for various types of feedback programs. We recommend that researchers continue their study up to the point that all participants' energy consumption behaviors have reached a relatively stable condition.
- Experiments should collect proper baseline data before the program is launched and also allocate a randomized control group for positive benchmarking. The longer the length of the baseline, the more reliable the benchmark will be.

- Experiments should consider seasonal changes in weather and its impact on occupants and energy consumption in buildings.
- Survey studies should be designed to yield high response rates to enable a fusion of information with energy consumption analytics for the sake of targeted energy feedback.

There are numerous parameters that are affecting targeted energy feedback studies and to date no absolute answer to energy feedback design. However, based on the reviewed literature, limitations, challenges, and gaps of knowledge, incorporating a new design and maintenance vision can potentially facilitate a more systematic approach to conducting such studies. Moreover, this vision can enable a more collaborative effort in any open data platform environment that will protect occupants' privacy and identity.

A targeted and tailored feedback program may be a more cost-effective approach compared to the conventional non-tailored feedback programs. After all, eliminating less potent energy savers from the program and maximizing the energy savings of others who have higher energy saving potential via personalized feedback may be a positive solution [10, 18, 44, 52, 57, 69, 70, 103]. Furthermore, adhering to the necessary considerations list discussed in this paper is crucial in order to create a common ground that will enable the studies in the field to be comparable and build off one another. Accordingly, disclosing important information (discussed in Section 4) such as limitations and biases, length, sample size, weather, climatic and cultural conditions, comfort or productivity constraints, etc., while releasing anonymous energy use data can empower a more coordinated research effort by following the proposed vision and enhance the efficacy of targeted energy feedback programs.

7. ACKNOWLEDGEMENTS

This text is based on work supported by the Department of Energy Building Technologies Program and the National Science Foundation under Grants No. 1142379 and 1461549. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors alone and do not necessarily reflect the views of the Department of Energy or the National Science Foundation.

APPENDIX 1-A

Table 5. List of methodologically analyzed Studies

Citation #	Authors	Year	Journal
[97]	Alahmad et al.	2012	*IEEE Transaction on Industrial Electronics*, 59(4), 2002-2013
[92]	Albert, Rajagopal	2013	*IEEE Transaction on Power Systems*, 28(4), 4019-4030
[18]	Allcott	2011	*Journal of Public Economics*, 95(9-10), 1082-1095
[44]	Allcott, Mullainathan	2010	*Science*, 327(5970), 1204-1205
[104]	Allcott, Rogers	2012	*The American Economic Review*, 104(10), 3003-3037
[23]	Amasyali, El-Gohary	2016	*Building and Environment*, 95, 251-263
[64]	Anderson, Lee	2014	*Journal of Computing in Civil Engineering*, 28(1), 30-39
[110]	Anderson, Lee	2016	*Applied energy*, 173, 272-282
[56]	Asensio, Delmas	2015	*Proceedings of the National Academy of Sciences*, 112(6), E510-E515
[30]	Attari et al.	2010	*Proceedings of the National Academy of Sciences*, 107(37), 16054-16059
[46]	Ayres et al.	2013	*Journal of Law, Economics, and Organization*, 29(5), 992-1022
[61]	Azar, Menassa	2012	*Journal of Computing in Civil Engineering*, 26(4), 506-518
[66]	Azar, Menassa	2015	*Energy and Buildings*, 97, 205-218
[93]	Beckel et al.	2014	*Energy*, 78, 397-410
[31]	Bonino et al.	2012	*Energy and Buildings*, 47, 383-393
[26]	Brounen et al.	2013	*Energy Economics*, 38, 42-50
[87]	Brounen et al.	2012	*European Economic Review*, 56(5), 931-945
[13]	Carrico, Riemer	2011	*Journal of Environmental Psychology*, 31(1), 1-13
[95]	Chen et al.	2014	*Energy and Buildings*, 70, 455-462
[54]	Chen et al.	2012	*Energy and Buildings*, 45, 106-115
[109]	Chen et al.	2013	*Applied Energy*, 105, 358-368
[108]	Chen et al.	2012	*Energy and Buildings*, 47, 515-524
[49]	Chiang et al.	2012	*Energy and Buildings*, 55, 471-480
[51]	Costanza et al.	2012	*Proceedings of the ACM Conference on Ubiquitous Computing* (pp. 216-225)
[11]	Delmas, Lessem	2014	*Journal of Environmental Economics and Management*, 67(3), 353-370

Citation #	Authors	Year	Journal
[89]	Grønhøj, Thøgersen	2011	*International Journal of Consumer Studies*, 35(2), 138-145
[42]	Gulbinas et al.	2015	*IEEE Transactions on Smart Grid*, 6(3), 1414-1424
[47]	Gulbinas, Taylor	2014	*Energy and Buildings*, 84(0), 493-500
[38]	Haben et al.	2016	*IEEE Transactions on Smart Grid*, 7(1), 136-144
[70]	Hargreaves et al.	2013	*Energy Policy*, 52(0), 126-134
[45]	Jain et al.	2013	*Energy and Buildings*, 66, 119-127
[6]	Jain et al.	2013	*Energy and Buildings*, 64, 408-414
[55]	Jessoe, Rapson	2012	*The American Economic Review*, 104(4), 1417-1438
[32]	Kang et al.	2012	*Energy and Buildings*, 46, 112-122
[22]	Karjalainen	2011	*Energy and Buildings*, 43(2-3), 458-467
[103]	Khosrowpour et al.	2016	(In Press), *Energy and Buildings*
[86]	Kobus et al.	2013	*Ergonomics*, 56(3), 451-462
[65]	Lee, Malkawi	2014	*Energy and Buildings*, 69, 407-416
[25]	Littleford et al.	2014	*Journal of Environmental Psychology*, 40, 157-166
[98]	Murtagh et al.	2013	*Energy Policy*, 62, 717-728
[35]	Mutanen et al.	2011	*IEEE Transaction on Power Delivery*, 26(3), 1755-1763
[28]	Nachreiner, Matthies	2016	*Energy Research and Social Science*, 11, 276-287
[37]	Panapakidis et al.	2015	*Engineering Applications of Artificial Intelligence*, 38, 1-13
[58]	Pereira et al.	2013	*In Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data* (pp. 237-255)
[72]	Peschiera et al.	2010	*Energy and Buildings*, 42(8), 1329-1336
[60]	Peschiera, Taylor	2012	*Energy and Buildings*, 49, 584-590
[36]	Quilumba et al.	2015	*IEEE Transaction on Smart Grid*, 6(2), 911-918
[52]	Quintal	2013	*In IFIP Conference on Human-Computer Interaction* (pp. 453-470)
[43]	Rettie et al.	2014	*Springer International Publishing*, 594-604
[29]	Sanquist et al.	2012	*Energy Policy*, 42, 354-364
[33]	Schwartz et al.	2013	*Proceedings of the National Academy of Sciences*, 110(30), 15242-15246
[53]	Schwartz et al.	2014	*Interacting with Computers*
[24]	Simcock et al.	2014	*Energy Policy*, 65, 455-464

Citation #	Authors	Year	Journal
[39]	Stephen et al.	2014	*IEEE Transaction on Power Delivery*, 29(1), 88-96
[71]	Strengers	2011	*Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2135-2144
[85]	Vassileva et al.	2012	*Applied Energy*, 90(1), 182-188
[57]	Vassileva et al.	2012	*Applied Energy*, 93, 575-582
[34]	Vassileva, Campillo	2014	*Renewable Energy*, 67, 59-63
[94]	Viegas et al.	2016	*Energy*, 107, 804-817
[63]	Yang, Wang	2013	*Energy and Buildings*, 56, 1-7
[111]	Yu et al.	2015	*IEEE International Conference on Smart Grid Communications* (pp. 865-870)
[27]	Zhang et al.	2013	*Energy Policy*, 62, 1120-1127

APPENDIX 2-B

Table 6. Temporal sequence of methods used in studies (From left to right)

Citation #	Survey	Analytics	Experiment	Survey	Analytics	Simulation
[97]			x	x		
[92]	x	x				
[18]			x		x	
[44]			x		x	
[104]			x		x	
[23]	x					
[64]						x
[110]			x			x
[56]			x			
[30]	x					
[46]			x			
[61]						x
[66]						x
[93]	x	x				
[31]	x					
[26]	x					
[87]	x	x				
[13]			x			
[95]			x	x		
[54]			x			
[109]			x			x
[108]			x			x
[49]			x			
[51]			x			
[11]			x			
[89]	x		x	x		
[42]		x				
[47]			x			
[38]		x				
[70]	x		x	x		
[45]			x			
[6]			x			
[55]			x			
[32]	x					
[22]	x					
[103]			x		x	
[86]			x	x		
[65]						x

Citation #	Survey	Analytics	Experiment	Survey	Analytics	Simulation
[25]	x					
[98]	x		x	x		
[35]		x				
[28]	x					
[37]		x				
[58]			x			
[72]	x		x	x		
[60]			x			
[36]		x				
[52]			x			
[43]			x	x		
[29]	x					
[33]			x	x		
[53]			x			
[24]	x					
[39]		x				
[71]	x					
[85]	x	x				
[57]	x	x				
[34]	x					
[94]	x	x				
[63]						x
[111]			x			x
[27]	x					

REFERENCE

1. U.S.EIA, *Monthly Energy Review/ 40th Anniversary Issue*, in *Monthly Energy Review*. 2014. p. 23.
2. U.S.EPA *The Inside Story: A Guide to Indoor Air Quality*. 2012.
3. Delmas, M.A., M. Fischlein, and O.I. Asensio, *Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012.* Energy Policy, 2013. **61**: p. 729-739.
4. Stern, P., *Toward a coherent theory of environmentally significant behavior.* Journal of social issues, 2000. **56**(3): p. 407-424.
5. Darby, S., *The effectiveness of feedback on energy consumption.* A Review for DEFRA of the Literature on Metering, Billing and direct Displays, 2006. **486**: p. 2006.
6. Jain, R.K., J.E. Taylor, and P.J. Culligan, *Investigating the impact eco-feedback information representation has on building occupant energy consumption behavior and savings.* Energy and Buildings, 2013. **64**: p. 408-414.
7. Yun, R., et al., *Toward the design of a dashboard to promote environmentally sustainable behavior among office workers*, in *Persuasive Technology*. 2013, Springer. p. 246-252.
8. Foster, D., et al. *Wattsup?: motivating reductions in domestic energy consumption using social networks*. in *Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries*. 2010. ACM.
9. Allcott, H. and T.T. Rogers, *How Long Do Treatment Effects Last? Persistence and Durability of a Descriptive Norms Intervention's Effect on Energy Conservation.* 2012.
10. van Dam, S.S., C.A. Bakker, and J.D.M. van Hal, *Home energy monitors: impact over the medium-term.* Building Research & Information, 2010. **38**(5): p. 458-469.
11. Delmas, M.A. and N. Lessem, *Saving power to conserve your reputation? The effectiveness of private versus public information.* Journal of Environmental Economics and Management, 2014. **67**(3): p. 353-370.
12. Schultz, P.W., et al., *The constructive, destructive, and reconstructive power of social norms.* Psychological science, 2007. **18**(5): p. 429-434.
13. Carrico, A.R. and M. Riemer, *Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education.* Journal of Environmental Psychology, 2011. **31**(1): p. 1-13.
14. Froehlich, J., L. Findlater, and J. Landay. *The design of eco-feedback technology*. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2010. ACM.
15. Petkov, P., et al. *Motivating domestic energy conservation through comparative, community-based feedback in mobile and social media*. in *Proceedings of the 5th International Conference on Communities and Technologies*. 2011. ACM.
16. Spagnolli, A., et al., *Eco-feedback on the go: Motivating energy awareness.* Computer, 2011. **44**(5): p. 38-45.

17. Gans, W., A. Alberini, and A. Longo, *Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland.* Energy Economics, 2013. **36**: p. 729-743.
18. Allcott, H., *Social norms and energy conservation.* Journal of Public Economics, 2011. **95**(9-10): p. 1082-1095.
19. Albert, A., R. Rajagopal, and R. Sevlian. *Segmenting consumers using smart meter data*. in *Proceedings of the Third ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*. 2011. ACM.
20. McKerracher, C. and J. Torriti, *Energy consumption feedback in perspective: integrating Australian data to meta-analyses on in-home displays.* Energy Efficiency, 2013. **6**(2): p. 387-405.
21. Faruqui, A., S. Sergici, and A. Sharif, *The impact of informational feedback on energy consumption—A survey of the experimental evidence.* Energy, 2010. **35**(4): p. 1598-1608.
22. Karjalainen, S., *Consumer preferences for feedback on household electricity consumption.* Energy and Buildings, 2011. **43**(2-3): p. 458-467.
23. Amasyali, K. and N.M. El-Gohary, *Energy-related values and satisfaction levels of residential and office building occupants.* Building and Environment, 2016. **95**: p. 251-263.
24. Simcock, N., et al., *Factors influencing perceptions of domestic energy information: Content, source and process.* Energy Policy, 2014. **65**: p. 455-464.
25. Littleford, C., T.J. Ryley, and S.K. Firth, *Context, control and the spillover of energy use behaviours between office and home settings.* Journal of Environmental Psychology, 2014. **40**: p. 157-166.
26. Brounen, D., N. Kok, and J.M. Quigley, *Energy literacy, awareness, and conservation behavior of residential households.* Energy Economics, 2013. **38**: p. 42-50.
27. Zhang, Y., Z. Wang, and G. Zhou, *Antecedents of employee electricity saving behavior in organizations: An empirical study based on norm activation model.* Energy Policy, 2013. **62**: p. 1120-1127.
28. Nachreiner, M. and E. Matthies, *Enhancing informational strategies for supporting residential electricity saving: Identifying potential and household characteristics in Germany.* Energy Research & Social Science, 2016. **11**: p. 276-287.
29. Sanquist, T.F., et al., *Lifestyle factors in U.S. residential electricity consumption.* Energy Policy, 2012. **42**: p. 354-364.
30. Attari, S.Z., et al., *Public perceptions of energy consumption and savings.* Proceedings of the National Academy of Sciences, 2010. **107**(37): p. 16054-16059.
31. Bonino, D., F. Corno, and L. De Russis, *Home energy consumption feedback: A user survey.* Energy and Buildings, 2012. **47**: p. 383-393.
32. Kang, N.N., S.H. Cho, and J.T. Kim, *The energy-saving effects of apartment residents' awareness and behavior.* Energy and Buildings, 2012. **46**: p. 112-122.
33. Schwartz, D., et al., *The Hawthorne effect and energy awareness.* Proceedings of the National Academy of Sciences, 2013. **110**(38): p. 15242-15246.

34. Vassileva, I. and J. Campillo, *Increasing energy efficiency in low-income households through targeting awareness and behavioral change.* Renewable Energy, 2014. **67**: p. 59-63.
35. Mutanen, A., et al., *Customer classification and load profiling method for distribution systems.* Power Delivery, IEEE Transactions on, 2011. **26**(3): p. 1755-1763.
36. Quilumba, F.L., et al., *Using Smart Meter Data to Improve the Accuracy of Intraday Load Forecasting Considering Customer Behavior Similarities.* Smart Grid, IEEE Transactions on, 2015. **6**(2): p. 911-918.
37. Panapakidis, I., M. Alexiadis, and G. Papagiannis, *Evaluation of the performance of clustering algorithms for a high voltage industrial consumer.* Engineering Applications of Artificial Intelligence, 2015. **38**: p. 1-13.
38. Haben, S., C. Singleton, and P. Grindrod, *Analysis and Clustering of Residential Customers Energy Behavioral Demand Using Smart Meter Data.*
39. Stephen, B., et al., *Enhanced load profiling for residential network customers.* Power Delivery, IEEE Transactions on, 2014. **29**(1): p. 88-96.
40. Carrie Armel, K., et al., *Is disaggregation the holy grail of energy efficiency? The case of electricity.* Energy Policy, 2013. **52**: p. 213-234.
41. Smith, B.A., J. Wong, and R. Rajagopal. *A simple way to use interval data to segment residential customers for energy efficiency and demand response program targeting*. in *ACEEE Summer Study on Energy Efficiency in Buildings*. 2012.
42. Gulbinas, R., A. Khosrowpour, and J.E. Taylor, *Segmentation and Classification of Commercial Building Occupants by Energy-Use Efficiency and Predictability.* IEEE Transaction on Smart Grids, 2014.
43. Rettie, R., K. Burchell, and T. Harries, *Energy consumption feedback: engagement by design*, in *Design, User Experience, and Usability. User Experience Design for Everyday Life Applications and Services*. 2014, Springer. p. 594-604.
44. Allcott, H. and S. Mullainathan, *Behavioral science and energy policy.* Science, 2010. **327**(5970): p. 1204-1205.
45. Jain, R.K., et al., *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.* Energy and Buildings, 2013. **66**: p. 119-127.
46. Ayres, I., S. Raseman, and A. Shih, *Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage.* Journal of Law, Economics, and Organization, 2013. **29**(5): p. 992-1022.
47. Gulbinas, R. and J.E. Taylor, *Effects of real-time eco-feedback and organizational network dynamics on energy efficient behavior in commercial buildings.* Energy and Buildings, 2014. **84**(0): p. 493-500.
48. Gulbinas, R., R.K. Jain, and J.E. Taylor, *"BizWatts": A modular socio-technical energy management system for empowering commercial building occupants to conserve energy.* Applied Energy, 2014.
49. Chiang, T., S. Natarajan, and I. Walker, *A laboratory test of the efficacy of energy display interface design.* Energy and Buildings, 2012. **55**: p. 471-480.

50. Midden, C. and J. Ham, *The Power of Negative Feedback from an Artificial Agent to Promote Energy Saving Behavior*, in *Design, User Experience, and Usability. User Experience Design Practice*. 2014, Springer. p. 328-338.
51. Costanza, E., S.D. Ramchurn, and N.R. Jennings. *Understanding domestic energy consumption through interactive visualisation: a field study*. in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. 2012. ACM.
52. Quintal, F., et al., *WATTSBurning: design and evaluation of an innovative eco-feedback system*, in *Human-Computer Interaction–INTERACT 2013*. 2013, Springer. p. 453-470.
53. Schwartz, T., et al., *What People Do with Consumption Feedback: A Long-Term Living Lab Study of a Home Energy Management System.* Interacting with Computers, 2014: p. iwu009.
54. Chen, H.-M., et al., *Persuasive feedback model for inducing energy conservation behaviors of building users based on interaction with a virtual object.* Energy and Buildings, 2012. **45**: p. 106-115.
55. Jessoe, K. and D. Rapson, *Knowledge is (less) power: Experimental evidence from residential energy use*. 2012, National Bureau of Economic Research.
56. Asensio, O.I. and M.A. Delmas, *Nonprice incentives and energy conservation.* Proceedings of the National Academy of Sciences, 2015. **112**(6): p. E510-E515.
57. Vassileva, I., et al., *The impact of consumers' feedback preferences on domestic electricity consumption.* Applied Energy, 2012. **93**: p. 575-582.
58. Pereira, L., et al., *Understanding the limitations of eco-feedback: A one-year long-term study*, in *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data*. 2013, Springer. p. 237-255.
59. McKerracher, C. and J. Torriti, *Energy consumption feedback in perspective: integrating Australian data to meta-analyses on in-home displays.* Energy Efficiency, 2012. **6**(2): p. 387-405.
60. Peschiera, G. and J.E. Taylor, *The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems.* Energy and Buildings, 2012. **49**: p. 584-590.
61. Azar, E. and C.C. Menassa, *Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings.* Journal of Computing in Civil Engineering, 2012. **26**(4): p. 506-518.
62. Azar, E. and C.C. Menassa, *Agent-based modeling of occupants and their impact on energy use in commercial buildings.* Journal of Computing in Civil Engineering, 2011.
63. Yang, R. and L. Wang, *Development of multi-agent system for building energy and comfort management based on occupant behaviors.* Energy and Buildings, 2013. **56**: p. 1-7.
64. Anderson, K., S. Lee, and C. Menassa, *Impact of Social Network Type and Structure on Modeling Normative Energy Use Behavior Interventions.* Journal of Computing in Civil Engineering, 2014. **28**(1): p. 30-39.
65. Lee, Y.S. and A.M. Malkawi, *Simulating multiple occupant behaviors in buildings: An agent-based modeling approach.* Energy and Buildings, 2014. **69**: p. 407-416.

66. Azar, E. and C.C. Menassa, *Evaluating the impact of extreme energy use behavior on occupancy interventions in commercial buildings.* Energy and Buildings, 2015. **97**: p. 205-218.
67. Fischer, C., *Feedback on household electricity consumption: a tool for saving energy?* Energy efficiency, 2008. **1**(1): p. 79-104.
68. Abrahamse, W., et al., *A review of intervention studies aimed at household energy conservation.* Journal of environmental psychology, 2005. **25**(3): p. 273-291.
69. He, H.A., S. Greenberg, and E.M. Huang. *One size does not fit all: applying the transtheoretical model to energy feedback technology design*. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2010. ACM.
70. Hargreaves, T., M. Nye, and J. Burgess, *Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term.* Energy Policy, 2013. **52**(0): p. 126-134.
71. Strengers, Y.A. *Designing eco-feedback systems for everyday life*. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2011. ACM.
72. Peschiera, G., J.E. Taylor, and J.A. Siegel, *Response–relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data.* Energy and Buildings, 2010. **42**(8): p. 1329-1336.
73. Pierce, J., et al. *Some consideration on the (in) effectiveness of residential energy feedback systems*. in *Proceedings of the 8th ACM Conference on Designing Interactive Systems*. 2010. ACM.
74. Batra, N., et al., *Data Driven Energy Efficiency in Buildings.* arXiv preprint arXiv:1404.7227, 2014.
75. Ruparathna, R., K. Hewage, and R. Sadiq, *Improving the energy efficiency of the existing building stock: A critical review of commercial and institutional buildings.* Renewable and Sustainable Energy Reviews, 2016. **53**: p. 1032-1045.
76. Vine, D., *The Effectiveness of Energy Feedback for Conservation and Peak Demand: A Literature Review.* Open Journal of Energy Efficiency, 2013. **02**(01): p. 7-15.
77. Armel, K.C., et al., *Is disaggregation the holy grail of energy efficiency? The case of electricity.* Energy Policy, 2013. **52**: p. 213-234.
78. Yun, R., et al., *Sustainability in the workplace: nine intervention techniques for behavior change*, in *Persuasive Technology*. 2013, Springer. p. 253-265.
79. Karlin, B., R. Ford, and C. Squiers, *Energy feedback technology: a review and taxonomy of products and platforms.* Energy Efficiency, 2014. **7**(3): p. 377-399.
80. Trinh, K. and G.A. Jamieson, *Feedback Design Heuristics for Energy Conservation.* Ergonomics in Design: The Quarterly of Human Factors Applications, 2014. **22**(2): p. 13-21.
81. Hong, T., et al., *Advances in research and applications of energy-related occupant behavior in buildings.* Energy and Buildings, 2015.
82. Jones, R.V., A. Fuertes, and K.J. Lomas, *The socio-economic, dwelling and appliance related factors affecting electricity consumption in domestic buildings.* Renewable and Sustainable Energy Reviews, 2015. **43**: p. 901-917.

83. Haider, H.T., O.H. See, and W. Elmenreich, *A review of residential demand response of smart grid.* Renewable and Sustainable Energy Reviews, 2016. **59**: p. 166-178.
84. Tsuda, K., et al., *Approaches to induce behavioral changes with respect to electricity consumption.* Journal of Environmental Studies and Sciences, 2016: p. 1-9.
85. Vassileva, I., F. Wallin, and E. Dahlquist, *Analytical comparison between electricity consumption and behavioral characteristics of Swedish households in rented apartments.* Applied Energy, 2012. **90**(1): p. 182-188.
86. Kobus, C.B., R. Mugge, and J.P. Schoormans, *Washing when the sun is shining! How users interact with a household energy management system.* Ergonomics, 2013. **56**(3): p. 451-62.
87. Brounen, D., N. Kok, and J.M. Quigley, *Residential energy use and conservation: Economics and demographics.* European Economic Review, 2012. **56**(5): p. 931-945.
88. Froehlich, J., et al. *The design and evaluation of prototype eco-feedback displays for fixture-level water usage data*. in *Proceedings of the SIGCHI conference on human factors in computing systems*. 2012. ACM.
89. Grønhøj, A. and J. Thøgersen, *Feedback on household electricity consumption: learning and social influence processes.* International Journal of Consumer Studies, 2011. **35**(2): p. 138-145.
90. Pierce, J., D.J. Schiano, and E. Paulos. *Home, habits, and energy: examining domestic interactions and energy consumption*. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 2010. ACM.
91. Meho, L.I., *E-mail interviewing in qualitative research: A methodological discussion.* Journal of the American society for information science and technology, 2006. **57**(10): p. 1284-1295.
92. Albert, A. and R. Rajagopal, *Smart meter driven segmentation: What your consumption says about you.* Power Systems, IEEE Transactions on, 2013. **28**(4): p. 4019-4030.
93. Beckel, C., et al., *Revealing household characteristics from smart meter data.* Energy, 2014. **78**: p. 397-410.
94. Viegas, J.L., et al., *Classification of new electricity customers based on surveys and smart metering data.* Energy, 2016. **107**: p. 804-817.
95. Chen, V.L., M.A. Delmas, and W.J. Kaiser, *Real-time, appliance-level electricity use feedback system: How to engage users?* Energy and Buildings, 2014. **70**: p. 455-462.
96. Mankoff, J., et al. *StepGreen. org: Increasing Energy Saving Behaviors via Social Networks*. in *ICWSM*. 2010.
97. Alahmad, M., et al., *A comparative study of three feedback devices for residential real-time energy monitoring.* Industrial Electronics, IEEE Transactions on, 2012. **59**(4): p. 2002-2013.
98. Murtagh, N., et al., *Individual energy use and feedback in an office setting: A field trial.* Energy Policy, 2013. **62**: p. 717-728.
99. Wang, Y., et al., *Clustering of Electricity Consumption Behavior Dynamics toward Big Data Applications.*

100. Kleiminger, W., et al., *Occupancy Detection from Electricity Consumption Data.* 2013: p. 1-8.
101. Yu, Z., et al., *A systematic procedure to study the influence of occupant behavior on building energy consumption.* Energy and Buildings, 2011. **43**(6): p. 1409-1417.
102. Rafsanjani, H.N. and C. Ahn, *Linking Building Energy-Load Variations with Occupants' Energy-Use Behaviors in Commercial Buildings: Non-Intrusive Occupant Load Monitoring (NIOLM).* Procedia Engineering, 2016. **145**: p. 532-539.
103. Khosrowpour, A., R. Gulbinas, and J.E. Taylor, *Occupant Workstation Level Energy-use Prediction in Commercial Buildings: Developing and Assessing a New Method to Enable Targeted Energy Efficiency Programs.* Energy and Buildings, 2016.
104. Allcott, H. and T. Rogers, *The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation*. 2012, National Bureau of Economic Research.
105. !!! INVALID CITATION !!! .
106. Olsen, M.E., *Consumers' attitudes toward energy conservation.* Journal of Social Issues, 1981. **37**(2): p. 108-131.
107. Jerry, B., *Discrete-event system simulation*. 1984: Pearson Education India.
108. Chen, J., J.E. Taylor, and H.-H. Wei, *Modeling building occupant network energy consumption decision-making: The interplay between network structure and conservation.* Energy and Buildings, 2012. **47**: p. 515-524.
109. Chen, J., R.K. Jain, and J.E. Taylor, *Block Configuration Modeling: A novel simulation model to emulate building occupant peer networks and their impact on building energy consumption.* Applied Energy, 2013. **105**: p. 358-368.
110. Anderson, K. and S. Lee, *An empirically grounded model for simulating normative energy use feedback interventions.* Applied Energy, 2016. **173**: p. 272-282.
111. Yu, J., et al. *Probabilistic estimation of the potentials of intervention-based demand side energy management*. in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*. 2015. IEEE.
112. Zeigler, B.P., H. Praehofer, and T.G. Kim, *Theory of modeling and simulation: integrating discrete event and continuous complex dynamic systems*. 2000: Academic press.
113. Klein, L., et al., *Coordinating occupant behavior for building energy and comfort management using multi-agent systems.* Automation in Construction, 2012. **22**: p. 525-536.
114. Coleman, M.J., et al., *Promoting behaviour change through personalized energy feedback in offices.* Building Research & Information, 2013. **41**(6): p. 637-651.
115. Gyamfi, S., S. Krumdieck, and T. Urmee, *Residential peak electricity demand response—Highlights of some behavioural issues.* Renewable and Sustainable Energy Reviews, 2013. **25**: p. 71-77.
116. Barzin, R., et al., *Peak load shifting with energy storage and price-based control system.* Energy, 2015. **92, Part 3**: p. 505-514.

117. Karatas, A., A. Stoiko, and C.C. Menassa, *Framework for selecting occupancy-focused energy interventions in buildings.* Building Research & Information, 2016. **44**(5-6): p. 535-551.
118. Oltra, C., et al., *A qualitative study of users' engagement with real-time feedback from in-house energy consumption displays.* Energy Policy, 2013. **61**: p. 788-792.
119. Mahdavi, A. and F. Tahmasebi, *Predicting people's presence in buildings: An empirically based model performance analysis.* Energy and Buildings, 2015. **86**: p. 349-355.
120. Hogg, R.V. and E.A. Tanis, *Probability and statistical inference*. Vol. 993. 1977: Macmillan New York.
121. Brewer, R.S., G.E. Lee, and P.M. Johnson. *The Kukui Cup: a dorm energy competition focused on sustainable behavior change and energy literacy*. in *System Sciences (HICSS), 2011 44th Hawaii International Conference on*. 2011. IEEE.
122. Grevet, C., J. Mankoff, and S.D. Anderson. *Design and evaluation of a social visualization aimed at encouraging sustainable behavior*. in *System Sciences (HICSS), 2010 43rd Hawaii International Conference on*. 2010. IEEE.
123. Jain, R.K., J.E. Taylor, and G. Peschiera, *Assessing eco-feedback interface usage and design to drive energy efficiency in buildings.* Energy and Buildings, 2012. **48**: p. 8-17.
124. Mahdavi, A. and C. Pröglhöf, *User behaviour and energy performance in buildings.* Wien, Austria: Internationalen Energiewirtschaftstagung an der TU Wien (IEWT), 2009.
125. Virote, J. and R. Neves-Silva, *Stochastic models for building energy prediction based on occupant behavior assessment.* Energy and Buildings, 2012. **53**: p. 183-193.
126. Ferraro, P.J. and M.K. Price, *Using Nonpecuniary Strategies to Influence Behavior: Evidence from a Large-Scale Field Experiment.* Review of Economics and Statistics, 2013. **95**(1): p. 64-73.
127. Pereira, L., et al. *The design of a hardware-software platform for long-term energy eco-feedback research*. in *Proceedings of the 4th ACM SIGCHI symposium on Engineering interactive computing systems*. 2012. ACM.
128. Gamberini, L., et al., *Tailoring feedback to users' actions in a persuasive game for household electricity conservation.* Persuasive Technology. Design for Health and Safety, 2012: p. 100-111.
129. Kastner, I. and E. Matthies, *Implementing web-based interventions to promote energy efficient behavior at organizations – a multi-level challenge.* Journal of Cleaner Production, 2014. **62**: p. 89-97.
130. Lo, S.H., G.J.Y. Peters, and G. Kok, *Energy-Related Behaviors in Office Buildings: A Qualitative Study on Individual and Organisational Determinants.* Applied Psychology, 2012. **61**(2): p. 227-249.
131. Allen, J.G., et al., *Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments.* Harvard TH Chan School of Public Health's Center for Health and

the Global Environment, SUNY Upstate Medical University, and Syracuse University, 2015.

3. ONE SIZE DOES NOT FIT ALL: ESTABLISHING THE NEED FOR TARGETED ECO-FEEDBACK

Ardalan Khosrowpour[1], Yimeng Xie[2], John E. Taylor[1], Yili Hong[2]

[1] Charles E via Department of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061, United States
[2] Department of Statistics, Virginia Tech, Blacksburg, VA 24061, United States

1. ABSTRACT

Despite all improvements in buildings shell, equipment, and design, CO_2 emissions from buildings are increasing. Since occupants spend more than 90% of their time indoors, they are inseparable and significant elements of building system dynamics. Hence, there is a great potential for energy efficiency in buildings using a wide range of programs such as intervention and eco-feedback. Despite the high level of individual differences and intra-class variability of occupants' behaviors, the current state-of-the-art eco-feedback programs treat all the occupants uniformly and do not target and tailor the feedback. Therefore, it leaves an opportunity to increase the efficacy of eco-feedback systems through the designing of tailored and targeted programs. In this paper, we conducted a comprehensive analysis and tested hypotheses on occupants' behavioral responses to a normative comparison feedback program, in addition to the impact of notifications on the level of engagement of each group of occupants. We categorized occupants who participated in the normative comparison feedback program into three groups (i.e. low, medium, and high energy consumers) based on their baseline energy consumption, and tested 9 hypotheses. A mixed-effect regression model (MRM) and a paired t-test was implemented to evaluate the proposed hypotheses. The hypotheses examine the variability of occupants' responses under the same eco-feedback program, and the effectiveness of notifications on reinforcing occupants' engagement in these programs. The contribution of this paper is two-fold: (1) reporting that the effectiveness of the notifications in eco-feedback programs are initially highly dependent on the type and the nature of the program, and then the interval and the content of the notification, and (2) demonstrating the variability of occupants' behavioral responses under the same normative comparison eco-feedback program. These findings indicate the need for a shift in focus toward targeted and tailored feedback programs which treat occupants based on their characteristics. Moreover, they highlight the need for eco-feedback design, development, testing and implementation research that acknowledges and addresses differences in occupant responses to feedback.

Keywords: Eco-feedback; Energy Efficiency; Historical Comparison; Normative Comparison; Occupant Behavior

2. INTRODUCTION

The building sector is accountable for almost 40% of energy-use in the US [1]. Despite all improvements in building shell, equipment, and design, the percentage of CO_2 emissions from both residential and commercial buildings in the U.S. has been projected to increase by 1.8% per year through 2030 [2]. As major energy-use sources, such as HVAC and lighting systems, become more efficient, the share of miscellaneous energy consumption (e.g. plug loads) which are commonly controlled by building occupants increase. Thus, it calls for investigating potential occupant-based energy saving opportunities in buildings. Since occupants spend more than 90% of their time indoors [3], buildings can benefit from a wide range of programs such as intervention and eco-feedback.

Although occupants can be a potential contributing component of building energy efficiency, due to high intra-class variability, complexity, and uncertainty of their behaviors, finding an appropriate motivation, estimating their potential energy savings, and sustaining changes in behavior are challenging. The behavior targeted in such energy efficiency programs is environmentally significant behavior [4]. More precisely, a subcategory of environmentally significant behaviors referred to as private-sphere environmentalism behavior. This subcategory is defined as a type of behavior in the private sphere that is focused on purchase, use, and disposal of personal and household products and equipment which have environmental impact [4]. In the past decade, a fair body of literature has been shaped around this topic with the primary focus on residential occupants' energy efficiency, and only a secondary focus on the commercial sector. Despite the significant progress being made in the field of occupant energy efficiency across building types, existing developed programs treat occupants uniformly. Yet, we know that motivations, demographics, habits, working conditions, and many other characteristics of the occupants are considerably different. This discrepancy between the variability of occupants' characteristics and the fact that they are treated uniformly is the point of departure for this paper. We examine the variability of occupants' responses to a uniform eco-feedback study.

In this paper, we build on a previous study [5] conducted in a 6 story commercial building located in Denver, CO to examine the effect of occupants' energy saving responses to a real-time eco-feedback program launched at their work place. The occupants' energy consumption was monitored at a workstation-level using wireless smart meters and they were provided with normative and historical comparison feedback based on their randomly assigned study group. We ranked and divided the occupants that participated in a normative comparison group into three categories (i.e. high, medium, and low energy consumers) and implemented a mixed-effect regression model (MRM) approach to test multiple hypotheses regarding the variability of behavioral responses received from occupants who participated in a normative comparison feedback program. Furthermore, the level of engagement (i.e. logins to the system after receiving a notification) of occupants in each group was tested using a paired t-test in order to investigate the effectiveness of notifications sent throughout the study.

3. RELATED WORK

There is a vast body of knowledge focused on occupants' energy efficiency in buildings. The majority of these efforts have been focused on residential buildings. Among a wide range of occupant-based energy efficiency programs, eco-feedback systems have been demonstrated to be among the more effective approaches. Thus, in this section, we provide a comprehensive literature review on the variety of eco-feedback programs implemented in commercial and residential buildings. First, we address the studies conducted in the residential sector with all psychological, computational, and design elements taken into account. Then, we review commercial building eco-feedback studies and discuss the existing gaps of knowledge in each area.

Eco-feedback studies in residential buildings can be categorized based on various characteristics. In this study, we have chosen to distinguish the studies based on their feedback resolution, psychological motivators, feedback methods, and the length of the experiments. Eco-feedback programs incorporate a wide range of feedback methods starting with the most conventional paper-based approaches [6, 7], to advanced computer-based feedback [8-12], and in-home display units [13-17]. The frequency and resolution of feedback is usually correlated with the level of technology incorporated in each program; however, one literature review conducted on eco-feedback systems [18] found frequent feedback along with digital presentation to be among the most important elements of such systems. Allcott [6] conducted a comprehensive analysis on a massive dataset captured through Opower Inc. and reported that among monthly, bi-monthly, and quarterly feedback provided to occupants, quarterly feedback was the most effective frequency considering the cost-benefit analysis of the program. While the body of research is in favor of more frequent feedback provided to occupants, the cost-effectiveness analysis favors less frequent feedback.

Feedback studies in residential buildings have been conducted in a wide range of lengths and sample sizes. Naturally, the longer the length of the study and the larger the sample size, the more reliable the results. Thus, the studies can be divided broadly into two categories: short-term and long-term. Based on the literature, the short-term effect of eco-feedback studies are relatively stronger than the long-term effect, meaning that the energy savings are higher and occupants are more engaged in the beginning of the program [19]. In terms of occupants' engagement in the program measured by the number of logins to the online platforms, visiting in-home displays, and also responding to the notifications sent out during the study, the general trend supports the decay of engagement over time [20]. However, studies have shown that the engagement and savings diminish to an extent and reach a plateau at some point [19]. Moreover, it has been established that the number of visits to eco-feedback platforms are statistically correlated to the level of energy savings over time [8].

There are various psychological motivators implemented in the aforementioned studies to motivate occupants to sustainably save energy. Social norms [6, 11, 21-24], historical comparison [12, 14, 25-27], goal setting [13, 28, 29], and many other approaches have been implemented in studies to evaluate the effectiveness of each on inducing energy savings. The social norm (e.g. normative comparison) has been shown to be among the most effective approaches [7]. Despite the limited efforts on targeting utilities' customers [30, 31] and understanding the underlying correlations between occupants' behavior and their energy consumption [32, 33], these programs (e.g. normative comparison, historical comparison, etc.) treat all occupants uniformly regardless of their characteristics, demographic information, and habits, which may lead to weak response from a substantial group of occupants who are not motivated by a non-differentiated eco-feedback program. Unfortunately, the effect of non-differentiated feedback has not been employed to improve the engagement and motivation of all occupants in eco-feedback studies. A tailored and targeted energy efficiency program may enhance the efficacy of such programs.

Commercial sector eco-feedback programs differ from residential sector programs for several reasons. In the commercial sector (especially office buildings), the majority of occupants do not have direct financial incentives to save energy in the building [34]. Moreover, in office buildings, productivity is a major concern of all employees [35], thus introducing the challenging issue of a productivity, comfort, and energy efficiency trade-off in the workplace. Similar to residential buildings, there are studies incorporating various psychological motivators in commercial eco-feedback systems. Social norms, historical comparison, and goal setting are the most dominant. Nevertheless, we lack long-term eco-feedback studies in the commercial sector to determine the long-term energy efficiency potential of occupant conservation programs. In terms of feedback methods, the approaches vary from energy efficiency campaigns [34] to real-time feedback [36-39]. Despite one limited effort in providing personalized feedback in commercial buildings [40], none of the aforementioned studies differentiate occupants with respect to their responses.

Considering the high intra-class variability in occupants' behavior, habits, work schedules, and demographics, it is surprising that eco-feedback studies conducted in the residential and commercial sectors have not examined these differences and incorporated them to provide occupants with various psychological motivators, tailored feedback information, and personalized feedback frequency to enhance the efficacy of current energy efficiency programs. In this paper, we take initial steps to examine whether non-differentiated feedback is effective. We examined three study groups: an organizational feedback group (i.e. received normative comparison feedback), an individual feedback group (i.e. received only individual feedback), and a control group (i.e. received no feedback) and monitored them for a period of three months. We then examined the occupant responses and reaction to normative comparison feedback provided in the course of the study. Moreover, we conducted a complementary analysis on statistical significance of the response rates (i.e. number of logins) to the notifications sent throughout the study, regardless of the energy savings obtained after each notification. In other words, we segregate the effect of notifications on energy savings from the logins to the platform. A mixed-effect regression model (MRM) was implemented along with a paired *t*-test for the sake of evaluation.

4. METHODOLOGY

Workstation energy consumption was collected using wireless smart meters. Occupants' interactions with an online platform, "BizWatts" [39], was monitored by capturing the date and duration of the logins, along with the clickstreams on the website. In order to create the group variables, we categorized occupants assigned to the normative comparison groups based on their energy consumption in the baseline period into three quantiles. Therefore, we have five groups in total: historical comparison, normative comparison, and three subgroups (i.e. low, medium, and high energy consumers) extracted from the normative comparison group based on their baseline performance. These two pieces of information enabled us to conduct a comprehensive analysis on occupants' response to a normative comparison study, in addition to a thorough analysis on notification impact on occupants' engagement in the study. The methodology section is divided into two parts. The first addresses the mixed-effect regression model used to analyze the variability of responses received from occupants based on their performance in the normative comparison feedback group. The second section explains the methodology used to test the response rates to each notification sent out during the study as a reminder to reinforce occupants' participation in the program.

4.1. Normative Comparison Response Analysis

Traditional longitudinal data analysis methods (e.g. ANOVA and MANOVA) are of limited use in our case due to the underlying assumptions regarding missing data across time, and the variance-covariance structure of the repeated measures [41]. To study the change of behavior in the normative comparison feedback group, we implemented a mixed-effect regression model to model the difference of log-transformed energy consumption before and after the baseline. There are several characteristics that make MRMs a more compelling approach in this study. First, since time is treated as a continuous variable, subjects are not required to be measured on the same number of data points [41]. Second, in order to capture any potential deviations of the subjects from the general trend, MRM can estimate the change for each subject [41]. And finally, MRM is capable of capturing the potential existing within-subject correlations.

Energy-use data was transformed into log scale because it did not have symmetry in the original scale. To control for the individual differences that might affect the trend over the length of the study, we calculated the average of baseline usage for each participant. To model the nonlinear energy behavior trajectory across time, we considered linear and/or quadratic time effects as fixed effects. Higher orders of time effect are not considered because of the small sample size. A group variable was included in the model to examine the effect on energy changes. The interactions between the group variable and time effects were also considered in the model. We included linear and/or quadratic random time effects to capture the possible variation in the rates of change across individuals. That is, we assumed that each individual can have a different pattern of energy-use over the study period. Equation (1) represents the final model chosen among all various combinations of variables, effects, and orders described above. The Akaike Information Criterion (AIC) [42, 43], which is a relative measure of statistical model quality, was used to select an appropriate model. The selected model includes linear, quadratic time effects and group variable as fixed effects, along with linear, quadratic random time effects. The interactions between the group variable and time effects are not statistically significant. All the analyses were performed in SAS 9.3.

$$y_{ij} = \beta_0 + \beta_1 \,\mathrm{Week}_{ij} + \beta_2 \,\mathrm{Week}_{ij}^2 + \beta_3 \,\mathrm{Group}_i + v_{0i} + v_{1i} \,\mathrm{Week}_{ij} + v_{2i} \,\mathrm{Week}_{ij}^2 + \varepsilon_{ij}\,, \qquad (1)$$

where y_{ij} is the log of average energy usage at week j for subject i minus the baseline usage, Week_{ij} takes values in $\{1, \ldots, 10\}$, and $\varepsilon_{ij} \sim N(0, \sigma^2)$. Here $i = 1, \ldots 75$ (number of subjects), $j = 1, \ldots, n_i$ (number of weeks).

Because we used the control group as a reference group in the model, the interpretation of the model parameters is as follows:

- β_0: average week 0 response (difference in log transformation of energy-use) for control group
- β_1: average weekly linear change for control group
- β_2 : average weekly quadratic change for control group
- β_3: average week 0 response change difference between groups
- v_{0i}: individual deviation from average intercept
- v_{1i} : individual deviation from average linear change
- v_{2i} : individual deviation from average quadratic change.

We calculate the variation of energy consumption for each group with respect to the baseline to further evaluate the effect of the eco-feedback program on the study groups. To do so, the following four hypotheses are formulated:

- Hypothesis 1: Low energy consumers in the normative comparison group changed their behavior statistically after the study was launched.
- Hypothesis 2: Medium energy consumers in the normative comparison group changed their behavior statistically after the study was launched.
- Hypothesis 3: High energy consumers in the normative comparison group changed their behavior statistically after the study was launched.
- Hypothesis 4: The historical comparison group occupants changed their behavior statistically after the study was launched.

The corresponding p-values for each hypothesis are provided in section 4.1 which determine the rejection of null hypotheses.

4.2. Notification Impact Analysis

In order to evaluate the statistical significance of notifications' impact on occupants' engagement in our eco-feedback platform, we categorized occupants based on the eco-feedback program they participated in. There are a total number of 5 notifications sent in the period of 69 days with an uneven interval between notifications. In order to assess the impact of notifications on occupants' engagement in the programs, we chose a three day window based on [20] recommendation to have a time window longer than weekends, and also to consider the possibility of delays in checking the emails (i.e. notifications). Thus, we summed up the number of logins three days prior and after each notification was sent (excluding the day notification was provided) and implemented a Kolmogorov-Smirnov hypothesis test [44] to check the normality of the data. Since our data is normally distributed, a paired t-test method was used to test the hypotheses proposed below to assess the effectiveness of notifications in engaging occupants in our study.

Moreover, the average logins prior to and after each notification was calculated to investigate the variation of engagement levels among various groups.

- Hypothesis 5: The normative comparison group's engagement level changed statistically after receiving each notification.
- Hypothesis 6: The historical comparison group's engagement level changed statistically after receiving each notification.
- Hypothesis 7: The normative comparison group's low energy consumers' engagement level changed statistically after receiving a notification.
- Hypothesis 8: The normative comparison group's medium energy consumers' engagement level changed statistically after receiving a notification.
- Hypothesis 9: The normative comparison group's high energy consumers' engagement level changed statistically after receiving a notification.

Fig 1 illustrates all occupants' logins during the study. The number of logins are distinguished by colors as labeled in the color bar. There were 82 total logins to the system with an average 0.75 logins per person for the historical comparison group, and an average 2.34 logins per person for the normative comparison group. The notification dates are represented with arrows at the bottom of the figure, and occupants are categorized based on their groups on the left side (the numbers on the Y-axis represent the range of subject/occupants' IDs).

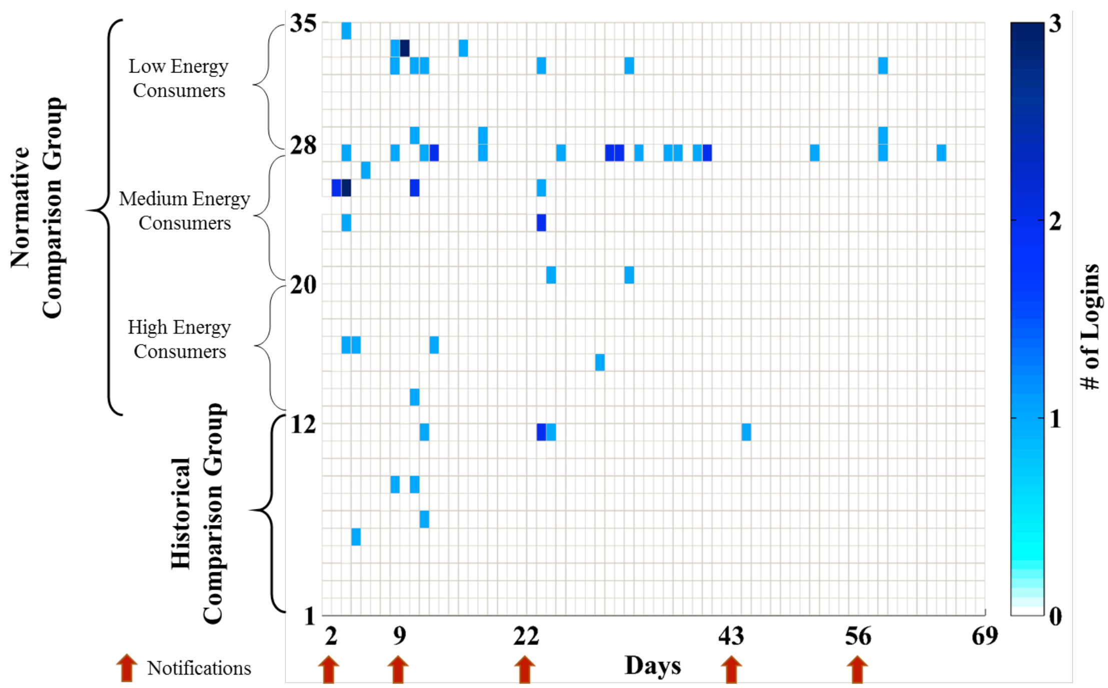


Figure 1. Surface plot of daily logins

In the following section, we report the results obtained from our MRM analysis, evaluate the p-values calculated for each hypotheses proposed in this section, and discuss the implications of our findings.

5. RESULTS AND DISCUSSION

The results obtained from the aforementioned analyses are reported in two separate sections, following the methodology structure. Section 4.1 addresses the hypotheses designed to test the occupants' responses to the normative comparison feedback based on their baseline energy consumption in the group. While, section 4.2 reports the results obtained for the five hypotheses designed to test the effectiveness of notifications in engaging individuals in the program in each group.

5.1. Normative Comparison Response Analysis

As described in section 3.1, we implemented SAS 9.3 to fit various MRMs with fixed and random linear/polynomial time effects in this study. After performing a log transformation on the weekly energy consumption data, the best model was chosen using the lowest AIC [42, 43]. The selected model includes linear, quadratic time effects and group variable as fixed effects, along with linear, quadratic random time effects. The p-values are reported for evaluating the hypotheses proposed in section 3.1. Table 1 includes the results for each study group's energy-use behavior compared to the control group with respect to the baseline.

Table 7. Occupants' behavior change results compared to control group during the eco-feedback study

Groups	**Energy Consumption Level**	**p-value**	**Energy Variation**
Normative Comparison	High	0.1066	-10.5%
	Medium	0.0930*	1.2%
	Low	0.0191**	-2.5%
Historical Comparison		0.1720	-3.8%

*0.05 < p-value ≤ 0.1, marginally significant
**p-value ≤ 0.05, significant

The p-values obtained for each hypothesis assess the level of energy-use change with respect to the control group. In the normative comparison group, the medium energy consumers results marginally (i.e. 0.05 < p-value ≤ 0.1) reject the null hypothesis 2. It has to be noted that unexpectedly, the level of energy consumption was increased with respect to the baseline for medium energy consumers. The low energy consumers results statistically (i.e. p-value ≤ 0.05) reject the null hypothesis 1, while decreasing the level of energy consumption compared to the baseline period, implicating the effectiveness of normative comparison eco-feedback programs on low energy consumers. This finding contradicts the previous works published in the field of residential sector normative comparison feedback systems reporting the potential existence of a boomerang effect [6]. On the other hand, there is not enough evidence to reject the null hypothesis for high energy consumers in the same group. The historical comparison group, did not show a statistically significant change of behavior compared to both their baseline and the control group. Thus, we could not find enough evidence to reject the other null hypotheses 3 and 4. In summary, the statistical status of the proposed hypotheses are as follows:

- Hypothesis 1: Low energy consumers in the normative comparison group statistically changed their behavior after the study was launched.
    - Null hypothesis statistically *rejected*, energy consumption *decreased*.
- Hypothesis 2: Medium energy consumers in the normative comparison group statistically changed their behavior after the study was launched.
    - Null hypothesis marginally *rejected*, energy consumption *increased*.
- Hypothesis 3: High energy consumers in the normative comparison group statistically changed their behavior after the study was launched.
    - Null hypothesis is *not rejected*, energy consumption decreased.
- Hypothesis 4: The historical comparison group occupants statistically changed their behavior after the study was launched.
    - Null hypothesis is *not rejected*, energy consumption decreased.

The obtained results support our conjecture that responses to a uniform eco-feedback program by various groups categorized based on their energy consumption vary. If different energy consumption level groups respond differently to the same feedback, then it suggests we may need targeted and tailored approaches to induce energy savings in all categories of occupants regardless of their behavioral and characteristic differences.

5.2. Notification Impact Analysis

In this study, we recorded the duration and dates of logins made into the eco-feedback system for each user. 5 notifications were sent with 7 to 21 day intervals in-between as reminders to reinforce users' engagement in the program. Since all of our groups passed the Kolmogorov-Smirnov normality test, we implemented a paired t-test to evaluate the aforementioned hypotheses in section 3.2. Table 2(a) demonstrates all p-values obtained for each group, for each notification, while Table 2(b) demonstrates the engagement variations averaged over three days prior to and after each notification.

Table 8. Occupants' engagement results during the eco-feedback program after each notification

(a)

		Notification Dates				
Study Groups		**May 7th**	**May 14th**	**May 27th**	**June 17th**	**June 30th**
Normative Comparison Group	**p-values**	0.0533*	0.0090**	0.0304**	0.3282	0.0829*
Historical Comparison Group		0.3388	0.1661	0.3388	0.3388	NAN

**0.05 < p-value ≤ 0.1, marginally significant*
***p-value ≤ 0.05, significant*

(b)		Notification Dates				
Study Groups		**May 7th**	**May 14th**	**May 27th**	**June 17th**	**June 30th**
Normative Comparison Group	**Engagement Variations**	+0.48*	+0.43**	+0.26**	-0.09	+0.13*
Historical Comparison Group	**Engagement Variations**	+0.08	+0.17	+0.25	+0.08	0

**0.05 < p-value ≤ 0.1, marginally significant*
***p-value ≤ 0.05, significant*

The p-values obtained for the normative comparison group provides relatively strong evidence to reject null hypothesis 5. More specifically, when looking at the entire normative comparison study group, in 4 out of 5 notifications, the results marginally or significantly support the effect of notifications sent out during the study in increasing the level of engagement of the occupants in the program. Moreover, the average number of logins per person in these 4 instances increased after each notification compared to the previous 3 days. However, due to an uneven distribution of the intervals between notifications, the fourth notification did not statistically change the level of engagement and a decreasing trend in the level of engagement was observed for two potential reasons. First, the delay between the 3rd and the 4th notification is close to 3 weeks which is the longest lag in this study. Furthermore, referring to Fig 1, it could be observed that some occupants returned to the eco-feedback platform 1-2 weeks before they received any notifications from us, suggesting a potential periodic performance observation behavior shaping among occupants. Some values are reported as NANs in Table 2; that is a result of 0/0 p-value generated due to a zero variance obtained from having identical datasets in the *t*-test calculation, and implies the insignificance of the hypotheses test results. There is not enough evidence to reject the 6th null hypothesis. Thus, it suggests the lack of effectiveness of notifications sent out to the historical comparison group. In another attempt, we concatenated the responses to all five notifications sent out during the study for each group and subgroup, and conducted a paired t-test to evaluate the overall response to all five hypotheses proposed in section 3.2 regardless of their dates. Because of this, we restricted the constraint for significance to a p-value of less than 0.05. The results of statistical tests along with the average variation of engagement level in each group are provided in Table 3.

Table 9. Occupants’ engagement results during the eco-feedback program for all notifications

Groups	***Energy Consumption Level***	***All Notifications***			
Normative Comparison Group	Low	**p-values**	0.0318**	**Engagement Variation**	+0.17
	Medium		0.0132**		+0.42
	High		0.0577		+0.13
	All		0.0003**		+0.24
Historical Comparison Group			0.0514		+0.12

** *p-value ≤ 0.05, significant*

Table 3 demonstrates a strong support for rejecting null hypotheses designed for low and medium energy consumers in the normative comparison group and also all normative comparison participants as a single group (i.e. Hypotheses 5, 7, and 8), while the historical comparison group, and high energy consumers in the normative comparison group lack statistical support for rejecting the null hypotheses (i.e. Hypotheses 6 and 9). In other words, the overall effect on notifications sent in this study were stronger on the low and medium energy consumers in the normative comparison group, while not being statistically effective on the high energy consumers. Furthermore, the normative comparison group (as a single unit) was encouraged by notifications to login to their accounts and check their energy consumption. On the other hand, the historical comparison group did not show a statistical change of behavior as a result of received notifications. In the following section, we discuss the limitations of our study and suggest the future venues of research.

6. LIMITATIONS & FUTURE RESEARCH

There are a few limitations in this study which prevented us from further investigating the underlying causes of behavioral changes observed among occupants in the normative and historical comparison eco-feedback programs. First, there was no demographic information collected in order to find any potential correlations between energy saving patterns and occupants’ characteristics. Second, the length of the study was only 69 days, which does not provide sufficient information to determine the potential decay of occupants’ engagement and energy efficiency in the long-term. The number of occupants involved in this study was only 35. 12 employees participated in historical comparison feedback study, and 23 in the normative comparison. The limited number of sample data potentially increases the variance, while decreasing the reliability of the reported results. However, this sample was adequate to demonstrate the important variances in responses to and engagement with feedback across occupants.

As reported in this paper, occupants did not exhibit uniform behaviors, and even demonstrated different performance levels while being in the same study group (i.e. normative comparison feedback group). Therefore, it highlights a great opportunity to investigate the methods and effect of tailored and targeted eco-feedback systems which maximize the potential energy saving of each individual in buildings. The results suggest that targeted eco-feedback programs have a great potential to further improve the efficacy of energy efficiency programs through tailoring both the notifications and the psychological motivators applied to each individual. Furthermore, the feedback provided in previous studies/programs did not have any subject-oriented context or information, and did not consider individual schedules, duties, workstation appliances, and many other impacting elements. Therefore, it provides an opportunity to examine context-aware and timely feedback tailored based on each individual's characteristics in these programs in future research.

7. CONCLUSION

In this paper, we conducted a comprehensive analysis and hypothesis test on occupants' behavioral responses to normative comparison feedback programs, in addition to the impact of the notifications sent throughout the study on the level of engagement of each group of occupants. We categorized the occupants who participated in the normative comparison feedback program into three groups (i.e. low, medium, and high energy consumers) based on their baseline energy consumption, and tested 4 hypotheses to assess the existence of potential behavioral differences among occupants in response to a normative comparison eco-feedback study. The results reported a significant change of behavior for low energy consumers, while indicating a decrease in the level of energy consumption. The medium energy consumers did marginally change their behavior compared to the baseline, with an unexpected increase in the level of energy consumption. The implication of these results suggest the need for targeted and tailored eco-feedback, which treats individuals based on their behaviors, habits, characteristics, etc.

Multiple hypotheses tests were conducted to investigate the effectiveness of the notifications sent during the study on occupants' engagement in the program (measured by the number of logins before and after each notification). The results support the positive and significant change of low and medium energy consumers' engagement in normative comparison feedback based on their responses to the notifications. However, the high energy consumers' engagement in normative comparison feedback did not significantly change under the influence of notifications. Moreover, when comparing the entire normative comparison group to the historical comparison group, the normative comparison group was statistically and positively affected by notifications while the historical comparison was not. To illustrate, the normative comparison group statistically responded to all notifications except the fourth one, whereas, the historical comparison group did not show any significant response to any of the notifications. The root cause of the lack of response to the fourth notification in the normative comparison group could be found in the longer interval between the third and fourth notifications. Furthermore, when concatenating the responses to all notifications, the statistical results further confirm the significance level of the normative comparison group's response to notifications, while the historical comparison group did not achieve a significant result.

The major implications of the aforementioned findings are two-fold. First, the results supporting the variability of behavioral responses under the same normative comparison program demonstrate the need for new venues of research in developing tailored and targeted energy efficiency programs in buildings. Second, the impact of notifications observed in this study initially emphasizes the importance of the nature of the program rather than the count and interval of the notifications. Though, the timing and the duration between the notifications can be an important factor as the 4^{th} notification in this study did not receive significant response due to the potential longer interval. In conclusion, the contribution of this paper is in providing a comprehensive analysis on the effect of notifications on occupants' engagement with an eco-feedback system, and claiming that the effectiveness of the notifications are highly dependent on external factors. Furthermore, we provide insight on variability of occupants' response to similar normative comparison eco-feedback, which suggests that future research on eco-feedback design, development, implementation, and analysis acknowledge and address user differences and incorporate tailored feedback to enhance the efficacy of eco-feedback programs.

8. ACKNOWLEDGEMENTS

This material is based upon work supported by the Department of Energy Building Technologies Program and the National Science Foundation under Grant No. 1142379. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Department of Energy or the National Science Foundation. The authors would like to thank the Alliance for Sustainable Colorado for hosting the study that provided the building occupant data used in the experimental data analysis in this paper.

REFERENCE

1. USDOE: 'Buildings Energy Data Book' (US Department of Energy, 2011. 2011)
2. U.S.EIA: 'Emissions of Greenhouse Gases in the United States', 2006
3. U.S.EPA: 'The Inside Story: A Guide to Indoor Air Quality', in Editor: 'Book The Inside Story: A Guide to Indoor Air Quality' (2012, edn.), pp.
4. Stern, P.: 'Toward a coherent theory of environmentally significant behavior', Journal of social issues, 2000, 56, (3), pp. 407-424
5. Gulbinas, R., and Taylor, J.E.: 'Effects of real-time eco-feedback and organizational network dynamics on energy efficient behavior in commercial buildings', Energy and Buildings, 2014, 84, (0), pp. 493-500
6. Allcott, H.: 'Social norms and energy conservation', Journal of Public Economics, 2011, 95, (9-10), pp. 1082-1095
7. Schultz, P.W., Nolan, J.M., Cialdini, R.B., Goldstein, N.J., and Griskevicius, V.: 'The constructive, destructive, and reconstructive power of social norms', Psychological science, 2007, 18, (5), pp. 429-434
8. Jain, R.K., Taylor, J.E., and Peschiera, G.: 'Assessing eco-feedback interface usage and design to drive energy efficiency in buildings', Energy and Buildings, 2012, 48, pp. 8-17
9. Ellegård, K., and Palm, J.: 'Visualizing energy consumption activities as a tool for making everyday life more sustainable', Applied Energy, 2011, 88, (5), pp. 1920-1926

10. Quintal, F., Pereira, L., Nunes, N., Nisi, V., and Barreto, M.: ‘WATTSBurning: design and evaluation of an innovative eco-feedback system’: ‘Human-Computer Interaction–INTERACT 2013’ (Springer, 2013), pp. 453-470
11. Chen, V.L., Delmas, M.A., and Kaiser, W.J.: ‘Real-time, appliance-level electricity use feedback system: How to engage users?’, Energy and buildings, 2014, 70, pp. 455-462
12. Pereira, L., Quintal, F., Nunes, N., and Bergés, M.: ‘The design of a hardware-software platform for long-term energy eco-feedback research’, in Editor: ‘Book The design of a hardware-software platform for long-term energy eco-feedback research’ (ACM, 2012, edn.), pp. 221-230
13. Grønhøj, A., and Thøgersen, J.: ‘Feedback on household electricity consumption: learning and social influence processes’, International Journal of Consumer Studies, 2011, 35, (2), pp. 138-145
14. Gans, W., Alberini, A., and Longo, A.: ‘Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland’, Energy Economics, 2013, 36, pp. 729-743
15. McKerracher, C., and Torriti, J.: ‘Energy consumption feedback in perspective: integrating Australian data to meta-analyses on in-home displays’, Energy Efficiency, 2013, 6, (2), pp. 387-405
16. Oltra, C., Boso, A., Espluga, J., and Prades, A.: ‘A qualitative study of users' engagement with real-time feedback from in-house energy consumption displays’, Energy Policy, 2013, 61, pp. 788-792
17. Schwartz, T., Stevens, G., Jakobi, T., Denef, S., Ramirez, L., Wulf, V., and Randall, D.: ‘What People Do with Consumption Feedback: A Long-Term Living Lab Study of a Home Energy Management System’, Interacting with Computers, 2014, pp. iwu009
18. Vine, D.: ‘The Effectiveness of Energy Feedback for Conservation and Peak Demand: A Literature Review’, Open Journal of Energy Efficiency, 2013, 02, (01), pp. 7-15
19. Allcott, H., and Rogers, T.T.: ‘How Long Do Treatment Effects Last? Persistence and Durability of a Descriptive Norms Intervention's Effect on Energy Conservation’, 2012
20. Peschiera, G., Taylor, J.E., and Siegel, J.A.: ‘Response–relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data’, Energy and Buildings, 2010, 42, (8), pp. 1329-1336
21. Peschiera, G., and Taylor, J.E.: ‘The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems’, Energy and Buildings, 2012, 49, pp. 584-590
22. Ayres, I., Raseman, S., and Shih, A.: ‘Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage’, Journal of Law, Economics, and Organization, 2012, 29, (5), pp. 992-1022
23. Rettie, R., Burchell, K., and Harries, T.: ‘Energy consumption feedback: engagement by design’: ‘Design, User Experience, and Usability. User Experience Design for Everyday Life Applications and Services’ (Springer, 2014), pp. 594-604

24. Midden, C., and Ham, J.: 'The Power of Negative Feedback from an Artificial Agent to Promote Energy Saving Behavior': 'Design, User Experience, and Usability. User Experience Design Practice' (Springer, 2014), pp. 328-338
25. Strengers, Y.A.: 'Designing eco-feedback systems for everyday life', in Editor: 'Book Designing eco-feedback systems for everyday life' (ACM, 2011, edn.), pp. 2135-2144
26. Alahmad, M., Wheeler, P.G., Schwer, A., Eiden, J., and Brumbaugh, A.: 'A comparative study of three feedback devices for residential real-time energy monitoring', Industrial Electronics, IEEE Transactions on, 2012, 59, (4), pp. 2002-2013
27. Jain, R.K., Taylor, J.E., and Culligan, P.J.: 'Investigating the impact eco-feedback information representation has on building occupant energy consumption behavior and savings', Energy and Buildings, 2013, 64, pp. 408-414
28. Brewer, R.S., Lee, G.E., and Johnson, P.M.: 'The Kukui Cup: a dorm energy competition focused on sustainable behavior change and energy literacy', in Editor: 'Book The Kukui Cup: a dorm energy competition focused on sustainable behavior change and energy literacy' (IEEE, 2011, edn.), pp. 1-10
29. Erickson, T., Li, M., Kim, Y., Deshpande, A., Sahu, S., Chao, T., Sukaviriya, P., and Naphade, M.: 'The dubuque electricity portal: evaluation of a city-scale residential electricity consumption feedback system', in Editor: 'Book The dubuque electricity portal: evaluation of a city-scale residential electricity consumption feedback system' (ACM, 2013, edn.), pp. 1203-1212
30. Taylor, N.W., Jones, P.H., and Kipp, M.J.: 'Targeting utility customers to improve energy savings from conservation and efficiency programs', Applied Energy, 2014, 115, pp. 25-36
31. Borgeson, S., Flora, J.A., Kwac, J., Tan, C.-W., and Rajagopal, R.: 'Learning from Hourly Household Energy Consumption: Extracting, Visualizing and Interpreting Household Smart Meter Data': 'Design, User Experience, and Usability: Interactive Experience Design' (Springer International Publishing, 2015), pp. 337-345
32. Vassileva, I., Wallin, F., and Dahlquist, E.: 'Analytical comparison between electricity consumption and behavioral characteristics of Swedish households in rented apartments', Applied Energy, 2012, 90, (1), pp. 182-188
33. Brounen, D., Kok, N., and Quigley, J.M.: 'Residential energy use and conservation: Economics and demographics', European Economic Review, 2012, 56, (5), pp. 931-945
34. Carrico, A.R., and Riemer, M.: 'Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education', Journal of Environmental Psychology, 2011, 31, (1), pp. 1-13
35. Yun, R., Scupelli, P., Aziz, A., and Loftness, V.: 'Sustainability in the workplace: nine intervention techniques for behavior change': 'Persuasive Technology' (Springer, 2013), pp. 253-265
36. Chen, H.-M., Lin, C.-W., Hsieh, S.-H., Chao, H.-F., Chen, C.-S., Shiu, R.-S., Ye, S.-R., and Deng, Y.-C.: 'Persuasive feedback model for inducing energy conservation behaviors of building users based on interaction with a virtual object', Energy and Buildings, 2012, 45, pp. 106-115

37. Murtagh, N., Nati, M., Headley, W.R., Gatersleben, B., Gluhak, A., Imran, M.A., and Uzzell, D.: 'Individual energy use and feedback in an office setting: A field trial', Energy Policy, 2013, 62, pp. 717-728
38. Yun, R.: 'Persistent workplace plug-load energy savings and awareness through energy dashboards', 2014, pp. 331-334
39. Gulbinas, R., Jain, R., and Taylor, J.: 'BizWatts: A modular socio-technical energy management system for empowering commercial building occupants to conserve energy', Applied Energy, 2014, 136, pp. 1076-1084
40. Coleman, M.J., Irvine, K.N., Lemon, M., and Shao, L.: 'Promoting behaviour change through personalized energy feedback in offices', Building Research & Information, 2013, 41, (6), pp. 637-651
41. Hedeker, D., and Gibbons, R.D.: 'Longitudinal data analysis' (John Wiley & Sons, 2006. 2006)
42. Akaike, H.: 'A new look at the statistical model identification', Automatic Control, IEEE Transactions on, 1974, 19, (6), pp. 716-723
43. Bozdogan, H.: 'Model selection and Akaike's information criterion (AIC): The general theory and its analytical extensions', Psychometrika, 1987, 52, (3), pp. 345-370
44. Lilliefors, H.W.: 'On the Kolmogorov-Smirnov test for normality with mean and variance unknown', Journal of the American Statistical Association, 1967, 62, (318), pp. 399-402

4. OCCUPANT WORKSTATION LEVEL ENERGY-USE PREDICTION IN COMMERCIAL BUILDINGS: DEVELOPING AND ASSESSING A NEW METHOD TO ENABLE TARGETED ENERGY EFFICIENCY PROGRAMS

Ardalan Khosrowpour[1], Rimas Gulbinas[2], John E. Taylor[1]

[1] Charles E via Department of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061, United States
[2] The Joan and Irwin Jacobs Technion-Cornell Innovation Institute, Cornell University, New York, NY 10011, United States

1. ABSTRACT

As buildings become more energy efficient and automated, the role of occupants becomes more significant to assist buildings in reaching their full energy efficiency potential. Predicting occupants' consumption behavior has been identified as one of the most challenging processes in energy efficiency programs and building management system operations. Thus, more accurate behavior learning algorithms for commercial buildings are needed to improve energy efficiency. In this paper, we propose a method to predict occupants' energy-use behavior based on individual energy consumption profiles and assess its potential to increase the effectiveness of energy efficiency programs. The proposed method implements a support vector machine in order to model and predict occupants' short term energy-use patterns and test hypotheses for the existence of a correlation between occupants' entropy, efficiency and prediction accuracy. The results show an average accuracy of 83% for individual energy-use pattern prediction while being positively correlated with individuals' energy-use behavior. The main contributions of this paper are: 1) proposing and validating a new method to predict individuals' energy-use patterns based on their individual workstation-level energy consumption patterns, and 2) assessing the feasibility and potential of implementing this method to enhance the efficacy of energy efficiency programs to further induce energy efficiency.

Keywords: Commercial Buildings; Energy Efficiency; Machine Learning; Occupant Behavior; Support Vector Machine.

2. INTRODUCTION

The commercial building sector is responsible for a substantial portion of energy consumption in the United States. Recent research indicates that, despite technology improvements and tightened standards for this sector, the energy demand continues to grow at an annual rate of 0.8%; this is the fastest growth rate after the industrial sector [1]. The advent of advanced metering technology provides the possibility of building energy monitoring and feedback at various granularities. The most recent generation of wireless sensors facilitate the process of real-time plug load monitoring and feedback. Benefiting from the rich data acquired through these sensors, a thorough analysis on occupants' energy consumption [2, 3], energy prediction [4, 5], and eventually a more accurate bottom-up building energy prediction could be conducted [6]. This not only could increase energy managers' information about occupants' energy-use, but would also enable them to provide more accurate feedback to occupants and increase the energy efficiency of the building. Building occupant-level energy prediction could significantly improve energy efficiency (EE) programs by providing targeted, personalized, and timely information regarding occupants' behavior [7-13]. This information can considerably increase the effectiveness of such programs while providing a more pleasant user experience for EE programs (e.g. through eco-feedback systems). However, due to the high degree of uncertainty in predicting an individual's energy consumption [14, 15], researchers suggest grouping these individuals to improve the prediction accuracy [16, 17]. Yet, this recommendation is in conflict with the potential for advanced sensors to provide high precision and high resolution data (at the individual occupant level) on consumption in order to empower eco-feedback programs through targeting occupants, and enhance building management system control predictive models.

In this paper, we approach the occupant energy prediction challenge from a behavioral perspective. We propose a method to predict individuals' energy consumption behaviors at a workstation-level. We accomplish this by creating energy-use codebooks based on individuals' historical energy-use, assessing the feasibility of designing a targeted EE program, and introducing a new approach to maximize the effectiveness of EE programs in commercial buildings. Lastly, to validate our method we tested two hypotheses: 1) there exists an interdependency between energy-use pattern prediction accuracy and occupants' energy-use entropy, and 2) there exists an interdependency between energy-use pattern prediction and occupants' energy efficiency. The results of these tests are critical to assess the efficacy of our proposed method to target inefficient occupants in commercial buildings.

3. RELATED WORK

3.1. Sensor-based Building Energy Monitoring

Sensor-based energy prediction has gained popularity in both the commercial and residential sector with recent advancements in sensor-based monitoring. However, the body of research is more focused on less granular scales (e.g. building, zone, city, etc.) [16-21]. High resolution sensors facilitate the implementation of bottom-up approaches which can potentially increase the prediction accuracy and provide diagnostics for identifying the areas of inefficiency in buildings [22]. Earlier datasets were captured at a relatively low resolution and building-level granularity, and energy prediction models were only capable of predicting building energy consumption at a high granularity [14]. Later, the metering technology was improved to a higher resolution by monitoring energy-use of central energy consumers in buildings such as HVAC systems, lighting systems, and domestic hot water systems [23-27]. Recent advancements in metering technology have provided an opportunity to meter end-user energy consumption at an appliance-level resolution. Despite these efforts on sensor-based energy feedback, there is still much research to be done to achieve metering infrastructure's full potential to induce energy savings.

3.2. Building Energy-use Prediction

In addition to sensor-based feedback approaches to understand energy use, various artificial intelligence (AI) approaches, such as machine learning algorithms, have been implemented to predict short and long term energy consumption of end-users in buildings. Early research in the commercial sector centered on ASHRAE's prediction competition in 1994. That year, MacKay [28] won the energy prediction competition by applying a Bayesian non-linear regression and an automatic relevance determination algorithm. The main focus later shifted toward Neural Networks (NN) and SVM-based algorithms, which represent more robust modeling approaches. Numerous researchers established novel modifications of NN models for energy consumption prediction. Adaptive artificial neural network algorithms [29] and feed forward neural networks [30] are variations that have already been implemented in the literature for energy prediction. However, algorithms are not necessarily the only impacting factor in occupants' energy prediction process. There is a substantial body of knowledge investigating the effects of various features impacting the training and testing of NNs. For example, Wong et al. [23] offered an energy prediction model by including building envelope type as a new input variable to train a model using artificial neural networks. The main differences in NN-based studies are in the input variables, architecture, parameter optimization, etc. In the residential sector, several similar studies on energy forecasting have been conducted. However, according to Edwards et al. [31] who examined various machine learning algorithms to predict residential electricity consumption, the different load shapes between residential and commercial buildings prevent the same algorithm from being effective in both sectors. Furthermore, Li et al. [32] compared the strength of SVM and NN algorithms in hourly energy prediction of cooling systems and found SVM as a more accurate algorithm in energy prediction compared to NNs. Moreover, Dong et al. [33] reported the advantages of SVM compared to NN as smaller sample pool, structural risk minimization approach, and also the fewer number of parameters required to be optimized in training process. Therefore, researchers such as Fan et al. [19] proposed a data mining approach to develop the next-day energy consumption and peak power demand prediction ensemble algorithms. Ensemble algorithms benefit from a combination of ML algorithms to reinforce the learning process and combine multiple underlying basis models, including: multiple linear regression (MLR), auto-regressive integrated moving average (ARIMA), support vector regression (SVR), random forests

(RF), multi-layer perceptron (MLP), boosting tree (BT), multivariate adaptive regression splines (MARS), and k-nearest neighbors (KNN). In this work, the ensemble algorithm prediction accuracy outperformed the individual algorithms. There are other advanced methods used to predict occupants' energy consumption in the residential sector such as [34, 35]. Variations of Markov processes (e.g. Hidden Markov Model, Random Markov field, Markov chain, etc.) have been used to develop more comprehensive prediction models with capability of considering prior, transitional, and emission probabilities in models. Among the aforementioned prediction methods, depending on the level of available information, type of data, and the length of data each method can outperform the others. Nevertheless, in this study due to incorporation of energy-use profiles, short length of study, and simplicity of SVM methods we decide to implement a support vector machine method for the sake of prediction.

3.3. Utilizing Occupant-level Monitoring to Improve and Target Energy Efficiency

There are a few studies that take advantage of high resolution end-user energy monitoring in residential and commercial buildings with a focus on energy analysis and energy efficiency. Chen et al. [36] utilized an appliance level real-time eco-feedback system to reduce energy consumption and analyze appliances energy-use in residential buildings. In a commercial building setting, Murtagh et al. [37] conducted an eco-feedback study with more than 80 participants, using historical comparison techniques to motivate occupants to save energy. Gulbinas et al. [2, 38] investigated the effect of real-time eco-feedback systems coupled with various psychological techniques on occupants' energy consumption behavior in a commercial building. This study examined individuals' energy consumption at a workstation level and provided novel metrics and insights to quantitatively evaluate occupants' energy efficiency. Likewise, Bradley et al [39] studied the effect of eco-feedback systems on individuals' energy consumption in an office environment. At a higher monitoring resolution, Yun et al. [40] designed an appliance-level eco-feedback system (e.g. main desktop computers and monitors, servers, modems, routers, refrigerators, etc.) to improve the occupants' energy awareness and efficiency through various psychological approaches. Moreover, Coleman et al. [41] implemented an appliance-level personalized eco-feedback system to promote energy efficient behavior in commercial buildings. These aforementioned studies provide high resolution and personalized feedback such that each occupant can observe the energy-use information related to their own appliances and workstations. In some cases, this includes normative comparison approaches that allow monitoring peers' energy consumption as well. However, there are a limited number of studies that approached promoting energy efficiency in a targeted way to follow a "one size does not fit all" notion as endorsed by numerous researchers [7-13]. In other words, there is a gap of knowledge in that previous studies did not take into account occupants' individual energy-use behavior to provide well-timed, personalized, and targeted energy efficiency feedback to induce further energy efficiency.

Building on this knowledge of existing high resolution and real-time eco-feedback systems [2, 38], we developed an energy-use behavior prediction algorithm which is trained based on individuals' historical energy-use codebooks and predicts upcoming time interval energy-use behaviors at an individual-level. The ability to predict energy-use behavior can impact the design of *targeted* and *sustainable* feedback systems by providing useful information in a timely manner on potential inefficient energy consumption behaviors and transform the efficacy of EE programs in the near future through promoting curtailment behaviors and inducing higher levels of energy efficiency. For example, such a feedback system could learn and predict when each individual will leave the office and send timely and targeted notification reminders to users that are unlikely to turn off workstation-level equipment. In this study, we utilize a novel occupant classification method to group individuals by their energy-use patterns. Energy-use data is segmented by workday and non-workday hours and energy-use codebooks are created for the morning (i.e. non-working hours), work hours, and evening (i.e. non-working hours). Based on individually classified codebooks, separate models are trained using a support vector machine (SVM) algorithm to infer the future energy-use behavior of segmented clusters of occupants. The main purpose of developing such an algorithm is to leverage the abstracted energy-use profile of each individual and predict the future energy consumption patterns. These patterns, along with the prediction accuracy of our method, provide the information required to evaluate hypotheses designed to validate the proposed methodology. The hypotheses are as follows: 1) an interdependency exists between energy-use pattern prediction accuracy and occupants' behavior, and 2) an interdependency exist between energy-use pattern prediction and occupants' energy efficiency, are tested.

4. METHODOLOGY

A three step process was taken place as illustrated in Fig. 1. Data collection includes the energy consumption data captured through plug load monitors. The collected energy consumption data was classified for each individual using a 3-step process as described in section 3.2.2. Finally, a support vector machine algorithm used to train and predict individuals' energy load patterns.

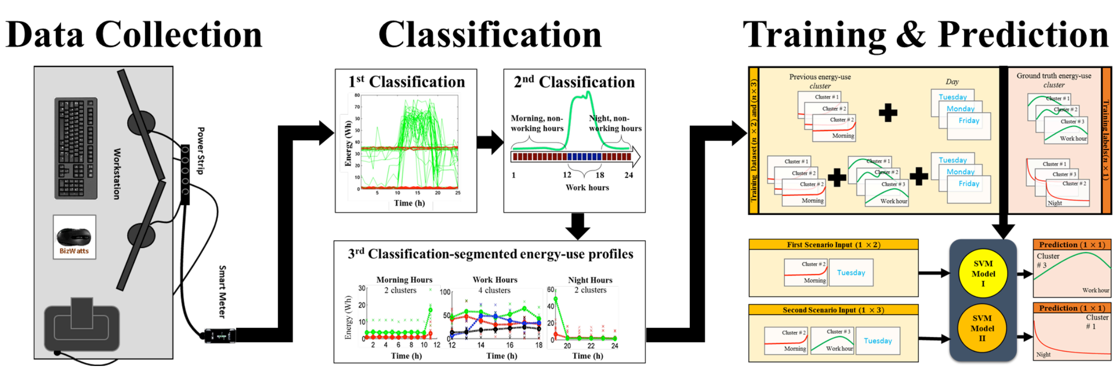


Fig 2. Overview of the process

4.1. Data Collection

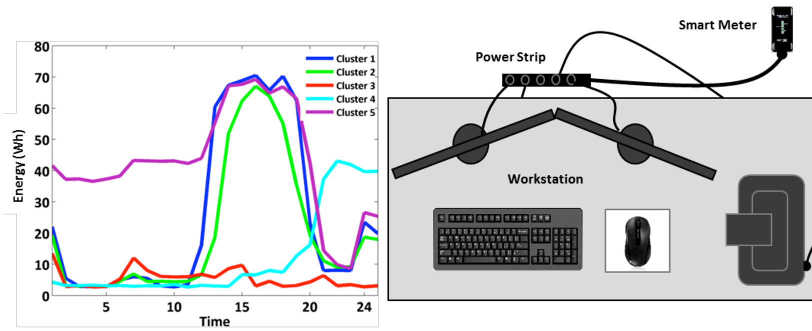
The data collection was conducted in a 6 story commercial building located in Denver, CO with approximately 115 full-time employees working in 27 non-profit organizations in that building. The workstation appliances were not identical, however, desktop computers or laptops, desk lamps, and in some cases printers were most common appliances. All appliances were connected to a power strip as illustrated in Fig 1 and the power strip energy data was captured through commercially available wireless plug load monitoring sensors. Each group of plug load monitors depending on the location communicate via 900 MHz RF signal with a central router that uploads the data to our database through Ethernet connection. Please refer to [42] for further information regarding infrastructure of our experiment.

4.2. Classification and Prediction

The proposed method consists of three key elements described in the following sub-sections. First, occupant energy-use behavior is classified and individual codebooks (i.e. individual energy-use profiles) are generated. Next, a support vector machine is used to learn the occupants' energy-use behavior using a set of features. Finally, energy-use predictions at various resolutions are tested and compared. A main goal of our algorithm is to leverage the existing occupants' energy consumption profiles created through incorporation of multiple modified K-means clustering algorithm on individuals' energy consumption by [2] to predict future energy consumption of each individual. The overview of the algorithms used in [2] are provided in the following subsections. We can then evaluate hypotheses that validate the potential of the approach to enhance energy efficiency programs through predictive models.

4.2.1. Daily Load Classification

Occupants generally follow specific energy-use patterns based on various factors (e.g. working hours, duties, appliances, energy efficiency, etc.). Thus, an individual's energy-use behavior is a variation of a specific set of energy consumption load shapes which slightly vary on a daily basis. The energy load shapes are highly dependent on individuals' energy consumption pattern, work hours, and also the equipment used at each workstation. These repetitive patterns enable codebooks (i.e. energy-use profiles) to be created for each occupant that capture the variability of the entire set of an occupant's load shapes over time [2]. This method could help reduce uncertainty in the predictability of occupants' complex behavior [43, 44]. A K-means clustering method is implemented for the means of classification due to application simplicity and the level of accuracy required in this study to distinguish the general pattern of occupants energy consumption. The K-means clustering algorithm is to classify N points in M dimensions into K clusters conditioned such that the sum of squares of data point distances to the assigned cluster is minimized. The algorithm requires the dataset and a set of K initial random cluster centers to start. The procedure is to search for K-partitions with locally optimal Euclidean distances by moving points from one cluster to another [45]. In our research, the K-means clustering algorithm will classify the data points into categories based on hourly energy-use values captured from workstations over each day. The appliances connected to the power strip at each workstation are not identical, and are usually consisted of a desktop computer or laptop, desk lamp, and in some cases a printer. Each classification follows an iterative process combined with a set of thresholds to check the closeness of the cluster centers and determine the K value. The range of K starts from 10 and can go down to 1 based on each iteration's result and the closeness of the clusters. These thresholds will prevent the disaggregation of similar patterns into separate clusters for an individual [2]. The authors refer readers to [2] for further details on the clustering algorithm implemented in this paper. Fig. 2 depicts (a) a sample codebook representing the most dominant energy consumption patterns collected from (b) a non-shared workstation through the duration of the study (i.e. approximately three months) for an individual employee.



(a) (b)

Fig 3. (a) Represents employee #49's energy-use codebook, and (b) illustrates a typical non-shared workstation

4.2.2. Segmented Load Classification

The classification is performed at various stages and resolutions. First, we classify working and non-working days of the week based on pre-set thresholds which check the shape and absolute value of energy loads during the day [2]. Workdays are defined as the days with a large variation of energy-use [2] and each day's data should pass through the same set of filters. The shape filter assures that there is at least a 15% increase in normalized load shapes and the value threshold checks the absolute difference between the maximum and minimum energy value in each day which has to be greater than 5 watts based on the minimum energy consumption of appliances connected to the smart meter. The second energy-use filtering layer is to assure the prevention of noisy cluster variations in user codebooks by enforcing a minimum threshold on cluster load values [2]. At the second stage, each working day will be segmented into two categories; work hours and non-work hours. The working hours and non-working hours are disaggregated by a k-mean clustering algorithm using Euclidean distance as a separation measure. Finally, the energy profiles are classified when each day's data is segmented to three categories; morning (i.e. non-working hours, before an occupant starts to work), work hours, and night (i.e. non-work hours, after an occupant leaves the building). Each classification is combined with a set of thresholds as explained in the *daily load classification* section. The daily segmentation is conducted only on working days, as non-working days are mostly flat-shaped and there are no working hours to be separately classified. Fig. 3 illustrates an overview of the segmented classification.

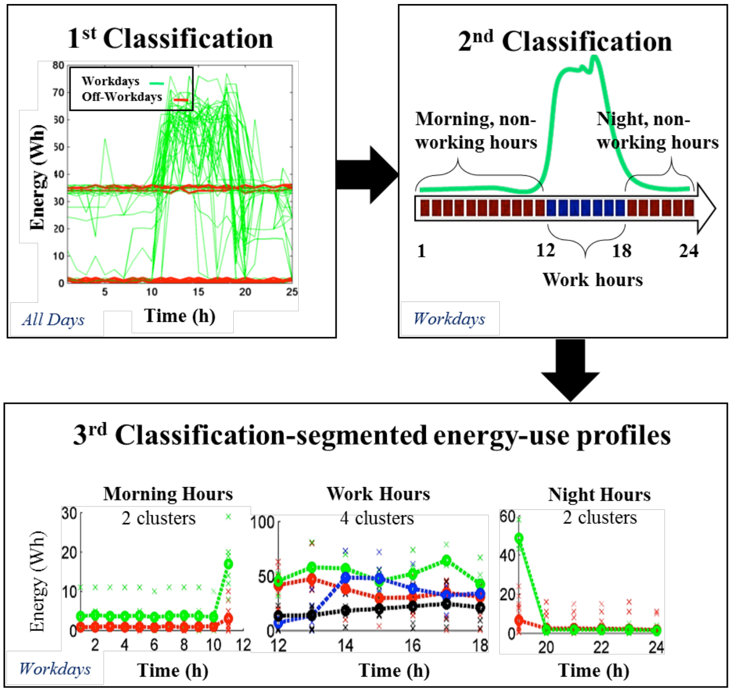


Fig 4. Classification process overview

4.2.3. Prediction Algorithm

As previously mentioned, there are several areas which could potentially benefit from occupant behavior prediction (e.g. tailored EE notification, office appliance diagnosis, more accurate bottom-up energy prediction, etc.). To learn specific models for each occupant, a multi-class one-vs-one Support Vector Machine (SVM) classifier was implemented. A discriminative machine learning algorithm which not only classifies based on the patterns but also optimizes the decision boundaries [46], is necessary to create more accurate models when dealing with inseparable sets of classes. For each occupant $o_j \in O$ [where O is the pool of all occupants], we trained a multi-class SVM classifier using given training data $\{p_i, q_i\}$. For this classifier, $p_i \in P_{j\text{-}train}$, and $P_{j\text{-}train}$ includes all training data points and possible labels are $q_i = \{1,2,3, \ldots \text{n}\}$ [where n is the number of energy-use cluster centers (i.e. energy-use patterns) each individual has]. One of the major advantages of SVM is the ability of the algorithm to fit models to the datasets which contain outliers and noise. The concept of slack variables ξ_i helps in fitting decision boundary hyperplanes within a soft margin approach. The SVM optimization problem with a linear kernel can be written as:

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i$$
$$\text{subject to: } y_i\left(w.x_i + b\right) \geq 1 - \xi_i \text{ for } i = 1,\ldots,N \tag{1}$$
$$\xi_i \geq 0 \text{ for } i = 1,\ldots,N$$

In (1), C represents a penalty constant which controls the trade-off between the margin size and the training error, and w represents the normal vector to the hyperplane. As a rule of thumb [47], a 5-fold cross validation is used to split our dataset into disjoint training and testing sets with 80% and 20% shares, respectively. During the testing phase, we predicted the labels $\{1,2,3,\ldots,\mathrm{n}\}$ for each testing example $p_i \in P_{test}$ with respect to the trained hypothesis for all existing occupants. Implementing a kernel to map the data into a higher dimensional feature space can help to improve the classification performance. Thus, a Gaussian Radial Basis Function (RBF) was chosen over other kernels such as linear, intersection of histograms, polynomial, and chi-square kernels due to a better performance in the prediction. Equation (2) represents the general form of RBF, in addition to the special case of Gaussian kernel.

$$K(x^{(i)}, x^{(j)}) = \exp(-\gamma \left\|x^{(i)} - x^{(j)}\right\|^2), \gamma \geq 0, \text{ for Gaussian: } \gamma = \frac{1}{2\sigma^2} \tag{2}$$

4.3. Daily Energy-Use Prediction

Individuals follow a certain set of energy-use patterns on a daily basis and each energy-use codebook is different from other occupants. In order to learn energy-use codebooks for each individual, we clustered energy-use patterns for each occupant to create a reduced set of representative daily energy-use load patterns. Furthermore, we took advantage of additional information such as time, working/non-working day, previous day's energy-use pattern, and energy value to create a robust model predicting the next day's energy consumption pattern. A 27 dimensional feature vector (i.e. 25 for previous days energy data points, 1 for previous day, and 1 for previous day's working status), is abstracted to a 3 dimensional space using our classification algorithm [2] and used as an input and mapped through a RBF kernel in order to train the SVM model. The next day's energy-use pattern (i.e. output) is predicted through a 5-fold cross validated process, and the accuracies are calculated. Fig. 4 provides an overview of the process.

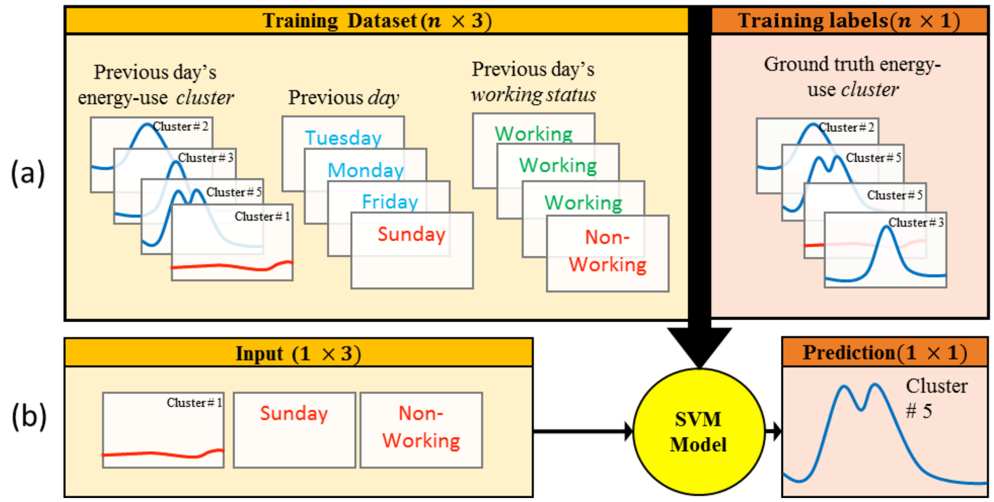


Fig 5. Daily energy-use prediction overview: (a) SVM model training process, and (b) energy-use behavior inference process

4.4. Segmented Energy-Use Prediction

The daily profiles were next classified into working vs. non-working hours. There are three segments in each day starting with "morning", before occupants enter the building and start using the appliances at their workstation (i.e. morning non-working hours). This segment usually starts at 12:00 am and ends in the morning between 8 to 10 am. The second part of the day is "working hour" which usually starts between 8 to 10 am and ends around 5 to 7 pm. In these hours, occupants are using their appliances and the energy-use level is higher than non-work hours. The last segment, "night" non-work hours, represents the hour range in which occupants leave the building and appliances are usually off or enter power saving mode. All ranges represent approximates of typical schedules and may vary based on the occupants' behavior and working hours. This segmentation helps to perform a more precise classification and create more detailed energy-use codebooks. Energy-use data for each occupant was classified for each part of the day as depicted in Fig. 3 and this became part of the input data to train a model based on the occupants' energy-use behavior. We include classification results in the training of specific models for morning and work hours for each occupant (total of two models per occupant) in order to predict the upcoming period's energy-use behavior. The features used to train the SVM models are energy-use clusters and the day of the week. Fig. 5 provides an overview of the algorithm.

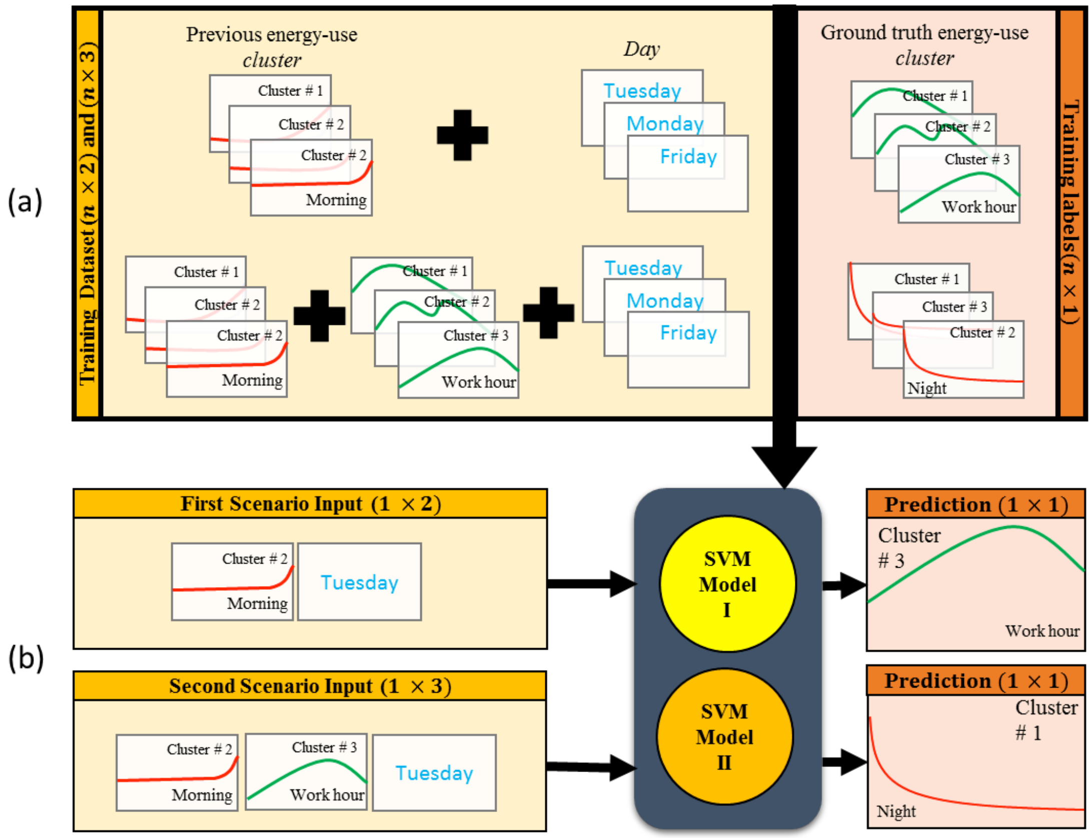


Fig 6. Segmented energy-use prediction overview: (a) SVM model training process, and (b) energy-use behavior inference process

4.5. Validation

In order to evaluate the interdependence of occupants' energy-use behavior and the accuracy of energy prediction models and validate our method, we tested two hypotheses: 1) energy-use pattern prediction accuracy and occupants' energy-use entropy are interdependent and 2) energy-use pattern prediction and occupants' energy efficiency are interdependent. The results of these tests are critical to assess the efficacy of our proposed method to target inefficient occupants in commercial buildings. These tests further validate the applicability of such a method to EE programs (e.g. tailored EE notification systems) in order to target the occupants with the highest energy saving potential. The hypotheses are focused on two types of behaviors previously defined by Gulbinas et al. [2] as described in section 3.4.3 of this paper—energy efficiency and energy-use entropy.

4.5.1. Hypotheses

Hypothesis 1: Occupants' *energy-use entropy* value is positively correlated with energy-use behavior prediction accuracy.

Hypothesis 2: Occupants' *energy efficiency* value is positively correlated with energy-use behavior prediction accuracy.

4.5.2. Hypothesis Testing

In this section we implement the behavioral measures (i.e. energy efficiency and entropy) based on energy-use patterns of commercial building occupants studied in [2]. Once time across all analyzed days has been effectively decomposed into various segments (e.g. morning non-work hours, work hours, night non-work hours), and the energy-use for each segment is separated into distinct clusters, as illustrated in Fig. 3, we calculate values representative of a building occupant's energy efficiency and energy-use entropy. Occupants' *energy efficiency* is defined as the percentage of time each individual spends in the lowest energy consumption cluster. The low energy clusters are defined based on a threshold, in this case is 7Wh based on an estimate of average power consumed by workstation appliances in off state. The formula used to calculate the level of energy efficiency is provided in [2]. And *energy-use entropy* is a measure of disorder or uncertainty of energy consumption and a function of the number of times each occupant changes energy-use clusters for each segment of the day over the course of study [2]. The occupants' energy-use entropy, S_i, is calculated as follows:

$$s_l = -\sum_{i=1}^{k} p(C_i) \log_{10} p(C_i) \tag{3}$$

$$S_i = \frac{\sum_{l=1}^{T} h_l s_l}{\sum_{l=1}^{T} h_l} \tag{4}$$

Where s_l is the entropy of segmented range, l, that has a length of h_l hours and a total of K different behaviors (i.e. clusters) obtained from the clustering algorithm. T is the total number of ranges that entropy is calculated for. Please refer to [2] for further information. Fig. 6 illustrates the mapping of occupants' classification based on energy efficiency and energy-use entropy.

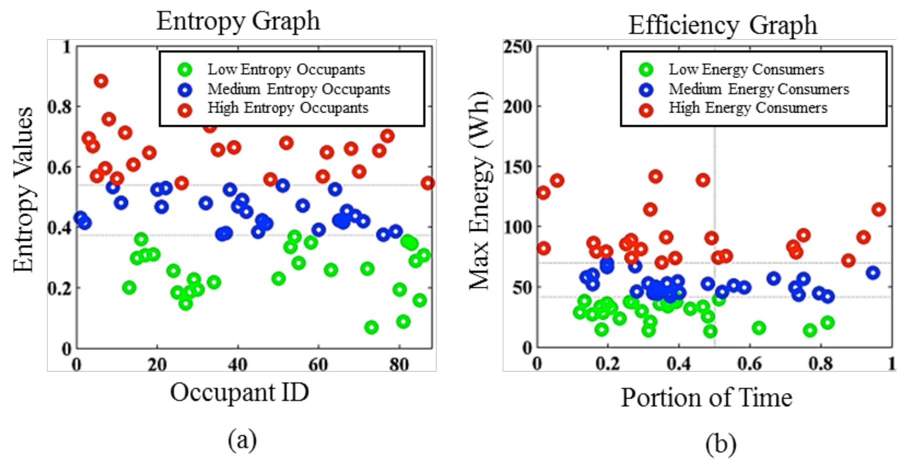


Fig 7. Occupants' classification based on: (a) energy-use entropy values and (b) energy efficiency

As presented by Fig. 6(a), occupants are separated into three quintiles, low entropy, medium entropy, and high entropy. Fig. 6(b) illustrates the classification of occupants to three quintiles based on the maximum energy consumed in the lowest energy cluster and two categories based on the percentage of time spent in the lowest energy consumption cluster. Based on calculated entropies and energy efficiencies and energy-use behavior prediction as described, we calculate p-values which are the probabilities of getting a correlation as large as the observed values by random chance, when the true correlation is zero. Furthermore, we analyze the prediction accuracies for each group of people to find the best target group that fits a tailored EE notification system. For example, if energy prediction accuracies are low for the group of inefficient occupants, chances are low to engage these individuals in implementing energy efficient behavior through a predictive and targeted notification system.

5. RESULTS AND DISCUSSION

We utilized LIBSVM [46], an open source machine learning package in order to train and infer energy-use behaviors. Energy-use prediction results were obtained through a 5-fold cross-validation process and the average of all four accuracies will be reported. A confusion matrix and a precision-recall graph were generated for each occupant to evaluate the performance of the model. We refer the reader to [48] for further information on the details of this evaluation method. The predicted energy-use behaviors will be compared to the ground truth data captured by our smart sensors and the coefficient of variation (CV) of the root means square errors, $CV(RMSE)$. $CV(RMSE)$ is defined as:

$$CV(RMSE) = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(y_i\text{-}\hat{y}_i)^2}}{\bar{y}} \tag{5}$$

where $\hat{y}_i$ is the predicted/clustered value, y_i is the observed value, $\bar{y}$ is the mean of the observed values and N is the total number of observations.

5.1. Classification Results

Initially, clustered energy-use patterns were mapped to the associated cluster centers in order to evaluate the accuracy of the clustering process. The set of cluster centers represent a simplified set of representative profiles. There is a cost associated with simplification and that is an increase in the coefficient of variation. In other words, the clustering process facilitates the task of occupants' energy-use behavior prediction; however, predicted energy-use values could vary slightly from the real values. The average CV calculated based on the cluster centers and ground truth data is 74.07 with a lowest value of 9.60. This is not the best obtainable result based on our classification method, since we did not optimize the CV error-prediction accuracy trade-off; however, when plotting the CV values of each occupant on the Y-axis, and plotting the number of cluster centers for each occupant on the other axis, it is observed that more cluster centers results in lower CV values. Therefore, it could be interpreted that occupants' consistency with specific energy consumption patterns affects the energy-use pattern prediction accuracy and also the energy-use value prediction error.

5.2. Daily Prediction

A SVM model was trained for individual occupants based on all the working and non-working days' energy-use. Each model was trained based on the automatically labeled clusters (i.e. energy-use patterns) and evaluated based on a disjoint set of data to prevent overfitting of the models. The overall accuracy of daily energy-use behavior prediction was 81.70% with the highest prediction rate of 100%. In order to demonstrate the trend between the prediction accuracy and number of clusters for each occupant, a box plot is graphed in Fig. 7. These results show a decrease in the energy-use prediction accuracy as the number of cluster centers increases. Therefore, there is a trade-off between the energy-use behavior prediction and our classification CV. The higher the number of cluster centers there are for each occupant, the lower the CV is. On the other hand, the higher the number of cluster centers there are, the lower the prediction accuracy is. We therefore seek to determine the optimum points at which our system reaches its maximum performance by bounding the number of cluster centers [49]. This approach effectively captures occupant energy-use behavior, and increases the energy value prediction accuracy of our system.

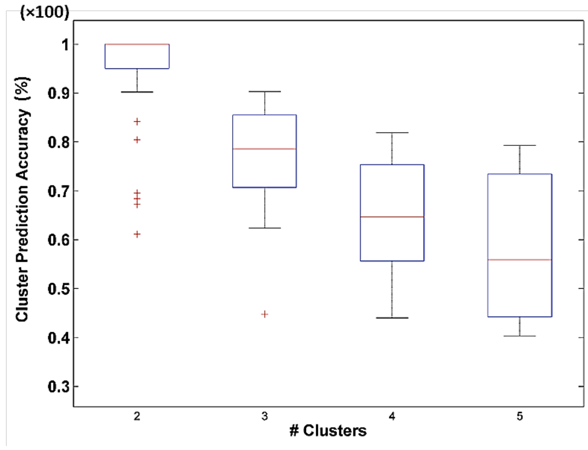
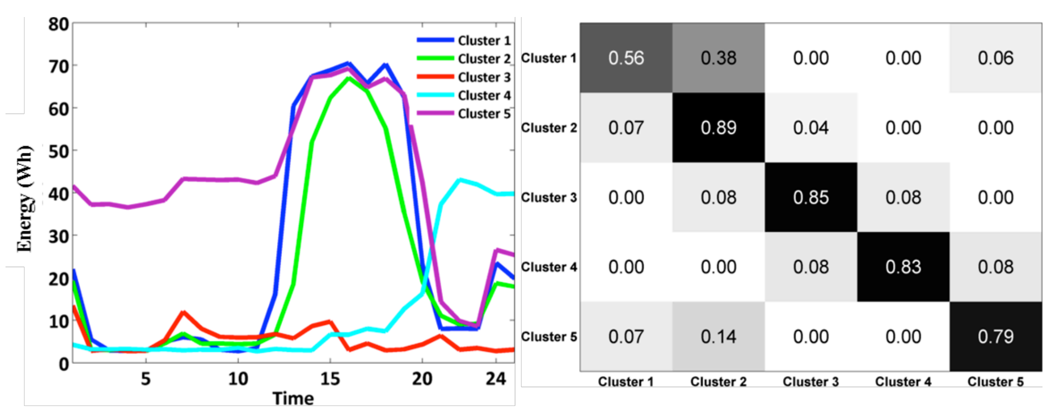


Fig 8.Daily energy-use prediction accuracy vs. number of clusters for each individual

Another measure by which we can evaluate our prediction algorithm is a confusion matrix. Confusion matrices present the false positive detections and the rate of confusion among various patterns for each occupant. This would help us identify the most confused patterns and find the source of confusion to improve the classification and prediction algorithms. Based on our investigation, the misclassifications in our model happen because of similar energy shapes and values in the training dataset, similar repetitions of the same patterns on the same day of the week, and lack of sample data. Fig. 8 illustrates a sample data analysis for occupant #49 in which the average prediction accuracy is 78.4%. Based on the confusion matrix, the maximum confusion was between clusters number 2 and 1. The energy-use cluster centers are presented in Fig. 8(a). Cluster #1 and #2 are very similar in terms of shape and value; however, cluster #2 has been repeated thirteen times more than cluster #1 in our dataset and this encouraged our algorithm to choose cluster #2 more confidently under similar conditions.



(a) (b)

Fig 9. (a) Sample energy-use codebook for an occupant #49; (b) confusion matrix for energy-use prediction for occupant #49

A precision-recall curve was also plotted for each occupant to study the overall performance of our algorithm. This was done by dividing the predicted results based on their confidence score given by SVM and considering that each interval has the same number of sample data points. The ideal plot is the one which has a precision close to 1 regardless of the recall value, this ideal condition shows that prediction accuracy is always 100% at all prediction confidence thresholds. As illustrated in Fig. 9, the precision rate drops as we increase the recall. When the recall rate is low, the decrease in the precision rate is extremely undesirable and shows the weakness of the model. In occupant #49's case, the precision fluctuates around 80% for most of the recall rates below 80%. However, when the recall rate passes 80% the precision drops precipitously.

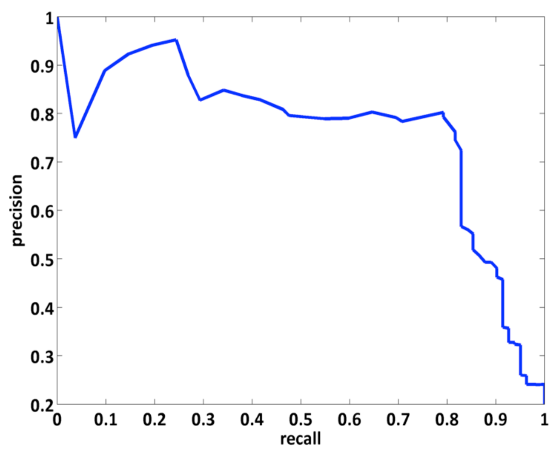


Fig 10. Precision-recall graph for energy-use prediction for occupant #49

To evaluate the prediction accuracy, we calculated the CV for predicted energy-use clusters by benchmarking the ground truth data. The result shows a lower performance due to the existing inaccuracies in the prediction algorithm with an average CV of 91.15 and the lowest CV of 14.03. The coefficient of variation is calculated for predicted energy-use clusters by benchmarking the associated ground truth cluster centers. The result shows an average CV of 45.08 and the highest performance of $CV = 0$.

5.3. Segmented Prediction

After exploring the energy-use behavior prediction and coefficient of variation for daily predictions, we are proposing a higher resolution classification and prediction as described in section 3.3 on *Segmented Energy-use Prediction*. The prediction algorithm will be applied to each segment of the day, and later the predictions are combined together to present the daily energy-use codebooks. Based on the collected data in the morning, the work hour energy-use pattern is predicted (i.e. first scenario), and based on the work hour energy-use, the night hour energy-use data is predicted (i.e. second scenario). There is little need for morning energy prediction (i.e. non-working hours before employees go to work) since it is very unlikely that employees work over night or

come back to the office after they leave for the day. This assumes that the morning energy-use pattern should follow the previous night energy-use pattern.
A multi-class one-vs-one support vector classifier was implemented to train mutually exclusive models for the aforementioned scenarios. The first one is to predict the *work hour* energy-use pattern and the second one to predict the *night hour* energy-use pattern. 5-fold cross validated results are reported for each prediction based on disjoint training and testing datasets. The average accuracy of the work hour prediction model is 88.01% with the highest accuracy of 100% and an average prediction accuracy of 77.99% for the night hour energy-use prediction with the maximum accuracy of 98.08%. The work hour predictions obtained lower accuracy since there is more intra-class variability in work hour behaviors for each occupant. Occupants' work hours energy-use behavior could vary from 2 to 7 different clusters, while non-work hour clusters typically varied between 2 to 3.

Energy-use prediction accuracies were plotted versus the number of energy-use clusters for each individual. As graphed in Fig. 10, a decreasing trend of prediction accuracies for both (a) night hours and (b) work hour energy-use prediction can be observed while increasing the number of clusters. Therefore, the lower the number of clusters, the more accurate our prediction algorithm would work.

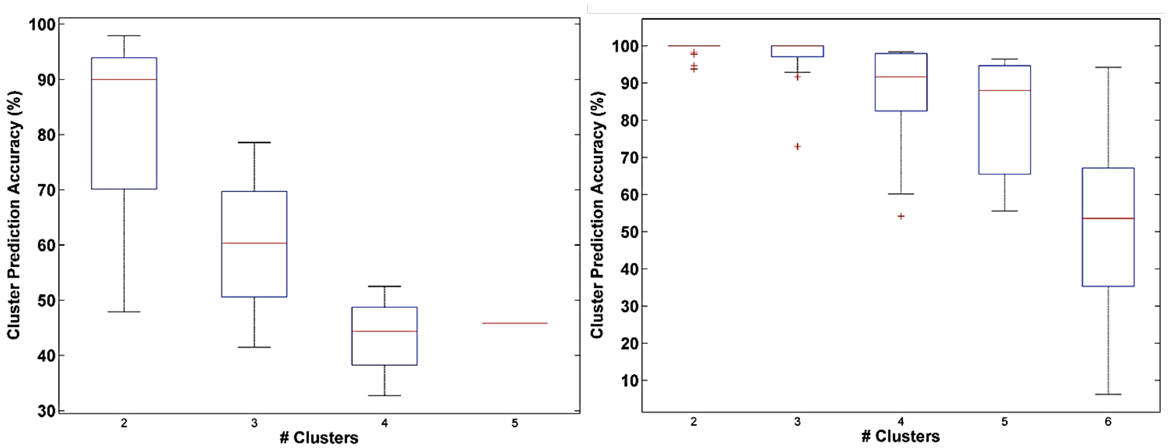


Fig 11. Prediction accuracy of segmented model versus the number of cluster centers for each individual; (a) night hour and (b) work hour

In addition to the prediction accuracy, the coefficient of variation (CV) is calculated for each occupant to observe how differences in the prediction compared to the ground truth data collected by the sensors. Fig. 11 graphs the 39th day energy-use prediction for occupant #80 superimposed on (a) the associated cluster centers and (b) the ground truth data. In this particular case, work hour and night hour energy-use predictions are both correct. Nevertheless, the prediction varies in terms of the value compared to ground truth data. As depicted in Fig. 11, our algorithm predicted that occupant #80 in all probability will forget to turn off the appliances at his/her workstation. This type of behavior could most likely be detected if an occupant has repeatedly forgotten to turn off the appliances and this behavior could be observed enough times in the dataset to train a model.

The ability to predict occupant energy-use patterns which reflect certain behaviors provides useful information for energy efficiency (EE) programs and automated notification and feedback systems. Three CV values are calculated to measure the goodness of our prediction algorithm in terms of energy values rather than energy-use patterns. As expected, cluster centers and the predicted clusters CV have the lowest value of 34.47 which outperforms the same CV value calculated in section B for the daily resolution prediction. The CV value calculated between cluster centers and the ground truth data (i.e. hourly energy data) was 48.03. Finally, the CV value calculated based on the ground truth data and the predicted cluster centers has the greatest value of 61.45 compared to the previous two. However, all of these CVs outperform the daily resolution CVs as described in previous sections, which indicates a more accurate energy value prediction for the segmented prediction method. Remarkably, the energy-use behavioral prediction accuracy of 83.00% for segmented load prediction outperforms the prediction accuracy of 81.70% for the daily load predictions. A better performance by segmented load prediction algorithm suggests the benefit of higher resolution energy monitoring and creating more informative models to enhance EE programs through occupants' behavior prediction and potentially providing more accurate bottom-up energy prediction approaches.

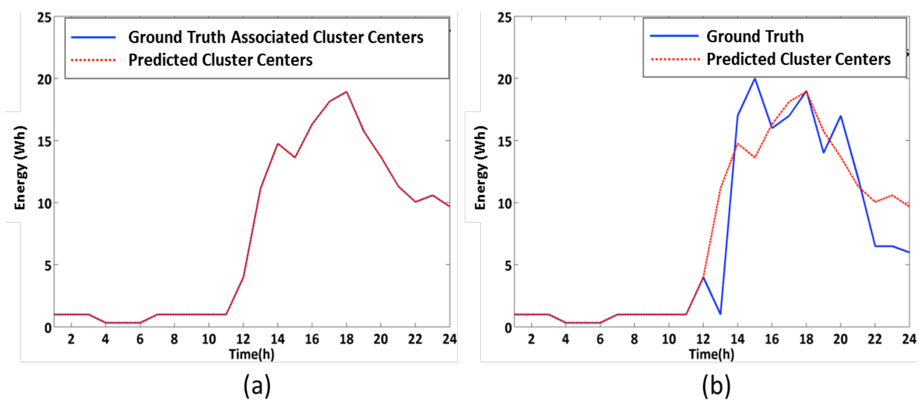


Fig 12. Joint graph of segmented predictions for the 39th day of occupant #80

5.4. Hypotheses Test Results

In this section we present the results obtained from cross-validated SVM models for 87 occupants for two different scenarios[1] as presented in Fig. 12. Six different categories of occupant energy-use are modeled and tested separately. As illustrated in Fig. 6, these 6 categories consisted of: low entropy occupants, medium entropy occupants, high entropy occupants, low energy consumers, medium energy consumers, and high energy

[1] First Scenario: using morning hour data as an input and predicting working hour energy-use cluster. Second scenario: implementing work hour data as an input and predicting night hours energy-use cluster.

consumers; determined by ranking occupants based on their performances in each category and dividing them into three quantiles. For each occupant a 5-fold cross-validated accuracy was calculated and compared to the rest of the group members. Fig. 12(a) presents the occupants' energy-use entropy which has been linearly scaled from $[0, 1]$ to $[100, 0]$ for the sake of easier visualization and comparison with SVM prediction accuracies. Thus, we define energy-use predictability, which is a linear transformation of our entropy values, as the consistency at which an occupant follows particular energy-use load profiles. The closer the predictability value is to 100, the more consistent an occupant's behavior is and vice versa. Equation (6) is the function used to transform the entropy to predictability data. The green bars in Fig. 12(a) represent the most consistent occupants, the blue bars show medially consistent occupants and the red bars are representative of occupants with low consistency in energy-use behavior. Fig. 12(b) demonstrates the prediction accuracies for each individual and is color-coded based on the predictability classification noted above.

$$Predictability = 100 \times (1 - Entropy) \tag{6}$$

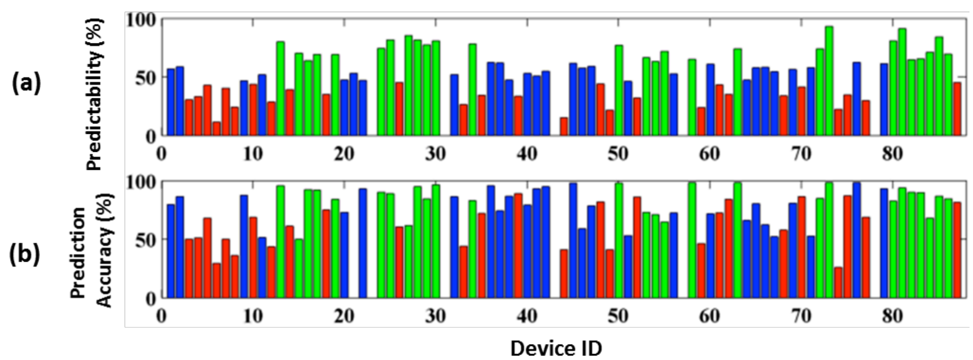


Fig 13. Comparison of: (a) predictability and (b) prediction accuracy.

Fig. 13(a) depicts the prediction accuracy for occupants with high predictability (most consistent energy-use behavior). Fig. 13(b) graphs medium predictable occupants and 13(c) low predictable occupants. The SVM prediction accuracy obtained for various groups of occupants classified based on their energy-use predictability and energy consumption rate are presented in Table 1. Table 1(a) shows the accuracies for prediction of work hour energy, while Table 1(b) represents SVM prediction accuracies for night hour classification. It should be considered that the results presented in Table 1 might be slightly different compared to the previously reported results due to the randomness of the cross validation function in selecting the training and resting datasets.

Lastly, statistical significance of correlations between behavioral classification and prediction accuracies were calculated. The p-value obtained for energy-use predictability and prediction accuracy correlation is below 0.01 and the p-value calculated for energy efficiency and prediction accuracy turned out to be different for various scenarios. Obtained p-values for energy efficiency correlation ranged from 0.00016 to 0.2257 for different conditions (i.e. scenarios). Therefore, more analysis is required to evaluate a possible positive correlation between energy efficiency of occupants and energy-use behavior prediction accuracy. Moreover, a review of the high, medium, and low energy consumption categories defined based on occupants energy consumption quantiles indicates that the SVM prediction accuracies are in the same range. This indicates that there is strong potential for targeting high energy consumers through automated EE programs through accurate prediction of their energy-use behaviors.

Table 10. SVM prediction accuracy for various occupant classes

(a) **Features:** Morning hour energy data ➔ **Prediction:** Work hour energy-use cluster			
Predictability Class	**SVM Prediction Accuracy**	**Energy consumption Class**	**SVM Prediction Accuracy**
High Predictability	88.68%	High Energy Consumption	79.95%
Medium Predictability	78.32%	Medium Energy Consumption	72.82%
Low Predictability	63.79%	Low Energy Consumption	78.28%
(b) **Features:** Work hour energy data ➔ **Prediction:** Night hour energy-use cluster			
Predictability Class	**SVM Prediction Accuracy**	**Energy consumption Class**	**SVM Prediction Accuracy**
High Predictability	90.02%	High Energy Consumption	84.23%
Medium Predictability	83.02%	Medium Energy Consumption	84.41%
Low Predictability	79.05%	Low Energy Consumption	83.41%

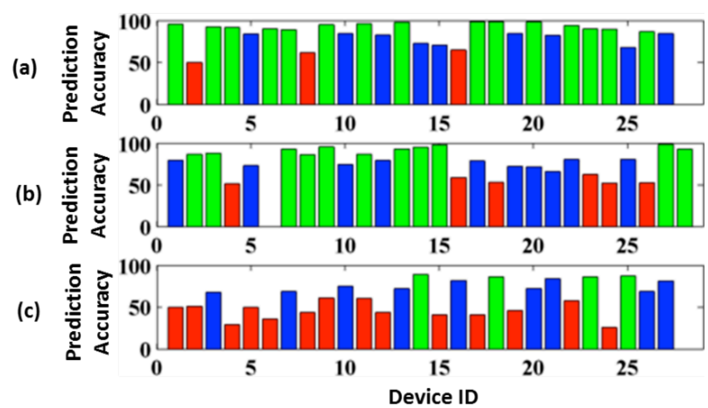


Fig 14. Comparison between: (a) high predictable, (b) medium predictable, and (c) low predictable occupants' SVM prediction accuracy

Occupants' energy-use behavior predictability is a critical factor in capturing value from an automated EE program. However, it is important to predict inefficient occupants' energy-use behavior as they have a relatively higher potential for energy savings. The best target for such systems are low efficient occupants whose behavior are highly predictable. Fig. 14 maps the occupants' distribution in a 3×3 matrix based on the predictability and efficiency measures. Nearly 50% of low efficient occupants are highly predictable and 36.6% are medially predictable (i.e. occupants fallen into second predictability quantile); the rest fall into the low predictable category. In other words, there is potential to target over 85% of inefficient occupants through targeted EE programs such as tailored energy efficiency notification systems. Furthermore, over 50% of medially efficient occupants fall into the high and medium predictability classes which adds further potential conservation targets to the targeted population. Based on our estimate, up to 45% of the occupants could be targeted effectively with automated EE programs and the rest are either already highly efficient or are not using energy predictably. Therefore, based on the energy efficiency and predictability analysis conducted with respect to occupants' energy-use pattern prediction accuracy, the proposed method has the potential to contribute to the advancement of EE programs by merging an occupant behavior learning algorithm with an individual-level energy consumption feedback system. Moreover, building on such energy-use behavior learning algorithms, a robust occupancy detection system [50] could be developed which significantly improves commercial building energy efficiency through optimization of the building management system operation.

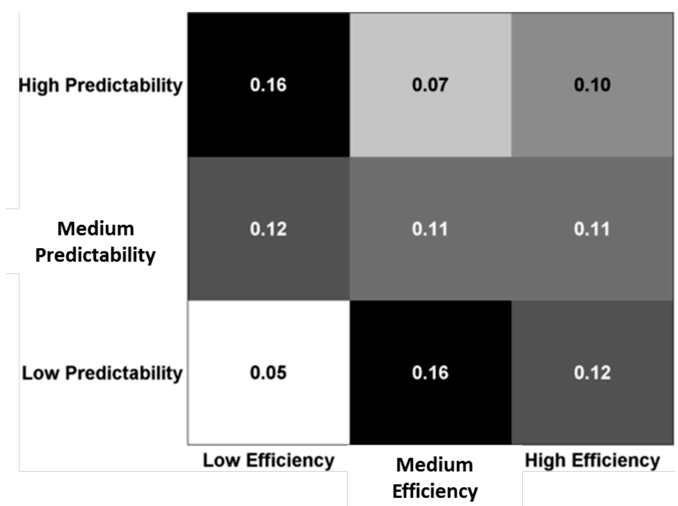


Fig 15. Occupant distribution map based on the energy-use behavior factors

6. LIMITATIONS & FUTURE RESEARCH

The research conducted in this paper is The data collection was conducted limited to assess occupants' workstation energy efficiency potential. However, in commercial office buildings with decentralized lighting and HVAC systems controlled by occupants, the impact of such EE programs can be extended beyond workstations. There are a few limitations which need to be addressed in order to improve the underlying algorithms in our method. It is not our intent to outperform state-of-the-art prediction algorithms. Improving upon prediction accuracy is, however, a planned area of future research. The SVM model may be improved by adding extra information, such as, demographic information of the occupants, occupancy sensor data, weather conditions, mobility patterns, and appliance energy-use disaggregation. Furthermore, there are instances where the system predicts false positives and false negatives. At this stage, we are only predicting atomic energy-use behaviors; however, in the future we could improve our model through implementing a Markov model and enable the prediction of long sequences of energy-use patterns and occupant behavior. This could potentially increase the accuracy of the prediction by creating conditional models based on a wide range of behavioral event probabilities. The focus of this work was not outperforming other energy prediction algorithms. However, to compare the accuracy of our method in bottom up energy prediction, we would like to compare the CV values obtained from our prediction to other data mining and regression models in future research, including: support vector regression, random forest, multivariate adaptive regression lines, etc. trained based on the current dataset. Future research should seek to improve the current energy-use pattern prediction accuracy to a level where it can be used to implement this automated tailored notification system in experimental case studies to evaluate the result of targeted interventions on near term and sustained energy savings. Potential benefits of a predictive energy feedback system are in providing timely and tailored feedbacks to individuals based on the predicted behaviors to prevent inefficient energy consumption habits such as leaving on the lights, printers, and personal computers while not in the office. Moreover, if such predictive feedback program is combined with an online control system, it can facilitate remote energy savings through web, computer, and cellphone platforms. Another advantage of such EE programs can be found in more comprehensive predictive systems where machine learning algorithms are trained based on individuals' classes and characteristics. This enables a targeted and tailored EE program based on psychological and demographic differences. To illustrate, one might be assigned to a normative comparison treatment, while other may achieve more energy-use reductions if targeted with monetary incentives. Unfortunately, our Institutional Review Board human subject research approval did not allow for collecting information regarding characteristics and demographics of the participants in our study. This may be an interesting avenue for future research.

7. CONCLUSION

Recent advancements in building technology and monitoring systems have definitely benefited building energy efficiency programs. However, considering that people spend more than 90% of their time indoors [51] coupled with the significant correlation between behavior and energy consumption [43], occupants remain a major factor that impacts building energy consumption and associated CO_2 emissions. Occupant classification and behavioral analysis are new approaches that can better address the occupant behavioral inefficiency challenge and potentially empower prediction models to better learn and infer occupants' energy-use behavior. Energy efficiency programs are evolving toward more personalized data collection and analysis using higher resolution data. There is a need for increasingly automated energy efficiency programs through the integration of high technology hardware, robust software, and the fundamentals of behavioral science to handle the massive data streams extracted from buildings and occupants.

In this paper, we were inspired by previous studies in customer classification and load profiling [2, 52-54] and developed a method that integrates energy-use classification and prediction algorithms to predict individual energy-use behaviors in a commercial building. We found that nearly 50% of low efficient occupants are highly predictable, and another 36.6% are medially predictable. This high level of individual energy use predictability can result in a new approach to energy efficiency programs by predicting occupants' behaviors and enabling predictive and relevant energy saving notifications. Sustainable behavioral change is a challenge that has not yet been thoroughly addressed, thus continuing to limit the effectiveness of behavior-oriented energy feedback systems [8, 37, 39-41, 55, 56]. The results presented in this paper hold definite promise for providing an automated and sustainable solution to occupant-level energy efficiency programs (e.g. automated tailored energy efficiency notification systems) and opening a new venue to enable targeted interventions by categorizing occupants based on their consumption behaviors. Moreover, merging these predictive models with already state-of-the-art occupant energy feedback methods, such as an online appliance control system [57], energy-use disaggregation [41, 57-59], and cellphone-based feedback [60] can potentially induce higher levels of energy efficiency.

Future research should incorporate a more comprehensive version of the behavior prediction algorithm that is trained on additional occupant data including mobility patterns, comfort preferences, work schedules, demographics, and workstation energy-use to examine whether more substantial and sustainable reductions in energy consumption can be realized through automated and targeted feedback. Occupant behavior learning algorithms not only will enable a cost-effective occupant-based energy savings in commercial buildings, but it also will empower the next generation of occupant-centered building management systems to operate more efficient and more intelligent as well as more comfortable buildings in the future.

8. ACKNOWLEDGMENTS

This material is based upon work supported by the Department of Energy Building Technologies Program and the National Science Foundation under Grant No. 1142379. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Department of Energy or the National Science Foundation. The authors would like to thank the Alliance for Sustainable Colorado for hosting the study that provided the building occupant data used in the experimental data analysis in this paper.

REFERENCES

1. U.S.EIA, *Annual Energy Outlook 2014 Early Release Overview*. 2014.

2. Gulbinas, R., A. Khosrowpour, and J.E. Taylor, *Segmentation and Classification of Commercial Building Occupants by Energy-Use Efficiency and Predictability.* IEEE Transaction on Smart Grids, 2014.
3. Kwac, J., J. Flora, and R. Rajagopal, *Household energy consumption segmentation using hourly data.* Smart Grid, IEEE Transactions on, 2014. **5**(1): p. 420-430.
4. Chen, J. and C. Ahn, *Assessing Occupants' Energy Load Variation through Existing Wireless Network Infrastructure in Commercial and Educational Buildings.* Energy and Buildings, 2014.
5. Milenkovic, M. and O. Amft, *Recognizing energy-related activities using sensors commonly installed in office buildings.* Procedia Computer Science, 2013. **19**: p. 669-677.
6. Hong, T. *Occupant behavior: impact on energy use of private offices*. in *ASim 2012-1st Asia conference of International Building Performance Simulation Association., Shanghai, China, 11/25/12-11/27/12*. 2014.
7. Vassileva, I., et al., *The impact of consumers' feedback preferences on domestic electricity consumption.* Applied Energy, 2012. **93**: p. 575-582.
8. Hargreaves, T., M. Nye, and J. Burgess, *Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term.* Energy Policy, 2013. **52**(0): p. 126-134.
9. Quintal, F., et al., WATTSBurning: design and evaluation of an innovative eco-feedback system, in Human-Computer Interaction–INTERACT 2013. 2013, Springer. p. 453-470.
10. He, H.A., S. Greenberg, and E.M. Huang. One size does not fit all: applying the transtheoretical model to energy feedback technology design. in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2010. ACM.
11. van Dam, S.S., C.A. Bakker, and J.D.M. van Hal, Home energy monitors: impact over the medium-term. Building Research & Information, 2010. 38(5): p. 458-469.
12. Allcott, H. and S. Mullainathan, Behavioral science and energy policy. Science, 2010. 327(5970): p. 1204-1205.
13. Allcott, H., Social norms and energy conservation. Journal of Public Economics, 2011. 95(9-10): p. 1082-1095.
14. Swan, L.G. and V.I. Ugursal, Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and Sustainable Energy Reviews, 2009. 13(8): p. 1819-1835.
15. Hoes, P., et al., User behavior in whole building simulation. Energy and Buildings, 2009. 41(3): p. 295-302.
16. Jain, R.K., et al., Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. Applied Energy, 2014. 123(0): p. 168-178.
17. Sevlian, R. and R. Rajagopal, Short Term Electricity Load Forecasting on Varying Levels of Aggregation. arXiv preprint arXiv:1404.0058, 2014.
18. Zhao, H.-x. and F. Magoules. New parallel support vector regression for predicting building energy consumption. in Computational Intelligence in Multicriteria Decision-Making (MDCM), 2011 IEEE Symposium on. 2011. IEEE.

19. Fan, C., F. Xiao, and S. Wang, Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. Applied Energy, 2014. 127: p. 1-10.
20. Zhao, H.-x. and F. Magoulès, A review on the prediction of building energy consumption. Renewable and Sustainable Energy Reviews, 2012. 16(6): p. 3586-3592.
21. Kavaklioglu, K., Modeling and prediction of Turkey's electricity consumption using Support Vector Regression. Applied Energy, 2011. 88(1): p. 368-375.
22. Lee, W.-Y., J.M. House, and N.-H. Kyong, Subsystem level fault diagnosis of a building's air-handling unit using general regression neural networks. Applied Energy, 2004. 77(2): p. 153-170.
23. Wong, S., K.K. Wan, and T.N. Lam, Artificial neural networks for energy analysis of office buildings with daylighting. Applied Energy, 2010. 87(2): p. 551-557.
24. Li, Q., et al., Applying support vector machine to predict hourly cooling load in the building. Applied Energy, 2009. 86(10): p. 2249-2256.
25. Ben-Nakhi, A.E. and M.A. Mahmoud, Cooling load prediction for buildings using general regression neural networks. Energy Conversion and Management, 2004. 45(13): p. 2127-2141.
26. Aydinalp, M., V. Ismet Ugursal, and A.S. Fung, Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks. Applied Energy, 2002. 71(2): p. 87-110.
27. Xuemei, L., et al. Building cooling load forecasting using fuzzy support vector machine and fuzzy c-mean clustering. in Computer and Communication Technologies in Agriculture Engineering (CCTAE), 2010 International Conference On. 2010. IEEE.
28. MacKay, D.J., Bayesian nonlinear modeling for the prediction competition. ASHRAE transactions, 1994. 100(2): p. 1053-1062.
29. Yang, J., H. Rivard, and R. Zmeureanu, On-line building energy prediction using adaptive artificial neural networks. Energy and buildings, 2005. 37(12): p. 1250-1259.
30. Karatasou, S., M. Santamouris, and V. Geros, Modeling and predicting building's energy use with artificial neural networks: methods and results. Energy and Buildings, 2006. 38(8): p. 949-958.
31. Edwards, R.E., J. New, and L.E. Parker, Predicting future hourly residential electrical consumption: A machine learning case study. Energy and Buildings, 2012. 49: p. 591-603.
32. Li, Q., et al., Predicting hourly cooling load in the building: a comparison of support vector machine and different artificial neural networks. Energy Conversion and Management, 2009. 50(1): p. 90-96.
33. Dong, B., C. Cao, and S.E. Lee, Applying support vector machines to predict building energy consumption in tropical region. Energy and Buildings, 2005. 37(5): p. 545-553.
34. Albert, A. and R. Rajagopal, Smart meter driven segmentation: What your consumption says about you. Power Systems, IEEE Transactions on, 2013. 28(4): p. 4019-4030.

35. Tanimoto, J., A. Hagishima, and H. Sagara, A methodology for peak energy requirement considering actual variation of occupants' behavior schedules. Building and Environment, 2008. 43(4): p. 610-619.
36. Chen, V.L., M.A. Delmas, and W.J. Kaiser, Real-time, appliance-level electricity use feedback system: How to engage users? Energy and Buildings, 2014. 70: p. 455-462.
37. Murtagh, N., et al., Individual energy use and feedback in an office setting: A field trial. Energy Policy, 2013. 62: p. 717-728.
38. Gulbinas, R., R.K. Jain, and J.E. Taylor, "BizWatts": A modular socio-technical energy management system for empowering commercial building occupants to conserve energy. Applied Energy, 2014.
39. Bradley, P., M. Leach, and S. Fudge, The Role of Social Norms in Incentivising Energy Reduction in Organizations. 2014.
40. Yun, R., et al., Toward the design of a dashboard to promote environmentally sustainable behavior among office workers, in Persuasive Technology. 2013, Springer. p. 246-252.
41. Coleman, M.J., et al., Promoting behaviour change through personalized energy feedback in offices. Building Research & Information, 2013. 41(6): p. 637-651.
42. Gulbinas, R., R. Jain, and J. Taylor, BizWatts: A modular socio-technical energy management system for empowering commercial building occupants to conserve energy. Applied Energy, 2014. 136: p. 1076-1084.
43. Virote, J. and R. Neves-Silva, Stochastic models for building energy prediction based on occupant behavior assessment. Energy and Buildings, 2012. 53: p. 183-193.
44. Mahdavi, A. and C. Pröglhöf, User behaviour and energy performance in buildings. Wien, Austria: Internationalen Energiewirtschaftstagung an der TU Wien (IEWT), 2009.
45. Hartigan, J.A. and M.A. Wong, Algorithm AS 136: A k-means clustering algorithm. Applied statistics, 1979: p. 100-108.
46. Chang, C.-C. and C.-J. Lin, LIBSVM: a library for support vector machines. ACM Transactions on Intelligent Systems and Technology (TIST), 2011. 2(3): p. 27.
47. Murphy, K.P., Machine learning: a probabilistic perspective. 2012: MIT press.
48. Manning, C.D., P. Raghavan, and H. Schütze, Introduction to information retrieval. Vol. 1. 2008: Cambridge university press Cambridge.
49. Khosrowpour, A., R. Gulbinas, and J.E. Taylor. An Empirical Comparison of Internal and External Load Profile Codebook Coverage of Building Occupant Energy-Use Behavior. in Computing in Civil Engineering 2015. 2015. ASCE.
50. Agarwal, Y., et al. Occupancy-driven energy management for smart building automation. in Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building. 2010. ACM.
51. U.S.EPA The Inside Story: A Guide to Indoor Air Quality. 2012.
52. Albert, A., R. Rajagopal, and R. Sevlian. Segmenting consumers using smart meter data. in Proceedings of the Third ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings. 2011. ACM.
53. Mutanen, A., et al., Customer classification and load profiling method for distribution systems. Power Delivery, IEEE Transactions on, 2011. 26(3): p. 1755-1763.

54. Quilumba, F.L., et al., Using Smart Meter Data to Improve the Accuracy of Intraday Load Forecasting Considering Customer Behavior Similarities. Smart Grid, IEEE Transactions on, 2015. 6(2): p. 911-918.
55. Gulbinas, R. and J.E. Taylor, Effects of real-time eco-feedback and organizational network dynamics on energy efficient behavior in commercial buildings. Energy and Buildings, 2014. 84(0): p. 493-500.
56. Allcott, H. and T.T. Rogers, How Long Do Treatment Effects Last? Persistence and Durability of a Descriptive Norms Intervention's Effect on Energy Conservation. 2012.
57. Yun, R., et al. Beyond eco-feedback: adding online manual and automated controls to promote workplace sustainability. in Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. 2015. ACM.
58. Giri, S. and M. Bergés, An energy estimation framework for event-based methods in Non-Intrusive Load Monitoring. Energy Conversion and Management, 2015. 90: p. 488-498.
59. Berges Gonzalez, M.E., A framework for enabling energy-aware facilities through minimally-intrusive approaches. 2010.
60. Petkov, P., et al. Motivating domestic energy conservation through comparative, community-based feedback in mobile and social media. in Proceedings of the 5th International Conference on Communities and Technologies. 2011. ACM.

5. CONCLUSION

This dissertation provides a comprehensive review and analysis of energy feedback literature, challenges, gaps in knowledge, and opportunities in research methods. The analysis conducted on methods used in the energy feedback studies in Chapter 1 (i.e., a literature review), sheds light on the shortcomings of the current art of energy feedback studies. Despite a long history of energy feedback research, studies still exist that do not take the necessary steps to fulfill the minimum requirements of a reliable energy feedback study needed to provide a comprehensive and robust result. Therefore, as one of the most important takeaways of this research, I provide a list of major and necessary considerations for conducting energy feedback studies in Chapter 1. These considerations are vital to provide reliable analysis and results.

I conducted a detailed investigation in the literature to identify the gaps of knowledge. One the most important identified gaps was a significant inconsistency in the research methods used in these studies and a lack of a systematic pipeline for researchers to use to conduct energy feedback research. The analysis indicated a lack of multi-disciplinary collaboration and coordinated effort between researchers. In order to fill this important gap in knowledge, I propose a systematic, adaptive, and targeted energy feedback design and maintenance research vision that leverages all research methods (i.e. experiments, surveys, analytics, and simulations) and an open data sharing platform to enhance the efficacy of a targeted energy feedback program.

Numerous researchers have recommended the importance of following a targeted and tailored feedback approach to enhance the effectiveness of energy feedback programs. In other words, there is an accepted notion that one size does not fit all. However, there is no quantitative analysis of dissimilarity of occupant responses to uniform feedback programs in the literature that has established the need for such targeted feedback. I conducted an analysis discussed in Chapter 2 on an energy feedback study conducted in a 6- story commercial building with more than 100 employees to address this gap in knowledge. The results suggest that providing a similar normative comparison feedback to occupants with different levels of energy consumption does not result in a similar level of energy savings and in some cases actually increases energy consumption. Therefore, I established a need for a targeted energy feedback program that treats each occupant differently based on their own energy consumption patterns, demographics, constraints, and characteristics. Also, I conducted a thorough analysis of the effectiveness of the notifications sent throughout the study to increase the level of occupant engagement in a feedback program. That analysis revealed a significant dependency of engagement level for the type of feedback that occupants were receiving (e.g., a normative comparison vs. historical comparison) rather than other components, such as content and timing of these notifications.

Chapter 3 aimed to evaluate the effectiveness and potential of targeted feedback programs. I implemented two metrics to categorize the occupants based on their predictability and energy consumption level. Predictability was used since a targeted energy feedback program requires sufficient learning and understanding of users' energy consumption behavior. If a user does not have a predictable behavior, then the task of targeting and tailoring feedback will become extremely difficult and ineffective. Energy efficiency level was used as a second metric due to the importance of efficiency in any cost-effectiveness of feedback programs. For example, if a user is already categorized as highly efficient, it might not be cost-effective to send his/her feedback due to a relatively lower energy saving potential. Based on the aforementioned metrics, it can be reported that almost 46% of users in a building can become qualified to enroll in a targeted energy feedback study based on their predictability and energy efficiency. These results help researchers better understand the potential of such feedback programs and take a more cost-effective approach toward designing, executing, and maintaining their feedback programs in the future.

6. CONTRIBUTION

The main contribution of this dissertation to the body of knowledge is found in three sections. In the first chapter, I contributed to the body of knowledge by conducting a comprehensive literature review on the known research methods used to carry out energy feedback studies and identifying the challenges, gaps in knowledge, and opportunities. I provided a thorough list of necessary considerations that researchers should take into account when conducting energy feedback studies. This contribution enables researchers to conduct multi-disciplinary energy feedback research and build off of each other's studies via a systematic data sharing approach. Furthermore, I identified the methodological gaps of knowledge in the literature that can help researchers to better focus on filling those gaps instead of simply discovering them. Finally, I proposed a 9-step research framework vision, designed using the aforementioned gaps of knowledge, together with a step- by- step guideline, to help researchers follow a systematic and reliable pipeline when conducting comprehensive energy feedback studies.

One of the most important identified gaps of knowledge in Chapter 1 is the validation of the need for a targeted energy feedback program as recommended by numerous researchers. The second chapter of the dissertation then analyzed the energy use responses of occupants to a uniform energy feedback program and provided a two-fold contribution: (1) establishing the need for a targeted energy feedback program due to a high level of variation in occupants' responses to a uniform feedback program and (2) demonstrating that the effectiveness of the notifications sent throughout the study (in order to further engage occupants in these programs) is highly dependent on the nature of the programs rather than the duration and content of the notifications. In other words, if an energy feedback program is not engaging enough in the first place, regardless of the number, duration, and content of notifications, the level of user engagement will not increase simply by sending notifications.

The third contribution of this dissertation relates to estimating the potential of targeted energy feedback programs in actual experiments. As established in Chapter 2 and supported by a large body of research, there is a need for a targeted energy feedback program to enhance the efficacy of energy feedback programs. Nevertheless, there is a gap of knowledge in identifying the actual potential of targeted energy feedback programs compared the use of non-tailored conventional programs. Chapter 3 of this dissertation contributes to the literature by estimating the potential of targeted energy feedback programs at the intersection of energy use behavior predictability and energy efficiency. As suggested by the literature studied, predictability and energy efficiency are the two major determinants of occupant behavior in targeted energy feedback programs. Chapter 3 reports that in a real world scenario, only 46% of occupants in a building can be targeted based on a low and medial level of energy efficiency and high and medial level of predictability. In other words, only 46% of occupants have a predictable behavior while still not being highly energy efficient. Therefore, the dissertation provides significant insight into cost benefit analyses of targeted energy feedback programs for future research.

7. BROADER IMPACT

Advancement in technology has provided great opportunities to better understand occupant behavior and induce energy savings in buildings. High resolution smart meters, real-time feedback solutions, occupancy sensors, and many other new technologies have facilitated the labor intensive process of data mining and analysis to create a better future. The pinnacle of occupant energy efficiency, which is starting to gain traction even in industry, does not directly target energy production and consumption issues. Rather, investments from the government and the private sector are aiming at a reduction of the associated CO_2 emissions of building energy consumption to leave a cleaner planet for generations to come.

Based on a report published by the Environmental Protection Agency in 2014, CO_2 accounts for more than 80% of all the U.S greenhouse gas emissions from human activity. To further clarify, the human energy consumption footprint is not merely limited to buildings. Transportation, industry, agriculture, and other sectors are also highly affected by human behavior. At a broader level, people are inseparable elements of their society and their behavior has a significant impact on the design, operation, and maintenance of its infrastructure systems. Therefore, it is impossible to reduce the environmental impact of our infrastructure system design and operation (e.g. energy costs) without educating people further and improving their behavior.

The findings of this dissertation may be a good example for other sectors to use to approach the design, execution, and maintenance of their feedback systems for reducing the carbon footprint of human activity through education and behavior improvement. The broader impacts of this dissertation can be found in the overall contribution of targeted feedback systems for defining human-infrastructure interactions in the society. We can educate, change, and learn human behavior through using similar systematic approaches as the one provided in this dissertation. Designing targeted and tailored feedback systems at the intersection of environmental psychology, data science, and infrastructure systems not only will have a substantial impact on the future of our planet and what we leave behind, but also have an impact on how we pass along our learnt lessons to the next generation and prevent man-made catastrophes, such as global warming.

REFERENCES

1. U.S.EIA, *Annual Energy Outlook 2014 Early Release Overview*. 2014.
2. Stern, P., *Toward a coherent theory of environmentally significant behavior.* Journal of social issues, 2000. **56**(3): p. 407-424.
3. Torcellini, P.A., et al. *Lessons learned from field evaluation of six high-performance buildings*. in *Proceedings*. 2004.