Title
Residential Energy Feedback: Research, Technology, and Potential for the Informed Home

Author
Karlin, Beth Mishon

Publication Date
2014

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Residential Energy Feedback: Research, Technology, and Potential for the Informed Home

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Social Ecology

by

Beth Karlin

Dissertation Committee:
Professor Daniel Stokols, Chair
Professor Richard Matthew
Associate Professor Joanne Zinger

2014

DEDICATION

To

Sadath Omar Garcia

Because I knew you, I have been changed for good

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I write this section feeling ever so grateful for the community of people that have assisted, advised, encouraged, and otherwise supported me through this journey over the past six years.

I would like to express the deepest appreciation to my committee chair, Professor Dan Stokols, who has served as an excellent advisor, co-author, teacher, and mentor since that I came to UCI in 2008. Even before formally matriculated, Dan welcomed me into the university community and allowed me to forge my own path as a student. He has provided guidance and support throughout my PhD and serves as a model for the type of scholar I hope to become —a person of high integrity who is highly supportive of and respectful toward everyone meets and continues to bring distinction to his field each year through scholarship, teaching, and service.

I would also like to thank Professor Richard Matthew for taking a chance on me early in my academic career and allowing me to incubate my research in the Transformational Media Lab. From our first real conversation late one night after a 3-hour lecture, he has continued to inspire me to think about my work and myself in ways that make me better after every interaction. He pushes me to go both deeper and broader with my research and teaches me how to be relevant in a world that I truly hope to impact. The doors he has opened, both with colleagues and within my own mind, are gifts I can never repay and I hope only to utilize them to the best of my ability.

Thank you to Professor Joanne Zinger (formerly Frattaroli), my final committee member, for working with me on Chapter 3 of this manuscript for nearly six years (the first paper I ever started in graduate school) and for patiently answering question after question and not laughing in my face when I kept thinking I would finish the study in “a year or so”. Her organization and attention to detail in both teaching and research are beyond compare and I hope that at least a little of them have rubbed off on me in my own career as well.

And to the other faculty at UCI and beyond who have served as mentors and models during my studies – David Kirkby, John Whiteley, Victoria Basolo, David Feldman, John Hipp, Janet Swim, Wesley Schultz, Cindy Frantz, John Petersen, Christie Manning, and Janet Stephenson.

Thanks to my amazing co-authors – Nora Davis, Angela Sanguinetti, Kristen Gamble, Dan Stokols, David Kirkby, Joanne Zinger, Richard Matthew, John S. Johnson, Birgit Penzenstadler, Allison Cook, Rebecca Ford, and Cassandra Squiers – and to all of the undergraduate students who have worked in the Transformational Media Lab over the years. Special thanks to the students who stuck with me for multiple seasons – Jamie Agius, Kehau Ahu, Amanda Iaali, Lee Yates, Katy Escobar, Aiesha Al-Inizi, Mariam Gheissari, Mariam Iskajyan, Jonathon Carrasco, Haley Hererra, Mikhael Kazzi, Jessie Baker, Kristen Figueira, Alyssa Wu, and Veronica Nasser.

Thanks to the Calit2 California Plug Load Research Center (CalPlug) at the University of California, Irvine for funding the data collection of Chapter Five as well as supporting conference travel to present this work and to the Center for Sustainability at the University of Otago for graciously hosting me for two months, where much of this manuscript was written.

Cue the waterworks.

To David Guerrieri - who inspired, encouraged, and enabled my love for and connection to the natural environment. I can't remember life before your name.

To Kathleen "Charli" Hibbert, Angela Sanguinetti, and Crystal Murphy - my epic study buddies who I've spent countless hours at cafes up and down the coast working (and chatting) with. Working hard is never as much fun as when it's with you.

To Nora Davis – my constant companion on the road and in the office. I am so grateful that you found Dan, UCI, and me. And thanks to Patrick for falling in love and getting her to move across the country… as well as for many great conversations, movies, meals, and laughs over the years.

To Becky Ford - the best collaborator, co-author, and friend with whom I have shared just about every thought about energy feedback I've ever had. I am a better scholar, teacher, mentor, and person because of you. I look forward to so many more years learning and growing together.

To the incredible cast of colleagues who have become friends over the years - Ezra Markowitz, Dina Biscotti, Dave Miller, Mary Beth Deline, Katie Pine, Victoria Lowerson, Marilyn Cornelius, Skip Laitner, Linda Schuck, Josh Brock, Kat Donnelly, Brittany Bloodhardt, Irina Feygina, Emily Wilkinson, Jill Smayo, Talitha Baker, and Johanna Blakeley. L.P. Jacks said that, "a master in the art of living draws no sharp distinction between his work and his play". You all make living just a little bit easier to master.

To my family (and friends like family) who have cheered and supported me well before I began this journey and on through the finish line – including, but not limited to the Toledos, Kelleys, Ugales, DeWitts, Kordyaks, Sloans, Leavens', Marchesinis, and Botticellis, as well as Vandra and RJ Lochridge, Ryan Connell, Emily Moore, Brian Silva, Maria Thomas, Arlene Santos, Jim Mead and, of course, Sadath Garcia.

To my parents – who raised me to belive that "I'm good enough, I'm smart enough, and dog gonnit people like me". Thanks Mom for teaching me to read, write, count, and correct other people's grammar before most children had learned their ABCs, Dad for keeping every dinner conversation filled with learning and laughter, and both of you for always encouraging my every crazy endeavor and taking me in when I came home from them.

To Eleazar Eskin - my partner, mentor, guiding star, and very best friend. You are 100% of the reason I took the plunge and embarked on this journey that I had been dreaming and talking about for a decade and 200% of the reason that I made it through (insert statistics joke here). There are no words.

CURRICULUM VITAE

Beth Karlin

EDUCATION

2014	Ph.D. in Social Ecology University of California, Irvine (UCI)
2007	Masters of Public Administration (MPA) California State University, Long Beach
1999	Bachelor of Arts (B.A.) in Psychology University of Redlands

AWARDS AND HONORS

2013	UC Irvine, UCI/Stanley Behrens Public Impact Fellowship Dean's Award for Community Engagement UC Irvine Social Ecology Alumni Fellowship
2012	American Psychological Association Division 34, Graduate Student Paper Award American Psychological Association Division 34, Citation for Outstanding Service UC Irvine, Martha Newkirk Award for Excellence in Graduate Student Research UC Irvine Outstanding Mentor Award Linda Latham Scholarship, American Council for an Energy-Efficient Economy American Psychological Association (APA) Student Travel Award
2011	Precourt Energy Efficiency Center Student Fellow UC Irvine Outstanding Mentor Award UC Irvine Newkirk Center for Science and Society Fellowship
2010	Don Owens Fellowship – Urban Water Research Center Environment Institute Interdisciplinary Research Grant Precourt Energy Efficiency Center Student Fellow
2009	UC Irvine Outstanding Mentor Award
2001	UC Irvine Outstanding Educator Commendation
1999	University of Redlands Global Impact Award University of Redlands Lifetime Achievement Award
1995 -1999	Dean's Honors (cumulative GPA – 3.89) Achievement Award Scholarship
1994	Presidential Achievement Award

PUBLICATIONS

Karlin, B., Penzenstadler, B., & Cook, A. (2014). Pumping up the Citizen Muscle Bootcamp. *Proceedings of the Human Computer Interaction Conference*. Crete, Greece: ACM.

Karlin, B., Davis, N., Sanguinetti, A., Gamble, K., Kirkby, D., & Stokols, D. (2012). Dimensions of conservation: Exploring differences among energy behaviors. *Environment and Behavior*, *46*(4): 420-449.

Karlin. B. (2014). Attitudes and behaviors. in Debra Rowe, ed. *Achieving Sustainability: Visions, Principles, and Practices*. Detroit: Macmillan.

Karlin, B. (2013). Technology and psychology—Natural enemies or just plain natural? *Ecopsychology*. *5*(4): 217-218.

Karlin, B., Ford, R. & Squiers, C. (2013). Energy feedback technology: A review and taxonomy of products and platforms. *Energy Efficiency*.

Ford, R. & Karlin, B. (2013). Graphical displays in energy feedback technology: A cognitive approach. *Proceedings of the Human Computer Interaction Conference*. Las Vegas, NV.

Karlin, B. & Ford, R. (2013). The usability perception scale (UPscale): A measure for evaluating feedback displays. *Proceedings of the Human Computer Interaction Conference*. Las Vegas, NV: ACM.

Karlin, B., Davis, N., & Matthew, R. (2013). GRASP: Testing an integrated approach to sustainability education. *Journal of Sustainability Education*. Spring 2013.

Karlin, B. (2013). Film to School (FtS) programs: Active engagement for filmmakers in education. *International Studies Association Conference Archive*. San Francisco, CA.

Karlin, B. & Matthew, R. (2012). Kony 2012 and the mediatization of child soldiers. *Peace Review, 24*(3), 255-261.

Karlin, B. (2012). Public acceptance of smart meters: Integrating psychology and practice. *Proceedings of the Summer Study on Energy Efficiency in Buildings.* Pacific Grove, CA.

Karlin, B. (2012). The social, the media, and the activism: Kony meets world. Opinio Juris.

Karlin, B. (2012). Power through participation: Impacts of youth involvement in Invisible Children. *International Studies Association Conference Archive*. San Diego, CA.

Karlin, B. & Johnson, J.S. (2011). Measuring impact: The importance of evaluation for documentary film campaigns. *M/C Journal 14(6).*

Karlin, B. (2011). Tracking and learning: Exploring dual functions of residential energy feedback. In *Proceedings of the International Conference on Persuasive Technology*. Columbus, OH: ACM.

INVITED PRESENTATIONS

The Art and Science of Film and Behavior Change
Environmental Activism in the Digital Age, NYU Polytechnic. April 2014
Garrison Institute Climate, Mind, and Behavior Symposium, June 2013

The Psychology of Sustainability.
California State University Fullerton Sustainability Symposium, April 2014
Center for Unconventional Security Affairs Sustainable Seminar Series. February 2010, 2012
The Newkirk Center Summer Seminar Series: Empowering Sustainability on Earth. July 2011

Residential Energy Feedback: Research, Technology and Potential for the Smart Home
U.S. Department of Energy Solar Decathlon XPO: October 2013

Storytelling, Engagement & Activism for Change (SEA Change) Panel
Hollywood Film Festival. October 2013
Topanga Film Festival. July 2013

Transformational Media: A New Approach to Sustainability
The Newkirk Center Summer Seminar Series: Empowering Sustainability on Earth. July 2013
Victoria University of Wellington Psychology Department, April 2013
Universtiy of Otago Center for Science Communication, March 2013

What's Behavior Got to Do with IT? Four Ways Understanding People Can Improve Technology
Emerging Technology Summit, Behavioral Session, October 2012

Public Acceptance of Smart Meters: Integrating Psychology and Practice
Chartwell Webinar: Don't Call it a Smart Meter, October 2012

Technology to the rescue? The potential and pitfalls of feedback in energy conservation.
Energy, Security and Stability: A Conference at Pennsylvania State University. October, 2012
University of California Irvine Social Ecology Colloquium. May 2012
Pennsylvania State University Social Psychology Proseminear. September 2011

Designing "Meaningful" Information and Devices for Customers
Electric Power Research Institute Workshop: Consumer Behavior in Three Acts. Sept. 2012

Better Living Through Mediatization
Center for Unconventional Security Affairs Sustainable Seminar Series. April 2012

CONFERENCE PRESENTATIONS

Graphical Displays in Energy Feedback Technology: A Cognitive Approach.
2013 Behavior Energy Climate Change Conference. Talk, Sacramento, CA: Nov. 2013.

Can data save the planet? Using technology enabled-feedback to promote energy conservation.
Society for Social Studies of Science (4S) Conference, San Diego, CA, Talk, Oct. 2013.

From Climate Science to Climate Impacts: Exploring the Role of Film As Boundary Object.
121st Convention of the American Psychological Association, Talk, Honolulu, HI, Aug. 2013.

Technology to the Rescue? The Potential and Pitfalls of Feedback in Energy Conservation.
121st Convention of the American Psychological Association, Chair, Honolulu, HI, Aug. 2013.

The Usability Perception Scale (UPscale): A measure for evaluating feedback displays.
2013 Human Computer Interaction Conference. Talk, Las Vegas, NV, July 2013.

The Art and Science of Film and Behavior Change: An Emerging Agenda.
Third World Congress on Positive Psychology, Poster, Los Angeles, CA, June 2013.

Affect to Action: The Use of Framing in Documentary Films
Behavior Energy and Climate Change Conference, Talk, Sacramento, CA, Nov. 2012.

Public Acceptance of Smart Meters: Integrating Psychology and Practice.
ACEEE Summer Study on Energy Efficiency in Buildings, Talk, Monterey, CA, Aug. 2012.

Diffusion of Feedback: Perceptions and Adoption of Devices in the Residential Market.
120th Convention of the American Psychological Association, Talk, Orlando, FL, Aug. 2012.

The Social, the Media, and the Psychology: Kony Meets World.
120th Convention of the American Psychological Association, Poster, Orlando, FL, Aug. 2012.

Residential Energy Feedback: Naturalistic Users and Their Experiences.
Association for Environmental Studies and Sciences Meeting, Talk, Santa Clara, CA, June 2012.

Power through Participation: Impacts of Youth Involvement in Invisible Children.
International Studies Association Annual Meeting, Talk, San Diego, CA, April, 2012.

Communicating Climate Behaviors – Framing and False Dichotomies.
Garrison Institute Climate, Mind, and Behavior Symposium, Talk, Feb. 2012.

Are we barking up the wrong tree? Exploring difference among energy behaviors.
Behavior Energy and Climate Change Conference, Talk, Washington, D.C., CA, Dec. 2011.

Technology to the rescue? Potential and pitfalls of feedback in residential energy conservation.
9th Biennial Conference on Environmental Psychology, Talk, Eindhoven, NL, Sept. 2011.

Energy research for the smart home: The uci@home project.
119th Convention of the American Psychological Association, Talk, Washington DC, Aug. 2011.

Film and social change – Psychological insights for leveraging impact.
119th Convention of the American Psychological Association, Talk, Washington DC, Aug. 2011.

Confronting complexity in energy conservation: Exposure, actions, and impacts.
Association for Environmental Studies and Sciences, Talk, Burlington, VT, June 2011.

Tracking and learning: Exploring dual functions of residential energy feedback.
Sixth International Conference on Persuasive Technology, Talk, Columbus, OH, June 2011.

Dimensions of conservation. Exploring differences in energy behaviors and their implications.
XVIIIth Conference of the Society of Human Ecology, Talk, Las Vegas, NV, April 2011.

Energy Feedback Devices: Early Adopters & Their Experiences.
Behavior Energy and Climate Change Conference, Talk, Sacramento, CA, November 2010.

Breaking down energy conservation.
Association for Environmental Studies and Sciences Meeting, Talk, Portland, OR, June 2010.

PROFESSIONAL EXPERIENCE

2011-current	Director, Transformational Media Lab Center for Unconventional Security Affairs, UCI
2013	Visiting Scholar University of Otago
2011	Research Fellow Harmony Institute
2008-2012	Graduate Teaching Assistant School of Social Ecology, UCI
2007-2008	Director of Research and Development Eucasia Schools, Inc.
2005-2006	Director of Student Life Fairmont Preparatory Academy
2003-2004	Naturalist High Trails Outdoor Science School
2002-2005	Educational Consultant Houghton Mifflin
2000-2002	Director of College and Career Center Mater Dei High School
1999-2000	Program Director Volunteer Center of the Inland Empire

PROFESSIONAL SERVICE

2014	Division 34 Program Chair, American Psychological Association
2013	Reviewer, Environment and Behavior Reviewer, Journal of Social Psychology Reviewer, Social Problems Reviewer, Journal of Sustainability Education Steering Committee, Garrison Institute Climate, Mind, and Behavior Symposium
2013-2016	Treasurer, American Psychological Association Division 34 (Environmental
2012-2013	Organizing Committee, Behavior Energy Climate Change (BECC) Conference Reviewer, Energy Efficiency Journal Reviewer, Journal of Environmental Psychology
2012	Program Committee, SPSP Sustainable Psychology Pre-Conference Reviewer, Ecopsychology
2011-2012	Session Chair, Association for Environmental Studies and Sciences

ABSTRACT OF THE DISSERTATION

Residential Energy Feedback: Research, Technology, and Potential for the Informed Home

By

Beth Karlin

Doctor of Philosophy in Social Ecology

University of California, Irvine, 2014

Professor Daniel Stokols, Chair

Scientists and elected officials agree that climate change is an issue that can no longer be ignored and residential energy use is a prime target for reducing emissions. One promising strategy for promoting conservation is the provision of feedback about energy use. Feedback—the process of giving people information about their behavior to reinforce and/or change behavior—is receiving increasing attention due to changes in technology and infrastructure that allow information to be collected, processed, and sent back to consumers quickly and cheaply. Many programs and products have emerged in recent years, demonstrating political and technical potential for wide-scale provision of energy feedback. However, past work has been critiqued for its lack of theoretical rigor; many have called for more attention to the conditions under which theories are successful in explaining conservation.

This dissertation presents an interdisciplinary, mixed-methods approach to understanding the role of feedback in residential energy conservation through four distinct yet interrelated studies. The first utilizes meta-analysis of 42 studies to examine whether feedback has an overall effect on energy use and how this effect is moderated by variables related to treatment, study quality, and publication. The second introduces a taxonomy of feedback technology derived from

a content analysis of 196 devices; it presents a list of key energy feedback characteristics and a taxonomy structure for categorizing energy feedback according to these features. The third presents mixed-methods analysis of characteristics and user experience of naturalistic users of energy feedback from an online survey of 846 individuals. And the final study introduces and tests the Usability Perception Scale (UPscale) with psychometric analysis from an 1103-person experimental study; it integrates approaches from psychology and human-computer interaction to begin addressing the need for scalable, replicable instruments for testing mediation of feedback effectiveness.

As a whole, this manuscript seeks to extend what is known about energy feedback and to make suggestions for future research. While there much research addressing *whether* feedback works, there has been little research into the more nuanced questions of *how and for whom* it works best. This dissertation aims to address this need.

CHAPTER 1: Introduction

Scientists and elected officials agree that climate change is an issue that can no longer be ignored and that the combustion of fossil fuels to create electricity is a leading cause of emissions (IPCC, 2007; United Nations, 1992). United States carbon emissions total over 6 billion tons annually (World Bank, 2011). Residential energy use is a prime target for intervention, accounting for over 20% of annual emissions (EPA, 2011). Household energy conservation has been identified as an efficient and effective means of reducing emissions, with roughly 25% potential savings using currently available technology, yielding up to $300 billion in gross energy savings through 2020 (Granade et al., 2009). These figures translate to a potential abatement of up to 300 million tons of greenhouse gases annually, twice the annual emissions of all three Scandinavian countries combined (World Bank, 2011).

Although physical scientists are working to develop alternative energy sources and energy-efficient appliances and electronics, there is also a role for psychologists to contribute to this issue by developing and testing interventions for demand-side reduction through behavior change. Energy use in identical houses has been found to vary by up to 260% (Parker, Mazzara, & Sherwin, 1996), indicating that, in addition to the building infrastructure itself, the behavior of occupants within the building impact overall energy use. As such, interventions targeting such behaviors can result in significant energy savings. Dozens of changes in the use of energy within the home can be made in the immediate term, without economic sacrifice or loss of well-being on the part of consumers (Dietz, Gardner, Gilligan, Stern, & Vandenbergh, 2009; Gardner & Stern, 2008). This savings potential, or “behavioral wedge,” provides “both a short-term bridge to gain time for slower-acting climate mitigation measures and an important component of a long-term comprehensive domestic and global climate strategy” (Dietz et al., 2009, p. 18455).

Although a variety of energy conservation actions are technically and economically viable, widespread adoption is lagging and policymakers are increasingly looking to psychologists for guidance (Lutzenhiser, 2009; Wilson & Dowlatabadi, 2007). Thirty years ago, Bittle, Valesano, and Thaler (1979) said that "the need for conservation of existing resources presents social scientists with an opportunity to develop techniques for guiding human behavior in such a way as to enable us to exist in greater harmony with our environment and its natural limitations" (p. 188). This is now truer than ever, and the analysis of psychological interventions in promoting residential energy conservation is a vital and important topic of study.

One such promising intervention is the provision of feedback to individuals and groups about their energy use. Feedback refers to the process of giving people information about their behavior that can be used to reinforce and/or modify future actions. It is considered an important dimension of behavior change (e.g., Skinner, 1938; Bandura, 1969) and has been used to influence behavior in a wide variety of fields, including education (e.g., Bridgeman, 1974; Hanna, 1976), public health (e.g., Becoña & Vázquez, 2001; Tate, Wing, & Winett, 2001), and organizational behavior (e.g., Guzzo, Jette, & Katzell, 1985; Pearce & Porter, 1986).

This emphasis has received increasing attention in recent years due to a rapidly changing energy infrastructure. Countries throughout the world are spending billions of dollars upgrading the current electric grid with what is referred to commonly as the "smart grid", a network of controls, computers, automation and new technologies that enable sensing of and response to conditions on the transmission lines, as well as two-way communication between utilities and customers. One important component of this is the replacement of traditional electricity meters with advanced metering infrastructure, or "smart meters", which are defined as "a metering system that records customer consumption (and possibly other parameters) hourly or more frequently and provides for daily or more frequent transmittal of measurements over a communication network to a central collection point" (pp. 5, Federal Energy Regulatory Commission, 2008). These "smart meters" allow for wireless communication of information back to the utility and potentially to the consumer as well. Currently, less than 10% of the world's meters are considered "smart", but this number is expected to change rapidly. In the United States, smart meters have already been installed in over 25 million homes, and an estimated 65 million will be installed by 2020, serving over 50% of U.S. households (Institute for Electric Efficiency, 2011). Likewise, Canada is on its way to meeting mandates for 100% coverage and the European Union Directives aim for 80% coverage by 2020 (Faruqui et al., 2010; Sánchez, 2012).

Both the public and private sectors have recognized this ability and are creating and supporting new technologies to provide feedback about energy use to consumers. The U.S. government is trying to accelerate this transition through programs like the American Reinvestment and Recovery Act (2009), which allocated $3.4 billion for smart meter installations. In addition, the U.S. White House recently launched the Green Button Initiative to encourage utilities to provide consumers with real-time access to their energy information and promote private sector development of technologies that integrate with this initiative (Chopra, 2011). Additionally, a variety of companies, ranging from major players such as General Electric and Panasonic to start-ups such as OPOWER and Navetas, are creating new technologies to provide energy feedback to consumers, both directly through hardware as well as through integration with smart meter technology.

Programs like the Green Button Initiative, as well as the hundreds of feedback products designed and studies conducted to date, are based on the idea that receiving information about energy use leads to better decisions about energy use. As the use of energy is “abstract, invisible, and untouchable” (Fischer, 2008, p. 80), feedback has been hypothesized to serve a vital function in making this energy visible and interpretable to the consumer. However, many questions remain as to how and for whom feedback works. Previous research on energy feedback has been critiqued for its lack of theoretical rigor, and researchers have called for more attention to the conditions under which theories are successful in explaining conservation behavior (Katzev & Johnson, 1987; Schultz, 2010; Steg & Vlek, 2009). Most previous studies have treated feedback as a unified construct, despite the wide variety in how it is provided, and have devoted little energy to understanding how or for whom feedback works. An improved understanding of the mechanisms underlying energy feedback would be of benefit at both a theoretical and practical level.

This dissertation presents an interdisciplinary, mixed-methods approach to understanding the role of feedback in residential energy conservation through five distinct, yet interrelated approaches: (1) literature review and integration into a new Eco-Feedback Intervention Theory (eFIT) (2) meta-analysis of past research on residential energy feedback, (3) taxonomy of energy-feedback technology, (4) mixed-methods analysis of naturalistic energy feedback users, and (5) introduction and psychometric testing of a Usability Perception Scale (UPscale).

Chapter Two introduces and analyzes past theoretical and empirical research on both feedback and environmental behavior to identify unresolved issues and introduces *eco-Feedback Intervention Theory* (eFIT), which integrates general feedback theories with the unique contexts and challenges associated with pro-environmental behavior.

Chapter Three utilizes statistical meta-analysis of 42 feedback studies published between 1976 and 2010 to examine whether feedback-based interventions have an overall significant effect on residential energy use and how this effect is moderated by variables related to study setting, methodology, and treatment. It applies eFIT to the domain of residential energy feedback, evaluating past reviews and examining, via statistical meta-analysis, the overall effectiveness of feedback on residential energy use and what variables moderate this effect; and integrates findings with eFIT, offering a set of concrete suggestions for future research and practice.

Chapter Four presents a taxonomy of feedback devices, derived theoretically (from literature review) and empirically (from content analysis of product data). Using data collected from 196 feedback products, it presents a list of energy feedback characteristics, identifies key variables for categorization, and presents a revised taxonomy of energy feedback that incorporates these key distinguishing features.

Chapter Five presents mixed-methods analysis of naturalistic users of energy feedback, i.e., individuals who choose on their own to use products that monitor energy consumption. It examines both who is using these devices as well as their user experiences through analysis of online survey data. Demographic and psychological characteristics of 86 individuals using feedback devices are compared to 749 non-users, revealing both demographic and psychographic differences. And qualitative analysis of open-ended responses reveal important patterns of user experience, including the role of social diffusion in adoption, differences in the use of feedback for tracking and for learning purposes, and evidence of diminished utility over time.

Chapter Six introduces and tests a new instrument, the Usability Perception Scale (UPscale), designed to measure ease of use and engagement with eco-feedback displays. After reviewing past research on eco-feedback, usability, and the limitations of current assessment methods, the UPscale is introduced and psychometrically tested against four types of psychometric properties: factor structure, reliability, validity, and sensitivity.

As feedback technologies become increasingly ubiquitous, with a growing capacity to leverage personalized energy information, there is an urgency to ensure that they are utilized to their full potential. As a whole, this manuscript aims to extend what is known about this energy feedback and to make suggestions for future research. While there is much research addressing *whether* feedback works, there has been little research into the more nuanced questions of *how and for whom* it works best. This dissertation aims to address this need.

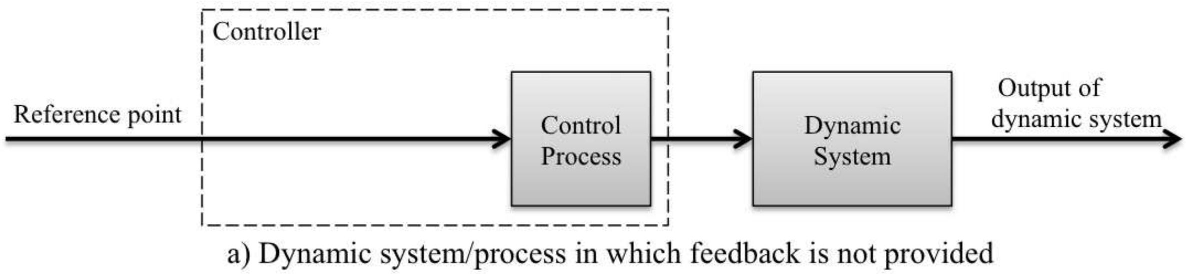
CHAPTER 2: Literature Review and eFIT Theory

Before investigating the effects of feedback on energy conservation, it is important first to examine past work that has been conducted on both feedback and pro-environmental behavior more broadly. How does feedback about performance (in any domain) affect behavior? And what are the unique characteristics of pro-environmental behavior that must be addressed in any behavioral intervention? The current chapter analyzes past theoretical and empirical research on both feedback and environmental behavior to identify unresolved issues and then introduces a new *eco-Feedback Intervention Theory (eFIT),* which integrates general feedback theories with the unique contexts and challenges associated with pro-environmental behavior.

An Introduction to Feedback

Feedback has been studied in both the physical and social sciences for decades (e.g., Skinner, 1938; Wiener, 1948). The basic premise is simple: feedback enables the output of a dynamic system or process (i.e. one whose behavior varies over time) to be compared to a goal or reference point, in order to enable improved control over that system or process (Goyal & Bakshi, 2008). Figure 2.1 illustrates the difference in the structure and control of a process when no feedback is provided (a), and when feedback is provided (b).

First applied to steam engines and other mechanical systems in the 18th century, feedback systems are based on control theory, which has three key aspects: (1) a goal or reference point with respect to which the system is controlled; (2) a means to compare actual performance to the goal or purpose; and (3) a process to communicate information about the output of the system back to the input to enable modification of the process (Duffy, 1984). Improved control over dynamic systems is thus enabled by the presence of feedback loops and the communication of information (Åström & Murray, 2009).



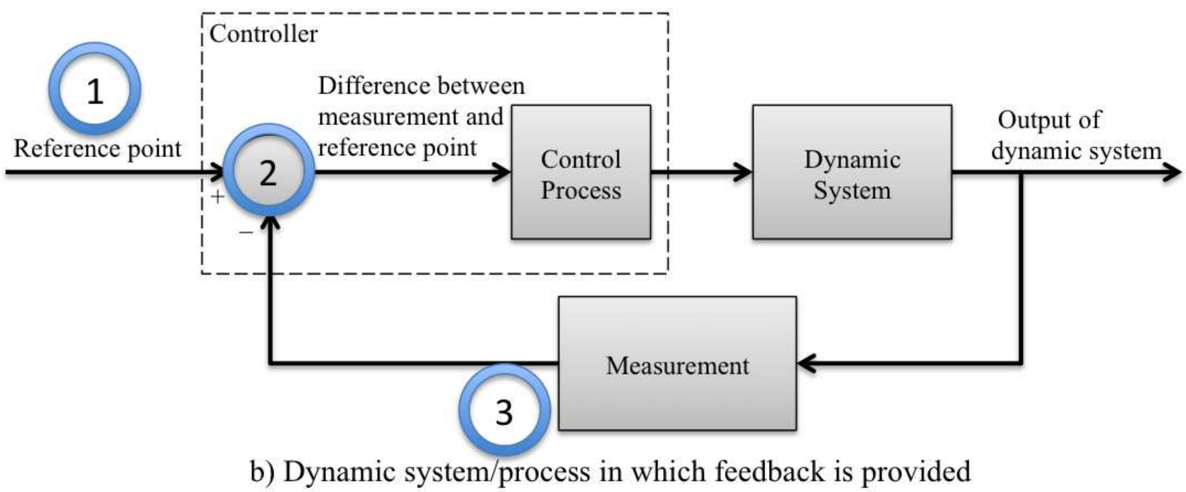


Figure 2.1. Control of dynamic systems with and without feedback

A simple example of this type of system is a home heating system. The system is set up with a desired temperature, either input by the user or provided as a default by the manufacturer. A sensor built into the system enables the temperature of the room to be measured and compared to this desired temperature. Any difference between the desired and actual temperature is then communicated back to a controller within the system, which in turn activates the heater to minimize differences between the actual and desired state.

In the 1940s, Norbert Wiener explored how these types of communication and control theories might be extended to human systems. This, he argued, called for a new science of feedback, human behavior, and information, for which he coined the term “cybernetics” (Wiener, 1948). Cybernetics is fundamentally concerned with the study of how information can be communicated around dynamic systems for the purpose of control, with a particular focus on behavior and circular communication (Carver & Scheier, 1981; Duffy, 1984). In cybernetic systems that integrate humans into the control process, the resulting system is often non-mechanical and more flexible than machine-only control counterparts; although it is more complex, it operates in much the same way (Klein, 1989). The movement toward specific goals, or reference points, requires individuals to identify current behavior with respect to an established reference, which may require more than a simple mechanical sensing of the existing environment. The discrepancy between current behavior and reference point(s) needs to be evaluated and a mechanism employed to reduce this discrepancy (Klein, 1989; Lawrence et al., 2002).

Although cybernetics have been implemented and validated across many disciplines, including epidemiology, environmental studies, engineering, and economics (Goetz, 2011), there are concerns with their use in social systems, particularly in cases where goals or reference points may not exist, accomplishments may not be measurable, or the information provided cannot be used (Hofstede, 1978). Psychological theory, therefore, has great potential to integrate traditional system principles of cybernetics with the complex landscape of human behavior.

Psychological Theories of Feedback

The earliest psychological research related to feedback focused on knowledge of results (KR) studies (e.g., Jones, 1910; Judd, 1905; Wright, 1906); these studies provided information back to the subject about the results of the experimental task (e.g., you answered 80% of questions correctly) and generally found a positive relationship between KR and performance.

Early work in behaviorism (e.g., Thorndike, 1927, Skinner, 1938) related KR to feedback through operant conditioning, which introduced the concepts of reinforcement and punishment, such that a desired response to a behavior serves as behavioral reinforcement and an undesired response serves as punishment. Knowledge of desired results could be seen as a reinforcement of behavior and knowledge of undesired results as a punishment, thus serving to encourage or discourage behavior. Neutral operants are environmental responses that neither increase nor decrease the likelihood of repeating a behavior.

Later work (Bandura, 1969) expanded this notion to include feedback about not only the *results* of a behavior, but the *process* of engaging in behavior (e.g., you attended three classes this week), as well as information relating results to a goal (e.g., you are on track to earn an A this semester) or peer performance (e.g., you are in the top 10% of your class). Bandura (1969), who contributed seminal research on the topic, found that providing a goal and information about progress towards that goal could serve as a form of behavior modification, much like a reward or punishment. Similarly, goal-setting theory (Locke & Latham, 1990) views behavior feedback as a form of self-regulation, asserting that behavior is inherently goal-directed and feedback about performance is needed to evaluate behavior in relation to these goals. Additionally, action-identification theory (Vallacher & Wegner, 1987) asserts that different levels of meaning can be attributed to an action; as mastery is gained, meaning moves from action-related (e.g., run a mile without stopping) to self-related (e.g., improve physical fitness) goals.

Feedback Intervention Theory (FIT). Kluger and DeNisi (1996) conducted a comprehensive review of psychological theories of feedback and a statistical meta-analysis of feedback studies across multiple behaviors (e.g., test performance, attendance, memory tasks)[1].

[1] Feedback about energy use was not included in their analysis.

They found that, despite many previous authors' assertions of feedback's effectiveness, the empirical evidence was mixed; some studies found strong positive effects for feedback, while others found no or negative effects. They introduced the Feedback Intervention Theory (FIT) to explain this variation. FIT integrates a series of basic arguments derived from their analysis of past empirical and theoretical contributions.

The first argument of FIT is that behavior is regulated by comparisons made between the feedback and pre-existing or intervention-provided *standards*. These standards can be personal goals (Latham & Locke, 1991; Carver & Scheier, 1981) or comparisons to past behavior or others in a social group (Festinger, 1954). When behavior differs from the standard, this creates a feedback-standard gap, and it is an individual's desire to decrease this gap that mediates the effectiveness of feedback. A standard can be created and provided by the intervention, but it is only effective if the individual accepts and values the standard as a goal. Four options are therefore available to individuals when provided with such a feedback-standard gap. They can respond by changing behavior to match the standard, changing the standard to match behavior, rejecting the feedback, or leaving the situation altogether.

While the desired response to feedback is typically behavior change, the specific response to feedback can be affected by variables related to the feedback information or by individual-level differences (e.g., level of self-efficacy or anxiety). Both the source and strength of the goal or standard and the size and direction of the feedback-standard gap can therefore impact this choice. For example, negative feedback is more likely than positive feedback to lead to behavior change (Anderson & Rodin, 1989; Campion & Lord, 1982; Podsakoff & Farh, 1989).

Next, FIT states that feedback loops are organized hierarchically. At the top of the hierarchy are self-salient goals (e.g., investing in a scientific career), whereas specific action goals sit at the bottom of the hierarchy (e.g., attending lectures). Goals relating to the focal task (e.g., passing university exams) sit between the self-salient goals and specific action goals. Consistent with action identification theory (Vallacher & Wedner, 1987), these span from low-level identities corresponding to a description of how the action is done (e.g., attending lectures—corresponding to goals at the bottom) to higher-level identities that focus on self-salient outcomes (e.g., becoming a scientist—corresponding the goals at the top).

Additionally, FIT proposes that the output of higher-level feedback loops may impact lower-level goals. Feedback-standard gaps that are salient to the self (e.g., gap between current perception and desired scientific identity) can be resolved in a number of ways, one of which may be to focus on the focal task (e.g., passing university exams) and the lower-level actions (e.g., attending lectures). However, such gaps may also be resolved by other activities (e.g., taking an internship at a scientific institute), which may result in the focal task (passing university exams) receiving less attention or being abandoned altogether. Alternatively, unattained high-level goals may cause people to respond by increasing the standard of focal-task goals; if scientific identity standards are not met, one may respond by raising goals related to passing university exams by aiming for an even higher grade. Satisfying these new task goals can also further the higher, self-salient goal. This view also provides a supporting explanation of why positive feedback can impact behavior even though it does not reduce a feedback-standard gap; an even higher-level goal can be set that creates a new standard.

This is a key aspect of FIT, as cybernetic (e.g., control theory) models of feedback only account for a single goal or standard, a means to compare performance against the goal, and a mechanism by which this can be communicated back to users (Duffy, 1984). While cybernetics can help understand the mechanism by which information can be collected, manipulated, and communicated to enable behavior change, understanding levels of motivation and feedback loops help explain the variation in feedback-standard goal setting and attainment.

Finally, FIT suggests that feedback is effective in so far as it changes the locus of attention of the individual to the feedback-standard gap. Only feedback-standard gaps that receive attention contribute to behavior regulation. The simple presence of feedback is not enough to regulate behavior—the feedback must draw attention of the individual to a feedback-standard gap that he/she has identified as self-relevant. While attention is generally directed at a level somewhere above physical action (Carver & Scheier, 1981) and below ultimate self-goals (Wicklund, 1975), this can vary as a function of task familiarity and goal attainment (Vallacher & Wegner, 1987). Feedback may direct attention to a specific action or standard and connect that action to self-related goals, serving not only to provide information about the behavior-standard gap, but also to draw attention to a behavior in the first place and place it in context with those goals. As such, the visibility and availability of feedback are also essential and serve as key factors in its effectiveness.

Task Characteristics of Pro-Environmental Behavior

In developing FIT, Kluger and DeNisi successfully integrated past research on feedback and provided a coherent set of theoretical assumptions that have implications for interventions across a wide variety of behavioral domains. However, it is important to take into consideration the specific task characteristics of pro-environmental behavior in order to apply this work successfully. Past research has discussed this need, but has done little to address it, noting that feedback researchers have largely “ignored the theoretical importance of task characteristics” (Kluger & DeNisi, 1996, p. 268).

Pro-environmental behavior refers to individual or collective actions that result in decreased resource use and/or environmental impacts. Three key task characteristics of pro-environmental behavior deserve attention, namely that the resource use and environmental impacts of such actions are: (1) abstract, (2) non-sensory, (3) addressed by a multiplicity of behaviors, and (4) of low personal relevance to most individuals.

Abstract. First of all, environmental impacts are somewhat abstract in nature. People do not consciously engage in behavior with the goal of impacting the environment; they travel from A to B by a car that is fueled by oil, which releases greenhouse gases as the oil is consumed; they use appliances in the home (lights, televisions, computers, etc.) that use energy that is generated in power plants burning fossil fuels, which releases greenhouse gases into the environment. Thus, an individual's abstract notions about the concept of environmental impacts are at least one step removed from her/his concrete (observable) behaviors that consume resources.

Although this is a minor distinction from a technical point of view, it can be seen as an important psychological distinction when considering strategies to promote behavior change. Markowitz and Shariff (2012) studied climate-change behaviors and found that their abstractness and cognitive complexity make efforts to promote energy-conserving behaviors difficult. Related to this point, they introduced an explanatory construct regarding the "blamelessness" of unintentional action. Most individuals are not trying to emit carbon on purpose when watching television or cooking dinner. Rather, it is seen as a necessary byproduct of these actions and not worthy of blame or a need to change.

Non-sensory. Related to the previous point is the non-sensory nature of energy use. Many forms of energy use, such as electricity, are invisible, silent, and untouchable. One cannot see electricity or touch it directly. We cannot pick a kWh up like an apple. While some environmental products, like reusable shopping bags and hybrid vehicles, can become elements of lifestyle as they are visible and easily seen by others, others are less visible by peers or even by the user. As such, receiving and paying attention to feedback about one's energy use is optional. That is, the person has the option to view or not view it in the case of utility-provided feedback, or even to purchase or not purchase it in the case of energy-feedback devices. Kluger and DeNisi (1996) suggest that the issue of locus of attention is "about the what (will receive attention) and not about the if (it will be perceived at all)" (p. 262). However, since energy feedback is optional for people most of the time, the "if" also matters a great deal—user experience and perception is crucial.

Multiple Behaviors. In addition, pro-environmental behavior does not consist of a single target action but rather refers to a large set of behaviors that can vary from watching television to driving to work. The principle of compatibility (Ajzen & Fishbein, 1977) suggests that behaviors and their influences should be measured at the same level of specificity. Research has shown an interest among the U.S. public in engaging in behaviors aimed at reducing their environmental impact, but the specific behaviors in which Americans overwhelmingly report engaging, such as turning off lights when leaving a room, have a minimal impact on energy savings as compared, for example, to reducing airplane trips (Attari, DeKay, Davidson, & Bruine de Bruin, 2010).

Although pro-environmental behavior is often addressed holistically with encouragements to "go green" as if it were a single action, there is great diversity in the types of environmental actions that a person can choose. Even within a specific area like home lighting, we can differentiate between turning off lights, installing energy-efficient lighting, or setting light timers in the home. Although the end result of all three behaviors is a decrease in energy use, they may be quite different in terms of influencing factors, environmental impact, and psychological consequences. These behaviors vary widely in task characteristics such as cost, effort, and required knowledge; research suggests they are predicted by different motivations as well as demographic characteristics (Karlin et al., 2012).

Personal Relevance. Finally, FIT asserts that feedback interventions “are unlikely to be ignored because any FI (feedback intervention) has potentially serious implications for the self” (p. 262). This is not necessarily the case with pro-environmental behaviors such as electricity use, as the implications are often minimal to the self (e.g., inexpensive, cause no immediate personal harm). Some behaviors and related feedback-standard gaps are more important (motivationally significant) to individuals than others. Individuals are less likely to pay attention to (and try to resolve) feedback-standard gaps associated with activity domains considered trivial or insignificant than for subjectively important activity domains (Stokols, 1979). Although Americans do report concern for environmental issues, such concerns often rank lower than others related to the economy, health care, and terrorism, which have more serious immediate implications for the self (Leiserowitz, 2008).

Psychological Theories of Pro-Environmental Behavior

Because of these unique task characteristics, a theoretical understanding of pro-environmental behavior and its predictors is therefore important for maximizing the potential utility of a feedback intervention. A substantial body of research has been conducted on the determinants of pro-environmental behavior (see Bamberg & Moser, 2007 for review). Psychological theories for predicting and explaining pro-environmental behavior have been historically grouped into two general categories: (1) rational (or individualistic) theories, and (2) moral (or altruistic) theories (Bamberg & Moser, 2007).

Rational Theories. Rational theories of focus on individuals' motivation to maximize benefits and minimize costs (Scott, 2000). Such theories presume that individuals are naturally information-seeking and make purposeful, carefully considered decisions about how to behave based on anticipated costs and benefits of available options. The Theory of Planned Behavior (TPB; Ajzen, 1991) exemplifies this perspective (Armitage & Conner, 2001). TPB classifies the beliefs guiding individuals' rational decision-making processes as: (1) behavioral beliefs (attitudes toward the behavior), (2) normative beliefs (social norms), and (3) control beliefs (perceived control over the behavior). According to TPB, these three sets of beliefs influence a person's behavioral intentions, which largely determine her/his behavior.

Moral Theories. Although rational self-interest may have a considerable influence on human behavior, it is not in and of itself sufficient to explain pro-environmental action. Because environmental issues generally involve the use of natural resources, which are both collective and limited, the optimal choice for the individual is often in direct conflict with the common interest (Hardin, 1968). As such, altruistic or moral motives are also important for understanding pro-environmental behavior. The norm activation model (NAM; Schwartz, 1977), for example, stipulates that the activation of a "personal norm," or sense of moral obligation, influences pro-social behavior. Although originally applied to behavior toward other people, later work expanded the notion to environmental behavior. Van Liere & Dunlap (1978) suggested that "to the extent that concern for the well-being of other humans is aroused, we would expect traditional moral norms which regulate interpersonal behavior to influence environmental behaviors as well" (p. 175). Stern and Dietz (1994) later expanded this notion to include concern for non-human species or the planet in general.

Although the contrast between rational and moral approaches to understanding behavior has been a recurring theme in psychology, recent scholarship emphasizes that the two are not mutually exclusive and that their integration can yield greater theoretical and explanatory value than either can alone (Turaga, Howarth, & Borsuk, 2010). Psychological variables that have been found to predict pro-environmental behaviors include those representing both a rational and a moral approach, such as energy concern (Curtis, Simpson-Housley, & Drever, 1984; Verhallen & Van Raaij, 1981), price sensitivity (Long, 1993; Verhallen & Van Raaij, 1981), environmental concern (Poortinga et al., 2003), and personal and social norms (Cialdini & Schultz, 2004; Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008).

Contextual Theories. Attitudes, while important in predicting and influencing behavior, may not always be sufficient to override individual and structural barriers to pro-environmental behaviors. A recent criticism of both rational and moral models of conservation behavior is their neglect of contextual influences (Steg & Vlek, 2009). Individual barriers include lack of time, money, or knowledge required for engaging in pro-environmental behaviors. Prior research points to home ownership, income, family size, and age as the most significant predictors of environmental behaviors, such that older, high-income families who own their homes are the most likely to engage in such behaviors (Black, Stern, & Elworth, 1985; Cialdini & Schultz, 2003; Dillman et al., 1983; Karlin, et al., 2012; Nair et al., 2010; Poortinga, Steg, Vlek, & Wiersma, 2003).

Integrated Approaches. Guagnano, Stern, and Dietz (1995) provided a useful theory that integrates psychological and contextual factors as well as differences in specific behaviors. Their A-B-C model posits that environmental behavior is influenced by both attitudes and contextual factors and that the stronger one set of factors is in predicting behavior, the less force the other exerts. If there are sufficient contextual barriers to engaging in a behavior, then individuals are unlikely to engage in it, regardless of rational or altruistic attitudes toward the behavior. For example, some behaviors, such as adding home insulation, are not associated with normative beliefs when constrained by contextual factors, such as household infrastructure and homeownership (Black et al., 1985). For others, like recycling behavior, the explanatory power of personal-norm beliefs decreased when convenient curbside pick-up became available (Guagnano et al., 1985). Therefore, psychological variables will be most influential on pro-environmental behavior when contextual variables do not exert great influence on either promoting or restricting the behavior. If a combination of attitudes and/or context places an individual above a certain threshold (see Figure 2.2), the desired behavior will take place. When attitudes and/or context place the individual below the threshold, the behavior will not take place.

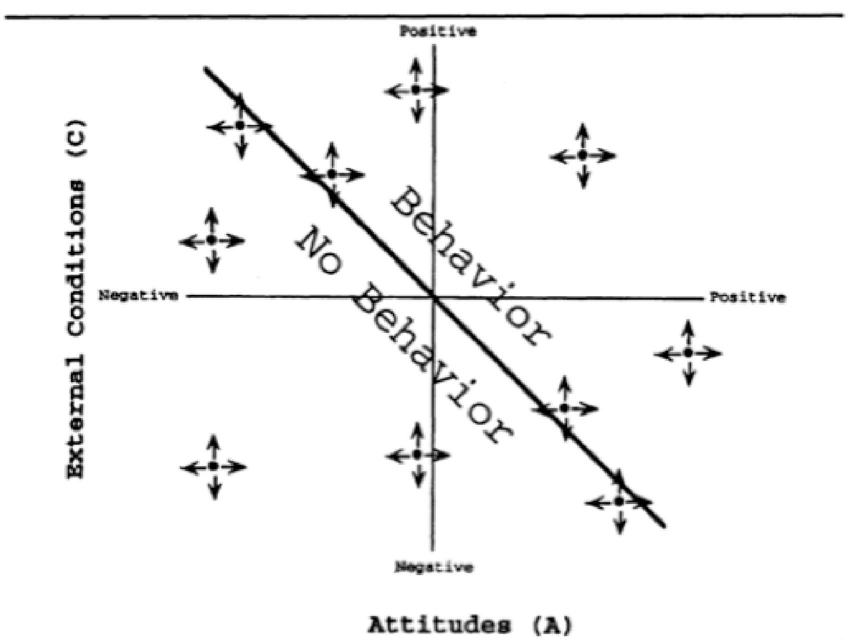


Figure 2.2. The A-B-C model.

The Fogg Behavior Model (Fogg, 2009) builds on the A-B-C model. Similar to A-B-C, Fogg suggests that motivation (attitudes) and ability (context) interact to create a threshold effect for behavior; individuals with low motivation may perform a behavior if it is simple enough and can also perform very difficult behaviors if sufficiently motivated. The model, however, expands on A-B-C with the addition to a third key element in behavior change: a trigger.

Fogg (2009) defines a trigger as something that brings attention to the target behavior at the appropriate time. Triggers act as signals, serving as a reminder to perform the behavior, and can take many forms, including a text message, alarm, post-it note on the mirror, and so on. "Whatever the form, successful triggers have three characteristics: First, we notice the trigger. Second, we associate the trigger with a target behavior. Third, the trigger happens when we are both motivated and able to perform the behavior." (p. 3) According to Fogg (2009), triggers are key to behavior change. Even if individuals are highly motivated and able to perform a target behavior, change may not occur without the provision of a trigger to highlight when and where it is needed. He identified three types of triggers: (1) sparks are triggers combined with a motivational element to both highlight and encourage behavior; (2) facilitators are triggers combined with an element that makes the behavior easier to engage in, and (3) signals are the simplest form of triggers and provide a simple reminder of the behavior at the appropriate time.

As such, feedback has been identified as a promising solution for a wide variety of pro-environmental behaviors. Feedback can serve as a trigger to highlight behavioral impacts that would otherwise not be seen. Providing a feedback-standard gap via social or goal comparisons can provide motivation, which can be based on rational and/or moral attitudes. And feedback can serve to help simplify the complex task of "saving energy" by providing data on specific appliance usage or providing tips or advice to assist with performing desired behaviors.

An Integrated Approach: Eco-Feedback Intervention Theory (eFIT)

This section introduces *Eco-Feedback Intervention Theory (eFIT),* which integrates psychological theories of feedback and behavior change with the unique contexts and challenges associated with pro-environmental behavior. Based on the review above, eco-feedback is defined as *information provided to an individual or group about the environmental impact of specific behavior(s) with the goal of guiding future behavior to reduce the individual or group's environmental impact*. According to eFIT, eco-feedback requires the following four interdependent and necessary preconditions to be effective: (1) *Perception*, (2) *Interpretation*, (3) *Motivation*, and (4) *Ability*.

The first precondition (*perception*) extends Kluger & DeNisi's original FIT theory (1996) and stems from the invisible nature of resource consumption in the industrial age. The second precondition (*interpretation*) relates to the abstract nature of environmental impacts (Markowitz & Shariff, 2012) and the need to simplify something that is cognitively complex. The third precondition (*motivation*) is largely addressed by FIT (Kluger & DeNisi, 1996); however, this work extends FIT in line with determinants of environmental behavior change by integrating rational (Azjen, 1991) and moral-psychological approaches (Schwartz, 1977), as well as social influence (Cialdini, 1984) and self-determination theory (Ryan & Deci, 2000). Finally, the fourth precondition (*ability*) further extends FIT to account for the multiplicity of behaviors available to households to reduce feedback-standard gaps (Karlin et al., 2012), and the (often large) contextual barriers that may prevent action (Guagnano et al., 1995). The following sections describe each of these preconditions, discuss their interdependencies and potential pathways to behavior change, and offer some general testable research propositions.

Perception. The first precondition states that eco-feedback cannot induce a behavior change unless it is first perceived. As the use of electricity in the home is "abstract, invisible, and untouchable" (Fischer, 2008, p. 80), feedback has been hypothesized to serve a vital function in helping individuals perceive energy use by making it visible and interpretable to the consumer. Climate change and environmental impacts are largely invisible and untouchable on an everyday scale and are often the result of habitual behaviors. We cannot directly or immediately see the impact of our actions on the environment; we cannot see how much of the planet's resources we are consuming when we drive to work or watch television. The environmental impacts of these actions are unlikely to be perceived or capture our attention without some external stimulus.

Eco-feedback, as a form of behavioral trigger, can provide this catalyst to direct attention toward environmental behaviors (Fogg, 2009). However, because this information does not have serious implications for the self (Leiserowitz, 2008), and it is optional for people most of the time, it may not demand the sort of attention that other feedback interventions do. Additionally, it is often provided via media that may not naturally receive attention such as leaflets posted through the mailbox, or through web-based applications, so it is important to consider the ability of the feedback system to draw users' perception to the information being provided.

Successful eco-feedback must also direct people's attention to the feedback-standard gap, as only discrepancies that receive attention will be acted on (Kluger and DeNisi, 1996). Users should be able to perceive the relationship between behavior change and the feedback-standard gap. Self-efficacy is a key component of behavior change and can be influenced by observation of past accomplishments (Bandura, 1982). Perceptions of previous mastery may increase self-efficacy, whereas the perception of repeated failures may diminish it. Thus, the ability of eco-feedback to enable perception of changes in feedback-standard gaps is also important.

Interpretation. Climate change and environmental impacts are abstract and cognitively complex concepts, and the second precondition addresses the issue of interpretability. As most eco-feedback is provided to users visually (e.g., in writing, in the form of numbers, in a graph), it is important to consider the attributes of feedback interventions that may affect a person's ability to process and interpret this type of data. Cognitive models of visual information processing suggests that the legibility and quantity of information to be assimilated, as well as the ability to integrate past experience, are key elements that moderate a person's ability to interpret visual data (Spoehr & Lehmkuhle, 1982). The average person can store about seven items of information simultaneously; more than this tends to overload our cognitive systems (Miller, 1956). Certain steps can be taken to increase information processing ability, such as breaking the data into sequences of smaller chunks (Miller, 1956; Ford & Karlin, 2013) or connecting it to previously stored information (Redish, 1989). Because energy is a vague and amorphous concept to many people, translating the feedback into a language more familiar, such as dollars, trees, carbon emissions, cars on the road, or equivalent use of batteries, can be an effective way to decrease cognitive burden and increase interpretability. Another option is to decrease the cognitive load needed to interpret feedback by removing any numerical data and just providing ambient feedback such as red or green lights, or a cartoon plant or animal (Ham & Midden, 2010).

Secondly, as indicated above, environmental impacts are abstract in nature. People do not so much "use energy" as they use appliances in the home that use energy, such as lights, television, and computers. Thus it is key that eco-feedback can help users to simplify these cognitively complex and abstract ideas, and interpret them in such a way that helps link together actions with environmental consequences.

Motivation. The third precondition stipulates that feedback will stimulate behavior change only if the individual receiving it is sufficiently motivated to take action to reduce discrepancies between the feedback and a pre-defined or intervention-provided standard. This standard may be past behavior (e.g., you used 20% less than last month), a goal (e.g., you are 80% of the way to meeting your goal), or the consumption level of peers (e.g., you are doing better than 80% of your neighbors). The standard may even be a vague reference to "ideal" energy use in the form of a smiling face or glowing green light. Such standards provide various reference points that can help people determine whether their use is normal (descriptive norm), good (injunctive norm), better than before (historical comparison), or what they are aiming for (goal comparison). This may help motivate behavior changes, so long as the standard selected is accepted and valued by users and does not induce feelings of guilt or uncertainty (as this may breed self-defense and rejection of feedback and/or standards).

Motivation to attend to eco-feedback may also stem from a discrepancy between an individual's actual environmental behavior and his or her pre-existing attitudes toward such behavior, in turn derived from behavioral beliefs, normative beliefs, control beliefs, personal norms and moral obligations (Ajzen, 1991; Schwartz, 1977). If users are able to evaluate eco-feedback with respect to salient self-goals, affective reactions may be induced, which may subsequently affect the level to which users act upon eco-feedback. Although it is expected that individual level differences will moderate the effectiveness of feedback at this level, key factors such as self-efficacy, anxiety, and expectations of performance may also influence the likelihood that individuals remain engaged with eco-feedback.

Additionally, feedback interventions that can cultivate intrinsic motivation will be more effective in the long term than feedback that relies solely on extrinsic motivations (Ryan & Deci, 2000). Thus, feedback interventions that are interactive and engaging, highlight the relatedness of users' behaviors to their higher-level motivations, and support users' perceptions of autonomy and competence are expected to foster higher-quality and more persistent forms of motivation over time.

Ability. The final component of eFIT states that the individual must be able to engage in some behavior change in response to the feedback information. To do this, three conditions must be met. First, they need to be able to identify at least one action they can engage in that they associate with the feedback—in this case, decreased environmental impact. As mentioned above, this can be difficult, as there are hundreds of behaviors that a person can engage in to reduce environmental impact. Second, in addition to identifying specific actions to take, feedback recipients must also know what to do to carry out this action. Hutton (1982) suggests that knowledge may be a more important indicator of behavior than attitude and describes two different types of knowledge that are needed to promote conservation behavior: (1) general knowledge and (2) knowledge of specific ways to decrease use, both of which are likely to influence energy use behavior. Feedback that enables this learning may be more effective at engaging action; however, feedback that provides this knowledge directly through various cues may serve as a crutch, preventing users learning from their own errors, which some suggest to be a superior learning mode (Kluger & DeNisi, 1996).

Third, people must actually be able to engage in the behaviors they have identified. This is not always possible even if they have favorable attitudes toward them and motivation to undertake them (Fogg, 2009). Contextual variables, such as housing characteristics or availability of time, money, and resources, can impede or enable behavior regardless of attitudes and motivation. For eco-feedback interventions, this final component is especially important due to the type of behaviors that the feedback is soliciting and the significant contextual barriers faced by households.

The interdependencies of eFIT. Although perception, interpretation, motivation, and ability are each separate preconditions for effective eco-feedback interventions, the mechanisms by which these processes operate are interdependent, and these interactions are important to acknowledge when hypothesizing about the effects of eco-feedback on pro-environmental behavior.

As eco-feedback is not publicly mandated and has limited implications for the self, people must have some higher-level motivation in order to attend to and perceive this type of feedback in the first instance; thus, higher-level motivations may influence the perceptibility of feedback interventions. However, one interesting and important finding across environmental research has been the weak relationship between pro-environmental attitudes and conservation behavior (e.g., Cook & Berrenberg, 1981; Gardner & Stern, 1996), which suggests that although a higher-level motivation might drive an initial use and engagement with feedback systems, to encourage sustained conservation, the eco-feedback must direct users' attention toward the discrepancy between their current patterns of environmental behavior and a desired level or standard of behavior (rather than a standard defined by their attitudes).

If users are unsuccessful with initial efforts to reduce the gap between their current environmental actions and the standard chosen for comparison, their attention may shift toward trying to identify particular strategies that can be undertaken to reduce consumption (Kluger & DeNisi, 1996). As users' motivation and attention shifts toward these specific actions, the way in which feedback is perceived and interpreted will also shift. Specifically, users will focus on identifying the links between specific behavioral strategies and consequences, and this will continue until either learning takes place and the feedback-standard gap is reduced, or until users desist from their efforts to meet the standard.

When users are engaged with these learning processes, feedback that enables users to identify links between actions and consequences will be more successful at increasing their knowledge gain and shifting their attention back toward their consumption-standard gap. Once learning has taken place, the type of feedback used for this learning process has served its purpose and users may begin to disengage with it (Karlin, 2011). Thus, the ways in which users interpret eco-feedback may be guided by their particular motivations and locus of attention, and the type (or interpretation) of information required to enable action identification is likely to be different from that needed to motivate conservation efforts.

If users experience success in reducing their feedback-standard gap, or if the feedback cues direct attention toward higher level motivations and self-related processes, affective processes may be triggered and users may look for opportunities to obtain other personal goals. Although this re-allocation of cognitive resources may result in a short-term performance reduction, long-term performance would be expected to improve as users become more familiar with eco-feedback and behavioral response becomes more automatic. Thus, if higher order goals are engaged as users become more familiar with eco-feedback, then the feedback can continue to be motivational long after their initial goals are met.

Although Eco-Feedback Intervention Theory (eFIT) can apply across a wide range of pro-environmental behaviors, from food consumption (e.g., food log that provides carbon instead of calories) to driving (e.g., dashboard that shows the environmental impact of driving style), the remaining chapters of this dissertation will focus on residential energy feedback.

CHAPTER 3: Meta-Analysis of Feedback on Energy Conservation

This chapter applies eFIT to the domain of residential energy feedback, evaluating past reviews and examining, via statistical meta-analysis, the effect of feedback on residential energy use and what variables moderate this effect. It seeks to address both the overall question of whether feedback is an effective intervention strategy for energy conservation as well as explore the underlying determinants that impact feedback effectiveness to help explain variance observed in the research conducted to date.

Past Reviews of Energy Feedback

Residential energy feedback has been studied extensively over the past 40 years and several reviews of this literature have appeared in recent years. Four of these reviews (Darby, 2006; Ehrhardt-Martinez et al., 2010; EPRI, 2009; Fischer, 2008) analyzed past empirical studies of energy feedback through the methods of qualitative literature review, where a set of empirical studies on a topic are "digested, sifted, classified, simplified, and synthesized" (Manten 1973, p. 75). Their overall findings were that feedback is effective, with an average of 10% savings; effects were found to range from negative (i.e. increase in energy consumption) to up to 20% in energy savings. In addition to discussing the general effects of energy feedback, these reviews also suggested that the effectiveness of feedback may vary depending on both external and internal moderating variables.

All four reviews discussed frequency as a moderator of feedback effectiveness. Darby (2006) distinguished feedback primarily as direct and indirect: direct feedback is available immediately, whereas indirect feedback is processed in some way before being provided to the consumer (e.g., utility bill). She emphasized the immediacy of information provision as the key variable moderating the effectiveness of feedback and suggested that direct/immediate feedback may lead to greater savings (5-15% for direct/immediate versus 0-10% for indirect). This is also supported by Fisher (2008), who found that more frequent (immediate) feedback is more effective, as it helps to improve links between actions and consequences. However, EPRI (2009) found very little difference in the energy savings of studies using various levels of feedback frequency/immediacy, with 9% savings for monthly feedback, 8% savings for daily/weekly feedback, and 7% savings for real-time/immediate feedback. Finally, the results of a meta-review by Ehrhardt-Martinez et al. (2010) found that real-time feedback/immediate appeared to result in *lower* conservation efforts (6.9%) than daily/weekly feedback (10.8%).

Additionally, while Darby (2006) found that indirect feedback may be effective in conveying effects of behavior on specific energy use (e.g., heating, appliances), Fischer (2008) argues that “the only way of providing a direct link between action and results” is by providing a breakdown within the feedback corresponding to individual appliance end-use. Findings do support the argument for increased effectiveness of individual appliance feedback (Fischer, 2008; EPRI, 2009), however, due to the nature of existing studies it is not possible to fully separate this effect with that of other possible moderators (Ehrhardt-Martinez et al., 2010).

Feedback duration has also been highlighted as an important feature in previous reviews (Darby 2006; Ehrhardt-Martinez et al., 2010; Fischer, 2008), though none of the reviews explain why this is the case and results are inconsistent across reviews. Darby (2006) and Fischer (2008) both found that feedback is more effective when provided for more than three months over a long time period, but Ehrhardt-Martinez et al., (2010) found that feedback is more effective for shorter (<6 months, 10.1%) rather than longer (>6 months, 7.5%) studies.

Darby (2006) found that providing feedback that includes comparisons to past use (rather than to a peer group or a target figure) was more effective. Fischer (2008) suggested that comparisons may work by stimulating specific motives to conserve or providing context within which to interpret usage, but none of the studies she analyzed demonstrated an effect due to normative comparisons, and as all the studies provided a historical comparison its effect could not be determined. Similar study design issues also prevented feedback content (i.e. the measurement used—kWh, cost) from being evaluated; although Fischer proposed energy measurement a possible moderator of feedback, she was unable to analyze this variable.

The combination of feedback with other interventions such as goal-setting, financial incentives, or conservation information was also hypothesized to increase effectiveness. Darby (2006) stated that a combination of interventions may be more effective. Fischer's (2008) analysis, however, reveals mixed findings; she suggests that these additional interventions may overload users with too much information, and their impact will also be affected by how the information is presented and how appropriate and relevant it is to the audience. As such, there is no current consensus regarding the impact of combined interventions.

Limitations of Past Reviews. Overall, prior reviews suggest that the effects of feedback are positive and that this effectiveness varies based on how it is provided, but there are several reasons why further study in the form of a meta-analysis is needed at this time. While qualitative reviews can list and describe findings, results must be interpreted with caution because effect sizes are not calculated and no inferential tests are performed to determine whether observed effects are statistically significant across studies (Rosenthal & DiMatteo, 2001). Similarly, differences between studies related to research settings, methodology, and characteristics of the feedback provided (i.e. feedback format, type, frequency, etc.) were observed (and in some cases, descriptive statistics, such as averages, were provided), but they were not analyzed inferentially to make determinations as to whether they *significantly* moderate the effectiveness of the interventions studied. Since both differences in effects and the number of studies that included each level of a variable may be relatively small (especially as compared to overall effect sizes), the techniques of meta-analysis are useful because they estimate the statistical significance of the differences, leading to more reliable conclusions than “eyeballing” self-reported findings or “vote counting” (Cooper & Hedges, 1994).

In addition, the literature reviews conducted to date present conflicting findings about several key moderators of feedback, including frequency, duration, and combination with other interventions. Using meta-analysis techniques allows for statistical analysis of both the overall effect of feedback as well as differences due to various moderating variables related to study setting, methodology, and treatment. This approach offers a more nuanced understanding of the overall effectiveness of feedback across multiple studies, as well as the different variables within and between studies with regards to the provision of feedback that may be more or less effective. Such an analysis at this point, including studies dating back over 40 years, can inform not only *whether* feedback overall is effective but *how* and *for whom* it is most effective. Such comparative analysis is potentially useful for identifying the most promising areas for future research on this important behavioral intervention.

Finally, none of the previous reviews summarized above have integrated psychological theory into their analyses of energy feedback. They present hypotheses and results, but do not integrate the significant contribution of psychology over the past century on understanding the role of feedback in behavior change. Thus, an approach that reconciles the large body of theoretical and empirical work on feedback in general from the field of psychology with the over 100 studies conducted to date on energy feedback in particular is both overdue and needed.

Current Study

An integrative framework was developed to guide this study based on eFIT theory and inclusive of the questions it seeks to answer through meta-analysis, as presented in Figure 3.1.

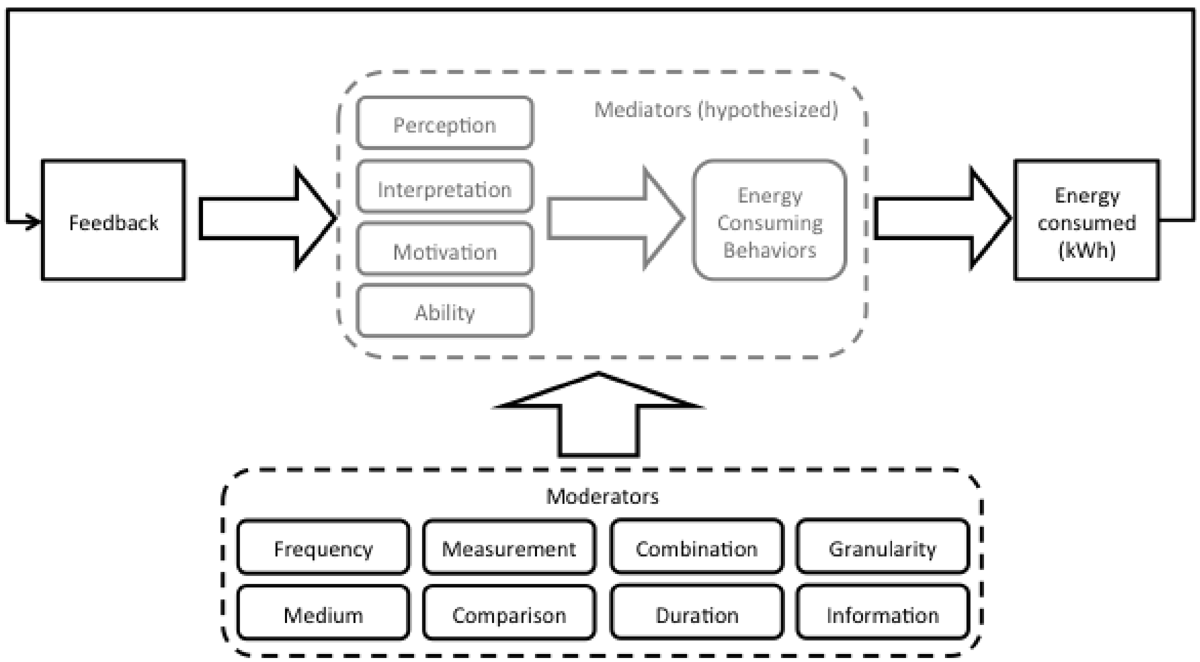


Figure 3.1 eFit model and proposed moderators

Feedback is the primary independent variable (strategy) tested and moderator variables were identified based on previous literature and designed to assess perception, interpretation, motivation, and ability, when possible. A description of proposed moderators, along with the hypothesized direction of their relations with effect size, is found in the following sections.

Treatment Variables. The ways in which energy feedback was hypothesized to impact conservation behavior follow five general guidelines: higher levels of perception should result in more effective feedback; greater ability to interpret the information should be more effective; greater stimulation of motivation should be more effective; the ability to identify actions should be more effective; and feedback that stimulates short-term interest in learning or long-term mastery and re-evaluation of self-salient goals should be more effective.

The first set of proposed treatment variables are related to the perceptibility of the residential energy feedback intervention. The *frequency* with which feedback is provided (e.g., in real time immediately after the event, daily, weekly, etc.) may impact its perceptibility, such that the more frequently the feedback is provided, the more it may draw the users' attention. Thus, increased frequency should lead to increased perceptibility, and greater energy savings. Additionally, people tend to be more motivated to pay attention to stimuli that are interesting and engaging, and feedback that captivates users through gamified approaches have the potential to draw users in over time. In this way, feedback that is computerized or interactive may cultivate an intrinsic interest and engage users with feedback for longer periods of time, suggesting feedback *medium* (i.e., the channel through which feedback is presented, such as a bill, device, or website) as a moderator, such that more interactive media will result in more substantial savings.

The next variable relates to the interpretability of the feedback system: the cognitive load of interpreting feedback can be reduced by translating feedback into a familiar language, so the type of the *measurement* used (i.e. the unit in which the feedback is being given, such as dollars, kWh, CO^2) is likely to affect interpretability. Additionally, this may help reduce the abstract nature of energy-related resource consumption, such that those units that are more familiar and concrete (e.g., equivalent number of car miles vs. kWh) will be more effective for energy feedback.

The third set of treatment variables relates to its ability to motivate, typically provided via feedback-standard gaps. The provision of *comparison* data can provide this feedback-standard and motivate further reductions in energy use. Thus, feedback that provides comparisons should be more effective. Further motivation may be achieved via *combination* with other interventions: goal-setting may help provide a relevant standard to use for comparison to feedback, or incentives may encourage motivation, though care must be taken when providing them that they don't crowd out intrinsic motivations.

The fourth set of treatment variables relates to the ability of the feedback to enable action: in order for users to take action, they must be able to identify specific behavioral changes to make, and this may be highlighted to users through increasing *granularity* in terms of both time and end use. More granular feedback should help users here, and thus be more effective in encouraging conservation. Additionally, the provision of information about energy-saving actions may help users identify specific strategies to take to reduce consumption, so long as this information is relevant to the user, at the appropriate level of specificity, and does not provide a crutch on which they come to depend.

Finally, it has been suggested above that the duration of the feedback intervention may moderate its effectiveness (Darby 2006; Ehrhardt-Martinez et al., 2010; Fischer, 2008). A duration effect, if found, is likely due to the different hierarchical feedback loops: initially, users are highly motivated to engage with new feedback interventions to learn about specific energy saving strategies. Interest tends to drop off after this initial engagement (e.g., Ueno et al., 2006); however, if feedback is provided over a long period of time, then users can develop mastery and start to focus on self-salient goals, possibly leading to shifts in task-specific goals and subsequent energy savings. Thus, feedback provided in the short term or long term should be more effective than feedback provided in the medium term.

Study Quality. While our primary goal is to determine variations in feedback that moderate its effects on energy conservation, variables related to study design may also moderate results and therefore are recommended for inclusion in meta-analysis (Stock, 1994). Examining methodological variables can inform us about the extent to which this intervention is robust (Cooper & Hedges, 1994) and can also be informative to future researchers as they make decisions about setting and methodology in their own studies. Therefore, in addition to treatment variables, study quality and publication bias are also tested.

Although the inclusion criteria (excluding studies that did not have a control group as well as those with clear confounding variables) ensure that the studies included in the analysis pass at least a minimum standard of quality, additional study-quality variables were identified to test for any bias that could result from threats to validity. The following five study-quality variables were coded and analyzed: (1) *sampling strategy*, (2) *response rate*, (3) *random assignment*, (4) *baseline data collection* (5) *blind control group*, and (6) *empty control group.*

Sampling strategy refers to the way that subjects were recruited to participate; if samples were recruited by convenience rather than systematically (e.g., whole population or random sample), this could introduce selection bias and threaten external validity. *Response rate* refers to the percentage of those contacted who elected to participate in the study; it was calculated as the number of study participants divided by the number of people contacted. A lower response rate could suggest self-selection bias among participants, potentially inflating effects. *Random assignment* refers to whether participants were randomly assignment to treatment conditions. If participants were not randomly assignment to treatment conditions, pre-existing differences between conditions could appear to be treatment effects, creating a Type I error. *Baseline data* refers to the collection of energy use information before the beginning of treatment in order to establish a baseline to compare treatment energy use. Collecting baseline data controls for the threat of history and therefore a failure to do so could introduce bias.

The type of *control group* used is also an important variable, as comparing a blind control to an active treatment group could result in a Type I error due to a Hawthorne effect, in which case being aware of being in the study (rather than the proposed intervention) affected participant response. Also, in some feedback studies, the control groups were not completely neutral; some studies also used “information-only” as a control group instead of an empty control group; 17 studies included conditions in which information was provided to subjects without feedback and, in 7 of those, the information-only group served as the only control group for the study. As such, all of these types of control groups are included in the main effects analysis and tested both blind vs. aware and info vs. empty control groups as study quality variables.

Publication Bias. Finally, two variables were included to test for publication bias: publication type and sample size. Publication type was tested because it is typically assumed that published studies will have larger effect sizes than unpublished studies (Smith, 1980). Similarly, it has been noted that studies with smaller effect sizes tend to take longer to get published (Rosenthal, 1991). Sample size is another variable that can be analyzed to test for publication bias. Studies with fewer participants have a greater likelihood of sampling error (Shadish & Haddock, 1994), but this error should be equally distributed among larger than average and smaller than average effect sizes, especially when an effort is made to include unpublished studies. However, studies with both a small effect size and a small sample size may be less likely to get published and circulated; even though a great effort was made to obtain unpublished studies, one cannot completely avoid the problem of unsuccessful studies being hidden away in file drawers.

In summary, the purpose of the present study was twofold: (a) to estimate the overall effect size of energy feedback on energy conservation using all available published and unpublished studies, to evaluate the precision of this effect size estimate by the confidence interval around the estimate, and to subject the obtained effect size to null-hypothesis significance testing using both random and fixed-effects models; and (b) to examine the potential impact of treatment and study variations using moderator analysis of the aforementioned variables.

Method

Meta-analysis is an established method for statistically comparing and combining research results with the goal of identifying patterns among studies, revealing sources of disagreement, and resolving conflicts or questions in theory about the relationship between an independent and dependent variable or set of variables. The method generally consists of translating individual study results into standard effect sizes and then comparing these effect sizes, both individually and in conjunction with a series of moderating variables present in the studies analyzed.

Literature search

Following procedures and guidelines suggested by Cooper (2010), the following six methods were used to locate relevant studies: (1) keyword search in reference databases, (2) conference program search, (3) backward search, (4) forward search, (5) emails to study authors, and (6) personal contacts. This search included articles published between 1976 (the year the first identified study was published) and 2010.

The original source (and inspiration) for this study was the Darby (2006) literature review on feedback and energy conservation (discussed above in literature review). An examination of the reference list of this review identified 28 relevant papers.

Next, keyword searches were conducted in PsycINFO, JSTOR, Web of Science, PubMed, and Google Scholar using the keywords *energy conservation* and *feedback* simultaneously, which returned 27 relevant results, including two additional review articles (Abrahamse et al., 2005; Fischer, 2008). Due to the nature of this research area, governments, utilities, and private firms also have performed studies, many of which do not appear as academic publications. Therefore, a general Google search was also performed using the same keywords, resulting in an additional five studies.

Searches also were conducted of the proceedings for the European Council for an Energy-Efficient Economy (ECEEE) and American Council for an Energy-Efficient Economy (ACEEE) conferences, as well as from the programs of the Behavior Energy and Climate Change (BECC) and Home Energy Display (HED) conferences, which are considered the leading conferences in this field. Eleven new papers were found using this method.

Next, backward searches were performed on all papers that were identified as either an empirical study or review of energy feedback. In the backward searches, the reference sections of selected papers were reviewed for additional potential studies. Forty-seven papers were identified by this method. In particular, the reference sections of the following three review articles included new and useful references: Abrahamse et al., 2005 (14 papers), Ehrhardt-Martinez et al., 2010 (9 papers), and Fischer, 2008 (6 papers).

In addition to the backward searches, forward searches were conducted on the five primary literature reviews of energy feedback conducted to date (Abrahamse et al., 2005, Ehrhardt-Martinez et al., 2010, Darby, 2006, EPRI, 2010; Fischer, 2008). This search method utilized Web of Science and Google Scholar to identify papers that have cited these review articles since their publication. Nine papers were located through this method.

At this point, the preliminary list of 127 potential feedback studies was compiled and sent to the corresponding authors of all identified studies and literature reviews for which contact information was available. The email request asked for any additional published and/or unpublished papers or information on relevant studies or active researchers in the field. Thirty-one articles were identified using this method. Three active researchers in this area (S. Darby, C. Fischer, and W. Schultz) were especially helpful at this stage.

Finally, informal inquiries via email and discussion with colleagues and personal contacts, including colleagues at our university, researchers at three energy-related conferences, and the demand-response manager of our local electricity provider, identified 14 additional papers, bringing the total number of papers initially compiled and reviewed to 172.

Inclusion criteria

Of the 172 papers originally collected, 69 were identified as review articles or unrelated research articles and set aside for reference. The remaining 103 were identified as empirical studies on energy feedback and examined independently by the first and second author for inclusion in the meta-analysis. Discrepancies regarding inclusion of a particular paper were resolved by discussion. To be included in the meta-analysis, a study had to meet the following criteria (the number of studies excluded due to each criterion is in parentheses):

1. The study must have been conducted using an experimental design. Case studies, survey data, and purely qualitative studies were excluded (5).
2. The study must have been conducted as a naturalistic field study measuring subjects' actual energy use in the home. Studies that were conducted in a lab-based or office setting were excluded. (7).

3. The study must have used the quantity of household energy use (appliance-specific or overall/household energy usage) for its dependent variable. Studies that measured only load-shifting behavior from peak to non-peak hours were excluded (7).
4. The study must have used feedback as the independent variable. Therefore, studies had to include at least one group in which feedback was provided (alone or in combination with other strategies) and the feedback treatment could be isolated for analysis (9).
5. The study must have included a neutral control group that did not receive any form of feedback. Participants in the control group may have either received no intervention at all or received a non-feedback intervention (e.g. information) (16).
6. The study must have provided sufficient statistical data to calculate an effect size. Authors of studies who met all other inclusion criteria were emailed in an attempt to garner such data whenever possible (7).

Altogether, 51 papers were excluded according to the criteria above; the remaining 52 were included. Of these, 13 papers were recognized as reports of overlapping data (e.g. two or more publications from the same data set); these papers were grouped together and given the same study code. Conversely, multiple studies from the same article were coded and analyzed separately if different samples were used, as was the case in four of the papers reviewed (three that included two studies and one that included three studies). A total of 42 independent studies from 52 research articles and reports were included and coded in this meta-analysis.

Coding Procedure

A detailed coding sheet was developed based on established guidelines of meta-analysis (Wilson, 2009); each study was coded according to the same criteria. For each study, the following information was extracted and coded:

1. Report identification: publication year, author(s), publication type, funding
2. Study setting: study year, location, population, home type, sample size
3. Study participants: demographics, housing characteristics
4. Methodology: recruitment, assignment, data collection
5. Treatment: feedback frequency, medium, measurement, comparison, combination with other intervention (e.g., goal-setting, financial), granularity, and duration.
6. Dependent variable: Energy use (kWh)
7. Statistics: cell means and standard deviations, inferential statistics

In some cases, information being coded for a particular study either was not obtainable from the study report (e.g., total number of subjects contacted) or was somewhat ambiguous (e.g., random assignment); therefore, not all studies could be coded on every variable. When information was missing in a study and there was no clue to support a reasonable estimate, the information was coded as missing data. All study variables were coded by the first author. Because the coding process involved some degree of subjectivity, the second author coded 12 randomly selected studies (28%) to establish reliability. Inter-rater reliability was acceptably high (kappa > .700 for categorical variables; r > .700 for continuous variables) for all variables.

Calculating Effect Sizes

Since the included studies measured and analyzed variables in different ways that do not allow direct comparison, all study results were converted into an *r-effect* size. Since effect size represents the degree to which the tested intervention (e.g., feedback) resulted in a reduction in energy use, a *positive* effect size indicates that feedback resulted in *decreased* energy use (compared to the control) and a *negative* effect size indicates that feedback resulted in *increased* energy use (compared to the control); an effect size of zero indicates that the feedback had no effect on energy use. Although the specific feedback intervention in each study was slightly different and the measurement of the dependent variable varied by frequency (daily, weekly, monthly) and style (meter read, self-report), an *r*-effect size was calculated for each study and these methodological differences were later analyzed as moderators.

Conversions to *r-effect* sizes were calculated according to established guidelines and procedures of meta-analysis (Rosenthal, 1991; Rosenthal & Rubin, 2003). In some cases, the study report indicated that a focused test had been conducted (e.g., *t*-test, *F* test with one degree of freedom in the numerator), but rather than reporting any statistical information, it stated only that the results were either significant or non-significant. In these cases, if the result was reported as significant, the *p* value was assumed to be one decimal place smaller than the alpha value (e.g., assumed to be .049 if the test was significant at the .05 level), and the *r*-effect size was calculated according to the procedures described by Rosenthal and Rubin (2003). If the result was reported as non-significant, the effect size was assumed to be zero, which is considered a conservative and acceptable approach (Rosenthal, 1991). Because it was predicted that feedback would have a positive effect (e.g., feedback groups would decrease energy use more than control), all *p*-values calculated were one-tailed (unless otherwise noted). Both authors independently calculated effect sizes for all included studies and discrepancies were resolved through discussion.

Significance Testing

Once the effect size estimates were calculated for the individual studies, un-weighted and weighted mean *r*-effect sizes were calculated for the total effect of interventions on energy use (where studies were weighted by a function of the sample size, as described in Rosenthal, 1991). In addition, both random-effects and fixed-effects approaches to significance testing of the effect sizes were conducted. Fixed-effects analyses treat the participants in each study as the unit of analysis and are typically used when a relatively small number of studies are available (Borenstein, Hedges, Higgins, & Rothstein, 2009). Fixed-effects analyses are a more powerful test of significance but can limit generalizability of findings, as one can only generalize to similar participants in the included studies but not to additional or future studies. Random-effects analyses treat the study itself as the unit of analysis and each effect size is its own data point. With fewer data points, random-effects analyses result in decreased statistical power, but allow broader generalizability to studies not included in the analysis (Field, 2001; Hunter & Schmidt, 2000). Both analyses are included to determine whether the effects are robust under a wide range of methodological assumptions; the fixed-effects approach was computed to accommodate the small number of studies in the analysis (k = 42) and the random-effects approach was computed to increase the generalizability of the findings. Fixed-effects analyses were computed using the Stouffer method (Mosteller and Bush,1954) and random-effects analysis were conducted through a one-sample t-test using k –1 degrees of freedom on the un-weighted mean. Effects were considered significant when the p value was less than .05.

Moderator Analysis

In addition to analyzing the overall effect of feedback on energy conservation, moderator analyses were conducted to examine which variables may moderate the effects of feedback on energy conservation. A value for each variable was extracted from each study report (e.g., feedback duration, energy granularity), and moderator analyses were conducted using a fixed-effects approach; the mean-effect sizes for each level of the moderator were compared (e.g. whole-home vs. appliance specific feedback).

Table 3.1. Main Effects of Feedback and Treatment Moderators

Author & Year of Publication	n	Reported % saving	r	p	Frequency	Medium	Measurement	Comparison	Combination	Granularity	Duration
Alcott (2010)	78492	2.4%	0.0096	0.0036	Monthly or less	Bill	kWh & Cost	Historical	None	Whole-home	6-12 months
Allen & Janda (2006)	60	--	0.0007	0.4980	Continuous	Monitor	kWh & Cost	None	None	Whole-home	1-3 months
Arvola (1993; 1996a;1996b); Arvola et al. (1994)	696	2.9%	0.1018	0.0036	Monthly or less	Card	Mixed	Mixed	None	Whole-home	> 12 months
Ayres et al. (2009)	84000	1.2%	0.0091	0.0045	Monthly or less	Bill	kWh & Cost	Mixed	None	Whole-home	6-12 months
Battalio et al. (1979); Winett et al. (1978)	70	0.9%	0.0303	0.4017	1-4 times/week	Card	kWh	Historical	None	Whole-home	< 1 month
Becker (1978); Seligman et al. (1978) Study 2	80	13.0%	0.3094	0.0022	1-4 times/week	Card	Goal only	Goal	Goal	Whole-home	< 1 month
Becker & Seligman (1978); Seligman et al. (1978) Study 3	20	15.7%	0.1899	0.2113	1-4 times/week	Card	kWh	Mixed	None	Whole-home	< 1 month
Bittle et al. (1979-1980)	353	--	-0.0164	0.3794	Daily	Card	kWh & Cost	None	None	Whole-home	< 1 month
Bittle et al. (1979)	30	--	0.0366	0.4212	Daily	Card	kWh & Cost	None	None	Whole-home	1-3 months
Brandon & Lewis (1999)	120	--	0.1602	0.0403	Mixed	Mixed	Mixed	Mixed	None	Whole-home	6-12 months
Dobson & Griffin (1992)	100	12.9%	0.1968	0.0243	Continuous	Computer	kWh & Cost	None	None	Appliance	1-3 months
Haakana et al. (1997)	755	19.0%	0.0715	0.0245	Monthly or less	Card	kWh & Cost	Mixed	None	Appliance	> 12 months
Harrigan (1992); Harrigan & Gregory (1994)	71	0.0%	0.0000	0.5000	Continuous	Monitor	kWh	None	None	Whole-home	6-12 months
Hayes & Cone (1981)	40	7.0%	0.0427	0.3968	Monthly or less	Card	kWh & Cost	Historical	None	Whole-home	3-6 months

Author & Year of Publication	n	Reported % saving	r	p	Frequency	Medium	Measurement	Comparison	Combination	Granularity	Duration
Hutton et al. (1986) Study 1	371	4.1%	0.1369	0.0042	Continuous	Monitor	Cost	None	None	Whole-home	3-6 months
Hutton et al. (1986) Study 2	377	5.0%	0.1387	0.0035	Continuous	Monitor	Cost	None	None	Whole-home	3-6 months
Hutton et al. (1986) Study 3	336	6.8%	0.0235	0.3340	Continuous	Monitor	Cost	None	None	Whole-home	3-6 months
Kasulis et al. (1981)	390	--	0.0461	0.1822	Monthly or less	Bill	kWh & Cost	None	Pricing	Whole-home	3-6 months
Katzev et al. (1980-1981)	22	15.0%	0.1508	0.2525	Mixed	Card	kWh & Cost	Mixed	Other	Whole-home	< 1 month
Kurz et al. (2005)	423	0.0%	0.0000	0.5000	1-4 times/week	Card	kWh	Social	None	Whole-home	3-6 months
Mansouri, & Newborough (1999); Wood & Newborough (2003)	31	20.0%	0.2567	0.0817	Continuous	Monitor	kWh	Historical	None	Appliance	1-3 months
Matsukawa (2004)	319	1.8%	-0.0266	0.3180	Continuous	Monitor	kWh	Historical	None	Whole-home	3-6 months
McClelland & Cook (1979-1980)	101	12.0%	0.1535	0.0637	Continuous	Monitor	Cost	None	None	Whole-home	6-12 months
Midden et al. (1983)	95	13.2%	0.2148	0.0173	1-4 times/week	Card	kWh & Cost	Social	Incentive	Whole-home	1-3 months
Mountain (2007) Study 1	118	18.1%	0.1816	0.0245	Continuous	Monitor	kWh & Cost	None	None	Whole-home	> 12 months
Mountain (2007) Study 2	110	2.7%	0.1882	0.0245	Continuous	Monitor	kWh & Cost	None	None	Whole-home	> 12 months
Mountain Economic Consulting (2006)	552	6.5%	0.0838	0.0245	Continuous	Monitor	kWh & Cost	None	None	Whole-home	> 12 months
Nexus Energy Software (2006)	249	19.0%	0.1420	0.0125	Mixed	Mixed	kWh & Cost	Mixed	Goal	Whole-home	3-6 months
Pallak & Cummings (1976); Pallak et al. (1980)	109	16.0%	0.2538	0.0039	1-4 times/week	Monitor	kWh	None	Commitment	Whole-home	1-3 months
Parker et al. (2008)	17	7.0%	0.4803	0.0219	Continuous	Monitor	kWh & Cost	Historical	None	Whole-home	> 12 months

Author & Year of Publication	n	Reported % saving	r	p	Frequency	Medium	Measurement	Comparison	Combination	Granularity	Duration
Robinson (2007)	141	--	-0.0830	0.1640	1-4 times/week	Mixed	Mixed	Mixed	None	Whole-home	3-6 months
Seaver & Patterson (1976)	75	--	0.0617	0.2971	Mixed	Card	kWh & Cost	Historical	None	Whole-home	3-6 months
Seligman & Darley (1977); Seligman et al.(1978) Study 1	29	10.5%	0.4317	0.0199	Daily	Card	Goal only	Goal	None	Whole-home	< 1 month
Sexton et al. (1987) Sexton et al. (1989)	269	--	-0.0803	0.0946	Continuous	Monitor	Cost	None	Pricing	Whole-home	6-12 months
Sipe & Castor (2009) Study 1	305	--	0.0702	0.1108	Continuous	Monitor	kWh & Cost	None	None	Whole-home	6-12 months
Sipe & Castor (2009) Study 2	588	--	-0.0156	0.3529	Continuous	Monitor	kWh & Cost	None	None	Whole-home	6-12 months
Summit Blue Consulting (2009)	85000	--	0.0941	0.0001	Monthly or less	Bill	kWh & Cost	Mixed	None	Whole-home	6-12 months
Ueno et al (2005); Ueno et al. (2006)	19	12.0%	0.4099	0.0407	Continuous	Computer	kWh & Cost	Mixed	None	Appliance	6-12 months
van Houwelingen & Van Raaij (1989)	235	6.2%	0.1206	0.0325	Mixed	Mixed	Mixed	Mixed	Goal	Whole-home	6-12 months
Wilhite & Ling (1995)	1284	10.0%	0.0549	0.0245	Monthly or less	Bill	Mixed	Mixed	None	Whole-home	> 12 months
Winett et al. (1982) Study 1	49	--	0.1598	0.1364	Daily	Card	kWh & Cost	Goal	None	Whole-home	1-3 months
Winett et al. (1982) Study 2	35	--	0.0202	0.4541	1-4 times/week	Card	kWh & Cost	Goal	None	Whole-home	< 1 month
Unweighted r-effect size			0.1174								
Weighted r-effect size			0.0396								
Fixed effects p-value				<.001							
R&om effects p-value				<.001							
Reported % savings		9.0%									
Total n	256536										
Total k	42										

-- Not reported

Results

Overall Effects of Feedback

A main-effect size for feedback on energy conservation was calculated for each of the 42 studies by comparing all feedback conditions with all control conditions in each study. In the cases where additional interventions were included in the study (e.g. goal-setting), data from these groups were only included if the main effect of feedback could be tested (e.g. feedback + goal-setting vs. goal-setting only). The total number of participants across the 42 studies was 256,536, with a median of 119 participants per study. A list of all included studies are provided in Table 3.1, along with each sample size, percent reported savings, *r*-effect size and associated statistical significance, and values for each treatment moderator.

Effect sizes for the main effect of feedback ranged from -.0803 to .4803; half of these were significant at the $p < .05$ level. The 42 studies had an un-weighted mean *r*-effect size of .1174 and a weighted mean *r*-effect size of .0396; this effect was highly significant in both fixed ($z = 8.347$, $p = 3.63 \times 10^{-17}$) and random-effects analysis ($t = 5.7441$, $p = 4.99 \times 10^{-7}$) indicating that feedback interventions, in general, do significantly decrease residential energy use.

However, a high level of variability was found across the individual effect sizes; five studies (12%) had a negative effect size, two (5%) had an effect size of zero, and 35 (83%) had a positive effect size. Of those with a positive effect size, 14 (33%) represented a small effect, three (7%) represented a medium effect, and three (7%) represented a large effect, according to Cohen's guidelines for statistical power (Cohen, 1998; 1992). A statistical test of heterogeneity among the effects was highly significant ($C^2 = 469.2089$, $p = 4.35 \times 10^{-74}$). These findings suggest that the effect of feedback on energy conservation may vary based on variables related to the study setting, quality, methodology, and treatment, justifying additional analyses to identify which specific variables may moderate this effect.

Moderator Variables

A series of moderator analyses were performed to better understand when, how, and to whom feedback is most effective. All of the proposed treatment and study quality variables introduced above were examined as potential moderators of the overall effect of feedback on energy conservation. Descriptions of analyses for each moderator variable are described in the sections below; Table 3.2 presents statistical results all moderator analyses.

Treatment variables. Seven treatment variables that described differences in the way that feedback was provided were tested: (1) frequency, (2) medium, (3) measurement, (4) comparison, (5) combination with other intervention, (6) energy granularity, and (7) duration.

Frequency of feedback was categorized as monthly or less (8 studies), 1-4 times per week (8 studies), daily (4 studies), or continuous (17 studies); five studies could not be categorized because frequency was mixed. Analysis revealed a significant linear relationship between feedback frequency and effect size (p = .0463); the studies that provided feedback monthly or less had the lowest effect size (r = .0537) compared to studies with feedback provided 1-4 times per week (r = .1169), daily (r = .1529) and continuously (r = .1293). Paired comparisons showed no significant difference between the three most frequent feedback groupings (continuous, daily, and weekly, all p's > .500). When collapsing these three groups into one "frequent feedback" group, the average effect size for this frequent-feedback group (r = .1292) was significantly larger than studies providing only monthly (or less) feedback (r = .0537, p = 0.0084).

Feedback medium was categorized as enhanced billing (e.g., feedback provided via an *enhanced* utility company bill, such that the feedback was part of the utility bill but the bill contained more detailed information/feedback than the standard utility bill, 5 studies), card (e.g., door hanger or other card/sign provided to the household by the researchers, 15 studies), monitor (e.g., electronic device or product that provides energy information, 16 studies), or computer (e.g., software or web-enabled program on the subjects' personal home computer, 2 studies); 4 studies could not be categorized because medium was mixed. Comparison of these groups was statistically significant (p = .0217); studies with feedback given by bill had the lowest effect size (r = .0428), followed by monitor (r = .1153), card (r = .1203), and finally computer (r = .3034), which had the highest effect size.

Energy measurement was coded as cost only (5 studies), kWh only (7 studies), and kWh and cost combined (23 studies); 5 studies could not be categorized because measurement was mixed and 2 did not provide an energy measurement (goal only). Analysis indicated no significant differences among these three energy-measurement groups (p = .3434). In addition, 3 studies that combined environmental information with cost/energy measurement were compared to the 32 studies that did not, but no significant difference was found (p = .1801).

Comparison (e.g., historical, social, goal) was analyzed in two ways. First, the overall effect of having a comparison was significant (p = .0315); the 19 studies whose feedback had a comparison (r = .1466) had higher effect sizes than the 17 studies that did not have a comparison (r = .0832); 6 studies could not be categorized because comparison message was mixed. Second, the effect of comparison type was marginally significant (p = .0742); among the studies that did have comparisons, the 4 studies with goal comparisons had the highest average effect size (r = .2303), followed by the 7 studies with historical comparison (r = .1409), further followed by the 2 studies with social comparison (r = .1074); 12 studies could not be coded because comparison type was mixed.

Table 3.2. Moderator Analysis

Variable	Grouping			Moderator analysis	
	Group	***k***	**mean *r***	**z**	**p**
Treatment variables					
Feedback frequency	Monthly or less	8	.0537	1.6817	.0463
	1-4 times/week	8	.1169		
	Daily	4	.1529		
	Continuous	17	.1293		
Feedback medium	Bill	5	.0428	2.0210	.0217
	Card	15	.1203		
	Monitor	16	.1153		
	Computer	2	.3033		
Energy measurement	Cost only	5	.0745	0.4031	.3434
	kWh only	7	.1006		
	kWh and cost	23	.1147		
	Environmental info	3	.1512	0.9151	.1801
	No environmental info	32	.1019		
Comparison message	No comparison	17	.0822	1.8594	.0315
	Comparison message	19	.1509		
	- Social	2	.1074	1.4457	.0742
	- Historical	7	.1409		
	- Goal	4	.2303		
Combined intervention	Feedback only	37	.1074	2.1677	.0151
	Feedback + Goal	5	.2255		
	Feedback + Incentive	2	.2402		
Energy granularity	Appliance-specific	4	.2337	1.5821	.0568
	Whole home	38	.1045		
Feedback duration	< 3 months	14	.1597	2.6145	.0045
	3-6 months	10	.0482		
	6-12 months	11	.0847		
	> 12 months	7	.1660		

Variable	Grouping			Moderator analysis	
	Group	*k*	mean *r*	z	p
Study Quality					
Sampling strategy	Convenience (low)	4	.1339	-0.6713	.2510
	Systematic (high)	35	.0908		
Response rate	Below 50% (low)	12	.0716	1.3016	.0966
	50% or higher (high)	16	.1266		
Random assignment	Not random (low)	7	.1413	-0.6855	.2465
	Random (high)	35	.1091		
Baseline	No baseline (low)	7	.0881	0.7298	.2328
	Baseline (high)	35	.1198		
Control group - aware	Blind (low)	11	.1276	-0.2563	.3989
	Aware (high)	29	.1168		
Control group - info	Information only (low)	17	.1302	-0.6970	.2429
	Empty (high)	25	.1039		
Study Quality (index)[a]				-0.3842	.3505
Publication Bias					
Publication type	Journal	24	.1089	-0.1126	.4552
	Conference	8	.1365		
	Report	9	.1321		
	Thesis	1	-.0830		
Sample Size[a]				4.1844	.0001

[a] Variable was not categorical, so no grouping variables provided.

The next treatment variable tested was combination with other intervention strategies. Five studies were identified where feedback was combined with a goal intervention (such that this "feedback + goal combo" intervention was compared to a control group)[2] and two studies were identified in which feedback was combined with an incentive intervention (such that this

[2] These include two studies—Vollink, 2004; Winett, Neale, & Grier, 1979—that were excluded from the primary meta-analysis because a feedback effect could not be isolated.

“feedback + incentive combo” intervention was compared to a control group). Effect sizes for these “combo” interventions were compared to the remaining 37 feedback-only effect sizes. The effect of combining interventions was significant (p = .0151); the feedback + goal combo interventions (r = .2255) and feedback + incentive combo interventions (r = .2402) both had higher effect sizes that studies using feedback alone (r = .1074).

Energy granularity was coded as whole home (38 studies) or disaggregated by appliance or use (4 studies). Energy granularity was found to be a marginally significant moderator of feedback effectiveness (p = .0568); studies that provided disaggregated feedback had a higher effect size (r = .2337) than the ones that provided whole-home feedback (r = .1045).

Finally, duration of feedback was categorized as less than three months (14 studies), 3-6 months (10 studies), 6-12 months (11 studies), and more than one year (7 studies). There was a significant curvilinear relationship between feedback duration and effectiveness (p = .0045); studies with a feedback duration of less than three months (r = .1597) and more than one year (r = .1660) had the highest mean effects, and studies ranging from 3-6 months (r = .0482) and from 6-12 months (r = .0847) had the lowest effect sizes.

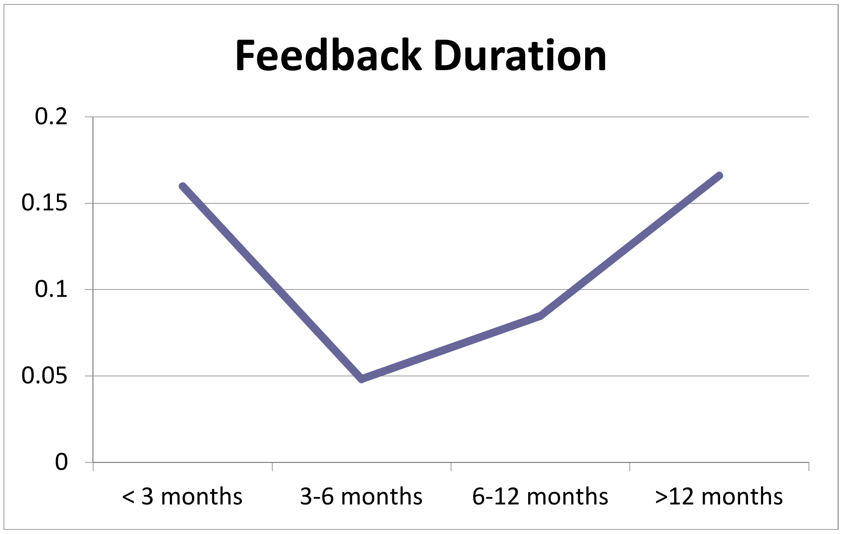


Figure 3.2. Feedback duration (x) as moderator of feedback effectiveness (y)

Study quality variables. Each study was given a quality rating based on six variables: (1) sampling strategy, (2) response rate, (3) random assignment, (4) baseline data, (5) control group – aware, and (6) control group – empty. Studies were given a score of 1 (good quality) or 0 (poor quality) for each of the variables.

Sampling strategy was coded as using either a convenience (low quality, 3 studies) or a probability (e.g., whole population or random) sample (high quality, 35 studies); 4 studies could not be rated because sampling information was not provided. Studies were coded as having a high response rate (high quality) when response rate was higher than 50% (16 studies); low-response (low quality) studies had a response rate of less than 50% (12 studies); 14 studies could not be rated because response rate information was not provided. Random assignment was coded as random (high quality, 35 studies) or non-random (low quality, 7 studies). Baseline data was coded as no baseline data (low quality, 7 studies) or baseline data collected (high quality, 35 studies). Control group was tested in two ways. In the first, control group was coded as blind when control subjects were not aware that they were participating in the research study (low quality, 11 studies) or aware when control subjects knew that they were participating in the study (high quality, 29 studies); two studies could not be categorized because control information was not provided. In the second, control group was coded as empty control when control subjects did not receive any treatment (high quality, 25 studies) or information control when control subjects received information only (low quality, 17 studies); 11 studies could not be categorized because control group was mixed. Each of the six study-quality variables was examined in relation to feedback effect size; there were no significant relationships between any of the study quality variables and study effectiveness.

To further examine the relations between aspects of study quality and effect size, the scores were then summed for a total quality score that ranged from 0 *(poorest quality)* to 6 *(best quality)* for each study. Most studies had at least one quality problem, with the mean quality rating being 3.98 out of 6.00 (range 0–6). To assess the impact of study quality on effect size, the relationship between the quality score and feedback effectiveness was examined; no significant effect was found (p = .3505).

Publication Bias. Finally, two variables were tested for publication bias: publication type and sample size. Publication type was categorized as a journal article (24 studies), conference paper (8 studies), technical report (9 studies), or thesis (1 study); differences were not significant, suggesting no bias according to publication type (p = .4552).

Moderator analysis of the number of participants in each study did reveal a significant negative relationship (p < .001); studies with larger samples had smaller effect sizes than those with smaller samples. This could suggest a biased sample—one that is missing studies that had both a small effect size and a small sample size. Therefore, a second analysis was undertaken to assess whether this effect represents a "file drawer" bias that asks the question: If it were possible to get all of the unsuccessful studies hiding away in file drawers, would the effect for feedback no longer be significant? To help answer this question, a fail-safe n (sample size) was calculated to determine the number of studies with null effects that would need to exist to make the reported feedback mean effect size non-significant (Rosenthal, 1991). With 42 studies containing feedback effect sizes and a sum of Zs of 58.8868, there would need to be 1,031 studies of comparable size with null effects hidden away in file drawers to make this feedback effect size non-significant. It seems highly unlikely that such a large number of these studies exists, suggesting that the reported mean-effect is not an artifact of publication bias.

Discussion

The current study served to apply Eco-Feedback Intervention Theory (eFIT) within the domain of residential energy consumption via statistical meta-analysis. Analyses were conducted to test the main effect of feedback on energy conservation and the effects of several variables that have been hypothesized to moderate the effectiveness of feedback. This section will review results in light of eFIT theory and a discussion of the limitations and implications follows.

Review of Findings

As hypothesized by eFIT, the main effect of feedback on energy conservation across all 42 studies was found to be highly significant. This finding also supports previous qualitative literature reviews, which found average savings across studies of approximately 10%. Although feedback was found to be effective, the significant heterogeneity in effects among studies justified further analysis into moderating variables related to treatment, study setting, methodology, and publication. These findings provide empirical support for eFIT and the role of feedback in energy conservation, and serve to clarify the direction and magnitude of the moderating variables discussed in previous literature reviews.

A number of variables moderating the effects of feedback on energy conservation were identified in this analysis. It is important to note that individual studies were not randomly assigned to different conditions or levels of each moderator, and therefore causal inference is not possible. Although questions of directionality are not an issue (it is clear that—with the exception of publication type—the moderator variable came before the dependent variable), effects due to untested variables cannot be ruled out. Moderator findings in the current study, therefore, should be viewed as a starting point for future testing rather than a known determinant of the effect.

Five general guidelines were hypothesized to govern the way in which treatment variables affected energy feedback, such that feedback would be more effective when it: (1) was more perceptible, (2) was easier to interpret, (3) induced appropriate motivations to conserve, (4) enabled actions and conservation strategies to be identified, and (5) stimulated either short term interest in learning or long term mastery and re-evaluation of self-salient goals. Findings provide qualified support for eFIT, as follows.

Frequency was proposed as a moderator of energy feedback such that more frequent feedback should draw users' attention to feedback standard gaps more often, and thus encourage greater savings. Results supported this hypothesis; frequency was found to significantly moderate feedback effectiveness such that feedback provided at least weekly was significantly more effective than feedback provided monthly or less. However, no significant difference was found between continuous, daily, and weekly feedback, suggesting that there is an upper limit to the amount of time in a week that people spend evaluating and responding to energy feedback for the purposes of reducing overall energy consumption.

The analysis of feedback medium also supported the hypothesis made by eFIT that computerized or interactive feedback may engage users more effectively and result in greater savings. Results showed that studies with feedback using the least engaging medium (a utility bill) reported the lowest average effect size, where studies with feedback using the most engaging/interactive medium (computer) had the highest effect size.

Energy measurement was predicted to moderate feedback effectiveness by helping to reduce the cognitive demands of the feedback information by linking the data to familiar units of measurement. However, this variable was not found to significantly moderate feedback effectiveness, indicating that either the units of measurement used in presenting energy feedback did not act a proxy for cognitive burden, the level of familiarity with different types of measurement is not homogenous across the study populations, or the cognitive impact of using more familiar units was not sufficient to have a significant impact. Further study would be needed to disentangle these effects.

The presence of a comparison message was hypothesized by eFIT to be integral to motivating conservation by providing a feedback-standard gap to which current behavior could be compared; thus feedback that provides comparisons should be more effective so long as the standard chosen is one that is valued by users (e.g., Kluger & DeNisi, 1996; see also Schultz, 2010). The overall effect of having a comparison message was found to be significant, supporting eFIT. The type of comparison message was marginally significant; goal comparisons had the highest average effect size, followed by historical and then social comparisons. This may be an indication of the relative importance and relevance of these different types of comparison messages, but may also be indicative of the size of the gap highlighted by the comparison (e.g., goal comparisons may have larger feedback-standard gaps that social or historical comparisons). Further research would be needed to separate the impact of comparison type, relevance, and feedback-standard gap size. Since a great deal of attention has been given to the use of socially comparative feedback (Allcott & Mullainathan, 2010), this is a highly relevant topic and one that requires further research to investigate in randomized experiments.

eFIT also suggests that motivation may be maximized via combination with other interventions, such as goal setting and/or provision of incentives. Both strategies were found to moderate the effectiveness of feedback. Concerns that the provision of incentives may undermine intrinsic motivation were not supported here; however, this may be due to a general lack of intrinsic motivation amongst feedback users in the included studies. Further research on both the type and level of motivation induced by different strategies may be beneficial to further improve understanding about the combination of strategies. In addition, future studies can test pre-existing levels of intrinsic motivation to test whether that moderates the effectiveness of extrinsically-oriented interventions, such as the provision of external incentives.

Feedback granularity was proposed to moderate feedback effectiveness such that more granular information would better support users' ability to identify specific behavior changes to make. The findings suggest support for eFIT: granularity was found to be a marginally significant moderator of feedback. The marginal significance could be due to the low number of studies that included appliance-specific feedback (k = 4), or it could be because this type of information may only be necessary at particular points in time when users are going through a learning process. Further research is needed to provide a more accurate picture of how users interact with more granular feedback and to prove the robustness of this effect.

Finally, duration was found to significantly moderate the effectiveness of feedback, but not in a direct linear relationship. Rather, analysis identified a significant curvilinear relationship; studies less than three months and more than one year in duration were more effective than those lasting 3-12 months. This provides support for eFIT in two ways—feedback in the short term is new, interesting, and engaging, but after time, participants may become bored and drop off from participation. However, feedback provided for longer time periods may allow habits to be created and maintained, thus leading to a rebound in effect size.

Limitations and Suggestions for Future Research

As with all meta-analysis, issues related to missing data, small numbers of studies for each moderator, correlations among moderator variables, and differing procedures between studies all decrease the ability to make definitive declarative statements. However, the results presented clearly meet the requirements of the Promising Practices Network (PPN, 2012), in that: (1) they represent an associated change in the dependent variable of more than 1%, (2) changes are significant at the $p < .10$ level, and (3) the samples exceed 10 people in both the treatment and control groups.

As meta-analysis is used to aggregate findings among results of multiple studies that use different procedures to test a common hypothesis, results are often referred to as *synthesis-generated evidence*, as opposed to the *study-generated evidence* that comes from the individual studies which are analyzed (Cooper, 2010). While only study-generated evidence is able to make causal attributions (as the variation between study procedures present potential third variables confounding results), synthesis-generated evidence is extremely useful in exploring associations not tested in individual studies, thus providing nuanced and guided suggestions for future empirical research. As explored in the following paragraphs, the current meta-analysis identified five such primary suggestions: (1) factorial designs isolating treatment variation between conditions, (2) greater attention to design and presentation of feedback displays, (3) collection of multiple dependent variables to allow testing of mediation, (4) repeated and persistent data collection to assess long-term impacts, and (5) comprehensive presentation of methodology and results to enable greater replication and interpretation of findings.

Factorial designs. A major limitation identified with the existing studies included a general lack of theoretical integration and subsequent failure to fully test hypotheses through isolating variables within treatment conditions. Moderator analysis in a meta-analysis is essentially correlational; given that studies were not randomly assigned to different levels of the moderator, causation cannot be inferred. However, treatment variables can be directly tested by incorporating them into the research design of primary studies. Among the included studies, the treatment conditions were often confounded (e.g., goal-setting and incentives), preventing study authors from determining which strategy was responsible for treatment effects. Of the 22 studies that had more than a single treatment group, 17 featured designs in which treatment groups received different conditions (e.g., control, feedback, feedback plus rebate) but without fully crossing conditions in order to isolate the treatment effect of each variable. An additional nine studies were excluded from analysis because feedback was tested in a between-subjects design, but it could not be isolated for analysis due to confounding variables.

As such, factorial designs are recommended in future research to test research hypotheses and to isolate treatment conditions. To fully understand the interaction between feedback and incentives, for example, one must not only include a control group and one that receives feedback and incentives, but also groups which receive only incentives and only feedback. Completely balanced designs allow for the variables themselves as well as the interactions between variables to be better understood. Only five studies utilized a complete multi-factor ANOVA design or multivariate regression model to isolate and analyze the relationship between conditions. Four studies (Becker & Seligman, 1978; Kurz et al., 2005; Mansouri & Newborough, 2003; Winett et al., 1982) tested a factorial design with feedback and another intervention strategy and one study (Robinson, 2007) included a factorial design of comparison message (historic vs. social) x medium (email vs. mail). Such studies are essential for a greater understanding of the many variations in which eco-feedback can be provided and the interactions among variables.

Design and Presentation. As suggested by eFIT, the way in which feedback information is presented to users can have an impact on the way in which it is perceived and interpreted, and its subsequent impact on motivation and action. However, there has been limited work investigating responses to different types of feedback displays, beyond energy measurement and comparison message. Froehlich, Findlater, & Landay (2010) found that the research in "environmental psychology has largely focused on the effect of the feedback intervention itself" and not on "the production of the eco-feedback artifact" (p. 5). Specifically, they found that only half of the environmental-psychology papers included a graphic or description of the feedback interface itself and of those that did describe the interface, the most common designs were bar or line graphs with usage breakdowns and simple LCD displays that lacked the interactivity and complexity present in both the new types of feedback in the marketplace as well as in papers coming out of the human-computer-interaction field. A logical first step is an exploration of the types of feedback that can be tested. Chapter 4 addresses this need, introducing an empirically derived taxonomy from analysis of 196 distinct eco-feedback products and platforms.

The few studies that have investigated displays did find differences in the effects of feedback based on the type of graph used (Egan, 1998) and comparing ambient (e.g., light changing color) to factual (numbers indicating kWh consumption) feedback (Ham & Midden, 2010). As indicated by these studies, successful design of energy feedback technologies can greatly benefit from psychological testing of the designs being used most in practice so that feedback design can take into account principles drawn from cognitive and social psychology. As such, it is suggested that psychologists work more closely with engineers and designers and to test theoretically derived design parameters in experimental settings.

Mediation Testing. Another limitation of the studies analyzed was the lack of sufficient mediation analysis to examine the role of the form of user experience as well as changes in attitudes, knowledge, and behaviors. It is important to include self-report measures to assess the psychological determinants of behavior and their relationship to feedback. Little is still known about the processes or mechanisms (mediators) of feedback that guide and lead to behavior change. Although the ultimate goal of feedback interventions is energy savings, it is important to understand why behavior is (or isn't) changing and what (if any) relationship between feedback and behavior change exists. If it is hypothesized that feedback will reduce energy use through cognitive dissonance, for example, then assessing cognitive dissonance in participants would be a simple and effective way of testing this hypothesis. Hypotheses about the role of increased knowledge (both general energy knowledge and knowledge about specific conservation behaviors) or motivation (e.g., saving money, helping the environment, reaching personal goals) could also be tested via a self-report measure before, during, and/or after the feedback intervention. Chapter 6 further discusses this need and introduces a Usability Perception Scale (UPscale) for assessing user experience of feedback displays.

Repeated and Persistent Data Collection. Most studies measured behavior during or immediately after the intervention had taken place; just five of 42 studies tested for persistence of effects after the intervention had ceased (Hayes & Cone, 1981; Katzev et al., 1979-1980; Kurz et al., 2005; Winnett et al., 1982). For those studies, the effect size was higher during the feedback intervention (r = .0790) than during the follow-up period (r = -.0121). However, this difference was not significant (p = .1850); it is unclear whether feedback across other studies would remain effective over the lifetime of a consumer or household. It is suggested that future research collect data more often and for a longer period of time, to examine the long-term effects of feedback as an intervention strategy, both during and after the provision of feedback.

Such studies may further assist in identifying the psychological determinants of behavioral impacts. If feedback serves as a learning tool (e.g., providing knowledge about specific behaviors), one would expect feedback to provide diminishing returns, such that the effects begin to fade after the subjects have learned everything they can from the information. However, if the role of feedback is to provide ongoing motivation for continued behavior, then one would expect energy savings to correlate directly with the provision of feedback, remaining stable as long as it is provided and rebounding back up when the feedback is removed. Repeated and persistent data collection, along with additional self-report data collection about motivation and user experience (see above), could help to provide clarity around the various mechanisms by which feedback interventions operate over time. Although not experimentally manipulated, Chapter 5 explores some of these issues through qualitative analysis from survey data of 86 naturalistic users of feedback, exploring questions related to motivation, user experience, and continued product use.

Improved Reporting. The final suggestion is for more comprehensive presentation of methodology and results to enable greater replication and interpretation of findings. Many studies failed to present a clear and comprehensive report of the methodologies employed in recruiting and assigning subject to conditions as well as the specific details of the intervention strategies tested. As indicated above in the results section, several studies could not be coded on key variables due to missing data (e.g., 33% did not report response rate). Such omissions prevent thorough and comprehensive analysis and replication. It is imperative that authors be clear about their target populations, recruitment and assignment strategies, response rates of participants, and the specific details of both the independent (treatment) and dependent (outcome) variables in the study.

Additionally, the presentation of statistical data was inconsistent; only a handful of studies reported means and standard deviations for the treatment groups, which is considered standard practice in the presentation of experimental research. Seven studies were excluded for not providing sufficient statistical data to calculate an effect size. The presentation of methodology and results of any statistical (or qualitative) analysis should be clear and comprehensive, in order to allow transparency in assessing and analyzing study findings. Simply saying that an intervention was "effective" is not as precise as providing the means and standard deviations for the treatment and control conditions or telling the reader which inferential tests were used (e.g., *t*-test, ANOVA), along with provision of the test statistics and associated *p*-value. More than a suggestion, this is a strong request of future researchers in this area.

Conclusion

Overall, results showed significant empirical evidence that feedback is an effective strategy for promoting energy conservation behavior, with a mean effect size of .1148 across 42 studies. The analysis also provides empirical support for eFIT, such that feedback is most effective when it is easily perceived, interpreted, motivational, and helps users identify actions – this can be done by giving feedback frequently, combining it with goal-setting or external incentive interventions, providing historical or goal-based comparisons, and giving information about appliance-specific behavior. In addition, several important limitations were introduced that suggest promising directions for future research, including those addressed in the subsequent chapters of this manuscript.

CHAPTER 4: Taxonomy of Energy Feedback Technology

As feedback technologies are becoming increasingly ubiquitous in our society, with a growing capacity to leverage personalized energy information, there is an urgency to ensuring that they are utilized to their full potential. The meta-analysis presented in the previous chapter found that the effectiveness of feedback varies based on the type of feedback provided and past reviews have proposed categories to better understand and distinguish between them. However, current classifications of feedback lack the technological sophistication to account for the diversity in available products and platforms. While there is a growing body of research on the potential effectiveness of feedback in trials, there has been little research into the actual products and platforms available in the marketplace.

The goal of this chapter is to analyze current energy feedback technologies and present a comprehensive taxonomy of feedback technology based on product characteristics. It reviews previous literature on energy feedback, focusing on past attempts to define, describe, and categorize feedback, and then introduces and describes a content analysis and classification of currently available feedback technology. Using data collected from 196 feedback technologies (both products and platforms), it presents a list of energy-feedback characteristics and key characteristics for categorization as well as a taxonomy structure of energy feedback that incorporates these characteristics.

Past Research on Energy Feedback

Over a hundred empirical studies of energy feedback have been conducted over the past 40 years and over 200 articles have been published about energy feedback during that time. Reviews of this research have found that feedback is effective, on average, with effects ranging from increases in energy use to savings of over 20% (see Chapter 3). However, definitions, descriptions, and categorization of feedback vary from report to report. Operational definitions for energy feedback, as well as key characteristics and categories, are lacking. Before presenting the current analysis, this chapter will review past attempts to define, describe, and categorize energy feedback. For the purposes of the current discussion, a characteristic is defined as a single variable with two or more levels, and a category or type as a group of products or platforms that share one or more characteristics.

Definitions of Feedback

While research on energy feedback is abundant, there seems to be gap in the literature regarding a specific operational definition of energy feedback. Both Darby (2006) and EPRI (2009) rely on dictionary definitions of feedback; although technically accurate, they are not specific either to energy or to consumer-facing information (e.g., that which involves people in the process). EPRI (2009) and Abrahamse et al. (2005) further characterize energy feedback as household-specific electricity consumption information and Ehrhardt-Martinez et al. (2010) define feedback in the context of consequence strategies for behavior change, which "attempt to change behavior by influencing the determinants of a behavior after the behavior in question has been performed" (p. 38). These definitions focus the definition on home energy use and incorporate motivational element of feedback, but are still vague with regards to what kind of information constitutes feedback.

Without a clear operational definition, it is difficult to determine what exactly distinguishes feedback from energy information or control. Areas of ambiguity include (but are not limited to) *estimated* feedback (e.g. carbon calculators, based on user input) and *automated* systems (e.g. appliances that receive and respond to feedback directly, removing the user from the loop). Within the literature, the feedback system relates to the energy consumption of a dwelling; therefore an *energy* feedback technology is one that receives information about the actual energy consumption of the dwelling (or part of the dwelling). Likewise, definitions focus on the role of feedback in informing consumers and affecting behavior; therefore a definition should include provision of this energy data back to the consumer. Therefore, energy feedback is defined herein as information about *actual energy use* that is collected in some way and provided back to the *energy consumer*.

Reviewing this definition helps to provide some clarity to ambiguous areas in past literature. Estimated feedback, which collects approximated energy-usage information from the user (therefore not actual energy use), and automated systems that completely remove the user from the feedback loop (i.e. not providing data back to the energy consumer) are, consequently, not classified as a feedback technology.

Characteristics of Feedback

Several authors over the past decades have discussed specific characteristics of feedback that may be most effective in promoting energy conservation or distinguishing between types of feedback technologies (see Table 3.1). The most commonly cited characteristic was immediacy (Darby, 2001, 2006; Donnelly, 2010; Ehrhardt-Martinez et al., 2010; EPRI, 2009; LaMarche et al., 2011; Stein & Enbar, 2006), which breaks down feedback into the two categories of direct (immediate) and indirect (not immediate). Additional characteristics relate to the frequency and duration of feedback collection and provision, the type of information provided, and the messages used, and variables related to both the visual display and hardware components of feedback.

It is important to note that non-technological factors can also impact the effectiveness of feedback. The previous chapter identified several such factors, including study duration, frequency of provision, combination with goal-setting and incentives, and the population from which the study sample was drawn. As most of these analyses are conducted from between-study (vs. within-study) comparisons, further research is needed to clarify the role of these non-technological variables, both separate from and in conjunction with any identified difference in treatment effect associated with the type of feedback, as will be discussed in this paper.

The current paper focuses on the type of feedback product or platform used, which has been identified as one of the key variables moderating the effects of feedback. Several authors have proposed specific categories, or types, of feedback to help distinguish among the many available technologies available. Although specific terms are used to describe different types of energy-feedback systems, they are not always clearly defined and authors may use different terms to describe similar functions, or similar terms to describe different functions. Before developing and presenting a revised taxonomy structure of feedback technologies, current types and typologies of energy feedback and discussed.

Types of Feedback

The most commonly cited types of feedback are *direct* and *indirect* feedback. Darby (2001, 2006) uses the term *indirect feedback* to refer to frequent utility bills, based on accurate usage data. EPRI (2009) uses it to categorize both standard and enhanced billing (billing with additional information and advice) as well as estimated appliance-specific feedback (e.g. through the use of home audit software). The ACEEE (Ehrhardt-Martinez et al., 2010) distinguishes between indirect feedback provided by the utility (offering improved customer service, better outage, power quality, more frequent meter readings, feedback to customers), and indirect feedback provided by vendors (offering improved feedback information, advice, estimated disaggregation, goal-setting capabilities, and social and historic comparisons).

Table 4.1. Characteristics identified during literature review

Characteristic Name	Characteristic Definition	Characteristic Levels	References
Immediacy*	How soon after an action feedback is provided	Direct, Indirect	Darby, 2006; Donnelly, 2010; Ehrhardt-Martinez et al., 2010; EPRI, 2009; LaMarche et al., 2012; Stein & Enbar, 2006
Data Collection*	How feedback information is collected	Estimated Feedback, Sensor	EPRI, 2009; Hochwalliner & Lang, 2009; LaMarche et al., 2011
Frequency	How often feedback is given	Continuous, Daily, Weekly, Monthly, Bimonthly	Fischer, 2008; Fitzpatrick & Smith, 2009; Froehlich, 2009
Duration	How long feedback is provide	Weeks, Months, Years	Fischer, 2008
Content (Measurement Unit)	The units of measurement the feedback is given in.	Electricity, Cost, Environmental Impact, Temperature, Utility Messages	Fischer, 2008; Fitzpatrick & Smith, 2009; Froehlich, 2009; Herter & Wayland, 2009; Stein & Enbar, 2006
Breakdown (Data Granularity)	The resolution of the feedback data	Room, Appliance/Device Level, Time of Day, Building, Indoor/Outdoor, Rate Period	Fischer, 2008; Fitzpatrick & Smith, 2009; Froehlich, 2009; Herter & Wayland, 2009; Hochwalliner & Lang, 2009
Presentation Mode (Visual Design)	The format feedback is presented in	Numeric, Graphic, Ambient, Artistic	Fischer, 2008; Fitzpatrick & Smith, 2009; Froehlich, 2009; Wood and Newborough, 2007
Presentation Medium	The medium through which feedback is presented	Electronic Media, Written Material, In Home Display, Mobile Apps, Web Portals and Social Media	Fischer, 2008; Froehlich, 2009; Hochwalliner & Lange, 2009; LaMarche et al., 2011

Characteristic Name	Characteristic Definition	Characteristic Levels	References
Comparisons	Whether feedback is measured against some standard	Historical, Normative, Forecast, Personal Goals; Other Buildings, Appliances, Rates or Periods,	Wood and Newborough, 2007; Fischer, 2008; Fitzpatrick & Smith, 2009; Froehlich, 2009; Herter & Wayland, 2009
Additional Information (Recommending Action)	Whether information other than usage	Incentives; Goals; Commitment; Advice	Fischer, 2008; Froehlich, 2009; Shultz, 2010
Location	Where the feedback display is found	Activity-Based, Embedded, Central, Localized, Independent	Wood and Newborough, 2007; Fitzpatrick & Smith, 2009; Froehlich, 2009
Push/Pull	Whether feedback is sent to the user or the user navigates to it	Push, Pull	Froehlich, 2009
Control Device (Automation)	Whether the feedback system enables control	Central, Device Level, On-board, Low Automation, High Automation, No Automation	Donnelly, 2010; Ehrhardt-Martinez et al., 2010; LaMarche et al., 2011
Feedback Level	Whether feedback is specific to an action or summative	Low-level Feedback, High-level Feedback	Froehlich et al., 2010
Communications	Devices used to enable data transformation	Fixed, Wireless, Gateways, Range Extenders, Home Area Networks	Hochwalliner & Lange, 2009; LaMarche et al., 2011
Communication Protocol	Standards used to enable data transmission	X10, UPB, Insteon, Z-Wave, Zigbee	LaMarche et al., 2011

*Characteristic names not used explicitly by authors

In contrast to indirect feedback, Darby (2001, 2006) defines direct feedback as feedback that is “immediate, from the meter or an associated display monitor” and “available on demand”. EPRI (2009) defines direct feedback as “feedback that is provided real-time or near-real-time”. The ACEEE build on this to further state that direct feedback systems “provide energy use information at the time of consumption (or shortly after consumption)” (Ehrhardt-Martinez at al., 2010). The terms *direct* feedback and *real-time* (or near real-time) feedback are therefore taken to be synonymous.

The terms *in-home display, in-home energy display* (Ehrhardt-Martinez et al., 2010), and *home energy display* (LaMarche et al., 2011), are all used to refer to an independent display that provides real-time energy-consumption information. These systems tend to be composed of a sensor as well as a display, which communicate wirelessly. The sensors tend to use current clamps to monitor the home’s main circuit panel, though some systems use optical sensors to track the power meter. They tend to provide whole home energy feedback, though some systems have extra clamps for measuring individual circuits and are therefore capable of providing a breakdown by circuit (Donnelly, 2010). Darby (2006) uses the terminology *direct displays*, which denotes a freestanding display, supplemental to the electricity meter, providing information on electricity and gas consumption.

Wood and Newborough (2007) use the term *Energy Consumption Display* to refer to anything that provides energy feedback using a technological format. They further distinguish between central displays (i.e. displays placed in a central location in the home) and activity-based displays (i.e. displays located next to the activity about which feedback is provided). Activity-based displays, defined as devices which sit between the wall outlet and an appliance (or group of appliances) and measure the energy consumption of that appliance (or group of appliances), have also been called plug-in electricity usage monitors and watt-meters (Hochwallner, 2009), plug monitors, outlet-level monitors and outlet readers

(LaMarche et al., 2011), plug-in devices (Fitzpatrick & Smith, 2009), and distributed direct sensors (Froehlich et al., 2011). When these *plug-load monitors* also offer control or automation, they are sometimes called smart plugs/sockets/outlets/strips (Donnelly, 2010; LaMarche et al., 2011), a type of *smart-device*.

Other types of *smart-devices* incorporate novel sensing and control algorithms for direct feedback and automation (Badami & Chbat, 1998); these include smart thermostats, smart lights, and smart appliances (Ehrhardt-Martinez et al., 2010). The most basic smart-devices have sensing and/or communicating networking chips, enabling data-collection and automation; more advanced options enable higher degrees of automation with wireless two-way utility communication for demand management control, delayed start functions, and pricing signal control (Donnelly, 2010).

Often, smart-devices form part of a Home Area Network (HAN). Donnelly (2010) uses the terms Home Automation Network and Home Area Network interchangeably, and states that the simplest HAN is a smart-thermostat that enables heating/cooling control and communicates with a central computer and/or the utility's metering system. However, she notes that a complete HAN includes: (1) smart-devices with embedded/attached networking and/or communicating chips for automation; (2) advanced network systems and software using mesh networks to provide measurement and feedback of appliance specific data; (3) the potential for two-way communication with the utility; and (4) some kind of consumer interface for direct, real-time feedback. Hochwallner (2009) defines a *home automation system* as one that "consists of "smart" devices and a communication bus that connects all devices in a home". The communications bus is used to both control appliances, and to receive information from the appliances about their current power consumption.

Typologies of Feedback

Darby (2001, 2006) proposed a typology of feedback focused on direct and indirect feedback, with three additional categories: inadvertent feedback (learning by association, e.g. through solar panels in the home), utility-controlled feedback, and energy audits. EPRI (2009) subcategorized feedback into six types: four indirect and two direct. They divide indirect feedback into (1) *Standard Billing*: traditional feedback that households receive from their utility company, generally in the form of a monthly bill or statement; (2) *Enhanced Billing*: detailed information about consumption patterns from the utility, such as historical or social comparison statistics; (3) *Estimated*: analysis of user-provided data to estimate energy usage; and (4) *Daily/Weekly/Periodic*: energy information presented to the user that is time-delayed by a day or more, but provided more often than the traditional energy bill. Direct feedback is further categorized as (5) *Real-time*: overall consumption level on a real-time or near-real-time bill, and (6) *Real-time Plus*: disaggregated (e.g. individual appliance) energy feedback and/or feedback that allows users to control appliances in the home.

Ehrhardt-Martinez et al. (2010) extend previous definitions, constructing an analogy based on an onion metaphor. The layers of the onion are defined as: (1) *Utility delivered* (utility bill or website), (2) *Vendor delivered* (whole home information), (3) *Deeper contextual information* (e.g., includes statistical analysis), (4) *In home energy display* (real time or nearly real time feedback), (5) *"Smart" devices* (e.g., provide simple automation), (6) *Disaggregated and contextual* (information about individual appliances), and (7) *Automation* (whole systems that include disaggregated real-time feedback, home automation, and sometimes energy generation and storage systems). The three outer layers of the onion (1, 2 and 3) correspond to indirect feedback mechanisms and the three inner layers (4, 5 and 6) correspond to direct feedback, with home automation at the core (7). As the layers of the onion are peeled away, the feedback becomes progressively more sophisticated.

In a meta-review of feedback studies based on these categories, Ehrhardt-Martinez et al. (2010) found “distinct differences in the average and median energy savings associated with different types of feedback”. However, they do note that significant variation exists within each of the feedback categories. While the authors attribute this “within category” variation to differences in study methodology, it is also possible that there are significant differences between types of feedback within these broad categories as well. For example, within the real-time plus category, a feedback intervention may or may not be electronic and may or may not provide appliance-specific information, both of which are variables which may impact the effectiveness of the feedback intervention.

The classification “taxonomy” proposed by LaMarche et al. (2011) takes a different approach, consisting of three basic categories intended to capture essential components of a typical feedback device such that feedback can fall into one or more of these categories: (1) *Control devices* (allow the consumer or utility to actively control energy use), (2) *User Interfaces* (provide energy feedback to consumers), and (3) *Enabling Technologies* (underlying support framework). Control devices can be centralized (communicate with multiple devices), device-level (user controls a single device), or on-board (control is integrated into the device). User interfaces can provide raw, i.e. direct feedback (e.g. real time or historic usage data), or processed, i.e. indirect feedback (e.g. comparisons, advice, goal-setting). Enabling technologies include sensors, communications (e.g. gateways), and communications protocols (e.g. Zigbee).

Limitations of Previous Research

Although past literature reviews have proposed categories to distinguish between the various types of feedback, current categorizations lack the technological sophistication to account for the diversity in available technologies and are not systematic in their classification of specific feedback technologies. Classification, or categorization, is the process of grouping like objects into categories based on their properties (Cohen & Lefebvre, 2005). Categories within a classification structure should be clearly defined (e.g., new objects can be easily categorized), mutually exclusive (e.g., each object fits in one and only one category) and collectively exhaustive (e.g., all objects fit into a category); the result is that every object within a classification structure fits in one and only one category. When categories are based on a fixed set of characteristics in parallel, the resulting structure is a typology; when these characteristics are considered in succession, the resulting classification structure is a taxonomy (Marradi, 1990).

A review of the existing classifications presented above identified three key issues. First, all existing products and platforms are grouped into four (or fewer) categories, which leaves single categories containing upwards of a hundred technologies, making distinction and selection difficult. Second, categories focus primarily on the type of information provided and ignore physical design and operating differences. Finally, no current classification structure provides a systematic description of the specific characteristics that vary by type, making categorization of emerging technologies difficult.

The current study addresses these limitations through the development of a comprehensive and systematic taxonomy of feedback technologies. It introduces and discusses the status of feedback technologies in the marketplace with a focus on physical characteristics of feedback products and platforms and presents a taxonomy of feedback technology from an empirical review of 196 technologies coded on over 100 characteristics.

Methods

The study utilizes content analysis and classification methodologies to derive a taxonomy of feedback technologies. Content analysis is a technique of compressing large amounts of text into a manageable data set by creating and coding the text into categories based on a set of specific definitions (Neuendorf, 2001; Stemler, 2001). Descriptive data on over 200 specific feedback technologies were identified and collected from March –August 2011. After identical devices were removed, product information was analyzed qualitatively using open coding followed by axial coding; themes were constructed from analysis of the codes in consultation with previous literature (Corbin & Strauss, 2007; Creswell, 2009). The set of final characteristics were screened for relevance and a taxonomy structure was derived to categorize all products and platforms such that the categories were mutually exclusive and mutually exhaustive to the dataset. The following four sections (data collection, inclusion, coding, and analysis) describe the methodology of this study in further detail.

Data Collection

The following four methods were used to identify and collect data about feedback technologies: (1) review of relevant literature, (2) Internet keyword search, (3) retail websites, and (4) personal contacts. As products and platforms were identified, a raw data file was created for each product with any available information (e.g., user manuals, product summaries, new articles, photos).

Data collection began by compiling a list of feedback technologies from the following reports: Anderson & White, 2009 (7 devices); Ehrhardt -Martinez et al., 2010 (12 devices); Herter, 2010 (49 devices); Herter & Wayland, 2009 (35 devices); Hochwallner & Lang, 2009 (4 devices); LaMarche et al., 2011 (38 devices); Stein, 2004 (11 devices); and Stein & Enbar, 2006 (27 devices). 101 unique feedback devices were identified from these reports.

Next, general searches were conducted in Google and Amazon.com using the keywords energy and feedback simultaneously. In addition to identifying additional technologies, these searches also uncovered third-party websites that specifically market and/or sell feedback technologies, including: www.powermeterstore.com, www.mymeterstore.com, www.smartgrid.gov and www.home-energy-metering.com. Each of these sites was also searched for any additional products or platforms.

Additional technologies were identified through informal inquiries via email and discussion with colleagues and personal contacts, including colleagues at our universities, researchers at energy-related conferences, and colleagues at the American Council for an Energy-Efficient Economy (ACEEE). The total number of feedback technologies compiled and reviewed using all four of the above search strategies was 259.

Inclusion

For the purpose of this work, energy feedback is defined as *information about actual energy use that is collected in some way and provided back to the energy consumer*. As such, the follow five criteria were used for inclusion in the analysis:

1. The feedback collects information about actual building electricity use.
2. The feedback technology provides this actual usage data back to the user.
3. The feedback technology is an actual product or prototype (not concept).
4. Sufficient information is available to describe the feedback technology.
5. The primary goal of the venture providing the technology is energy feedback; feedback provided to consumers by electric utilities was excluded.

Feedback technologies that met all five of the above criteria were included. Among the initial 259 devices/systems collected, 196 were identified that met all of the above criteria.

Coding

Code development was iterative and utilized the constant comparison method and multi-phase coding (Corbin & Strauss, 2007; Creswell, 2009). Each product or platform was treated as the unit of analysis for coding and analysis utilized a manifest approach, such that the exact information was pulled from the data. An initial set of codes was developed based on previous literature (e.g., frequency, immediacy, content, medium—see review above); additional codes were created, as needed, as technologies were added. Variables relating to key hardware and system properties of the feedback technology were added to account for both physical design and operating conditions (and differences). Further characteristics were added in an iterative procedure; opening coding from the 196 products and platforms resulted in a total of 117 distinct codes, divided into five primary categories: development, hardware, system, data collection, and data presentation.

In the second round, the 196 technologies were re-coded according to these characteristics. All coding was then reviewed for accuracy; discrepancies were resolved through discussion between all three authors. When information was missing and there was no clue to support a reasonable estimate, the information was coded as missing data. Because the coding process involved some degree of subjectivity, all technology variables were coded by at least two authors and results on 10% of the data were compared for reliability. Inter-rater reliability was acceptably high (kappa > .700) for all variables (Cohen, 1960).

Analysis

During axial coding, the 117 distinct codes were reviewed and collapsed into 36 primary characteristics. For example, codes that represented multiple levels of the same characteristic were condensed (e.g., Linux, Mac, and Microsoft combined as levels of the characteristic "operating system compatibility"). The next phase of analysis distinguished those codes related to the primary goal of the present study (e.g., categorizing feedback devices) from others related to the quality of personal preference (Corbin & Strauss, 2007). A taxonomy classification structure based on these characteristics was then constructed and all technologies were reviewed for fit. Final categories were derived based on an integration of analysis results with previous literature as well as data regarding the most important device characteristics for consumers.

Results

Feedback Characteristics

After coding, 36 feedback characteristics within five broad categories were identified; these characteristics, grouped by category, are listed in Table 4.2. From this list, a set of typing characteristics were identified—variables necessary to distinguishing between categories of feedback. Typing characteristics were identified based on the following criteria:

1) Stable and inherent to the technology in itself;
2) Consistently identifiable for at least 80% of the devices;
3) Theoretically relevant; and
4) Had an even distribution across variable options (i.e. no more than 80% in one type)

Table 4.2. Characteristics identified during coding

Category	Attribute	Category	Attribute
Development	Status of technology	System	Technology requirements
	Cost[1]		OS compatibility[1]
	Target audience		Amount of memory[1]
Hardware	**Sensor units**		Memory location[1]
	External transmitters		Integration w/other systems
	Physical displays		Documentation availability
	Power supply options	Data collection	Data granularity
	Measurement capabilities [1]		**Collection point**
	Monitoring channels [1]	Data presentation	**Medium of presentation**
	Measurement resolution [1]		Display update frequency[2]
	Voltage/current ranges [1]		Temporal granularity[2]
	Collection update frequency[1]		Comparison messages
	Power factor correction[1]		Units of measurement
	Communication channels[1]		**Appliance control**
	Communications range[1]		Visualizations used
	Communication protocol		Level of configurability
	Installation protocol		Recipient of feedback [2]
	Additional components		Provision of advice

[1] Insufficient data - Missing data for 20% or more of dataset.
[2] Insufficient variation - Over 80% of dataset fell into one category.

Those that met these criteria are identified in bold text in Table 4.2. These were further grouped into six primary taxonomy characteristics: product hardware (sensor units, external transmitters, and physical displays), communications (communication protocol), control (appliance control), display (medium of presentation), collection (collection point), and protocol (communication protocol). These characteristics, their definitions and levels are listed in Table 4.3 and further information is provided below.

Table 4.3. Taxonomy characteristics

Characteristic Name	Characteristic Definition	Characteristic Levels
Hardware	Does it have physical hardware?	No (platform) Yes (product)
Communications	Does it have communications abilities?	No (monitor) Yes (network)
Control	Can it be used to control electronic devices remotely?	No (information) Yes (management)
Display	What type of display is feedback presented on?	None (existing channels) Embedded (within device) Autonomous (standalone display)
Collection	Where does the data come from?	Grid Sensor Appliance
Protocol	Does the system use proprietary communications protocols only?	Yes No

Hardware. Hardware describes the physicality of the feedback technology, asking whether or not the technology requires the purchase of any new sensors, transmitters, and/or displays. Any system that provides feedback via existing channels (i.e. does not require the user to purchase new hardware devices) and collects data via existing sources (e.g. utility meters, data loggers) does not have hardware. Any system that requires the purchase of a device or devices, such as a display or a sensor, has hardware.

Communications. Communications refers to whether or not the physical component or components of feedback systems are able to communicate with each other and/or pre-existing electronic devices. These communications can be either wired or wireless. Feedback systems that consist of various hardware components that communicate with one another, or consist of a single hardware component that communicates with other electronic devices in the household or building have communications capabilities. Individual feedback products that collect and provide data within the same device do not have communications capabilities. This characteristic does not apply for feedback systems that have no physical components (i.e. have no hardware).

Control. Control refers to whether or not the feedback system enables remote control of electronic devices within the home and/or building. This includes automation, e.g. setting devices to turn on or off or change setting at a specified time, as well as the ability to manually turn devices on and off from a remote location.

Display. Display refers to the physical medium on which the feedback data is presented to the user. When feedback is displayed via existing channels, such as a utility bill, website, computer software, or phone, it has no display. When feedback is presented on an independent display, whether it is wall-mounted or portable, it has an autonomous display. When the display is built into the device that collects feedback data (i.e. the sensor), it is classified as an embedded display.

Collection. Data collection describes where the feedback information comes from. Data collected by a meter or provided by the utility is classified as grid. Data collected by the feedback product is classified as sensor. Data that comes from an existing home appliance or device, such as refrigerator or home thermostat, is classified as appliance.

Protocol. Protocol refers to whether or not the feedback system uses only non-standard communication protocols such that it can only communicate with itself. Feedback systems that are capable of using public communications standards can communicate with other devices, such as smart meters or smart appliances that use the same communication protocol. Feedback systems that use only proprietary communications cannot.

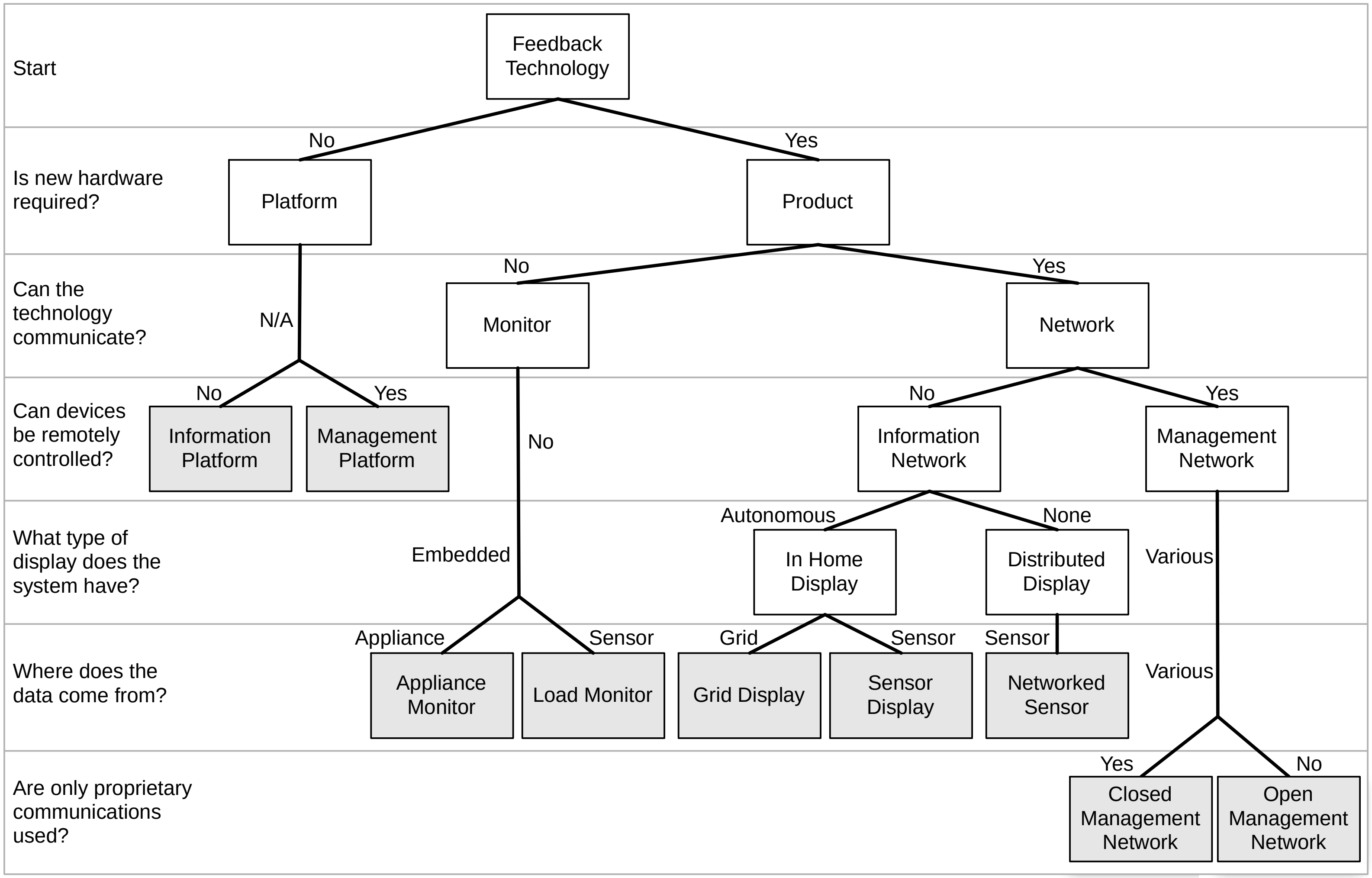


Figure 4.1 Taxonomy of energy feedback technology

Feedback Taxonomy

The six typing characteristics identified in Table 4.3 were analyzed across the 196 included technologies in order to identify meaningful categories. A simple factorial typology of the six variables reveals a possible 144 combinations. Besides being an unwieldy number of categories to be useful, many of these combinations are not physically possible (e.g. feedback technologies that do not have hardware, by definition, would not have sensors to collect data). Therefore a taxonomy structure was derived to create mutually exclusive and exhaustive categories while retaining parsimony in the final construction. Figure 4.1 presents the final taxonomy structure of feedback technology, which was constructed from analysis of these characteristics with respect to both existing technology as well as past literature on the most meaningful characteristics of feedback.

This taxonomy is comprised of nine categories divided into two primary groups: *platforms* and *products*. A platform does not require the purchase of any new hardware; instead it integrates with existing hardware that users already have (e.g. smart appliances, smart meter) and provides energy-use data to consumers via enhanced energy bills or reports, mobile apps, web browsers, or computerized software. Feedback platforms are broken down further into *information platforms* and *management platforms*. The key difference between a management and an information platform is that a management platform enables two-way communication such that they can be used to remotely control appliances; communication in an information platform flows one-way, so appliances cannot be remotely controlled.

Examples of information platforms include enhanced energy bills and customer web portals, provided by companies such as OPOWER and Efficiency 2.0. These platforms rely on smart meter data from a partner utility, which is processed and presented to consumers via a paper-based report and/or online web portal. Additional services such as comparisons to peers, energy advice, estimates of appliance consumption, and rewards programs, can further distinguish between the different information platforms available to users but are not stable and inherent to the technology in itself and so are not used for categorization.

Management platforms allow the user to automate “smart” electronic devices connected to the platform (e.g., lights, thermostats, appliances). Examples of management platforms include Silver Spring Network’s Smart Energy Platform and the FutureDash Greendash Hub. These technologies rely on smart meters and smart devices already in the home for information and control. The information is provided to consumers via a web-based portal, and users are able to remotely control their smart devices via the web interface. These devices may also be controlled via a utility-delivered demand response program.

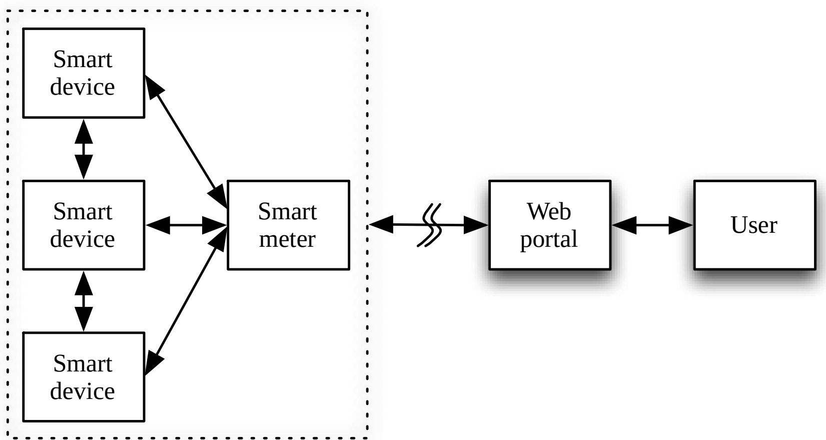


Figure 4.2. Network architecture of a management platform

Figure 4.2 illustrates the type of network architecture involved. Different companies use different protocols to transmit information from the smart meter and smart devices to the consumer portal. The Silver Spring system provides information to consumers via the utility, whilst FutureDash is aims to work with consumer-electronics manufacturers to skip this link and enable data transfer over the Internet.

Feedback products, unlike platforms, do require the user to purchase some sort of hardware, and are also subdivided into two categories based on communication capabilities. A product consisting of a single component that does not communicate data with any other device is a *monitor*. Feedback monitors contain sensors (to collect energy use data) and a display (to provide data back to users) in a single piece of hardware. A product with multiple hardware components that communicate with each other, or a single component that communicates with third-party devices, is classified as a *network*. These networks tend to be confined to a physical space within a single building, and may therefore be thought of as local area networks, or, in the residential setting, as home area networks (Donahue, 2007).

Feedback monitors are further broken into *appliance monitors* and *load monitors*, both of which contain inbuilt sensors and embedded displays. Because they are not capable of communications, they do not enable remote control of appliances; however, some products are fitted with timers that can be pre-programmed to allow some amount of automation.

An appliance monitor collects data from and displays data about an individual appliance (i.e. the appliance has inbuilt energy sensors and an embedded display showing this information). Fridges, freezers, washing machines and tumble dryers that have an embedded display to present their energy use to consumers are all classified as appliance monitors.

(a) (b) (c)

Figure 4.3. Examples of energy load monitors

A load monitor is a separate piece of hardware that serves as a proxy between the energy source and energy-consuming device. Most load monitors collect data at the plug level (although some collect at the meter level), sitting between the wall socket and appliance plug. Some load monitors offer the option of viewing the data on computer software (facilitated via USB/SD connection). These features and others such as viewing options (i.e.

instantaneous power consumption, total energy use, energy use over a pre-defined period), memory availability, and cost, distinguish different products in this feedback category. Examples of load monitors include Belkin's Conserve Insight Monitor, the Kill-a-Watt, and Watts Up, as illustrated in Figure 4.3 (a), (b), and (c) respectively.

Similar to platforms, feedback networks are categorized based on whether they enable the user to remotely control appliances. *Management networks* enable remote control of appliances whereas *information networks* do not. Information networks are divided into in-home displays (*grid displays* and *sensor displays*) and *networked sensors*. Management platforms are divided into *open management networks* and *closed management networks*.

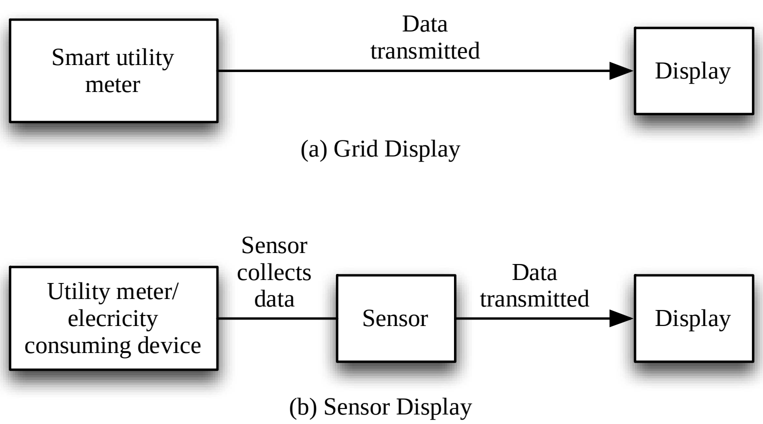


Figure 4.4. Basic system architecture of in-home displays

In-home displays that have a physical display providing energy usage information to users in real (or near real) time and collect data from either a sensor (*sensor displays*) or the user's electricity meter/utility (*grid displays*). The basic architecture of grid displays and sensor displays are shown in Figure 4.4 (a) and (b) respectively. Some in-home displays offer the option of additionally viewing the data online or via accompanying software.

All grid displays provide whole-home level energy usage information and some receive and display peak demand pricing and other messages from the utility. AzTech's In-Home Displays, Ambient's Energy Joule, and GEO's Duet II for Smart Meters are all types of grid displays. The main difference between these displays is how the information is presented to users (including the units used, the availability of historical data, features of the display in terms of size and color, and so on) and what additional features the display provides, such as pricing information from the utility.

The most common type sensor display consists of at least one pair of CT clamps, a transmitter, and a portable display. While most sensor displays transmit data from sensor units to displays using wireless or power-line communications, some rely on wired communications, using, for example, CAT-5 LAN cable installations. Examples of sensor displays include Current Cost's ENVI, Ewgeco's Electricity Monitor, and the TED 1001. Of all the types of feedback identified in this research, sensor displays formed the largest category, containing 61 separate products.

Figure 4.5. The TED 5000G.

Networked sensors are feedback products that have a sensor or sensors, but no physical display. Physical sensors collect energy usage data and communicate it to external servers, where it is processed for viewing on a web browser, app, or computer software. The TED 5000 G series, depicted in Figure 4.5, falls into this category. It includes (left to right) one set of current clamps and measuring transmitting unit for breaker panel installation, and one gateway to transmit data externally.

The two forms of management platforms, *closed management networks* and *open management networks*, enable users to remotely control connected devices. Data is collected from a variety of sources, including smart meters, sensors, and smart-appliances, and presented to users on a combination of physical displays and existing channels (i.e. web portals, computer software, or mobile app). The defining feature that distinguishes between closed management networks and open management networks is the type of communication protocol utilized by the system. Closed management networks communicate using only proprietary protocol, and form closed communication networks to which only proprietary devices can join. Open management networks may use proprietary communication protocols on some layers, but they are also capable of using public communication protocols to form open networks to which any device communicating with the same protocol (e.g. smart meters, smart appliances, etc.) can join. This also means that utilities can send demand response signals to devices and appliances on the network via the smart meter.

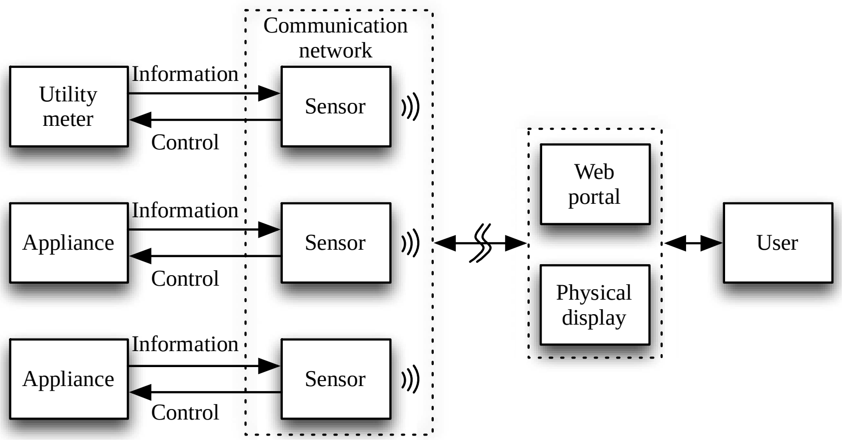


Figure 4.6. Basic system architecture of closed management networks.

The majority of closed management networks, such as AlertMe Smart Energy, Plugwise, and thinkeco Modlet, use plug-in sensors to measure and control the energy usage of plug-in devices, as shown in Figure 4.6.

The majority of open management networks (see Figure 4.7), such as EnergyHub and Greenwave Reality, have a physical display and sensors, and some offer control to both users and third parties, thus enabling utilities to manage large connected loads such as pool pumps.

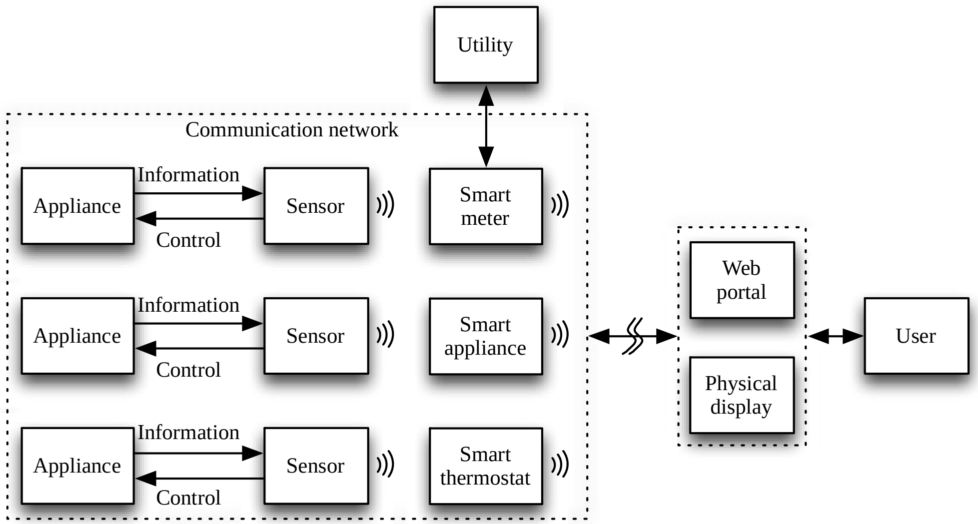


Figure 4.7. Basic system architecture of open management networks.

Table 4.4 summarizes the characteristics of each of the 9 types of feedback with respect to hardware, ability to communicate data, options to control appliances remotely, display options, data collection, and communications protocol used by the system.

Table 4.4. Characteristics of each feedback type

Feedback Type	Hardware	Communications	Control	Display	Collection	Protocol
Information Platform	No	NA	No	--	--	--
Management Platform	No	NA	Yes	--	--	--
Appliance Monitor	Yes	No	No	Embedded	Appliance	--
Load Monitor	Yes	No	No	Embedded	Sensor	--
Grid Display	Yes	Yes	No	Autonomous	Grid	--
Sensor Display	Yes	Yes	No	Autonomous	Sensor	--
Networked Sensor	Yes	Yes	No	None	Sensor	--
Closed Management Network	Yes	Yes	Yes	Various	Various	No
Open Management Network	Yes	Yes	Yes	Various	Various	Yes

Discussion

Although feedback has been widely studied and is a much-anticipated part of our national and global transition to the Smart Grid, there have been few attempts to clearly distinguish among the hundreds of feedback technologies and their unique characteristics. This study is a vital first step toward an energy feedback “market”, in which consumers can feel confident to select and purchase products and platforms that help them understand their energy usage in the home.

This work provides a novel contribution to the energy-feedback literature by linking together the theoretical underpinnings of feedback technologies with actual commercial or pre-commercial ventures. However, it must be noted that the energy-feedback market is a fast-paced sector with many companies entering and leaving the market each year. This taxonomy was derived empirically from data collected in 2010-2011; since then a number of players have left this space (e.g. Google) and others have entered (e.g. Chai Energy, Bidgely). This is not a problem in itself, as the main goal of this work was development of a taxonomy of energy-feedback technologies and not to compile a current and complete list of them.

However, these changes could result in the creation or disappearance of whole categories of feedback technologies. Energy-feedback technology does not present a unique situation in this respect, and this issue can be managed by reviewing key characteristics and resulting categorizations as technologies develop over time, as has been done for other technologies. For example, as camera technology has advanced in recent years, additional categories, such as “Megazoom” and “Interchangeable-Lens Camera (ILC)”, have been added to existing categorizations to account for the differences in key camera characteristics described by the new technologies. This means that the taxonomy must be viewed as dynamic rather than static, requiring regular reviews and revisions to ensure that the categories describing commercial and pre-commercial feedback technologies remain fully representative of the marketplace. Although this presents a potential time-sensitivity to the usefulness of the current categorizations, without them it would be much harder for consumers and reviewers to compare different models and determine which is most appropriate for a given situation. Furthermore, the identification of key characteristics in the development of the taxonomy structure provided in this work can help guide the creation of additional categories as needed.

As such, this work aims to develop a categorization to assist practitioners and researchers organize future work on energy feedback. It does not provide a value-based comparison between technologies; rather, it introduces a categorization that can serve as the basis for publicly available product information on feedback devices and systems, much like that which is available for other consumer electronics (e.g. televisions, cameras, etc.). These categories can also serve as the basis for subsequent work comparing and rating/ranking feedback products and platforms. The categorization presented herein is seen as a vital first step for that work to take place.

This chapter extends previous literature, in that the taxonomy presented is derived both theoretically and empirically and all categories are designed to be mutually exhaustive and mutually exclusive, given current technological capabilities. It is hoped that this chapter will assist both researchers and practitioners in the fields of energy efficiency and conservation and that it may serve as the basis for publicly available product information on feedback technology as this market grows in future years.

CHAPTER 5: Naturalistic Users of Energy Feedback

As discussed in Chapter 3, the effectiveness of energy-use feedback has been found to vary based on both on the way that it is provided as well as to whom it is provided. However, virtually all studies have employed experimental designs in which participants are recruited to use feedback. These participants may not represent naturalistic users of feedback (i.e., those who independently seek out and use feedback in their daily lives). As a result, little is known about the characteristics and experiences of naturalistic users of energy feedback.

There is a great demand for this information. Schatsky and Wheelock (2009) suggest that utilities "will want to look for insights about what types of platforms and interfaces click with different segments of their customer base" (p. 3). Pierce et al. (2010) note several potential issues with residential energy feedback (e.g., disappointment with actual versus anticipated behavior change, difficulty fine-tuning consumption, staying engaged) and emphasize the need for further research on the quality of feedback user experience as well as how feedback affects users' specific knowledge, attitudes, and behaviors.

The current chapter investigates naturalistic users of feedback—i.e., those individuals who have voluntarily obtained and used energy feedback outside of an experimentally controlled research setting. In doing so, we seek to answer two questions: (1) who uses energy feedback? and (2) what is their user experience? Using online survey data collected from 836 individuals, it statistically examines demographic and psychological differences between feedback users and non-users and explore the experiences of feedback users through qualitative analysis of open-ended survey questions pertaining to acquisition, usability, and outcomes of feedback use. By focusing on a sample of naturalistic feedback users, compared to non-users, and collecting both quantitative and qualitative data about the user and their experiences, this study is able to address previously neglected questions about how best to design and market feedback technologies to the public.

Literature Review

As discussed in previous chapters, more than 100 studies of feedback have been conducted during the past 40 years with widely varying results in terms of energy savings (see Chapter 3). In addition to measuring reductions in electricity consumption, a small percentage of these studies have also collected self-report data on the experiences of users. Qualitative responses from these studies highlight participants' motivations to receive feedback, the quality of their experiences with feedback, and the impacts and effectiveness of feedback. A review of this literature follows.

Feedback Users

While most previous studies of energy feedback have actively recruited subjects for participation, a few of these investigated participants' voluntary acquisition and use of feedback devices, or compared feedback users with non-users. Hargreaves, Nye, and Burgess (2010) found that men used technological feedback monitor displays more often than women, who were more likely to report not understanding or not being interested in such devices. Additional predictors of feedback use have included positive attitudes toward energy conservation (Kurz et al., 2005), and previous energy-conservation behavior (Battalio et al., 1979). Other studies comparing voluntary participants in feedback studies with a blind control group found no significant differences in conservation commitment, energy awareness, or conservation behavior (Robinson, 2007; Winett et al., 1979). While it is not clear whether these participants would have elected to use feedback if they were not invited to participate in the study, these findings suggest that there may indeed be differences between naturalistic users of feedback and non-users, but further research is still needed to explore these differences.

Motivation

Liikkanen (2009) recruited a sample of 20 utility customers who had borrowed an electric power meter from their utility and conducted semi-structured interviews to determine motivation as well as user experience and satisfaction. They found that respondents were motivated primarily by gathering information, technological curiosity, and/or a general sense of curiosity about energy use. Three types of motivations were identified among these users: (1) determining the "truth" about their home energy use by doing an extensive walk-through of all appliances in the home; (2) attributing blame to a cluster or group of energy-intensive appliances; and (3) acquiring information on a singular new or suspicious appliance. Additional studies that inquired about subject motivations (Hargreaves et al., 2010; Parker et al., 2008) found that the most common reported motivation for feedback use was financial savings, followed by environmental concerns.

Usability

User satisfaction has been generally high across a variety of feedback technologies, including utility billing (Arvola et al., 1994); in-home displays (Hargreaves et al., 2010; Mountain 2007), appliance monitors (Mansouri & Newborough, 1999), and plug-load monitors (Liikkanen, 2009)[3]. Subjects reported overall that using energy-feedback devices significantly improved their ability to manage and curtail their energy use. However, problems with usability were also reported, mostly pertaining to the display of information. Feedback delivered via mail or email was found to be unclear and not useful (Robinson, 2007), in-home display users reported difficulty reading and interpreting numerical information and graphs provided (Allen & Janda, 2006; Hargreaves et al., 2010), and users of plug-load monitors reported accessibility issues with certain appliances (e.g., refrigerators) whose size would block any information displayed by the device (Liikkanen, 2009).

[3] See Chapter 4 for a description of feedback categories.

Outcomes

Participants across studies reported gains in both knowledge and conservation behavior. Knowledge gains include a general increased awareness of energy-use patterns (Allen & Janda, 2006; Haakana et al., 1997; Hutton et al., 1986; van Houwelingen, & Van Raaij, 1989) as well as specific knowledge about *how* to reduce energy use (Kasulis et al., 1981; Parker et al., 2008; Vollink & Meertens, 2006). Many participants reported learning that their energy use was either more (Mountain, 2007) or less (IBM, 2007, Hargreaves et al., 2010) than expected. Feedback users also reported specific changes in their behavior, including replacing light bulbs (Mountain 2007; Robinson, 2007), lowering thermostat and hot-water settings (Haakana et al., 1997; Mountain, 2007; Winett et al., 1979), closing the refrigerator more quickly (Kurz et al., 2005), identifying and disposing of “greedy appliances” (Hargreaves et al., 2010), shifting use to off-peak hours (Nexus, 2006), and turning off lights when not in use (Haakana et al.,1997; Mountain, 2007).

Continued Use

The long-term usefulness of feedback is uncertain. Many participants expressed a strong desire to continue using feedback after the study (Arvola et al., 1994; Kurz et al., 2005; Wilhite & Ling, 1995) and reported a decrease in energy awareness and conservation behavior when the feedback device was removed (Allen & Janda, 2006; Dobson & Griffin, 1992). On the other hand, some reported declines in usage after satisfying initial curiosity (Hargreaves et al., 2010) or settling into a regular usage pattern (Allen & Janda, 2006). Furthermore, some feedback users reported a preference for renting (rather than buying) feedback products (Hutton et al., 1986; van Houwelingen & Van Raaij, 1989).

Limitations of Past Research

Overall, the qualitative data support the notion that there is potential utility in the provision of energy feedback to promote conservation, but that further research is still needed to answer many of the important questions about for whom feedback best serves and how users experience and benefit from its use. Limitations identified in the studies conducted to date include the following:

1. Since most feedback devices are sold commercially, widespread use requires market adoption; analysis of actual market actors (e.g., those not recruited to participate in a study) is vital to understanding diffusion of this technology (Rogers, 2003).
2. Some types of information (e.g. how and where users acquire feedback products) are impossible to collect in experimental studies, leaving gaps in our knowledge.
3. Although there are over 200 different feedback devices commercially available (see Chapter 4), less than a dozen products have been tested in published studies and few have compared different types of feedback.

The current study, which reports results of an online survey of naturalistic adopters of feedback technology, addresses these issues.

Methods

Procedures

Data were gathered through an online survey in 2010. A purposive sample of potential energy feedback users was recruited online via email, Facebook, and professional/environmental listservs. Approximately half of survey respondents (53%) found out about the survey from a personal contact and the remaining found out via a listserv or newsletter. Survey design was based on Dillman's Tailored Design Method (2007); progress indicators, multiple screens, and a simple layout were used to maximize survey completion. The survey took approximately 15 minutes to complete and respondents were entered into a raffle for a $50 gift certificate to Amazon.com. All respondents were asked to forward the survey via email to their own contacts after completion and a reminder email was sent 30 days after the initial contact email.

Participants

838 individuals completed the survey. A subset of survey respondents was identified as *feedback users* according to the following criteria:

1. The individual responded that s/he was currently using a feedback product.
2. At least one open-ended question concerning feedback was answered.
3. The reported product was used in the home[4].

Among the initial 836 survey respondents, 101 indicated that they had used a feedback product. Of those, seven were excluded because they did not list a product or later reported not using a device, four were excluded because they reported vehicle-related feedback and four were excluded because their responses were not recognizable as feedback devices (e.g. one respondent reported "low-flow toilet") and subsequent responses did not relate to energy feedback. This left 86 respondents who met our inclusion criteria for feedback users. The remainder of the sample (including those excluded above) constitutes the comparison group, *non-users.*

Measures

Data analyzed in this study were collected as part of a residential energy survey, which was designed to address three major topics: (1) energy-conservation behavior and its predictors, (2) perceptions of energy use and feedback, and (3) use of residential energy-feedback devices. The current chapter presents results from analyses of the last part of the survey (i.e., use of residential energy-feedback devices) as well as demographic and psychological data. The variables examined in this study are described below.

Feedback user responses. Respondents were asked whether they had used a feedback device. If they said yes, they were asked a series of open-ended questions about the product and their experiences with it. These questions were designed to inquire about the

[4] If an unrecognizable or unspecified product was reported, subsequent responses related to home energy use and/or feedback.

product(s) used and address three general topics of interest: adoption (how, where, and why they obtained feedback), usability (likes and dislikes about the use of feedback), and outcomes (changes in knowledge and/or behavior due to use of feedback). If the respondent had used more than one feedback product, s/he was asked to answer these questions separately for each product.

Demographic variables. Demographic variables were included in the survey to characterize the general sample and to compare feedback users with non-users. Demographic items included gender, age, race, marital status, political affiliation, education, income, and homeownership (own vs. rent).

Psychological variables. A series of questions were included to test for psychological differences between feedback users and non-users. Questions were grouped within three general categories: environmental, financial, and social. Environmental concern was measured using an abbreviated (three-item) version of the New Ecological Paradigm (NEP) Scale (Dunlap, Van Liere, Mertig, & Jones, 2000; Zelezny, Chua, & Aldrich, 2000). Financial considerations were measured with a single question about bill consciousness. Social norms were tested with two items (Cialdini, Kallgren, & Reno, 1991); the first item measures descriptive norms (perceptions of how others behave) and the second measures injunctive norms (perception of what others approve). Finally, three two-item scales (adapted from on Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008) were included to measure environmental, financial, and social motivations to use and/or conserve energy. For all measures, questions were reverse-coded when needed to ensure that all responses scored in the same direction. Psychological survey items are presented in Table 5.1.

Table 5.1. Psychological Survey Items

Environmental
Environmental Concern[a] • Energy conservation is one of the top issues facing our world. • Environmental problems are not affecting my life personally. • I think that each individual has a responsibility to do their part for the environment.
Environmental Motivation[b] • How likely is environmental impact to encourage you to decrease home energy use? • How much does environmental impact affect your home energy use?
Financial
Bill Consciousness[c] • I pay close attention to my monthly energy bill.
Financial Motivation[b] • How likely is saving money to encourage you to decrease home energy use? • How much does cost of energy bill affect your home energy use?
Social
Social Norms[a] • People in my community expect me to do my part to conserve energy. • Most people are not willing to make changes or sacrifices to protect the environment.
Social Motivation[b] • How likely is your neighbors' use to encourage you to decrease home energy use? • How much does your neighbors' energy use affect your home energy use?

[a] Scale ranged from 1 = Strongly Disagree to 5 = Strongly Agree.
[b] Scale ranged from 1 = Not at All to 4 = A Great Deal.
[c] Binary variable normalized to a maximum of 1.

Data Analysis

The data were analyzed using a mixed-methods approach consisting of two methods. First, respondents who were identified as feedback users ($n = 86$) were compared to non-users ($n = 749$) quantitatively. Independent t-tests compared feedback users and non-users on all demographic and psychological variables indicated above; binary logistic regression analysis was used to determine unique variance attributed to each variable that varied significantly between the two groups. Next, open-ended responses of the feedback users were analyzed qualitatively using open coding followed by axial coding, and themes were constructed from analysis of the codes (Corbin & Strauss, 2007; Creswell, 2009).

Results

Feedback User Characteristics

Independent sample t-tests revealed several differences between feedback users and non-users. Table 5.2 presents descriptive statistics for demographic variables. Feedback users were significantly more likely than non-users to be male (t=4.14, p <.001), married (t=2.52, p=.013), and homeowners (t=5.73, p<.001). Feedback users were also significantly older (*t* =3.34, *p* = .001), more liberal (t=2.36, p=.019), higher-income (t=2.64, p<.01), and more educated (t=1.96, p=.05) than non-users. The only demographic variable that was not associated with use of a feedback device was race (t=1.38, p=.170).

Table 5.2. Demographic Characteristics of Feedback Users Compared to Non-users

	Feedback users	Non-users
Gender***	46% female 54% male	70% female 30% male
Age**	45.5 years	39.9 years
Race	80% Caucasian 1% Hispanic 8% Asian 1% African-American 10% Other/Decline	82% Caucasian 7% Hispanic 6% Asian 2% African-American 3% Other/Decline
Marital status*	65% married 35% not married	51% married 49% not married
Political affiliation[a]*	3.96	3.67
Education	18.0 years	17.4 years
Income*	$106,000	$88,000
Homeownership**	83% own 17% rent	57% own 43% rent

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

[a] Scale ranged from 1 = Extremely Conservative to 5 = Extremely Liberal.

Table 5.3 presents descriptive statistics for psychological variables. Feedback users rated significantly higher than non-users on both environmental concern (t = 3.74, p < .001) and bill consciousness (t = 2.09, p = .020). Non-users were more motivated by financial considerations than feedback users (t = 3.40 p = .001), whereas, feedback users were more motivated by environmental considerations (t = 3.36 p = .001). No significant differences were found for either social norms (t = 1.36 p = 176) or social motivation (t = 1.05 p = .295).

Table 5.3. Psychological Variables Comparing Feedback Users to Non-users

	Feedback users		Non-users	
Psychological Variables	*M*	*SD*	*M*	*SD*
Environmental				
Environmental concern[a*]	4.40	0.51	4.18	0.67
Environmental motivation[b]	3.18	1.03	2.80	0.98
Financial				
Bill consciousness[c*]	0.70	0.46	0.59	0.49
Financial motivation[b]	2.67	1.01	3.07	1.03
Social				
Social norms[a]	3.04	0.80	2.92	0.77
Social motivation	1.95	1.05	1.83	1.01

$^{*}p$ < .05. $^{**}p$ < .01. $^{***}p$ < .001.
[a] Scale ranged from 1 = Strongly Disagree to 5 = Strongly Agree.
[b] Scale ranged from 0 = Not at All to 4 = A Great Deal.
[c] Binary variable normalized to a maximum of 1.

A binary logistic regression of variables that were significant at the bivariate level was run to determine unique variance attributed to each predictor (see Table 5.4). The final regression model found being male, a homeowner, and having higher environmental motivation and lower financial motivation to conserve energy to be the strongest independent predictors of being a feedback user.

Table 5.4. Binary Logistic Regression (Standardized Betas) on Feedback Users

Variable	Step 1	Step 2	Step 3	Step 4
Demographic				
Gender	0.36***	0.34***	0.32***	0.33***
Age	1.02	0.20	1.00	1.00
Marital status	1.39	1.11	1.07	1.08
Political affiliation	1.56**	1.65**	1.36	1.33
Education	0.98	0.98	1.00	0.99
Household income	1.00	1.00	1.00	1.00
Housing type		1.73	1.62	1.75
Homeownership		3.51**	3.50**	3.39**
Psychological				
Environmental concern			1.33	1.38
Environmental motivation			1.54**	1.55**
Bill consciousness				1.47
Financial motivation				0.76*
Nagelkerke R^2	0.11	0.16	0.19	0.21

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

Types of Feedback Used

Because the sample consisted of self-selected feedback users, a variety of products were reported. The 86 respondents reported using a total of 99 feedback products (12 respondents reported using more than one type of feedback device). These products are categorized by the feedback types introduced in Chapter 4, as follows.

Load Monitors. The most frequently reported type of feedback (55) were load monitors, defined as a single piece of hardware that connects an energy source and energy consuming device and displays information directly to the user via a visual display. Among these, 42 reported using a *Kill-A-Watt* and four reported using *Watts Up;* both are devices that plugs into the wall and provide usage information on whatever is plugged into it. An additional five did not specify the product name but reported using a plug-in energy monitor more generally. Three respondents indicated that they *self-monitor* their own energy use by checking their energy meters and one reported using a *Square D PowerLogic*, a circuit monitor that measures current, voltage, power, and energy.

In-Home Displays. Fifteen people reported using in-home displays, defined as devices that display energy use information collected from the electric meter or a separate sensor. Nine reported using *The Energy Detective (TED*), two reported using *BlueLine PowerCost Monitor,* and one each reported using a *Home Energy Cost Monitor* and a *Wattson*[5]. All three products are home energy monitors that present information about whole home energy use in real-time. One person reported receiving feedback from a computer display of his wind turbine and another reported using an *ampere meter*, which reads the flow of electricity running through a series of wires.

Information Platforms. Twelve people reported receiving feedback via an information platform, defined as feedback provided to users with data from existing infrastructure (e.g., electric meters, self-report) via existing infrastructure (e.g., utility bill, website, mobile app). Nine reported receiving feedback via their *utility bill* (3) or *utility website* (6). One reported receiving feedback via *Google Power Meter*, which was a free energy monitoring tool developed by Google that allowed users to view whole home energy use, provided by a utility or with a partner device, from anywhere online[6]. Two people reported receiving estimated feedback (Darby, 2006; EPRI, 2009): the first was an *online carbon footprint calculator,* which are websites that calculate the amount of land area required to sustain an individual's consumption based on user-input data, and the second was *Wattbott*, which is a website that provides free, personalized energy recommendations and connections to products, services, and financing.

[5] Only available in the UK
[6] This service was discontinued on September 16, 2011.

Management Networks. Two people reported using energy-management networks, defined as systems that collect data (from a smart meter, appliance, or sensor) and both communicate data to the consumer and allow users to remotely control connected devices. One reported using *Plugwise*, a kit that includes a plug-in device that can monitor and control appliances via a wireless network, and the other reported using *Green Switch*, a wireless home energy control system that enables the user to turn off all the electronics in the home using a single switch.

Heating, Ventilation, and Air Conditioning (HVAC). An additional category for HVAC was added for this analysis. Despite the fact that these products do not meet the technical definition of *energy* feedback devices, respondents reported them as feedback products and referred to feedback provided on other home parameters (e.g., temperature, thermal leaks) in their responses. Since the present study is interested in the subjective experience of using energy feedback, they were included in the sample. Reported HVAC products included *automated thermostats* (5), digital thermostats that automate home temperature, *thermal sensors* (4), devices used to identify thermal leaks in buildings, *Hobo Data Loggers* (3), products that can be tailored to fit data logging needs for commercial sectors, and *home thermometers (1)* measure and provide a display of room temperature.

Other Products. Specific type of feedback used was unidentifiable for two respondents. These two could not be identified because one reported being "not sure" of the device was and the other indicated using a "prototype".

Adoption

Questions about acquisition of and motivation to use feedback revealed several key findings. Users learned about and obtained products through various means, including social, professional, retail, and environmental sources. Reported motivations primarily focused on general interest in energy usage, both at the household level (aggregated for the residence as a whole) and the individual appliance (disaggregated) level.

Exposure and Acquisition. The influence of social diffusion processes (Rogers, 1995) was seen in both exposure to and acquisition of feedback technologies. A quarter of respondents reported that they found out about feedback through social means, including friends and family (17%) and environmental groups (4%). An additional 15% learned about feedback devices in a work/professional context. When respondents were asked how they acquired the product, several again mentioned social (12) and/or work (2) sources.

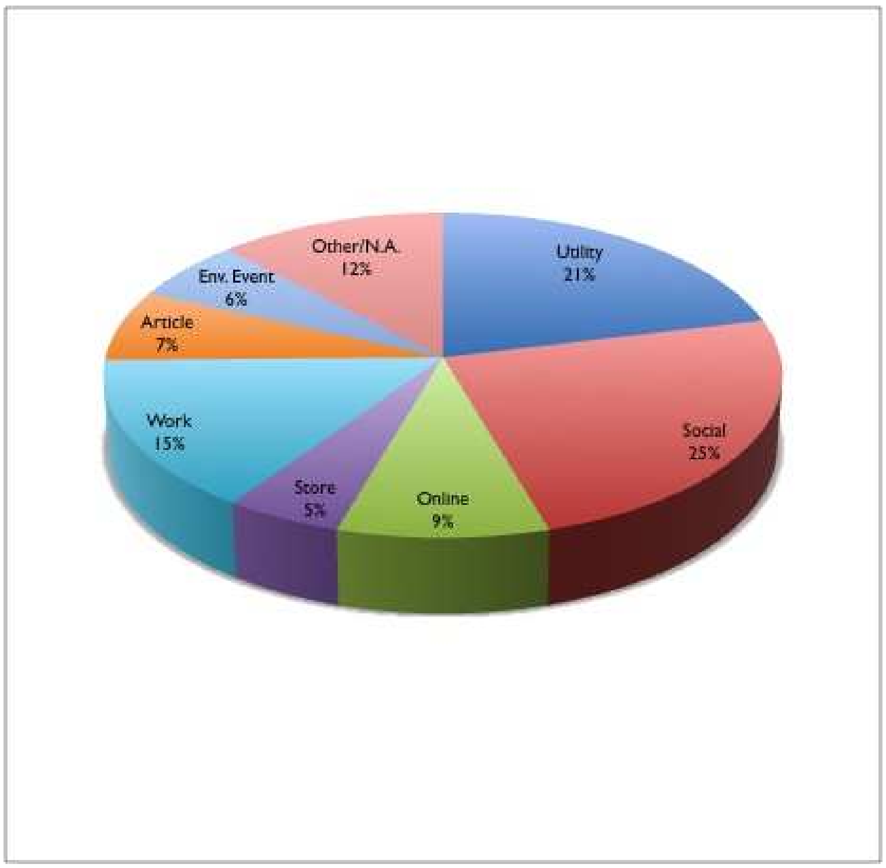


Figure 5.1. Means of exposure to feedback products reported in percentages.

Utility companies represented another important source for feedback adoption across both exposure and acquisition. Twenty-one people indicated exposure and/or acquisition through utilities. In addition to those who reported utility-related feedback, users also found out about and acquired HVAC and load monitors from utilities. Of the six HVAC products in this category, five were automated thermostats offered as part of utility programs.

Additional exposure sources to feedback included online, retail stores, magazine and newspaper articles, and displays at energy fairs/events (see Figure 5.1). Environmental or "green" sources were reported across exposure categories, with a total of 19 responses indicating some environmental source for learning about feedback. These included environmental groups (5), renewable energy events (e.g., conference, fair) (3), energy audit (3), and "green" stores (2).

Additional acquisition sources were online retailers (e.g. Amazon.com), brick-and-mortar retailers (primarily hardware and electronics stores), and manufacturers (see Figure 5.2). Of products purchased directly from manufacturers, six were load monitors (Kill A Watt, Watts Up, Plugwise) and three were in-home displays (TED, Blue Line). At the time of the survey, Plugwise and TED devices were available only through the manufacturers, but Blue Line, Watts Up, and Kill A Watt were all available at multiple retail locations.

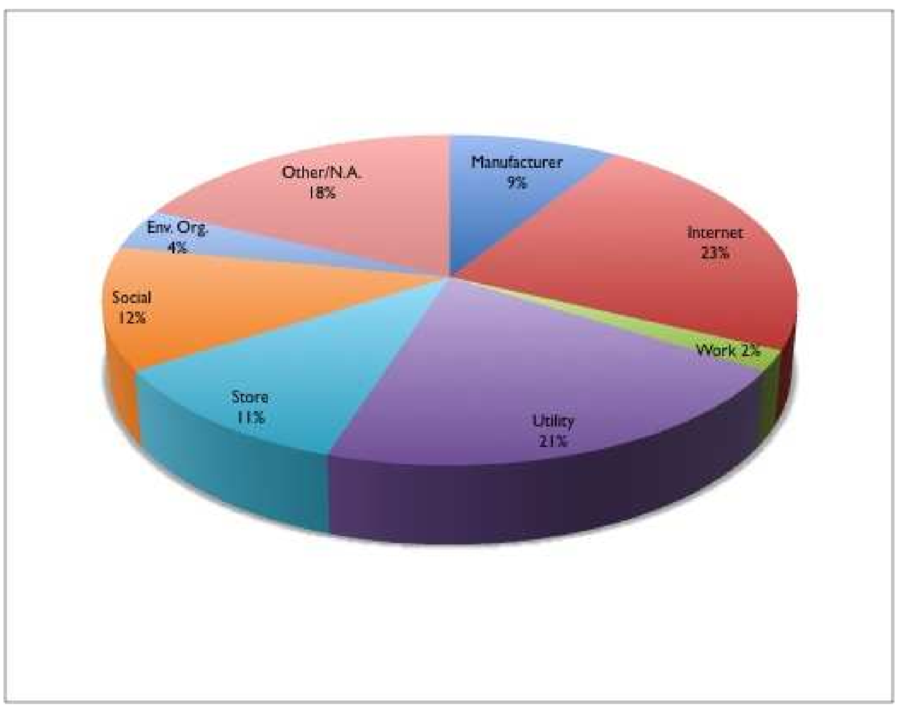


Figure 5.2. Modes of acquiring a feedback product reported in percentages.

Finally, a recurring theme of borrowing rather owning devices emerged across acquisition categories; a total of 13 respondents reported borrowing instead of purchasing feedback. Two thirds of products obtained via social means were borrowed. Respondents also reported borrowing products from utility companies (2), the library (1), and the workplace (1). The most commonly borrowed products were inexpensive load monitors (e.g. Kill A Watt, which currently costs about $20).

Motivation. The most frequently cited reasons for using feedback were a general curiosity or desire for knowledge about household energy use. Analysis revealed a distinction between *tracking* ongoing energy use and *learning* about the energy load of specific appliances. Those motivated by *tracking* reported an interest in ongoing information about home energy use: "*interested in tracking instantaneous home energy use overall", "to track energy use and compare over time more easily"*. The second category related to an interest in *learning* discrete pieces of information about energy use throughout the home: "*trouble shoot inefficient devices*", "*measure power draw on suspect appliances*", "*see what energy use was on a plug load.*" Specific energy sources in the home mentioned included home heating and cooling, computers, pumps, a deep freezer, and an entertainment center.

Other reported motivations included curiosity (15), work-related reasons (9), saving energy (5), saving money (4), and because the product was free or on sale (6). Two respondents mentioned interest in a product because it was "*the first device of its kind*" or "*the gold standard for the class of products.*" Interestingly, none of the respondents explicitly noted environmental motivations.

Usability

Respondents reported overall positive experiences across feedback types, as well as several specific design and display issues. Positive responses focused on ease of use and effectiveness in communicating energy information. Negative responses mentioned both hardware (e.g. installation, accessibility) and software (voltage, information displayed) issues. Also, users of both whole-home (aggregate) and appliance-specific (disaggregated) feedback reported feeling as though they received an "incomplete picture" of energy use.

General Satisfaction. A large number of respondents reported positive experiences with feedback. Sixty-five respondents mentioned being happy or satisfied with their feedback product; when asked what they *disliked* about the product, 15 said "nothing." Specifically, users emphasized ease of use (34) and the quality of information presented about energy use (29): "*Educational to my husband and other people that are not as interested in conserving energy as I am*" (TED), "*ease of use and quick comparison information*" (plug-in energy monitor). A few responses simply noted having fun using feedback: "*it was fun to see graphical info*" (Hobo Data Loggers), "*very cool to see the number change when using appliances*" (TED). Users of automated thermostats specifically reported ease of use in terms of the lack of effort needed to see results; load monitor users consistently mentioned receiving "instant" feedback from the devices. Additional features praised across products included multi-functionality, comparative feedback, and interactivity.

Design Issues. Negative responses across multiple types of feedback emerged regarding the physical design and information displayed by feedback products. Five responses referred to difficulties with installation: "*totally difficult/hazardous*", "*much more difficult to install than I thought it would be*" (*TED*). Eight respondents expressed complaints about inconveniences associated with the physical design of the product, primarily with regard to plugging in load monitors (e.g. Kill A Watt): *"have to get behind large appliances to plug it in", "bulky,", "[needed]…an extension cord often" (Kill A Watt).* Three respondents reported a desire for increased voltage detection: "*allow it to record power data from 220 VAC outlets (clothes dryers and electric stoves)."*

Concerns regarding software and display were noted by several users, including small displays (four users), and complex presentation of information (five users): *"lots of complicated readings"*, *"hard to read, tiny tiny numbers"*, and *"just a bunch of numbers (not easy to interpret)."* Nine users expressed frustration about lack of data storage, reflecting an interest in tracking ongoing energy use, rather than receiving one-time immediate feedback: *"information is not recorded, indexed, or tabulated"*, "*no on board memory (e.g. needs to be plugged into computer in order to log data)."*

Incomplete Picture of Energy Use. Many users mentioned that they received an incomplete energy picture and their desire to be able to see both comprehensive as well as specific energy information. Users of aggregate (whole-home) feedback reported a desire for isolating appliances: "*would be more effective if it could tell you specifically which appliance was causing the most usage*", *"it didn't isolate particular appliances.*" Users of appliance-specific feedback products expressed a desire for whole-home energy information: "*turning appliances on individually to measure their energy consumption [is OK] for researching and learning, but not for modifying behavior on an ongoing basis"*, *"hard to implement for long term or whole house."*

Outcomes

Responses related to outcomes of energy-use feedback included knowledge gains, behavior change, and continued product use. Feedback enabled users to correct inaccurate assumptions about their energy use and several reported changing behaviors to conserve energy, yet there was also indication of a possible rebound effect. The rebound effect refers to the lost part of energy conservation due to the fact that "one tends to consume more productive services" when gains in efficiency are made (Berkhout et al., 2000). A distinction between *tracking* and *learning* again emerged in the data, where some users referred to gaining information about energy use patterns and others reported a one-time knowledge gain. Responses about both knowledge gains and behavior change revealed consistency between the specificity of feedback provided (e.g., aggregate, appliance specific) and outcome specificity. Nearly half of respondents reported that they do not still use feedback, suggesting the possibility of a perceived diminished utility of feedback over time.

Knowledge Gains. When asked about their most surprising experience of using feedback, 44 responses mentioned a gain in specific and/or general knowledge. A common realization was the discovery that actual energy consumption of appliances was considerably above (17) or below (13) their expectations: "*how much LOWER the watts used were than what was reported on Energy Star type lists for plug loads*" (Kill A Watt), "*I had no idea how much energy computers use*" (Watts Up). Phantom loads were frequently mentioned (10) when actual use was found to be greater than expected: *"love to … see how much electricity something is using, especially electronics that are off but still plugged in"*. Specific appliances mentioned included audio amp, computer, cell phone, heating/cooling, lighting, microwaves, refrigerator, entertainment center, TV, and stereo.

There was strong consistency between the specificity of feedback provided and the specificity of reported knowledge gain in respondents. The majority of appliance-specific responses were reported by users of load monitors (24) and HVAC (5) products: *"I checked refrigerators, entertainment center, and devices I thought would be our largest contributors to energy usage"* (*Kill A Watt*); *"I seem to have a constant 150-200 Watt baseline…that can represent 1/3 of our energy use"* (*WattsUp*). A third of in-home display users also reported being surprised by individual appliances and phantom loads, but also mentioned their increased awareness and knowledge of energy use more generally as well as in terms of appliances. Standard and enhanced billing, estimated, and daily/weekly feedback users generally reported an increased ability to track change and reduce usage, but without reference to appliance-level information: *"I know what my energy usage is and how much it costs"*, *"I use less than the average home in my neighborhood"* (*utility website*).

Behavior Change. Over half of respondents mentioned at least one behavior that they changed as a result of using a feedback product; no changes were reported in 24 instances. Most commonly reported behavior changes were unplugging and switching off power (20), decreased use of appliances (15), and increased use of power strips (7). As mentioned with regard to knowledge gain, specificity of reported behaviors generally matched the specificity of feedback. Billing users reported very general changes in energy use: *"cut back"*; *"used less energy by lowering electrical usage."* In-home display users reported both general behavior changes (e.g. "*generally more aware and conscious*") as well as appliance-specific behavior changes: "*stopped using a second refrigerator", "changing water heater set point."* Load-monitor users primarily changed their appliance-specific behaviors, as well as reducing phantom loads and increasing use of power strips: *"got rid of one always-on server due to power draw, line dry when possible", "incorporated the use of Power Strips with "on and off" switches" (Kill A Watt).*

The data also provide some evidence of a rebound effect, whereby users cease efforts to conserve or even use more energy upon learning actual energy-consumption levels: *"I've actually wound up using more energy on some devices when I see how little energy they use"* (*Kill A Watt*). Although only two respondents explicitly mentioned this effect, 15 respondents reported being surprised by how little energy various appliances use, which may contribute to a rebound effect: "*in some cases I'm less diligent about unplugging some devices which showed 0 phantom load"* (Kill A Watt).

Continued Product Use. When asked about continued feedback use, over half (54) responded that they still use their product. Reasons provided included continued usefulness (5), saving energy (4), saving money (3), and because it is hard to remove (1): "*I like to check* *myself and make sure I'm on track*", "*still useful, especially for measuring long-term usage on an appliance*", "*it's become a habit.*" Nine responses mentioned that they still use the feedback, but to a lesser degree: "*I use it less frequently… when I want to check out draw of a new appliance*" (TED), "*only once in a while if I'm chasing down a draft*" (Kill A Watt).

These statements suggest a potential diminished utility of feedback technologies as they are used over time, as evidenced by the nearly half (46) of respondents who reported that they no longer use feedback. When asked why they no longer use feedback, 25 (primarily HVAC and load monitors) users indicated that they are no longer in possession of the product because they borrowed it, it was removed by the company, or they moved away. Four mentioned that they no longer used feedback because they had all the information they needed: *"it's served its purpose."* It appeared that individuals who used feedback for *tracking* purposes were more likely to continue using it than those who used feedback primarily for *learning*. One user even distinguished between the two, saying: "*I checked almost every device I have, so continued usage isn't very informative unless I start tracking usage in a spreadsheet—way too much work.*"

Discussion

The current study expands upon previous research that has tested participants in feedback intervention studies through analysis of the characteristics and user experience of consumers who have purchased such products in the marketplace. Both quantitative analysis of user characteristics and qualitative analysis of user experience revealed patterns that can be integrated into future design, marketing, and research of residential energy feedback. The following section presents a few such areas.

Market Segmentation

Naturalistic users of feedback differ from non-users in several important respects. The present study revealed several demographic characteristics related to the adoption of feedback products including gender, age, marital status, income and homeownership, supporting previous findings that men tend to engage more with feedback technologies (Hargreaves et al., 2010) as well as research on demographic variables related to general energy conservation behavior (e.g. Curtis et al., 1984; Gatersleben et al., 2002; Painter et al., 1983; Sardianou, 2007). These findings suggest that market segmentation strategies may prove useful in future efforts to promote residential energy conservation. Although findings should be regarded as preliminary, the statistical significance of differences among feedback users and non-users suggests that efforts to market feedback products are currently most successful in targeting older, married, male homeowners. Further studies are needed to identify key attributes of current feedback users as well as perceived barriers and benefits of feedback use perceived by different demographic groups. Such findings could assist in both targeting the current feedback market and also expanding future marketing efforts to a wider audience.

Motivation & Messaging

The results from this study support previous findings that feedback users have pro-environmental attitudes (Kurz et al., 2005) but lower financial motivation than non-users. The latter finding appears to conflict with previous research that found financial motivation to be significant among feedback users (Hargreaves et al., 2010; Parker et al., 2008; Liikkanen, 2009). Earlier studies, however, did not compare feedback users to non-users. Taken together, the implications of these findings are unclear—they may suggest that messages promoting the financial benefits of using feedback are less effective in promoting product adoption than messages that highlight environmental benefits among early adopters; or, conversely, that greater use of financial messaging may increase the potential market of these products. This finding also has implications for the presentation of feedback and which messages may be most effective. Further research is needed to elucidate the relationships among environmental and financial concerns among users and non-users of energy feedback.

Leveraging Networks and Utilities

Respondents were much more likely to learn about feedback though existing peer networks (e.g., friends, family, work) and utilities than from traditional mass-media sources (e.g., news articles, internet, advertising). It is not clear, however, whether peer networks afford more effective dissemination strategies or if traditional media sources currently contain very little coverage of feedback (or a combination thereof). Social contacts and utilities were also found to be significant sources of acquisition of feedback technologies, along with more traditional retail venues such as the Internet and retail stores. These findings clearly reveal the value of both social-network and utility-based marketing programs as influential venues for disseminating feedback products, but also suggest the importance of developing additional diffusion strategies for promoting the use of energy use feedback technologies.

Feedback Lending Programs

The number of respondents who obtained their feedback products through borrowing suggests another promising avenue for dissemination of feedback devices. Several feedback borrowing programs already exist, primarily through utility companies and local libraries. The findings that many feedback users report diminishing returns on the utility of feedback and that over half no longer use their feedback products further supports continued investigation into temporary lending programs.

Importance of Product Testing

Users reported positive experiences across feedback types, but several software and hardware design issues were noted by respondents, including difficulties with installation, low voltage detection, and difficulty reading and interpreting displays. Peters and McRae

(2009) assert that product reliability is key to widespread dissemination—if a program or product does not undergo thorough reliability testing prior to market dissemination, early adopters will have inferior experiences and the dissemination and adoption curves of energy-use-feedback products may decrease (Peters & McRae, 2009). This is an important concern as energy-feedback technologies are not yet widely known by the public and, therefore, product usability issues could severely diminish the likelihood of adoption by a wider population if feedback technologies acquire negative connotations early on.

Whole-Home Systems

A primary complaint across feedback types was dissatisfaction with a lack of comprehensive information provided by feedback products. Users of appliance-level feedback express a desire for aggregate household information and users of whole-home feedback express a desire for appliance-specific information. Appliance-specific (disaggregated) feedback seems to lead to more specific behavior changes, but may also convey rather inconsequential amounts of usage of some appliances, leading to increases in energy use (the rebound effect). Aggregate feedback providing the big picture of whole-home energy use may be more motivating, but the user is given little direction in terms of specific energy-use behaviors and opportunities for conservation. An integrated system that gives feedback on aggregate household energy use as well as disaggregated (appliance-specific) information offers great promise for the future of persuasive feedback technologies to identify and encourage pro-environmental behavior changes. In addition, users of plug-load monitors complained of inconveniences associated with getting behind large appliances to measure plug loads and an inability to read displays plugged in behind furniture, suggesting that non-intrusive load monitoring or wireless displays may meet less resistance than plug-level data collection and display products.

Rebound Effects

As mentioned above, study findings highlight important concerns about the potential rebound effects of feedback information; with some users reportedly adjusting behavior upwards as they find out they are using less energy than anticipated. While this is not a new finding, it is an important reminder of the need for feedback designers to acknowledge unintended consequences of energy information provision. Research investigating ways of countering this rebound effect through message framing and the inclusion of motivational elements into feedback could thus prove quite useful.

Dual Feedback Functions

The emergent distinction between the uses of feedback for *tracking* and *learning* across user responses introduces a new way of thinking about and understanding feedback. There has been little research on the psychological mediators of feedback, and this finding suggests a promising avenue for future study. The present data suggest that these two feedback functions are related to users' motivations to adopt feedback technologies, the way users interact with those technologies, and the outcomes of feedback use.

Reviewing themes across responses reveals a set of key characteristics of tracking and learning feedback (see Table 5.5). Tracking takes place over time and requires many "bits" of information to present patterns and comparisons (to past use, others, or a goal). Therefore, it is generally associated with feedback systems that collect, store, and present temporal-use data, such as the feedback provided by utilities and in-home displays. Learning, as the acquisition of knowledge, can take place instantly and with as little as one piece of information. This type of feedback is therefore easier to translate to specific behaviors or actions and is generally associated with device-specific (e.g., load-monitor) feedback.

Table 5.5. Key Characteristics

Attribute	Tracking	Learning
Temporality	Happens over time	Happens in a moment
Data	Many "bits" of information	One "bit" of information
Behavior	Not correlated to specific action(s)	Correlated to specific action
Comparisons	Enables comparisons (e.g., historical, social, goal)	Does not enable comparisons
Motivation	Provides additional motivation for conservation behavior (e.g., competition, goal-setting)	Potential for rebound and/or decreased attention to smaller conservation behaviors
Type	Generally associated with aggregate (whole-home) feedback	Generally associated with disaggregated (appliance) feedback

Although there is a correlation between the type of feedback received and these categories (e.g., recipients of information platforms are more likely to use feedback for tracking, whereas users of load monitors are more likely to use feedback for learning), both tracking and learning functions were mentioned among users of all feedback types and it is possible to receive feedback that serves both a tracking and learning function, though such systems currently are uncommon. Further investigation into this distinction may lead to advances in both the design and marketing of feedback technologies.

Limitations

The sampling technique and measurement of key variables used in this study may limit the generalizability of its findings. Online sampling is still a relatively new method, though a number of studies have indicated that Internet samples are as diverse as more traditional samples and that their findings are consistent with traditional methods and generalizable across presentation formats (Gosling, Vazire, Srivastava, & John, 2004; Kaplowitz, Hadlock, & Levine, 2004; Smith, 1997). A comparison of the study sample with U.S. Census data indicated reasonable representation and we believe that our intention to capture a specific market segment justifies the use of a non-random sample.

To maintain the desired breadth of the survey, abbreviated measures were used for all of the psychological variables. All psychological variables were measured using two- or three-item scales, with the exception of bill consciousness, which was measured as a single item. In addition, because our study sought information from *naturalistic* users of feedback, there was an unbalanced representation of energy feedback technologies reported, with overrepresentation of certain devices (i.e. Kill A Watt) and underrepresentation of others. Although this is a reflection of the actual market of feedback devices, it decreases somewhat the ability to conduct comparative analyses.

Finally, there was some non-completion of survey items, particularly in the demographic section. This could be due to participants' preferences regarding disclosure of personal information or a potential fatigue effect, as demographics were presented at the end of the survey. Analyses were run using both a listwise and pairwise deletion with no significant differences between results, so final analyses were conducted using pairwise deletion.

Conclusions

Although there has been a great deal of research on the use of feedback to promote energy conservation over the past 40 years, the lack of wide-scale adoption in the marketplace suggests that research into naturalistic users of these products is vital for better understanding of wide-scale adoption. This study provided a preliminary picture of these users and their experiences. Study found that males, homeowners, and individuals with high environmental concern were among those most likely to purchase and use feedback, which is consistent with research on other energy-conservation behaviors. Users indicated generally positive impressions of feedback devices, and their experiences revealed great promise for novel approaches to the design and marketing of feedback, including the provision of both aggregate and disaggregate energy-use information and dissemination through utility and social-network channels. Design and usability issues identified in this study indicate that this technology, despite great potential, still has some hurdles to overcome before being marketed to the general American public. Further research testing use across devices and isolating key features of feedback will greatly enhance our understanding of its use and potential for energy conservation.

CHAPTER 6: The Usability Perception Scale (UPscale)

Past psychological research on eco-feedback has largely ignored feedback displays, despite a clear understanding that the way information is presented can impact response. Eco-feedback research in psychology has primarily tested feedback experimentally but with little attention to display features or user experience (Fitzpatrick & Smith, 2009). Research in the Human-Computer Interaction (HCI) field, on the other hand, has largely focused on the design process and production of eco-feedback artifacts, but without experimental design or statistical analysis (Froehlich et al., 2010). An integration of these two approaches has great potential for leveraging key mechanisms to maximize the effectiveness of eco-feedback (Froehlich et al., 2010).

As the overarching goal of eco-feedback is reducing environmental impact, most field studies measure changes in energy use as the primary dependent variable (see Chapter 3). Although such measurement is vital, additional information about the subjective experience of study participants could add significantly to our understanding about not only *whether* different types of feedback work, but *how* they work. Additionally, among those studies that have collected additional data, significant variation exists in the variables collected and specific questions used; no standard measures or scales currently exist to conduct such assessment. Consistency in measurement across studies would improve our overall ability to account for variation in treatment effects and verify findings both within and across studies.

This chapter introduces a new instrument, the Usability Perception Scale (UPscale), designed to measure ease of use and engagement with eco-feedback displays. After reviewing past research on eco-feedback, usability, and the limitations of current assessment methods, the UPscale is introduced and psychometrically tested against four types of psychometric properties: factor structure, reliability, validity, and sensitivity. The chapter concludes with suggestions for future research to both refine and use the UPscale in field studies.

Literature Review

Approaches to Eco-Feedback. Contributions in the area of eco-feedback have been largely conducted in two fields—environmental psychology and human-computer interaction (HCI; Froehlich, et al., 2010). Although psychological research on energy feedback dates back to the 1970s, inclusion of eco-feedback research in the HCI literature is more recent, with over 90% of HCI papers on eco-feedback published since 2008 (Froehlich, et al., 2010). This increase is largely a result of advances in data-sensing and analytics, which allow the collection and provision of energy use data to consumers via a multitude of in-home and web- or mobile-based displays. At its core, human-computer interaction (HCI) is focused on applying scientific methodology to understand how people interact with computers, and how computers may be designed so that they are "easy, efficient, error-free—even enjoyable" (Card, Moran, & Newell, 1983). As eco-feedback becomes increasingly available and pervasive, HCI is well-placed to contribute to the evaluation and design of display interfaces. Measure such as preference, usability, and satisfaction, central to HCI, can yield useful insights for effective design (Davis, 1989; Toomin, Kriplean, Pörtner, & Landay, 2011).

A review comparing the approaches of psychology and HCI to eco-feedback (Froehlich et al., 2010) found that HCI studies have been primarily lab-based or qualitative with an emphasis on "understandability, aesthetic, and perceived usefulness"; the few field trials conducted were relatively brief (1-4 weeks) and used small samples (average 11 participants). On the other hand, studies from psychology have focused on field trials to assess behavioral outcomes of feedback compared to a control condition and/or pre-treatment baseline. The average sample size is 6,108 participants and average study length is nine months (see Chapter 3). Data collection in these studies is typically quantitative, with energy usage data as the most common variable collected. The review concludes that both approaches are valuable and suggest efforts toward greater integration (Froehlich et al., 2010).

One way to integrate these two approaches is to include subjective measures of user experience and perceptions of eco-feedback into larger scale field trials, to understand their impact on behavioral outcomes. As qualitative data can be cumbersome to collect and analyze for larger samples and also does not allow inferential analysis, the development of a quantitative instrument would be ideally suited. In addition, it is vital that such an instrument be designed with specific intention. Although questions assessing a person's gender or age may be fairly objective, questions about perceptions and attitudes are often subjective in nature and therefore care must be taken in question design. Psychometrics is a branch of psychology that addresses this issue through the development of methods for creating and assessing the quality of variables used to measure subjective human experience (Kline, 2000).

Past work in HCI has led to the development of multiple scales assessing the user experience of computer systems, but this work has yet to be applied to eco-feedback. The next sections will discuss past work and scales in usability as well as why a new instrument is needed for eco-feedback at this time.

Characteristics of Usability. A key function of HCI research is to assess the subjective user experience of computer systems, programs, and interfaces (Card et al., 1983). As such, a great deal of effort has been spent defining and determining the key characteristics of usability. Although the definition of usability is sometimes simplified to "ease of use", a more comprehensive definition takes into account several characteristics related to user experience (Quesenbery, 2001). The ISO 9241 standard definition of usability is "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use". Additional work has defined several characteristics of usability within the above definition. Although variations abound, a common definition of usability includes five key characteristics: effectiveness, efficiency, error tolerance, ease of use, and engagement (Quesenbery, 2001).

Effectiveness, efficiency, and error tolerance all refer to the users’ ability to complete tasks with the system or interface. Effectiveness refers to overall ability to accomplish the task, efficiency refers to the speed and accuracy of completion, and error tolerance refers to the ability to minimize errors. They are typically measured objectively via usability studies in which subjects complete a task and metrics related to overall performance (effectiveness), time to completion (efficiency), and number of errors (error tolerance) are evaluated (Lewis, 1995).

Ease of use refers to the ability of a user to learn and use a system or interface; it is sometimes broken into sub-characteristics of learnability and memorability (Nielsen & Hackos, 1993). Engagement refers to the whether a system or interface is pleasing and satisfying to use. As both ease of use and engagement are inherently subjective, self-report is the primary form of data collection for these characteristics. These two variables have been determined to be particularly important in predicting the degree to which people accept and use particular information technologies (Davis, 1989).

Current Usability Scales. A number of instruments have been developed to evaluate the usability of a system or interface, assessing a number of characteristics related to usability, including perceived efficiency, learnability, and satisfaction. A list of these scales is presented in Table 6.1. These scales have been shown to predict similar responses for user satisfaction; the System Usability Scale (SUS) has been found to correlate with both the Software Usability Measurement Inventory (SUMI) (r=0.86) and the Usability Metric for User Experience (UMUX) (r=0.96) (Finstad, 2010).

Among them, the System Usability Scale (SUS) is by far the most commonly cited and utilized scale in the HCI literature (Bangor, Kortum, & Miller, 2008; Lewis & Sauro, 2009). It consists of 10 Likert-scale items which ask respondents to agree or disagree with given statements on a 5-point scale. Odd-numbered items are worded positively and even-numbered items are worded negatively. SUS has proven popular and cost effective for evaluating usability across a wide variety of systems including cell phone equipment, modems, voice response systems, and websites (Bangor et al., 2008). It has been shown to outperform other scales at small sample sizes, has been found to be easy to administer and score, and is the only scale that addresses the whole system rather than a particular feature of the system (Bangor et al., 2008).

Table 6.1: Commonly cited usability scales in HCI literature

Scale	Items	Dimension assessed
After Scenario Questionnaire (ASQ)[a]	3	User satisfaction with system usability
Post-Study System Usability Questionnaire (PSSUQ)[b]	19	User satisfaction with: 1) system usefulness; 2) information quality; 3) interface quality
Computer System Usability Questionnaire (CSUQ)[c]	19	User satisfaction with: 1) system usefulness; 2) information quality; 3) interface quality
Questionnaire for User Interface Satisfaction (QUIS)[b]	27	1) Overall reaction 2) learning; 3) terminology & information flow; 4) system output; and 5) system characteristics
System Usability Scale (SUS) [c]	10	Perceived system usability and learnability
Software Usability Measurement Inventory (SUMI)[d]	50	1) Global usability plus perception of: 2) affect; 3) efficiency; 4) learnability; 5) helpfulness; and 6) control
Usability Metric for User Experience (UMUX) [e]	4	Perceived usability (efficiency, effectiveness, and satisfaction)

[a] Lewis, 1995
[b] Chin, Diehl, & Norman, 1988
[c] Brooke, 1996
[d] Kirakowski & Corbett, 1993
[e] Finstad, 2010

No psychometric analyses on SUS were initially published and it was originally thought to be a unidimensional scale (Brooke, 1996). Subsequent researchers assessed the measure (Bangor, Kortum, & Miller, 2008; Borsci, Federici, & Lauriola, 2009; Lewis & Sauro, 2009) and found "inconsistent results regarding the factorial structure of its items" (Borsci et al., 2009). Both Lewis and Sauro (2009) and Borsci et al. (2009) identified two factors, which they termed usability (eight items) and learnability (two items).

Limitations of Current Scales. The SUS and other usability scales provide much instructional value for the design of an eco-feedback usability scale, but two primary limitations suggest the need for a new instrument targeted to this purpose. First of all, current usability scales have been designed primarily to evaluate products or systems rather than info-visualizations such as those provided via eco-feedback displays (Borsci et al., 2009). Although in some cases simple wording changes from system/product to image/information are possible, this is not always the case. Additionally, there are items measured by the SUS, and included in the total score, that are not relevant when evaluating usability of info-visualizations, e.g. SUS item 5: "I found the various functions in this system were well integrated" (Kirakowski & Corbett, 1993).

Additionally, as user interface design progresses from functional (i.e. pre-defined tools designed for fixed tasks) to experiential (i.e. interactive interfaces designed for sociability and pleasure), alongside an increasing selection of technology options, the metrics used to evaluate subjective user responses must also progress (Angeli, Sutcliffe, & Hartmann, 2006). Operational interfaces were appropriately assessed with metrics primarily associated with ease of use, such as learnability and the efficiency with which tasks could be carried out. However, experiential interfaces should also be evaluated with metrics that account for continued engagement, as a good interface design may result in increased time on task and this can't be captured by ease of use metrics (Angeli et al., 2006).

As such, no instrument has yet been developed that (1) addresses the unique needs of eco-feedback displays (as opposed to systems or products), and (2) incorporates psychometrically validated sub-scales for both the ease of use and engagement characteristics of usability. The current study is designed to meet this need.

Method

The present study introduces and tests the Usability Perception Scale (UPscale), which was designed to measure the user experience of eco-feedback displays. UPscale builds from previous system usability scales, but was designed to be different from the work reviewed above in that the UPscale questions were designed to: (1) measure information received from a feedback graph or other info-visualization and (2) incorporate and distinguish between hypothesized subscales for ease of use and engagement.

Participants and Procedure

The scale was tested via an online survey conducted in spring 2012. Participants were recruited via Amazon Mechanical Turk and then directed to a website that hosted the survey. The survey took approximately 10 minutes to complete and participants were paid $0.31 for successful completion. Participation was completely anonymous and no identifiable data were collected. The primary criteria for inclusion were age of 18 years or over, living in the United States, and ability to read and write in English. Besides being asked to only complete the survey once, there were no exclusion criteria for this study.

1470 US residents completed the survey. After excluding incomplete responses as well as those who completed the survey in less than 5 minutes or answered a trick question incorrectly, 1103 responses remained for analysis. Table 6.2 presents summary data on demographic variables for the survey sample compared to U.S. Census data (2010).

Table 6.2. Demographic characteristics of the sample (n=1103) compared to U.S. Census data

Demographic variables	Sample	Census
Gender	47% Male	49% Male
Average age*	31.3 Years	36.8 Years
Race	78% White	79% White
Average education*	14.6 Years	13.3 Years
Average income**	$52,940	$67,609

* Sample and census significantly different based on independent t-test ($p < .01$)

Measures

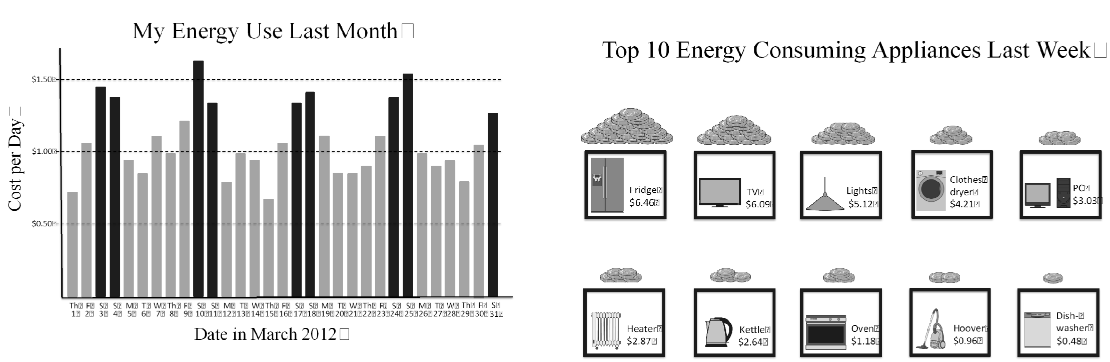
Data analyzed in this study were collected as part of a larger online survey, which was designed to address three major topics with the eco-feedback literature: (1) perception of graphical displays based on information density, (2) the role of message framing in behavioral intention, and (3) measuring subjective appraisal of user experience. The current paper presents results related to the third goal; measures examined in this study are described below.

UPscale. The Usability Perception Scale (UPscale) consists of eight Likert-scale items, which ask respondents to agree or disagree with given statements on a 5-point scale (from 1 = "strongly disagree" to 5 = "strongly agree"). Odd-numbered items are worded positively and even-numbered items are worded negatively. It includes four questions designed to test for ease-of-use attributes, including complexity, interpretation, and learnability. An additional four questions test engagement attributes, which include relevance, usefulness, and intention to use. Questions included in the UPscale are listed in Table 6.3.

Table 6.3. Questions included in the UPscale

Ease-of-Use Questions:	Engagement Questions:
1. I am able to get the information I need easily.	1. I gained information from this image that will benefit my life.
2. I think the image is difficult to understand.	2. I do not find this image useful.
3. I feel very confident interpreting the information in this image.	3. I think that I would like to use this image frequently.
4. A person would need to learn a lot in order to understand this image	4. I would not want to use this image.

Experimental design. Participants were randomly shown one of four images depicting energy use by time, or one of four images depicting energy use by appliance. Figure 6.1 shows example images from each of these groups.



a) Energy use by time

b) Energy use by appliance

Figure 6.1: Example of energy use by time and use by appliance images shown to participants

Participants were then presented with the 8-item UPscale and asked to respond to each statement using a 5-point Likert scale. Negatively worded (even-numbered) items were recoded for use in analysis.

Behavioral Intention. As the goal of eco-feedback is to reduce environmental impact via individual behavior, two questions were included that asked participants about their intention to change their behavior based on the information presented to them. These questions were intended to serve as a proxy for actual behavior and were tested for criterion validity of the instrument.

Demographic Variables. Demographic questions were included to determine the representativeness of the sample and to test for the sensitivity of the instrument. Traditional demographic data included gender, age, race, income, and education. Since the study was concerned with pro-environmental behavior, a single item measuring environmentalism ("Do you consider yourself to be an environmentalist?") was also included.

Results

Statistical analyses were conducted to test for four key aspects of psychometric quality: factor structure, reliability, validity and sensitivity (Lewis, 1995).

Factor Structure

Factor structure refers to naturally occurring groups of items that arise from multiple items. A scale may have just one or several factors, depending on the questions included. Factor structure is generally measured using factor analysis; factors include all the items with loading scores above a set point (generally .40).

Factor Analysis on the UPscale items yielded a 2-component solution, which accounted for 68% of total variance (see Table 6.4). Items corresponding to ease of use clustered strongly as one component, and engagement as another, with no cross-loading items. The sub-scales were both tested separately and no additional sub-factors emerged.

Table 6.4. Factor Structure of UPscale.

Item	Factor 1: Ease of Use	Factor 2: Engagement
I am able to get the information I need easily.	**.696**	.368
I think the image is difficult to understand.	**.830**	.180
I feel confident interpreting the information in this image.	**.791**	.219
A person would need to learn a lot in order to understand this image.	**.818**	.045
I gained information from this image that will benefit my life.	.113	**.793**
I do not find this image useful.	.309	**.751**
I think that I would like to use this image frequently.	.031	**.828**
I would not want to use this image.	.349	**.710**
Explained Variance	50%	18%

Note: values in bold indicate which items load to each factor.

Reliability

Reliability refers to the internal consistency among the items within the scale. Once factors are established or confirmed, each factor, as well as the overall scale, is tested for reliability. Reliability is generally measured using Cronbach's co-efficient *a*; if *a* is sufficiently high (> 0.70), items can be combined to produce a scale. Reliability tests revealed high levels of internal consistency for the overall scale (α=.85), and for both the ease of use (α=.84) and engagement (α=.83) subscales.

Validity

Validity refers to whether an instrument measures what it claims to measure. One of the main forms of validity, criterion validity, compares the scale to other indicators of a construct to assess any relationships. Validity is generally measured using Pearson correlation coefficient *r*. Validity was tested by correlating UPscale scores with self-reported behavior-change intention scores. Results suggest evidence of predictive validity, with significant correlations (p<.001) for the overall scale (r=.536) as well as both subscales: ease of use (r=.213), and engagement (r=.685).

Sensitivity

Sensitivity refers to how much the scale varies based on different users or independent variables. Sensitivity is typically measured using t-tests for binary variables or analysis of variance (ANOVA) for categorical variables.

Image Type. A one-way analysis of variance (ANOVA) was run to assess the sensitivity of UPscale scores across the different images. Results indicated a significant effect of image type on the full scale (F=3.616, p=.001) and ease of use subscale (F=6.411, p<.001), and a marginally significant effect on engagement subscale (F=1.744, p=.095). This suggests that UPscale is reasonably responsive to different image properties.

Demographic Variables. ANOVAs were run test the sensitivity of the UPscale and its two subscales across the demographic variables: gender, age, race, income, education, and environmentalism. Results revealed that age (F=2.624, p=.004) and environmentalism (F=11.092, p=.001) had a significant effect on the overall scale, while gender (F=4.082, p=.044), age (F=6.169, p<.001), environmentalism (F=18.635, p<.001) and income (F=2.117, p=.026) all had a significant effect on the engagement subscale. No tested variables display significant effects on ease of use.

Discussion

The UPscale, building on insights from existing usability measures, was developed to evaluate user perceptions of information visualizations such as those provided by eco-feedback displays. It incorporates and psychometrically evaluates questions relating to the ease of use (complexity, interpretability, and learnability) and engagement (relevance, usefulness, intention to use) characteristics of usability.

The psychometric properties of the UPscale point to its reliability and validity. Factor analysis supported the two theoretically derived subscales for ease of use and engagement. Both the overall scale and both subscales were found to be high in internal consistency, proving reliability. These two tests are vital for instrument validation, as they indicate that the questions can be summed and/or averaged into a single variable “item” for statistical analysis. As such, the UPscale can be used as a single eight-item scale, and the two four-item sub-scales for ease of use and engagement can also be used on their own.

The overall scale and both subscales also correlated with behavioral intention, suggesting criterion validity with energy savings. These results indicate that perceived ease of use and engagement may be key mediators of feedback effectiveness, though there are limitations with this method, as behavioral intention does not always accurately predict actual behavior. Further research testing this hypothesis with actual behavior would be beneficial to explore this hypothesis more fully.

Finally, the UPscale was found to be sensitive to experimental manipulation, which suggests it can be used successfully to determine differences in usability among feedback types. As the scale was also sensitive to demographic variables (gender, age, income, environmentalism), it is highly recommended that they be included and controlled for in analysis to account for variability in subsequent findings.

As eco-feedback becomes more common, the need to ensure that it is useful and engaging to consumers is paramount. Programs like the U.S. Green Button Initiative (Chopra, 2011), as well as the 200+ feedback products and services that have emerged on the market (see Chapter 3), are based on the idea that consumers will be engaged with and transformed by access to energy information. Attention to the usability of such eco-feedback displays is a key step toward this goal and the UPscale provides an instrument that can be used at scale in the hundreds of field trials planned in the coming months and years.

Designed to complement rather than replace existing measures of program effectiveness (e.g., kWh reductions, self-report behavior), the inclusion of UPscale in eco-feedback studies can yield useful insights into effective program design help model and predict the effectiveness of future interventions based on an increased knowledge of how and for whom they are effective. Broad use of such standardizes instruments can improve and aggregate our overall knowledge across studies and contribute to a more robust understanding of eco-feedback and how it can best be leveraged for energy savings.

CHAPTER 7: CONCLUSION

As feedback technologies become increasingly ubiquitous in our society, with a growing capacity to leverage personalized energy information, there is a need to ensure that they are utilized to their full potential. An improved understanding of the mechanisms underlying energy feedback is needed at both a theoretical and practical level. Taken together, the studies conducted in this dissertation explore the topic of residential energy feedback from an interdisciplinary perspective with a focus on applying psychological science to a behavioral domain that has received much study but little theoretical attention to date (Katzev & Johnson, 1987; Schultz, 2010; Steg & Vlek, 2009).

Review of Findings

This dissertation presents a mixed-methods approach to understanding the role of feedback in residential energy conservation through five distinct, yet interrelated approaches: (1) literature review and introduction of Eco-Feedback Intervention Theory (eFIT); (2) meta-analysis of main effects and key moderators on past research on residential energy feedback; (3) taxonomy of energy feedback technology derived from content analysis; (4) analysis of naturalistic energy feedback users via online survey data; and (5) introduction and psychometric testing of a Usability Perception Scale (UPscale). Most previous research on energy feedback has treated it as a unified construct and devoted little energy to understanding how or for whom eco-feedback works best. Rather than continuing to answer and ask the same question of "does feedback work?", the studies presented each take as their starting point the idea that "feedback *can be* effective but *it depends*". In doing so, they explore the questions of what moderates the effects of energy feedback, how can we categorize the 200+ commercially available technologies, what is the current and potential market for feedback outside of a lab setting, and how can we measure user experience to help make more engaging and easy to use displays? A review of findings for each study follows.

Eco-Feedback Intervention Theory

Chapter 2 explored psychological theories of both feedback and pro-environmental behavior and integrated them with the development of *eco-Feedback Intervention Theory* (eFIT). The theory includes the four elements of perception, interpretation, motivation, and ability and extends past feedback theory (notably Feedback Intervention Theory; Kluger & DeNisi, 1996) by it with the unique contexts and challenges associated with pro-environmental behavior.

The *perception* condition extends previous theory by integrating the invisible nature of energy use and suggesting eco-feedback as a key way to make individuals aware of energy use. I*nterpretation* addresses the abstract nature of environmental impacts and the need to simplify information that is cognitively complex. M*otivation* is a key consideration in past feedback theories and is extended to incorporate moral determinants of behavior and social influence. Finally, *ability* further extends past feedback theory to account for the multiplicity of behaviors available to save energy and the contextual barriers that can prevent action.

Meta-Analysis

While several literature reviews of feedback have made claims about which types or features are most effective, such claims are problematic because effect sizes vary and had never been systematically studied using statistical methodology that takes into account within-group variability and uses inferential testing to draw conclusions across studies. In addition, discrepancies among sample, design, measurement, and experimental conditions require statistical inquiry (e.g., moderator analysis) to compare effects between studies, which provides greater detail into which aspects of feedback that may be more effective, as well as the users and behaviors for which feedback may be most effective.

Chapter Three applied eFIT to the domain of residential energy feedback via statistical meta-analysis of 42 feedback studies published between 1976 and 2010. Results found that feedback is effective overall (r = .1179, p < .001), but with significant variation in effects (r-effect size varied from -.0803 to .4803). Several treatment variables were found to moderate this relationship, including frequency, medium, comparison message, duration, and combination with other interventions (e.g., goal, incentive).

Taxonomy of Feedback Technology

Many energy feedback products (i.e., technologies with hardware) and platforms (i.e., technologies without hardware) have emerged on the market in recent years. Past research had suggested that the effectiveness of feedback varies based on distinct characteristics, and proposes categories to better understand and distinguish between these characteristics. However, existing categories have the following issues: (1) structures grouped feedback technologies into four (or fewer) categories, making device distinction and selection onerous; (2) categories often ignored technical and psychological distinctions of interest to researchers; and (3) none provided a systematic description of the specific characteristics that vary by category.

Chapter Four presented presents a classification structure of energy-feedback technology, derived theoretically from a review of relevant literature and empirically via content analysis of 196 feedback products and platforms. The taxonomy structure was derived based on the characteristics of hardware, communications, control, display, and data collection. The resulting taxonomy included the following nine categories: (1) information platform, (2) management platform, (3) appliance monitor, (4) load monitor, (5) grid display, (6) sensor display, (7) networked sensor, (8) closed management network, and (9) open management network. These categories are mutual exclusive and exhaustive of the identified technologies collected and are based on characteristics which are both stable and important to feedback provision. The taxonomy enables a greater understanding of the ways that current technologies vary, which can assist with future study as well as deployment.

Naturalistic Users

Feedback is widely promoted as a promising strategy for promoting energy conservation based on its effectiveness in field studies, and dozens of devices providing feedback have emerged on the market in recent years. However, these products have not yet taken a strong hold in the marketplace and policymakers are increasingly looking to behavioral scientists for guidance. It is not clear whether this lack of uptake is due to device usability or simply a slow adoption curve, as virtually all studies of feedback devices have actively recruited participants. Little is known about naturalistic users, i.e., individuals who choose on their own to use devices that monitor energy consumption.

Chapter Five presented mixed-methods analysis of naturalistic users of energy feedback, i.e., individuals who choose on their own to use products that monitor energy consumption. It examined both who is using these devices as well as their user experiences through analysis of online survey data. Demographic and psychological characteristics of 86 individuals using feedback devices were compared to 749 non-users. Regression analyses revealed that feedback users were more likely than non-users to be male, homeowners, liberal, and environmentally concerned. Qualitative analyses revealed important patterns of user experience, including the role of social diffusion in adoption, differences in the use of feedback for tracking and for learning purposes, and evidence of diminished utility over time.

Usability Perception Scale (UPscale)

While the metrics used to measure *whether* feedback works is fairly standard and easy to compare between studies, the variables and metrics used to measure *how* and *for whom* they work have been left to individual researchers, with little attempt at creating a replicable model. Such standardization is common in related fields such as education and psychology, but has yet to take hold in energy-program evaluation.

Chapter Six introduces and tests a new instrument, the Usability Perception Scale (UPscale), designed to measure ease of use and engagement with eco-feedback displays. After reviewing past research on eco-feedback, usability, and the limitations of current assessment methods, the UPscale is introduced and psychometrically tested in an online experimental design against four types of psychometric properties: factor structure, reliability, validity, and sensitivity. Factor analysis supported a two-factor solution, supporting subscales for ease of use and engagement. Reliability tests revealed high levels of internal consistency for the overall scale and both subscales. A test of criterion validity with behavioral intention found significant correlations with both subscales, suggesting that usability is a key mediator for behavior change. Finally, ANOVA results found differences between randomly assigned images, suggesting the scale has sufficient sensitivity for use in experimental research.

Taken together, the results of these five studies contribute to a more contextual, social ecological understanding of the nature of energy feedback and the situational circumstances under which such feedback truly "matters". They help to identify key contextual moderators of feedback effectiveness, broad categories of energy feedback products, characteristics of those who elect to use energy feedback, and metrics of user experience that are significantly with correlated behavioral intention, thereby moving toward a more nuanced, social ecological framework for understanding the key dimensions and effectiveness of feedback.

Policy Implications

As part of its transition toward a "smarter" electricity grid, the U.S. National Science and Technology Council released a report outlining enabling policy recommendations that included key actions to "ensure that consumers receive timely access to, and have control over, machine-readable information about their energy consumption" and to "help consumers understand and act upon the feedback they receive" (Chopra et al., 2011, pg. 40-43), so that they can decrease energy waste and save money. The Green Button initiative, which is the utility industry's response to the White House recommendations (Chopra et al., 2011), has opened up energy data market by making consumers' electricity-use information available to them via a "green button" on the utility website. Furthermore, the adoption of common technical standards by participating utilities means that third-party software developers can leverage this information to produce commercially available software on which people can view their energy data.

As more and more utilities and regulatory agencies focus their attention on energy feedback, there is an urgency to ensure that evaluation of such programs are done in as rigorous a manner as possible. It is important when analyzing research that is conducted in an applied setting and has significant implications for practice that the magnitude of effects is interpreted in terms of relevance. Thus, one must review not only the *effectiveness* of a policy or program but also the *efficiency* and *feasibility* of deploying it within a general population (Kraft & Furlong, 2004).

Effectiveness

The effectiveness of the program is of the utmost importance, as this is a vital issue that impacts all members of our community and larger society. In its most basic definition, effectiveness refers to whether a program achieved stated goals (Kraft & Furlong, 2004). In the case of energy feedback, this is often measured in percent energy savings, compared to a control group. The studies analyzed in Chapter 3 reported an average savings of 9%, with a range from 0-20%. Translated to an effect size (e.g., the difference in energy use attributed to the provision of feedback), this resulted in an unweighted mean-effect size of .1174. As such, feedback was shown to be highly effective across the 42 studies analyzed but with a high degree of variation in effectiveness. This supports previous findings in literature reviews (Darby, 2006; EPRI, 2009; Ehrhardt-Martinez et al., 2010).

However research into naturalistic feedback users (Chapter 5) suggests additional questions into feedback effectiveness outside of the lab. Study findings suggest a possible rebound effect of feedback information, with some users reportedly adjusting behavior upwards as they find out they are using less energy than anticipated. eFIT suggests that over time, users may respond to feedback in different ways, shifting their attention between different motivational and learning processes. This hypothesis is supported Chapter 5, which revealed a distinction between the use of feedback for tracking (e.g. monitoring ongoing energy use) and learning (e.g., gaining specific information about energy use). In addition, nearly half of the feedback users in the sample reported no longer using feedback, citing reasons that included, "*it's served its purpose*" and "*continued usage isn't very informative*". These statements suggest a potential diminished utility of feedback technologies as they are used over time, making unclear the long-term effectiveness of such information.

Efficiency

Efficiency refers to the relationship between program benefits and program costs (Kraft & Furlong, 2004). Efficiency is a very important criterion, as programs are constantly fighting against limited resources. Any program that uses resources must therefore not only be effective, but also efficient. Whether feedback is an efficient intervention (or what types of feedback constitute efficient forms) therefore varies by product and program. Efficiency requires an understanding of the cost of the intervention with respect to the cost savings associated with the behavior change. Allcott and Mullainathan (2010) addressed this issue, finding that feedback provided through improved billing, despite small effect sizes, may be more efficient than studies which use more technological forms of feedback, despite the latter leading to larger effect sizes in trials.

The current dissertation supports further research in this area. Meta-analysis results (Chapter 3) found higher effects for feedback provided via a computer than via a device, which may also be a more cost-efficient option. Higher effect sizes were found for studies with electronic or computerized media, frequent provision (weekly or more), and appliance-specific information. All of these variables are thought to coincide with greater costs and therefore savings per dollar spent on specific interventions would be very useful. Schultz (1998) performed such an analysis for four different recycling interventions that are similar in scope and design and identified which were most cost-effective to implement at the city level.

Companies, ranging from major players such as Google and IBM to start-ups such as OPOWER, C3 Energy, Tendril and Navetas, are creating new products to enable home energy management, both directly through hardware and through integration with smart meter technology. Savings in pilot studies vary from 2-3% (OPOWER) and 6% (C3 Energy) to 20+% for large-scale systems (Ehrhardt-Martinzez et al., 2010), yet little research comparing products has been conducted and there has been no public information about which devices are available or how they vary in terms of these key characteristics. These products vary in several ways, including data collection (e.g., internal sensor, from smart meter) and display medium (e.g., website, in-home monitor); such variation affects not only potential savings but also potential costs to deploy. The data collected in Chapter 4 represents the most comprehensive cataloging and categorization of feedback technologies to date, with over 200 products collected and grouped into nine distinct categories and coded based on 36 key characteristics. Such a data collection is the vital first step to the type of rigorous cost-benefit calculations needed to determine which broad categories and specific products may lead to the greatest and most cost-efficient energy savings.

Feasibility

This discussion of feasibility will address issues related to both social acceptability and administrative feasibility of feedback interventions. The social acceptability of a program is the extent to which program participants and the public will accept and support the program (Kraft & Furlong, 2004). It is important to ensure that any feedback (or other behavior-based energy efficiency) intervention is accepted by consumers so that they actually use it; otherwise, it will not lead to the outcomes found in studies. Since most studies included self-selected participants, it is not clear whether these programs would be socially acceptable at a larger level.

Chapter 5 directly addresses the issue of social feasibility through mixed-methods analysis of naturalistic users of feedback—i.e., those individuals who have voluntarily obtained and used energy feedback outside of an experimentally controlled research setting. The study found several significant differences between feedback users and non-users, suggesting that there is a specific market that current products are attracting; more data on these "early adopters" as well as the impressions of non-users of feedback would be very useful in understanding the current and potential social feasibility of wide-scale adoption of energy feedback. Additionally, design and usability issues identified in this study suggest several hurdles that current energy-feedback technology still has to overcome before being marketed to the general American public.

Administrative feasibility refers to how easy or difficult it will be for a public or private agency to implement the program. Some forms of feedback may be more feasible to manage than others. The taxonomy introduced in Chapter 4 presents categories and definitions of energy feedback based on characteristics inherent to the technology itself that will be useful in determining and grouping feasibility of feedback products in different settings. As smart meters are being rolled out throughout the U.S. and world, there is increased administrative feasibility for certain types of feedback, especially those that leverage Green Button data to provide information (Chopra, 2011; Institute for Electric Efficiency, 2011). However, more advanced systems that require hardware installed into homes may be less feasible than those that collect data directly from the energy utility or electricity meter. Therefore, it is important to ascertain the feasibility of managing any new program before deciding upon its implementation.

Recent technological advances are also affecting the administrative feasibility of energy feedback and creating an environment in which providing feedback to residential consumers is not only possible, but increasingly common. Advances in data sensing, storage, and dissemination have made it possible for information about behavior to be collected, stored, and presented to consumers at speeds and on scales that were previously impossible. “Adding sensors to the feedback equation helps solve problems of friction and scale. They automate the capture of behavioral data, digitizing it so it can be readily crunched and transformed as necessary. And they allow passive measurement, eliminating the need for tedious active monitoring“ (Goetz, 2011). Such changes in data collection also require changes in data storage—Austin Energy, for example, increased yearly data storage from 20TB to 200TB for just 500,000 meters (Danahy, 2009). Additionally, changes in data presentation are being seen in the form of ambient displays, gamification strategies, and innovative dashboard designs for both mobile and web platforms. These changes bring both new opportunities and new challenges that will continue to impact the feasibility of residential energy feedback in years to come.

Closing Thoughts

New technologies are changing how people interact with our natural, built, and social worlds. We are now a technological species (Kahn, 2013) and we must take our technological nature into consideration in our work as psychologists. Much of the focus in both popular press and psychological research is on the negative role of technology, critiquing such advances and discussing how new technologies may undermine or prevent human flourishing (Kahn, 2011). We read about technology-caused ailments such as Nature Deficit Disorder (Louv, 2008), Continuous Partial Attention (Stone, 2007), and are warned of the “coming dark age" (Jackson, 2008) caused by new technology and its psychological effects on us. We are warned in the popular media and by psychologists that Google will make us stupid (Carr, 2008), Facebook will make us narcissists (Rosen, 2007), and data will make us drown (Sudeman, 2008).

While this research is quite compelling and it is important to study the negative implications of new technology, such analysis does not provide a complete picture of the role and the potential role of technology in our lives. Focusing only on the negative impacts of technology use and ignoring its potential benefits within the field of human behavior may not only erroneous, but also counterproductive. In closing this dissertation, I wish to situate this work within the larger discussion of the role of technology in our lives.

First of all, the idea of technology impacting human life is not new - not even close. Technological innovations have been significantly changing how humans interact with the natural environment and with one another for thousands of years (Stearns, 2010). Over 10,000 years ago settled agriculture began to appear throughout the world, leading to what is often called the Neolithic revolution. This technological innovation had massive impacts on the natural environment through plant cultivation, construction of irrigation systems, and the use of domesticated animals. This led to more reliable food supplies, enabling population increase and the development of increasingly complex social structures. Likewise, the industrial revolution also brought with it unprecedented changes to how we obtain and use energy, enabling large-scale growth throughout the world. This newest revolution, often called the technological or digital revolution, is bringing similar changes to the world of information that we've already seen in the worlds of food (agricultural) and energy (industrial).

As such, the view that this current form of technological innovation is "the enemy" seems not merely short-sided but also quite flawed since technology is a vital and continued part of the human experience. “Indeed, the techniques of shaping tools are taken as the chief evidence of the beginning of human culture” (Rutherford & Ahlgren, 1990). Both biologically and psychologically, humans are inherently connected to one another as well as to the natural world (Kahn, 2013). Rather than view technology as severing these connections, another approach views technology as a part of human innovation and remains critical but impartial in analyzing both the positive and negative impacts of any new technology on the cultures that created it.

In addition, these newest forms of technology can be used to further *connect* us to the natural world and to one another. Phenomenology argues that direct experience is key to both knowledge and to connection (Kahn, 2013). When direct experience is not possible, research indicates that technological experience can serve as something of a proxy (Kahn, 2011). As such, providing data in the form of energy feedback can serve to replace more traditional forms of connection between people and energy use (e.g., the physical exhaustion caused by cutting down a tree to produce firewood).

Within our own homes, we are largely disconnected from the energy use being consumed by our televisions, computers, washing machines, and home heating and cooling systems. Through the industrial revolution, we’ve been provided with a system for immediate transmission of energy into our homes, but the feedback loop that goes along with that energy is only now becoming readily available. Technology in the form of smart meters and sensors can give us feedback about energy use so we know how much energy (or money) is being spent powering our computers and televisions when we are sleeping. This can scale up to millions of dollars and carbon savings across the millions of individuals who have the ability to conserve energy in the home.

Although we should approach all new forms of technology with a critical eye, we should not openly assume that they will be either our savior or our downfall. New digital technologies are tools just like the knives, chairs, and paper that preceded them when introduced by humans centuries ago. It is the role of scholar to study them critically and impartially and to assess the most practical ways to utilize technology to connect and to enhance our lives. As such, this dissertation provides an important analysis of some of the key issues in leveraging energy feedback technology to increase energy efficiency and reduce carbon emissions.

REFERENCES

* Studies with an asterisk are included in the meta-analysis.

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). A review of intervention studies aimed at household energy conservation. *Journal of Environmental Psychology, 25*, 273-291. doi:10.1016/j.jenvp.2005.08.002

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2007). The effect of tailored information, goal-setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. *Journal of Environmental Psychology, 27,* 265-276

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. doi:10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin, 84,* 888-918. doi:10.1037/0033-2909.84.5.888

* Alcott, H. (2010). Social Norms and Energy Conservation. Working Paper, Massachusetts Institute of Technology. doi: 10.1016/j.jpubeco.2011.03.003

Allcott, H. & Mullainathan, S. (2010). Behavior and Energy Policy. *Science, 327*, 1204-1205.

* Allen, D., & Janda, K. (2006). The effects of household characteristics and energy use consciousness on the effectiveness of real-time energy use feedback: A pilot study. Proceedings from ACEEE '92: *American Council for an Energy-efficient Economy Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA: ACEEE.*

American Council for an Energy-Efficiency Economy (ACEEE). (2007). *Emerging technologies report: In-home energy use displays*. Washington, DC.: ACEEE.

Anderson, S., & Rodin, J. (1989). Is bad news always bad?: Cue and feedback effects on intrinsic motivation. *Journal of Applied Social Psychology, 19*, 449-467. doi: 10.1111/j.1559-1816.1989.tb00067.x

Anderson, W. & White, V. (2009). *Exploring consumer preferences for home energy display functionality Report to the Energy Saving Trust*. Centre for Sustainable Energy.

Angeli, A. De, Sutcliffe, A., Hartmann, J. (2006). Interaction, Usability and Aesthetics: What Influences Users' Preferences? In: *8th ACM Conference on Designing Interactive Systems* pp. 271–280.

Armitage, C.J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: A meta-analytic review. *British Journal of Social Psychology, 40*, 471–499.

* Arvola, A. (1993). Billing feedback as a means to encourage household electricity conservation: A field experiment in Helsinki. In R. Ling and H. Wilhite (Eds). *The Energy Efficiency Challenge for Europe.* Retrieved from http://www.eceee.org/conference_proceedings/eceee/1993/Panel_3/p3_2

* Arvola, A. (1996). The effect of billing feedback on consumption results of an experiment in Helsinki. In *Research program on consumer habits and energy conservation.* (pp. 61-77). Helsinki, Finland: LINKKI.

* Arvola A., Uutela A. & Anttila U. (1994). Billing feedback as a means of encouraging conservation of electricity in households: A field experiment in Helsinki. Proceedings from ECEEE '94: *European Council for an Energy-efficient Economy Summer Study on Energy Efficiency in Buildings.* Toulon/Hyères, France: ECEEE.

Åström, K. J., & Murray, R.M. (2009). *Feedback systems: an introduction for scientists and engineers.* Princeton, NJ: Princeton University Press

Attari, S. Z., DeKay, M. L., Davidson, C. I., & Bruine de Bruin, W. (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences*, *107*(37), 16054-16059.

* Ayres, I., Raseman, S., & Shih, A. (2009). Evidence from two large field experiments that peer comparison feedback can reduce residential energy use. *Journal of Law, Economics, and Organization.* doi: 10.1093/jleo/ews020

Badami, V.V., & Chbat, N.W. (1998). Home appliances get smart. *Spectrum, IEEE*, 35(8), 36-43.

Bamberg, S., & Moser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behavior. *Journal of Environmental Psychology*, *27*(1), 14-25.

Bandura, A. (1969). *Principles of Behavior Modification.* New York: Hold, Rinehart & Winston.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist, 37*(2), 122-147.

Bangor, A., Kortum, P.T., Miller, J.T.(2008). An Empirical Evaluation of the System Usability Scale. *International Journal of Human-Computer Interaction, 24*, 574–594.

* Battalio, R. C., Kagel, J. H., Winkler, R. C., & Winett, R. A. (1979). Residential electricity demand: An experimental study. *The Review of Economics and Statistics, 61*, 180-189. Retrieved from http://www.jstor.org/stable/1924585

* Becker, L. J. (1978). Joint effect of feedback and goal setting on performance: A field study of residential energy conservation. *Journal of Applied Psychology*, *63*, 428-433. doi: 10.1037/0021-9010.63.4.428

* Becker, L. J. & Seligman, C. (1978). Reducing air conditioning waste by signaling it is cool outside. *Personality and Social Psychology Bulletin*, *4*, 412-415. doi: 10.1177/014616727800400310

Becoña, E & Vázquez, F. L. (2001). Effectiveness of personalized written feedback through a mail intervention for smoking cessation: A randomized-controlled trial in Spanish smokers. *Journal of Consulting and Clinical Psychology*, *69*(1), 33-40. doi: 10.1037/0022-006X.69.1.33

Berkhout, P. H. G., Muskens, J. C., & Velthuijsen, J. W. (2000). Defining the rebound effect. *Energy Policy*, *28*, 425-432.

* Bittle, R. G., Valesano, R., & Thaler, G. (1979). The effects of daily cost feedback on residential electricity consumption. *Behavior Modification*, *3*, 187-202. doi: 10.1177/014544557932004

* Bittle, R. G., Valesano, R., & Thaler, G. (1979-1980). The effects of daily feedback on residential electricity usage as a function of usage level and type of feedback information. *Journal of Environmental Systems*, *9*, 275-287. doi: 10.2190/91AA-P97G-JF92-T7EJ

Black, J. S., Stern, P. C., & Elworth, J. T. (1985). Personal and contextual influences on household energy adaptations. *Journal of Applied Psychology*, *70*, 3-21. doi: 10.1037/0021-9010.70.1.3

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Chichester, England: Wiley.

Borsci, S., Federici, S., Lauriola, M. (2009). On the dimensionality of the System Usability Scale: a test of alternative measurement models. *Cognitive Processing, 10*, 193–7.

* Brandon, G., & Lewis, A. (1999). Reducing household energy consumption: A qualitative and quantitative field study. *Journal of Environmental Psychology, 19*, 75-85. doi: 10.1006/jevp.1998.0105

Bridgeman, B. (1974). Effects of test score feedback on immediately subsequent test performance. *Journal of Educational Psychology, 66,* 62-66. doi: 10.1037/h0035803

Brooke, J. (1996). SUS - A quick and dirty usability scale. In: Jordan, Thomas, Weerdmeester, McClelland, Eds. Usability evaluation in industry, 189, 189–194.

Campion, M.A. & Lord, R.G. (1982). A control systems conceptualization of the goal-setting and changing process, *Organizational Behavior and Human Performance, 30*(2), 265-287. doi: 10.1016/0030-5073(82)90221-5

Card, S.K., Moran, T.P., Newell, A. (1983). *The Psychology of Human-Computer Interaction*. Lawrence Erlbaum Associates.

Carr N. (2008). Is Google making us stupid? What the Internet is doing to our brains. *The Atlantic*. Available at: http://www.theatlantic.com/magazine/archive/2008/07/is-google-making-us-stupid/306868.

Carver, C. S., & Scheier, M. F. (1981). *Attention and self-regulation: A control-theory approach to human behavior*. New York, NY: Springer-Verlag.

Chin, J.P., Diehl, V.A., Norman, K.L. (1988) Development of an Instrument Measuring Human-Computer User Satisfaction Interface. In: Proc. CHI '88. pp. 213–-218. ACM Press.

Chopra, A. (2011, September 15). Modeling a green energy challenge after a blue button. *White House Office of Science and Technology Policy.* Retrieved from http://www.whitehouse.gov/blog/2011/09/15/modeling-green-energy-challenge-after-blue-button.

Cialdini, R.B. (1984). *Influence*. New York: William and Morrow Company.

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focused theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. *Advances in Experimental Social Psychology, 24*, 201-234.

Cialdini, R. B., & Schultz, W. (2003). *Understanding and motivating energy conservation via social norms*. William and Flora Hewlett Foundation.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*, 37− 46.

Cohen, H., & Lefebvre, C. (2005). *Handbook of Categorization in Cognitive Science*, Elsiver, NY:NY.

Cook, S. W., & Berrenberg, J. B. (1981). Approaches to encouraging conservation behavior: A review and conceptual framework. *Journal of Social Issues, 37*, 73-107. doi: 10.1111/j.1540-4560.1981.tb02627.x

Cooper, H. (2010). *Research Synthesis and Meta-Analysis*. Thousand Oaks, CA: Sage Publications, Inc.

Cooper, H. & Hedges, L. V. (1994). *The handbook of research synthesis*. New York: Russell

Sage Foundation.

Corbin, J., & Strauss, A. (2007). *Basics of qualitative research: Techniques and procedures for developing grounded theory* (3rd Ed). Thousand Oaks, CA: Sage Publications, Inc.

Creswell, J.W. (2009). *Research design: Qualitative, quantitative, and mixed methods approaches* (3rd Ed). Thousand Oaks, CA: Sage Publications, Inc.

Curtis, F., Simpson-Housley, P., & Drever, S. (1984). Household energy conservation. *Energy Policy 12*(4), 452–456.

Danahy, J. (2009). *The coming smart grid data surge. Blogging the Grid*. Retrieved from http://www.smartgridnews.com/artman/publish/News_Blogs_News/The-Coming-Smart-Grid-Data-Surge-1247.html

Darby, S. (2001). Making it obvious: Designing feedback into energy consumption. In *Proceedings, 2nd international Conference on Energy Efficiency in Household Appliances and Lighting. Italian Association of Energy Economists/EC-SAVE programme.*

Darby, S. (2006). *The effectiveness of feedback on energy consumption. A Review for DEFRA of the Literature on Metering, Billing and Direct Displays.* Oxford, UK: Environmental Change Institute. Retrieved from http://www.eci.ox.ac.uk/research/energy/downloads/smart-metering-report.pdf

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319—340.

Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., and Vandenbergh, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions.

Proceedings of the National Academy of Sciences of the United States of America, 106, 18452–18456. doi: 10.1073/pnas.0908738106

Dillman, D., Rosa, E., & Dillman, J. (1983). Lifestyle and home energy conservation in the United States: The poor accept lifestyle cutbacks while the wealthy invest in conservation. *Journal of Economic Psychology*, *3,* 299–315. doi: 10.1016/0167-4870(83)90008-9

* Dobson, J. K., & Griffin, J. D. A. (1992). Conservation effect of immediate electricity cost feedback on residential consumption behavior. Proceedings from ACEEE '92: *American Council for an Energy-efficient Economy Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA: ACEEE.*

Donahue, G. (2007). *Network warrior*. O'Reilly Media, Incorporated

Donnelly, K. (2010). The technological and human dimensions of residential feedback: An introduction to the broad range of today's feedback strategies. In *People-Centered Initiatives for Increasing Energy Savings*.

Duffy, P. R. (1984). Cybernetics. *Journal of Business Communication*, 21(1), 33-41.

Duncan, J. (1984). Selective attention and the organization of visual information. *Journal of Experimental Psychology: General, 3*(4), 501-517.

Dunlap, R. E., Van Liere, K. D., Mertig, A. G., & Jones, R. E. (2000). Measuring endorsement of the new environmental paradigm: A revised NEP scale. *Journal of Social Issues, 56,* 425-442.

Egan, C. (1998). Graphical Displays and Comparative Energy Information: What Do People Understand and Prefer? Proceedings from ACEEE '98: *American Council for an Energy-*

efficient Economy Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA: ACEEE.

Ehrhardt-Martinez, K., Donnelly, K., Laitner, J.A. (2010). *Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities*. Washington DC: American Council for an Energy-efficient Economy (ACEEE). Retrieved from http://aceee.org/research-report/e105.

Electric Power Research Institute (EPRI). (2009). *Residential electricity use feedback: A research synthesis and economic framework.* Palo Alto, CA: Electric Power Research Institute (EPRI) Report #1016844.

Environmental Protection Agency (EPA). (2011). *Inventory of U.S. greenhouse gas emissions and sinks: 1990-2009 (*USEPA #430-R-11-005).

Faruqui, A., Harris, D., Hledik, R. (2010) Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. *Energy Policy, 38* (10), 6222-6231.

Federal Energy Regulatory Commission (2008). *Assessment of Demand Response & Advanced Metering*. Staff Report.

Festinger, L. A. (1954). A theory of social comparison processes. *Human Relations, 7*(2), 117-140.

Field, A. P. (2001). Meta-analysis of correlation coefficients: A Monte Carlo comparison of fixed- and random-effects methods. *Psychological Methods, 6,* 161–180.

Finstad, K. (2010). The usability metric for user experience. *Interacting with Computers, 22,* 323–327.

Fischer, C. (2008). Feedback on household electricity consumption: A tool for saving energy? *Energy Efficiency*, *1*, 79–104. doi: 10.1007/s12053-008-9009-7.

Fitzpatrick, G., Smith, G., (2009). Technology-enabled feedback on domestic energy consumption: Articulating a set of design concerns. *Pervasive Computing*, *IEEE*, (8)1, 37-44.

Fogg, B. J. (2009). A behavior model for persuasive design. In: *Proceedings of the 4th International Conference on Persuasive Technology* (p.40). ACM.

Ford, R. & Karlin, B. (2013). Graphical displays in energy feedback technology: A cognitive approach. *Proceedings of the Human Computer Interaction Conference*. Las Vegas, NV.

Froehlich, J. (2009). *Promoting energy efficient behaviors in the home through feedback: The role of human-computer interaction*. Seattle, WA: University of Washington. Tech Note #09-02-01.

Froehlich, J., Findlater, L., Landay, J. (2010). The Design of Eco-Feedback Technology. Proceedings from CHI '10: *28th international conference on Human factors in computing systems.* Atlanta, GA: ACM.

Froehlich, J., Larson, E., Gupta, S., Cohn, G., Reynolds, M.S., & Patel, S.N. (2011). Disaggregated end-use energy sensing for the smart grid. *Pervasive Computing, January-March*, 28-39.

Gardner, G. T., & Stern, P. C. (1996). *Environmental problems and human behavior.* Needham Heights, MA: Simon & Schuster.

Gardner, G. T., & Stern, P. C. (2008). The short list: The most effective actions US households can take to curb climate change. *Environment: Science and Policy for Sustainable Development*, *50(5)*, 12-25.

Gatersleben, B., Steg, L., & Vlek, C. (2002). Measurement and determinants of environmentally significant consumer behavior. *Environment and Behavior, 34*, 335-362.

Goetz, T. (2011). Harnessing the Power of Feedback Loops. Wired Magazine. http://www.wired.com/magazine/2011/06/ff_feedbackloop/all/1. Accessed 20 April 2012

Gosling, S. D., Vazire, S., Srivastava, S., & John, O. P. (2004). Should we trust web- based studies? A comparative analysis of six preconceptions about Internet questionnaires. *American Psychologist*, *59*, 93-104.

Goyal, S. C. & Bakshi, U. A. (2008) Chapter 1. In *Principles of Control Systems*: Technical Publications Pune

Granade, H. C., Creyts, J., Derkach, A., Farese, P., Nyquist, S., & Ostrowski, K. (2009). *Unlocking energy efficiency in the U.S. economy*. Washington, DC: McKinsey and Company. Retrieved from http://www.mckinsey.com/client_service/electric_power_and_natural_gas/latest_thinking/unlocking_energy_efficiency_in_the_us_economy

Guagnano, G., Stern, P., & Dietz, T. (1995). Influences on attitude-behavior relationships: A natural experiment with curbside recycling. *Environment and Behavior, 27*(5), 699-718.

Guzzo, R. A., Jette, R. D., & Katzell, R. A. (1985). The effects of psychologically based intervention programs on worker productivity: A meta-analysis. *Personnel Psychology, 38*, 275-291. doi: 10.1111/j.1744-6570.1985.tb00547.x

* Haakana, M., Sillanpaeae, L., & Talsi, M. (1997). The effect of feedback and focused advice on household energy consumption. Proceedings from ECEEE ‘97: *European Council for an Energy-efficient Economy Summer Study on Energy Efficiency in Buildings.* Toulon/Hyères, France: ECEEE.

Ham, J., & Midden, C. (2010). Ambient Persuasive Technology Needs Little Cognitive Effort : The Differential Effects of Cognitive Load on Lighting Feedback versus Factual Feedback. *In Persuasive 2010: Proceedings of 5th International Conference on Persuasive Technology*, 132–142.

Hanna, G. S. (1976). Effects of total and partial feedback in multiple- choice testing upon learning. *Journal of Educational Research, 69*, 202-205.

Hardin, G. (1968). The Tragedy of the Commons. *Science*, *162*, 1243–1248.

Hargreaves, T., Nye, M., & Burgess, J. (2010). Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors. *Energy Policy*, 6111-6119.

* Harrigan, M. (1992). *Evaluating consumer energy education: A field test of three education packages in support of a residential conservation and load-shifting program.* Washington DC: Alliance to Save Energy.

* Harrigan, M. S., & Gregory, J. M. (1994). *Do savings from energy education persist?* Washington DC: Alliance to Save Energy.

* Hayes, S.C., & Cone, J.D. (1981). Reduction of residential consumption of electricity through simple monthly feedback. *Journal of Applied Behavior Analysis, 14,* 81-88. doi: 10.1901/jaba.1981.14-81

Herter, K., & Wayland, S. (2009). *Behavioral Experimentation with Residential Energy Feedback through Simulation Gaming*. California Energy Commission.

Hochwallner, T., & Lang, L. (2009). Approaches for monitoring and reduction of energy consumption in the home. In *Seminar-Thesis: Lecture series on sustainable development and information and communication technology.*

Hofstede, G. (1978). The poverty of management control philosophy. *The Academy of Management Review*, 3(3), 450-461.

Hunter, J. E., & Schmidt, F. L. (2000). Fixed effects vs. random effects in meta-analysis models: Implications for cumulative research knowledge. *International Journal of Selection and Assessment*, *8*, 275–292.

Hutton, R. R. (1982). Advertising and the Department of Energy's campaign for energy conservation. *Journal of Advertising*, *11*(2), 27-39.

* Hutton, R. B., Mauser, G. A., Filiatrault, P., & Ahtola, O. T. (1986). Effects of cost-related feedback on consumer knowledge and consumption behavior: A field experimental approach. *Journal of Consumer Research, 3,* 327-336.

IBM (2007). Ontario energy board smart price pilot: Final report. *Consultation document*. Toronto, Ontario, Canada: Ontario Energy Board.

Institute for Electric Efficiency. (2011). *Utility-Scale Smart Meter Deployments, Plans & Proposals.* Washington, DC: Edison Foundation.

Intergovernmental Panel on Climate Change (IPCC). (2007). *Summary for policymakers* (Synthesis Report). Retrieved from www.ipcc.ch

Jackson, M. (2008). *Distracted: The erosion of attention and the coming dark age*. Amherst, NY: Prometheus Books.

Jones, G, M. (1910). Experiments on the reproduction of distance as influenced by suggestions of ability and inability. *Psychological Review,* 77, 269-278. doi: 10.1037/h0074504

Judd, C. H. (1905). Practice without knowledge of results. *Psychological Review Monographs,* 2, 185-198.

Kahn, P. H., Jr. (2011). *Technological nature: Adaptation and the future of human life*. Cambridge, MA: MIT Press.

Kahn, P. H. (2013). The Next Phase for Ecopsychology: Ideas and Directions. *Ecopsychology*, *5*(3), 163–166.

Kaplowitz, M. D., Hadlock, T. D., & Levine, R. (2004). A comparison of web and mail survey response rates. *Public Opinion Quarterly, 68*, 94-101.

Karlin, B. (2011). Tracking and learning: Exploring dual functions of residential energy feedback. *Proceedings from Persuasive '11: 6th Annual International Conference on Persuasive Technology.* Columbus, OH: ACM.

Karlin, B., Davis, N., Sanguinetti, A., Gamble, K., Kirkby, D., & Stokols, D. (2012). Dimensions of conservation: Exploring differences among energy behaviors. *Environment and Behavior, 46*(4): 420-449. doi: 10.1177/0013916512467532.

* Kasulis, J. J., Huettner, D. A., & Dikeman, N. J. (1981). The feasibility of changing electricity consumption patterns. *The Journal of Consumer Research, 8*, 279-290.

* Katzev, R., Cooper, L., & Fisher, P. (1980–1981). The effect of feedback and social reinforcement on residential electricity consumption. *Journal of Environmental Systems, 10*, 215–227. doi: 10.2190/M8W4-JUYV-NB03-CUFL

Katzev, R., & Johnson, T. 1987. *Promoting energy conservation: An analysis of behavioral research*. Boulder, Colorado: Westview press.

Kirakowski, J. & Corbett, M.: SUMI: The software usability measurement inventory. *British Journal of Educational Technology*, *24,* 210—212.

Klein, H.J. (1989). An integrated control theory model of work motivation. *The Academy of Management Review, 14*(2), 150-172.

Kline, P. (2000). *Handbook of Psychological Testing*. Routledge, London.

Kluger, A.N. & DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin, 119*(2), 254-284. doi: 10.1037/0033-2909.119.2.254

Kraft, M. E. & Furlong, S. R. (2004). *Public policy: Politics, analyses, and alternatives.* Washington D.C.: CQ Press.

* Kurz, T., Donaghue, N., & Walker, I. (2005). Utilizing a social-ecological framework to promote water and energy conservation: A field experiment. *Journal of Applied Social Psychology, 35*, 1281-1300. doi: 10.1111/j.1559-1816.2005.tb02171.x

LaMarche, J., Cheney, K., Christian, S., & Roth, K. (2011). *Home Energy Management Products & Trends*. Cambridge, MA: Fraunhofer Center for Sustainable Energy Systems.

Latham, G. P., & Locke, E. A. (1991). Self-regulation through goal setting. *Organizational Behavior and Human Decision Processes, 50,* 212-247. doi: 10.1016/0749-5978(91)90021-K

Lawrence, J.W., Carver, C.S., & Scheier, M.F. (2002). Velocity toward goal attainment in immediate experience as a determinant of affect. *Journal of Applied Social Psychology,* 32(4), 788-802.

Leiserowitz, A. (2008). *International Public Opinion, Perception, and Understanding of Global Climate Change*. Technical Report, Human Development Report Office.

Lewis, J. R. (1995). IBM computer usability satisfaction questionnaires: Psychometric evaluation and instructions for use. *International Journal of Human-Computer Interaction, 7,* 57–78.

Lewis, J. & Sauro, J. (2009). The factor structure of the system usability scale. *Human Centered Design*, 94-103.

Liikkanen, L.A. (2009). Extreme-user approach and the design of energy feedback systems. *5th International Conference on Energy Efficiency in Domestic Appliances and Lighting.* Berlin, Germany.

Locke, E. A., &Latham, G. P.(1990). *A theory of goal setting and task performance.* Englewood Cliffs, NJ: Prentice Hall.

Long, J. E., (1993). An econometric analysis of residential expenditures on energy conservation and renewable energy sources. *Energy Economics, October, 232-238.*

Louv, R. (2008). *Last Child in the Woods: Saving Our Children from Nature Deficit Disorder*. Chapel Hill, NC: Algonquin Books.

Lutzenhiser, L., Cesafsky, L., Chappells, H., Gossard, M., Moezzi, M., Moran, D., Wilhite, H. (2009). *Behavioral assumptions underlying California residential sector energy efficiency programs*. Oakland, CA: CIEE. Retrieved from http://uc-ciee.org/downloads/ba_ee_res_wp.pdf

* Mansouri, I., & Newborough, M. (1999). Dynamics of energy use in UK households: End-use monitoring of electric cookers. Proceedings from ECEEE '99: *European Council for an Energy-efficient Economy Summer Study on Energy Efficiency in Buildings.* Toulon/Hyères, France: ECEEE.

Markowitz, E.M. & Shariff, A.F. (2012). Climate change and moral judgement. *Nature Climate Change, 2*, 243-247.

Manten, A. A. (1973). Scientific literature review. *Scholarly Publishing 5,* 75–89.

Marradi, A. (1990). Classification, typology, taxonomy. *Quality and Quantity, XXIV*(2), 129-157.

* Matsukawa, I. (2004). The effects of information on residential demand for electricity. *The Energy Journal, 25(1),* 1-17. doi: 10.5547/ISSN0195-6574-EJ-Vol25-No1-1

* McClelland, L., & Cook, S. W. (1979–1980). Energy conservation effects of continuous in-home feedback in all-electric homes. *Journal of Environmental Systems, 9,* 169–173. doi: 10.2190/L8BU-ECLK-PEC5-KKTW

* McClelland, L., & Cook, S. W. (1980). Promoting energy conservation in master-metered apartments through group financial incentives. *Journal of Applied Psychology, 10(1),* 20–31. doi: 10.1111/j.1559-1816.1980.tb00690.x

* Midden, C. J. H., Meter, J. F., Weenig, M. H., & Zieverink, H. J. A. (1983). Using feedback, reinforcement and information to reduce energy consumption in households: A field-experiment. *Journal of Economic Psychology, 3*, 65-86. doi: 10.1016/0167-4870(83)90058-2

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *The Psychological Review, 63*, 81-97.

* Mountain, D.C. (2007). *Real-time feedback and residential electricity consumption: British Columbia and Newfoundland and Labrador Pilots.* Mountain Economic Consulting.

* Mountain Economic Consulting and Associates (2006). *The impact of real-time feedback on residential electricity consumption: The hydro one pilot. Ontario.* Mountain Economic Consulting.

Mosteller, F., & Bush, R. R. (1954). Selected quantitative techniques. In G. Lindsey (Ed.), *Handbook of social psychology: Vol. 1. Theory and method.* Cambridge, MA: Addison Wesley.

Nair, G., Gustavsson, L., Mahapatra, K. (2010). Factors influencing energy efficiency investments in existing Swedish residential buildings. *Energy Policy*, *38*, 2956-2963. doi: 10.1016/j.enpol.2010.01.033

Neuendorf, K.A. (2001). *The Content Analysis Guidebook.* Thousand Oaks, CA: Sage Publications.

* Nexus Energy Software. (2006). *California Bill Analysis Pilot Final Report. A Research Project Conducted as Part of the California Statewide Pricing Pilot (R) 02.06.001.* San Francisco, CA: Calmac. Retrieved from

http://www.calmac.org/publications/CA_BILL_ANALYSIS_PILOT_FINAL_04-06ES.pdf

Nielsen, J. & Hackos, J. T. (1993). *Usability engineering*. Academic press, San Diego.

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., Griskevicius, V. (2008). Normative social influence is underdetected. *Personality and Social Psychology Bulletin,* 34, 913-923.

Painter, J., Semenik, R., & Belk, R. (1983). Is there a generalized conservation ethic? A comparison of the determinants of gasoline and home heating energy conservation. *Journal of Economic Psychology, 3*, 317-331.

* Pallak, M. S., & Cummings, N. (1976). Commitment and voluntary energy conservation. *Personality and Social Psychology Bulletin, 2(1)*, 27–31. doi: 10.1177/014616727600200105

* Pallak, M., Cook, D. & Sullivan, J. (1980). Commitment and energy conservation. *Applied Social Psychology Annual, 1*, 235-253.

* Parker, D. S., Hoak, D., & Cummings, J. (2008). *Pilot evaluation of energy savings from residential energy demand feedback devices.* Cocoa, FL: Florida Solar Energy Center. Retrieved from http://www.fsec.ucf.edu/en/publications/pdf/FSEC-CR-1742-08.pdf

Parker, D., Mazarra, M., & Sherwin, J. (1996) Monitored energy use patterns in low-income housing in a hot and humid climate. Proceedings from IBSHHC '96*: Tenth Symposium on Improving Building Systems in Hot Humid Climates*, Fort Worth, TX: TAMU.

Pearce, J. L., & Porter, L. W. (1986). Employee responses to formal performance appraisal feedback. *Journal of Applied Psychology, 71*, 211-218. doi: 10.1037/0021-9010.71.2.211

Peters, J. & McRae, M. (2009). Process Evaluation Insights on Program Implementation. Prepared for CIEE Behavior & Energy Program.

Pierce, J., Fan, C., Lomas, D., Marcu, G., & Paulos, E. (2010). Some consideration on the (in) effectiveness of residential energy feedback systems. In *Proceedings of the 8th ACM conference on designing interactive systems.*

Podsakoff, P.M., & Farh, J.H. (1989). Effects of feedback sign and credibility on goal setting and task performance. *Organizational Behavior and Human Decision Processes, 44*, 45-67. doi: 10.1016/0749-5978(89)90034-4

Poortinga, W., Steg, L., Vlek, C., & Wiersma, G. (2003). Household preferences for energy-saving measures: A conjoint analysis. *Journal of Economic Psychology*, *24*, 49–64. doi: 10.1016/S0167-4870(02)00154-Xhttp://dx.doi.org/10.1016/S0167-4870(02)00154-X

Promising Practices Network (PPN). (2012). *How programs are considered.* Retrieved from http://www.promisingpractices.net/criteria.asp.

Quesenbery, W. (2001). What Does Usability Mean: Looking Beyond 'Ease of Use'. In *Proceedings of the 48th Annual Conference, Society for Technical Communication*.

Redish, J. C. (1989). Reading to learn to do. IEEE *Transactions on Professional Communication, 32*, 289-0293.

* Robinson, J. (2007). *The effect of electricity-use feedback on residential consumption: A case study of customers with smart meters in Milton, Ontario*. (Thesis), University of Waterloo, Waterloo, Canada. Retrieved from https://uwaterloo.ca/sustainable-energy-policy/sites/ca.sustainable-energy-policy/files/uploads/files/Robinson-finalthesis.pdf

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York: The Free Press.

Rosen C. (2007). Virtual friendship and the new narcissism. *The New Atlantis, 17,* 15–31.

Rosenthal, R. (1991). *Meta-analytic procedures for social research* (rev. ed.). Newbury Park, CA: Sage. doi: 10.4135/9781412984997

Rosenthal, R. & DiMatteo, M.R. (2001). Meta-analysis: recent developments in quantitative methods for literature reviews. *Annual Review of Psychology*, *52*, 59-82.

Rosenthal, R., & Rubin, D. B. (2003). R-sub (equivalent): A simple effect size indicator. *Psychological Methods, 8,* 492–496. doi: 10.1037/1082-989X.8.4.492

Rutherford, F.J. & Ahlgren, A. (1990). *Science for All Americans*. Washington DC: American Association for the Advancement of Science.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68.

Sánchez, M. (2012, December). *Status on the roll-out of Smart Metering in the EU.* Presented at the Eurelectric and ESMIG event, Brussels, Belgium.

Sardianou. (2007). Estimating energy conservation patterns in Greek Households. *Energy Policy, 35,* 3778-3791.

Schatsky, D., & Wheelock, C. (2009). *Executive summary: Home energy management: Energy information displays: In-home display devices, web dashboards, and mobile applications.* Boulder, CO: Pike Research.

Schultz, P.W. (2010). Making energy conservation the norm. In Ehrardt-Martinez, K. & Laitner, J.A. (Eds.), *People-Centered Initiatives for Increasing Energy Savings*. ACEEE, Washintgon, DC, 251-262. Retrieved from http://www.aceee.org/people-centered-energy-savings.

Schwartz, S. H. (1977). Normative influences on altruism. In L. Berkowitz (ed.), *Advances in experimental social psychology* . (Vol. 10, pp. 221–279). New York, NY: Academic Press.

Scott, J. (2000). Rational choice theory. In *Understanding Contemporary Society: Theories of The Present,* (Eds) Browning, G., Halcli, A., & Webster, F. Sage Publications.

* Seaver, W. B., & Patterson, A. H. (1976). Decreasing fuel-oil consumption through feedback and social commendation. *Journal of Applied Behavior Analysis, 9(2),* 147-152. doi: 10.1901/jaba.1976.9-147

* Seligman, C., & Darley, J. M. (1977). Feedback as a means of decreasing residential energy consumption. *Journal of Applied Psychology*, *62(4)*, 363-368. doi: 10.1037/0021-9010.62.4.363

* Seligman, C., Darley J.M. & Becker L.J. (1978). Behavioral approaches to residential energy conservation. *Energy and Buildings, 1,* 325-337. doi: 10.1016/0378-7788(78)90012-9.

* Sexton, R.J., Johnson, N.B. & Konakayama, A. (1987). Consumer response to continuous-display electricity-use monitors in a time- of-use pricing experiment. *Journal of Consumer Research, 14*, 55-62. doi: 10.1086/209092

* Sexton, R.J., & Sexton, T.A. (1987). Theoretical and methodological perspectives on consumer response to electricity information. *The Journal of Consumer Affairs*, *21*, 238-257. doi: 10.1111/j.1745-6606.1987.tb00201.x

* Sexton, R. J., Sexton, T. A., Wann, J. J., & Kling, C. L. (1989). The conservation and welfare effects of information in a time-of-day pricing experiment. *Land Economics, 65*, 272-279.

Shadish, W. R., & Haddock, C. K. (1994). Combining estimates of effect size. In H. Cooper & L. V. Hedges (Eds.), *The handbook of research synthesis* (pp. 261–282). New York: Russell Sage Foundation.

* Sipe, B., & Castor, S. (2009). The net impact of home energy feedback devices. Proceedings from IEPEC '09: *International Energy Program Evaluation Conference,* Portland, OR: IEPEC.

Skinner, B. F. (1938). *The Behavior of Organisms: An Experimental Analysis*. New York: Appleton-Century.

Smith, C. B. (1997). Casting the net: Surveying an Internet population. *Journal of Computer-Mediated Communication*, *3*(1). Retrieved from http://jcmc.indiana. edu/vol3/issue1/smith.html#discussion.

Smith, M. L. (1980). Publication bias and meta-analysis. *Evaluation and Education, 4*, 22–24. doi: 10.1016/0191-765X(80)90004-X,

Spoehr, K.T., & Lehmkuhle, S.W. (1982). *Visual Information Processing*. W.H. Freeman, San Francisco.

Stearns, P.N. (2010). *World History: The Basics.* New York, NY: Routledge.

Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behavior: An integrative review and research agenda. *Journal of Environmental Psychology*, 29, 309-317. doi: 10.1016/j.jenvp.2008.10.004

Stein, L. F. (2004). *Final Report California Information Display Pilot Technology Assessment*. 1750 14th Street, Suite 201 Boulder, CO 80302: Primen, Inc.

Stein, L. F., & Enbar, N. (2006). *EPRI Solutions Custom Report Direct Energy Feedback Technology Assessment*.

Stemler, S. (2001). An overview of content analysis. *Practical Assessment, Research & Evaluation*, 7(17).

Stern, P.C. & Dietz, T. (1994). The value basis of environmental concern. *Journal of Social Issues, 50*(3), 65-84.

Stock, W. A. (1994). Systematic coding for research synthesis. In H. Cooper & L. V. Hedges (Eds.), *The handbook of research synthesis* (pp. 125–138). New York: Russell Sage Foundation.

Stokols, D. (1979). A congruence analysis of human stress. In I.G. Sarason & C.D. Spielberger (Eds), *Stress and anxiety, Vol. 6.* New York: John Wiley, 27-53

Stone L. (2007). Living with continuous partial attention. *Harvard Business Review February*, 28–9.

* Summit Blue Consulting. (2009). *Impact evaluation of OPOWER SMUD Pilot Study*. Summit Blue Consulting.

Suderman P. (2008). Staying afloat: treading water in a sea of data. *The New Atlantis, Fall,* 104–106.

Tate, D.F., Wing R.R., & Winett, R.A. (2001). Using Internet Technology to Deliver a Behavioral Weight Loss Program. *Journal of the American Medical Association, 285*(9), 1172-1177. doi: 10.1001/jama.285.9.1172.

Thorndike, E. L. (1927). The law of effect. *American Journal of Psychology, 39*, 212-222. doi: 10.2307/1415413

Toomim, M., Kriplean, T., Pörtner, C., Landay, J.A. (2011). Utility of human-computer interactions: Toward a science of preference measurement. In: *Proc. CHI'11*. pp. 2275--2284. ACM Press.

Turaga, R. M. R., Howarth, R. B., & Borsuk, M. E. (2010). Pro-environmental behavior: Rational choice meets moral motivation. *Annals of the New York Academy of Sciences, 1185*, 211-224.

* Ueno, T., Inada, R., Saeki, O., & Tsuji, K. (2005). Effectiveness of displaying energy consumption data in residential houses. Analysis on how the residents respond. Proceedings from ECEEE '05: *European Council for an Energy-efficient Economy Summer Study on Energy Efficiency in Buildings.* Toulon/Hyères, France: ECEEE.

* Ueno, T., Inada, R., Saeki, O., & Tsuji, K. (2006). Effectiveness of an energy-consumption information system for residential buildings. *Applied Energy, 83*, 868-883. doi: 10.1016/j.apenergy.2005.09.004

United Nations. (1992). *United Nations framework convention on climate change (UNFCC).* Retrieved from http://unfccc.int/resource/docs/convkp/conveng.pdf

United States Congress. (2009). *American Recovery and Reinvestment Act of 2009 (*Pub. L. No. 111-5). Washington, DC. U.S. Government Printing Office.

Vallacher, R.R., & Wegner, D.M. (1987). What do people think they're doing? Action identification and human behavior. *Psychological Review, 94,* 3-15. doi: 10.1037//0033-295X.94.1.3

* Van Houwelingen, J. H., & Van Raaij, W. F. (1989). The effect of goal-setting and daily electronic feedback on in-home energy use. *Journal of Consumer Research,16*(1), 98-105. doi: 10.1086/209197

Van Liere, K. D., & Dunlap, R. E. (1978). Moral norms and environmental behavior: An application of Schwartz's norm-activation model to yard burning. *Journal of Applied Social Psychlogy, 8*, 174-188.

Verhallen, T. M. M., van Raaij, W. F. 1981. Household behavior and the use of natural gas for home heating. *Journal of Consumer Research, 8*, 253-57

* Vollink, T. (2004). *Go for less: The effect of feedback and goal setting on household energy and water consumption.* (Doctoral Dissertation). University Maastricht, Maastricht, Netherlands.

* Vollink, T. & Meertens, R. (2006). Technological Innovations and the Promotion of Energy Conservation: The Case of Goal-Setting and Feedback. In Verbeek, P. & Slob, A. (Eds.), *User Behavior and Technology Development: Shaping Sustainable Relations Between Consumers and Technologies,* 139-148. Dordrecht: Springer. doi: 10.1007/978-1-4020-5196-8_14

Wicklund, R. A. (1975). Objective self-awareness. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology* (Vol. 8(3), pp. 233- 237). New York: Academic Press. doi: 10.1016/0022-1031(73)90059-0.

Wiener, N. (1948) *Cybernetics: or the Control and Communication in the Animal and the Machine* (2nd Ed). Cambridge, MA: MIT Press.

* Wilhite, H., & Ling, R. (1995). Measured energy savings from a more informative energy bill. *Energy & Buildings*, *22(2)*, 145-155 doi: 10.1016/0378-7788(94)00912-4

Wilson, D.B. (2009). Systematic coding. In Cooper, H., Hedges, L.V., & Valentine, J. C. (Eds.), *The Handbook of Research Synthesis and Meta-Analysis*, 159-176. New York: The Russell Sage Foundation.

Wilson, C., & Dowlatabadi, H. (2007). Models of decision-making and residential energy use. *Annual Review of Environment & Resources, 32*, 169-203. doi: 10.1146/annurev.energy.32.053006.141137

* Winett, R. A., Kagel, J. H., Battalio, R. C., & Winkler, R. C. (1978). Effects of monetary rebates, feedback, and information on residential electricity conservation. *Journal of Applied Psychology, 63(1)*, 73-80. doi: 10.1037/0021-9010.63.1.73

* Winett, R. A., Neale, M. S., & Grier, H. C. (1979). Effects of self-monitoring and feedback on residential electricity consumption. *Journal of Applied Behavior Analysis, 12*, 173-184. doi: 10.1901/jaba.1979.12-173

* Winett, R.A., Hatcher, J.W., Fort, T.R., Leckliter, I.N., Love, S.Q., Riley, A.W., et al. (1982). The effects of videotape modeling and daily feedback on residential electricity conservation, home temperature and humidity, perceived comfort, and clothing worn: Winter and summer. *Journal of Applied Behavior Analysis, 15*(3), 381-402. doi: 10.1901/jaba.1982.15-381

* Wood, G., & Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: Environment, behavior and design. *Energy & Buildings, 35*, 821-841. doi: 10.1016/S0378-7788(02)00241-4

Wood, G., & Newborough, M. (2007). Energy-use information transfer for intelligent homes: Enabling energy conservation with central and local displays. *Energy and Buildings*, 39(4), 495-503.

World Bank (2011). *World Development Indicators*. Retrieved from http://data.worldbank.org/indicator/EN.ATM.CO2E.PC/countries/1W-US?display=graph.

Wright, W. R. (1906). Some effects of incentive on work and fatigue. *Psychological Review, 13,* 23-34. doi: 10.1037/h0076041.

Zelezny, L. C., Chua, P. P., & Aldrich, C. (2000). Elaborating on gender differences in environmentalism. *Journal of Social Issues, Promoting Environmentalism, 56*, 443-457.

APPENDIX A. Compiled List of Feedback Technologies

Name / Developer	Type
Aclara's ENERGYprism	Information Platform
Advanced Telemetry's EcoView - Commercial - Residential	Closed Management Network
Accuenergy's Acuview	Information Platform
Agentis Platform	Information Platform
Agilewaves	Open Management Network
Akuacom Demand Response	Information Platform
AlertMe SmartEnergy	Closed Management Network
Ampy Email Metering's ecoMeter	Grid Display
AzTech	Grid Display
Battic Door Home Energy Monitor	Sensor Display
Belkin Conserve Insight Monitor	Load Monitor
Black & Decker Power Monitor	Sensor Display
Blue Line Innovations - PowerCost Monitor - Energy Meter II	Sensor Display
Brand Electronics - 20-CTR Whole House - ONE meter	Sensor Display
Brand Electronics - Digital Power Meter 4-1850 - Digital Power Meter 20-1850 - Digital Power Meter 20-1850CI - Digital Power Meter 21-1850CI	Load Monitor
British Gas EnergySmart Monitor	Sensor Display
Brultech ECM-1220	Sensor Display
Brultech - ECM-1240 - GreenEye Monitor	Networked Sensor
Brunswick Electric PowerStat	Grid Display

Name / Developer	Type
Cisco Business Energy Management Services	Information Platform
Cisco Home Energy Management Solution	Open Management Network
Control4 Energy Management System 100	Open Management Network
Current Cost - EnviR - The Classic - TREC	Sensor Display
Dent Instrument’s Customer Interface Display	Grid Display
Dent Instruments PowerPal Meter w/Customer Interface Display	Sensor Display
Dent Instruments - ELOGsoftware - SMARTware	Information Platform
Digi X-Grid Solutions	Open Management Network
DreamWatts	Open Management Network
E-Mon Energy Software	Information Platform
Eco-Eye - Elite - Elite 100 - Elite 200 - Elite Mini - Elite Mini 2 - Smart - Smart PC - Smart PV	Sensor Display
Eco-Eye Plug-In	Load Monitor
EcoDog FIDO Home Energy Monitoring System	Networked Sensor
EDF Energy’s EcoManager	Closed Management Network
Efergy Technologies - E2 - Elite Wireless Monitor	Sensor Display
Efergy Technologies - Energy Monitoring Socket	Load Monitor
Efficiency 2.0’s PEER	Information Platform
eGauge	Networked Sensor

Name / Developer	Type
Energy Monitoring Technologies' EM 2500	Load Monitor
Powerhouse Dynamics' eMonitor	Closed Management Network
Energy Cite EMS-2020	Grid Display
Energate Home Energy Managament Suite	Open Management Network
eMeter Energy Engage	Information Platform
Noveda Technologies' EnergyFlow Monitor	Networked Sensor
EnergyHub Home Base	Open Management Network
Ambient's Energy Joule	Grid Display
GaugeTech's Energy Manager EXT Software	Information Platform
eQ-3 Energy Master	Load Monitor
Schneider Electric EnergyView Online	Information Platform
Eco1SaveOMeter	Sensor Display
eSight Energy	Information Platform
Ewgeco - B100, B200, B300 - H300 EEE, H300 ERG, H300 EWG	Sensor Display
Flukso	Networked Sensor
FutureDash Greendash Hub	Management Platform
General Electric Nucleus	Open Management Network
Green Energy Options (GEO) My Energy	Information Platform
Green Energy Options (GEO) - Minim - Npower Monitor - Prelude - Quartet - Solo	Sensor Display
Green Energy Options (GEO) - Duet - Solo II	Grid Display
Green Energy Options (GEO) Ensemble	Closed Management Network
Green Energy Options (GEO) - Chorus - Trio & Trio+	Open Management Network

Name / Developer	**Type**
Google PowerMeter	Information Platform
GreenWave Reality Energy Management Platform	Open Management Network
Greenwire Energy Monitor	Grid Display
GridPoint Energy Manager	Management Platform
iControl OpenHome - Utility	Open Management Network
In2Networks' In2MyHome	Information Platform
Insteon Energy display	Sensor Display
Insteon - HouseLinc - SmartLinc	Closed Management Network
Intamac	Open Management Network
Intel Home Energy Dashboard	Open Management Network
Island Power's Cent-a-Meter	Sensor Display
LS Research RateSaver display	Grid Display
Lucid Design Group: Dashboard	Information Platform
Lucid Design Group - Lucid Building Dashboard – B - Lucid Building Dashboard - C	Networked Sensor
Mi Casa Verde SmartSwitch & Vera	Closed Management Network
Microsoft Hohm	Information Platform
Motorola 4Home	Open Management Network
Navetas - Energy Monitor - Smart Hub	Sensor Display
Needy Needs' Wireless Energy Monitor	Sensor Display
Nokia Home Control Center	Management Platform
Onzo	Sensor Display
OpenFrame 7E (OpenPeak)	Open Management Network
OPOWER - Energy Reports - Web portal	Information Platform
Owl Electricity Monitors	Sensor Display

Name / Developer	Type
P3 International - Kill-A-Watt - Kill-A-Watt EZ - Kill-A-Watt Graphic Timer & Plug Power Meter - Kill-A-Watt Power Strip	Load Monitor
P3 International Kill-a-Watt Wireless	Sensor Display
People Power 1.0	Information Platform
People Power Energy Services Platform + Surf Module	Closed Management Network
PICOwatt/Tenrehte Plug	Closed Management Network
Plugwise	Closed Management Network
Power Aware Cord	Load Monitor
Power Cost Display Monitor	Sensor Display
Powertech Silk	Information Platform
PowerWatch-DR	Open Management Network
Pulse Energy - Manager - Check	Information Platform
Quby - Power Player - The Energy Stick	Grid Display
RCS Whole home monitor & control	Closed Management Network
Reliance Controls AmWatt Appliance Load Tester	Load Monitor
San Vision Mobile Energy Assistant (MEA)	Open Management Network
San Vision Power Dashboard	Sensor Display
Salt River Project (SRP) M-Power Meter	Grid Display
Secure Together - E-Watch - Ewatch 100 - Ease II Manager - Scroller	Information Platform
Secure Together Home Energy Controller (HEC)	Open Management Network
Secure Together Freedom	Grid Display
Seasonic Electronics PowerAngel Monitor	Load Monitor
Senquentric System	Open Management Network

Name / Developer	Type
Shaspa Smart Home	Open Management Network
Shenzhen Sailwider - Centralized Electricity Energy Management System - Wireless Bi-directional Electricity Energy Saving Monitor & Control System	Closed Management Network
Shenzhen Sailwider Wireless Uni-directional Electrical Energy Saving Monitor	Sensor Display
Silver Spring Networks’ CustomerIQ Energy Portal	Information Platform
Silver Spring Network’s Smart Energy Dashboard	Management Platform
SolarCity’s PowerGuide	Information Platform
Square D PowerLogic - EPO Energy Profiler Online - ION EEM Software - ION Enterprise Software - PowerView Software - System Manager Software - Tenant Metering Software	Information Platform
Square D PowerLogic SCADA Software	Management Platform
Stanley 77-028 Energy Meter EM100	Load Monitor
SunPower Monitor	Sensor Display
Techtoniq Energy Station	Information Platform
The Energy Detective (TED) - 1001, 1002 - 5000-C, 5002-C, 5003-C, 5004-C	Sensor Display
The Energy Detective (TED) - 5000-G, 5002-G, 5003-G, 5004-G	Networked Sensor
Tendril	Open Management Network
Trilliant’s The Energy Valet,	Management Platform
Energy Aware Technology The PowerTab	Grid Display
UPM - Dual Rate Energy Meter- EM130 - EM100 Energy Meter - Plug-in Energy Meter and Electricity Cost Calculator	Load Monitor
UtiliFlex Juice	Information Platform
UtiliFlex Joule	Networked Sensor

Name / Developer	Type
U-Vue	Sensor Display
WANF Electricity Energy Watt Usage Meter	Load Monitor
Watts Up .Net	Closed Management Network
Watts Up Smart Circuit 21	Networked Sensor
Watts Up - Watts Up Standard - Watts Up Pro ES	Load Monitor
Wattson	Sensor Display
Wattvision Energy Sensor	Networked Sensor
Wilting Flower	Sensor Display
thinkeco Modlet	Closed Management Network
Wattsclever - Compact - Energy Monitor - Energy Monitor for Smart Meter	Sensor Display
Wattsclever Energy Watch Monitor	Load Monitor
Zerofootprint Talking Plugs	Closed Management Network