Applied Energy 228 (2018) 512–523

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Opportunities for behavioral energy efficiency and flexible demand in data-limited low-carbon resource constrained environments

Diego Ponce de Leon Barido[a,*], Stephen Suffian[b], Daniel M. Kammen[a,c], Duncan Callaway[a,*]

[a] The Energy and Resources Group, University of California, Berkeley, CA, United States
[b] Department of Electrical and Computer Engineering, Villanova University, PA, United States
[c] The Goldman School of Public Policy, University of California, Berkeley, CA, United States

HIGHLIGHTS

- First flexible demand and behavioral energy efficiency pilot in Latin America.
- 60 participants from low-middle income neighborhoods of Managua, Nicaragua.
- Wireless sensor networks enabled flexible demand and high-resolution feedback.
- 9% behavioral energy savings and ≥ 80% participation in flexible demand events.
- Co-benefits included improved energy literacy and financial management.

ARTICLE INFO

Keywords:
Behavior
Technology
Smart grid
Developing countries
Demand response
Energy efficiency

ABSTRACT

Sensor networks, information and communication technologies, and advances in behavioral science can allow for the design and implementation of inclusive information and automation systems for ongoing low-carbon transitions. Here, we present results of the first randomized pilot providing tandem behavioral energy efficiency and flexible demand services through the use of distributed sensor networks in Latin America (Managua, Nicaragua). We show that the houses and micro-enterprises randomly assigned to the intervention reduced their energy consumption by nine percent relative to the control group, and participated at length in peak-shaving flexible demand events (≥80% of events). Identified social co-benefits included increased energy literacy, financial management and user empowerment, and find that improved access to energy information was more important than cash when incentivizing project participation with a high user willingness to pay. Several challenges may hinder the success of smart systems in resource constrained environments, including temporal and financial scarcity at the household level, lack of institutional support, and a panoply of top-down misaligned incentives. We document the multiple barriers to scale flexible demand and energy efficiency strategies, including bottom-up (e.g., appliance financing) and top-down (e.g., decoupling) challenges and discuss ways to overcome them. As more low, low-middle income countries transition away from fossil fuels, the use of sensor networks and information and communication technologies for building smart and inclusive smart systems will become increasingly necessary and attractive.

1. Introduction

The ongoing global transition towards renewable energy is now occurring across all regions, incomes and levels of human development – with most new renewable energy capacity being installed in low, low-middle, and middle-income countries [1]. At the same time, access and ownership of cellphones, smartphones and information and communication technology (ICTs) has spanned the globe. Currently, there are more active mobile connections than people in the world (7.8 billion SIM connections vs. 7.6 billion people), and the number of 3G/4G users is expected to double by 2020 (2.5 billion users) [2]. The combination of these two trends presents a unique opportunity to develop and use low-cost information and communication technologies to address the inherent challenge in managing increasing penetrations of uncertain and variable renewable energy, particularly in data-limited contexts without a smart grid. However, despite the cost reductions in efficient appliances, renewable energy technologies, and ICTs, there are very few pilot demonstrations in low, low-middle and middle-income

* Corresponding authors.
E-mail addresses: diego.leon@berkeley.edu (D. Ponce de Leon Barido), dcal@berkeley.edu (D. Callaway).

https://doi.org/10.1016/j.apenergy.2018.06.115
Received 12 March 2018; Received in revised form 8 June 2018; Accepted 21 June 2018
0306-2619/ © 2018 Elsevier Ltd. All rights reserved.

economies that harness the synergy of these technologies.

Energy efficiency has a large potential role in reaching global goals related to energy security [1,2,3], economic efficiency [3,4], local pollution reduction, and climate abatement [5–7]. However, the size of the efficiency resource is not well understood. Some estimates suggest that there is vast economic potential with two-thirds of the resource remaining unfulfilled [2,5], while other analyses suggest that the resource is significantly smaller due to physical constraints, risk and opportunity costs, costs to project participants, and unobserved factors that can reduce the effectiveness of energy efficiency interventions (e.g., behavioral aspects) [8–10].

There is also widespread interest in using flexible demand as a means to reduce electricity system operation and infrastructure costs [9,10]. Within this area, there is a deep literature that provides (i) reliability, optimization and engineering analyses of load flexibility [2,11–20], (ii) evaluations for available sensing, actuation and control solutions [2,21–24], and (iii) pilots to validate theoretical assumptions, and understand the physical engineering aspects, and business opportunities that can inform large-scale deployments [2,21,25–29]. The role of user behavior and engagement, however, is an often overlooked yet crucial factor that will critically affect the success of these programs [30–33]. Behavioral science research has developed a diversity of theories explaining the many reasons why and how energy efficiency programs succeed and fail [34–36]. Social comparisons and access to information [34], social cognitive theory and moralized consumer choice [34,35], the role of autarky and self-determination [37], sustainability leanings [38], political ideology [39], and monetary incentives and loss aversion [40], have all been used to explain the mechanisms through which individuals (or households) chose to participate and remain engaged in renewable and energy efficiency programs [41–43].

Thus far, the majority of research exploring residential and small-business flexible demand focuses on modeling, as well as regulatory and technical innovation [42]. There is little work focusing on users' physical, temporal, and budget constraints and even less emphasis on understanding the barriers and drivers that have been uncovered by advances in behavioral science [30,43–47]. A deeper understanding of these issues could be leveraged to use flexible demand programs as a tool for inclusive and social participatory engagement. Motivations for participating in demand-side management (e.g., monetary, environmental, altruistic, community-oriented) could be as varied as concerns towards it (e.g., health, privacy, costs) [48], and more research is needed to develop approaches and technologies that can reach the greatest number of people. Furthermore, there is very little applied and interdisciplinary research that informs how to evaluate and narrow the energy efficiency and smart infrastructure gap in data-limited low-carbon resource constrained environments. This research is crucial, however, as most future electricity demand will occur in emerging economies and the rising south [49–51].

Here, we present what we believe to be the first randomized pilot of a behavioral energy efficiency and flexible demand intervention in low, low-middle income neighborhoods in Latin America. Behavioral energy efficiency is defined as messaging grounded on behavioral science to produce simple, actionable messages to motivate end-users to save energy [52]. Flexible demand is defined as the use of communication and control technology to shift electricity demand across time (e.g., seconds, minutes, hours) while delivering end-use services (e.g., cooling, heating, electric vehicle charging) [53]. There are several notable findings and contributions from our approach. First, we demonstrate that low-cost wireless sensor networks can be used to achieve large monetary savings through flexible demand and behavioral energy efficiency in data-limited resource-constrained environments. We find that the houses and micro-enterprises (MEs) randomly assigned to our intervention reduced their energy consumption by nine percent relative to a control group, and participated at length (> 80%) in peak-shaving flexible demand events. Second, we use state-of-the-art analysis to characterize both the parameters and uncertainty of our estimates through Bayesian Inference and Markov Chain Montecarlo (MCMC), a novel approach that could significantly benefit many pilot projects with small sample sizes across the world. Third, our pilot uncovered many co-benefits to smart grid interventions that had previously not been identified or discussed at large in the literature, including improvements in energy literacy, knowledge creation, household and small-business management, small business and women empowerment, as well as reducing perceived stress of energy expenditures. Finally, our pilot implementation suggested that under some circumstances, monetary incentives are not the preferred or the most successful method of encouraging end-user project participation – even in resource constrained environments. When given the option to choose a reward for program participation of either detailed energy information or direct cash payments, most participants chose information over cash, consistent with literature that suggests that non-monetary rewards can be equally or more effective than financial incentives at motivating behavioral change. We discuss all these themes at length throughout the paper.

2. Materials and methods

2.1. Study design and recruitment

Nicaragua has one of the highest penetrations of non-large hydropower renewable energy among countries in the Western Hemisphere (~%60) [54]. While it has significantly improved access to basic services and quality of life after decades of civil unrest, Nicaragua still has relatively high electricity prices and relatively low scores on ease of doing business and infrastructural quality [54–56]. In January 2015, we implemented a baseline survey (N = 435) to collect household and small-business characteristics (e.g., age, education level, gender, and appliance ownership) on neighborhoods of similar social demographics (overcrowding, access to basic services, housing quality, education level, economic dependency and poverty), performed a basic needs assessment, and gained insight on local perspectives of climate change, energy costs and grid adequacy, the perceived usefulness of energy information, and a variety of local energy management perspectives. Our surveys and interviews included 216 households and 219 micro-enterprises (e.g., butcheries, chicken shops, corner stores).

The pilot's baseline survey elucidated many themes that allowed us to design adequate project invitation mechanisms, and later, effective information technology systems to retain our project participants. Energy, food, and access to basic services were the top three self-perceived present concerns in our sample (23%, 20%, and 12% of the sample ranking an issue as a top concern, respectively) with most members finding it very-hard (18% of sample) or hard (43% of sample) to pay their monthly electricity bill. The combination of relatively high electricity prices (0.21$/kWh) and low incomes created a constant source of stress in the sampled neighborhoods, with 60% of the sample checking their energy meter on a daily basis and keeping an energy calendar, or simply taking “energy notes” (energy meters are sometimes located outside houses, and other times located with other energy meters on a street corner) in an attempt to control their energy consumption. Furthermore, 72% of the surveyed households and micro-enterprises unplugged their refrigerator once a day, or at different times of the day in an attempt to reduce their energy consumption. Many of the households and MEs perform this practice on a daily basis while explicitly acknowledging that they don't know if their strategies are being successful. An additional incentive for a careful energy management approach by our project participants is that a monthly consumption below 150 kWh leads, on average, to a 60% reduction in the unit cost of energy $US/month (cost of energy for 150 kWh/month vs. 300 kWh/month). Many of our participants were actively engaged in attempts to save energy to receive a subsidized cost per unit of electricity, albeit many of them doing so unsuccessfully.

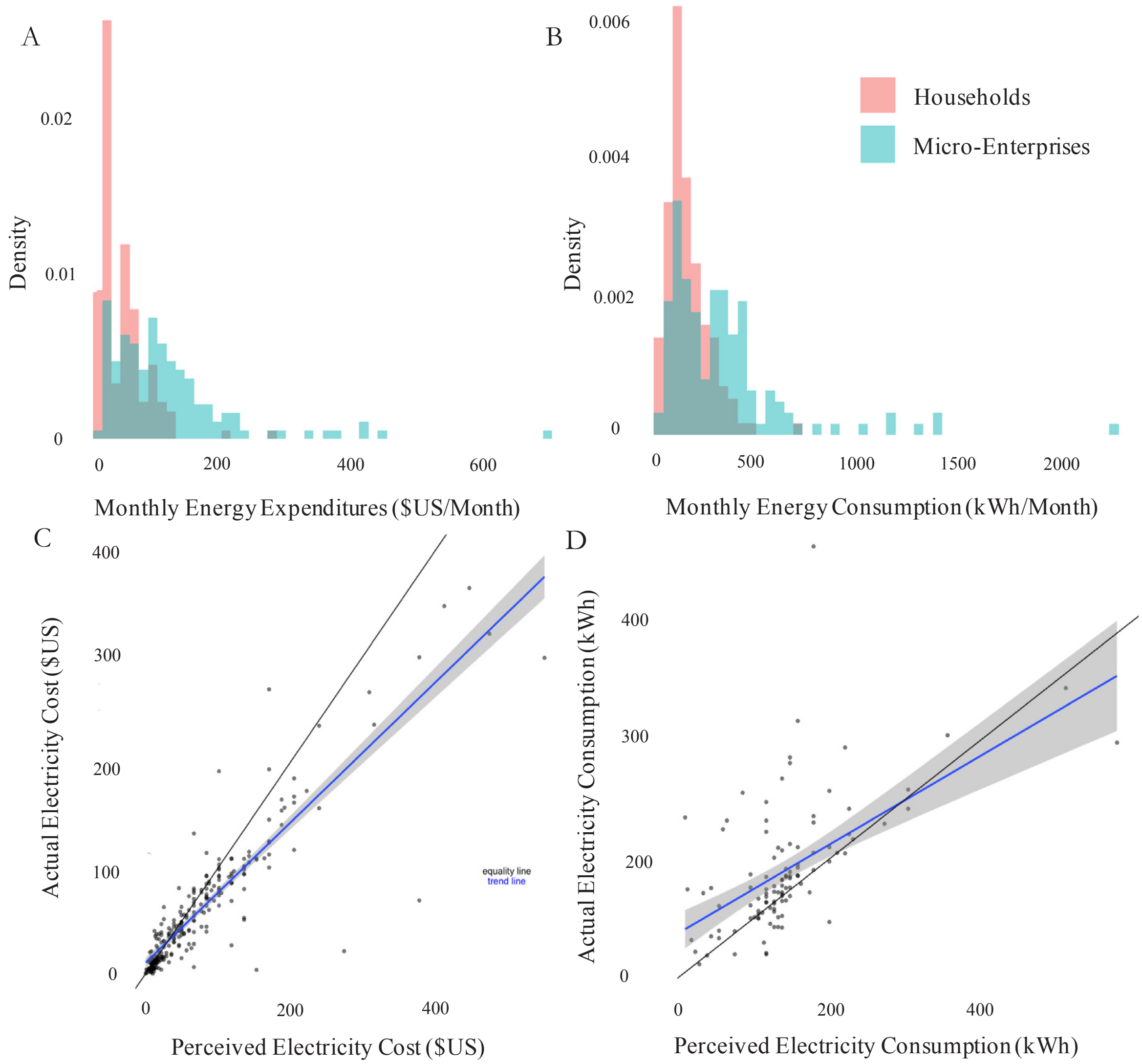

Fig. 1. Distribution of [A] Monthly Energy Costs ($US), [B] Monthly Consumption (kWh), [C] Perceived vs. Actual Monthly Costs ($US), and [D] perceived vs actual consumption (kWh) for Households and Micro-Enterprises. [A] and [B] depict histograms of the distribution of monthly energy expenditures ($US) and monthly energy consumption (kWh) for households (red) and micro-enterprises (blue). Both distributions depict micro-enterprises spending more and consuming more energy than households. Micro enterprises consume 145 kWh ($US 31) more per month than households. Figures [C] and [D] depict users perceived monthly electricity costs ($US) and consumption (kWh) against their actual consumption (from their paper energy bills). Users perceive that they spend one and half more times on electricity than they actually do, and underestimate the energy they consume (kWh) by 20%. The blue line depicts the data trend line, and the blackline represents the equality line or a 1:1 relationship. Data below the equality line suggests that users overestimate their costs ($US/month), and data above the equality line suggests that users underestimate their consumption (kWh/month). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Three key survey results motivated a behavioral energy efficiency and demand side flexibility intervention: (i) 70% of users were already shifting and reducing their demand on a voluntary basis without any price or grid incentives (unplugging refrigerators in an attempt to save energy), (ii) users had a widespread positive perception of service reliability despite experiencing frequent outages (e.g., once a week), and (iii) users experienced relatively higher energy costs that in the United States (0.21 US$/kWh). In addition, users expressed a personal goal of lowering their monthly energy consumption in order to receive a subsidized unit cost (monthly consumption below 150kWh is 60% less expensive than consumption above that threshold), they perceived to spend 1.5 times more on electricity that they actually did ($US/month), and they underestimated their actual energy consumption (kWh/month) by approximately 20% (Fig. 1).

We randomly selected sixty households and micro-enterprises from the baseline sample to be part of the study (30 treatment and 30 control), and recruited them into the study with an entry to win a raffle for a new refrigerator or freezer (or the equivalent in cash) at the end of the study. All participants agreed to share their historical energy consumption profiles ($US and kWh) for up to a year and participated in a baseline, midline and endline survey. We also invited half of the participating micro-enterprises and half of households to join a treatment group in exchange for high-resolution energy information, real time energy alerts, and a flexible demand payment of 175 Cordobas (~$6 per month, treatment details below). The control group received nothing. At baseline, treatment and control groups were balanced with respect to education, number of appliances, energy consumption and expenditures, and perceived vs. actual energy expenditures ($US/month) and consumption (kWh/month). Extended details on the survey used, sampling methodology and complete survey results including perspectives on climate change, the usefulness of information, and the accuracy of perceived vs. actual energy costs are available in the SI. All the randomly selected participants in both the treatment and control group consented to participate in the project as approved by University

Table 1
Selection of baseline characteristics and perspectives on financial burden and future concerns.

Sample	
Houses	N = 219
Micro-Enterprises	N = 216
Age – Mean (Standard Deviation)	47 (SDV = 15)
Education	First two-years of high school
Household size	5.5 people per household
Average vs. Disposable Income ($US/Month)	
Houses	$550 vs $70
Micro-Enterprises	$520 vs $182
Median Monthly Energy Consumption (kWh/month), Energy Costs ($US/month) and Cost per Unit of Energy ($US/kWh)	
Houses	160 kWh/month, 30$US/month, 0.19$US/kWh
Micro-Enterprises	305 kWh/month, 71$US/month, 0.23$US/kWh
Total bill Houses vs. Micro-Enterprises[1]	22$US/month vs. 86$US/month
Financial burden[2]	
What is a problem that is recurrently on your mind?	
(1) Energy, (2) Food, (3) Access to basic services	23%, 20%, 12%
What is the biggest financial burden on your small business?[2,3]	
(1) Energy, (2) Loans, (3) Employees	88%, 5%, 3%
Approximately what fraction of your total costs are energy related costs? Median (25th percentile - 75 th percentile)	
Houses	8% (4% - 19%)
Micro-Enterprises	30% (12% - 48%)
Future issues[3]	
Of the following issues, which ones do you consider to be of most concern in the future?	
(1) Climate change, (2) Oil dependency, (3) Electricity prices	36%, 24%, 20%

[1] The total monthly bill is lower than the total monthly energy cost because the total cost is reduced if the house or micro-enterprise manages to be below a monthly consumption of 150 kWh/month.
[2] Perceived financial burden.
[3] Only the three most popular perceived financial burdens and future issues are presented.

of California Berkeley's Institutional Review Board and Committee for the Protection of Human Subjects (CPHS Protocol Number 2014-12-6955). Table 1 and Fig. 1 summarize several elements from the pilot's baseline survey, with more in depth details being presented below and in the Supplemental Information.

2.2. Intervention

The intervention, consisted of a sensor gateway configured to collect consumption and temperature data and to interrupt power to connected refrigerators (also called a Flexbox) [2], monthly reports with high-resolution energy information, real time energy alerts (warning users when they approached their monthly energy consumption goals), and a demand flexibility program that curtailed appliances using the Flexbox according to user-defined schedules and during daily peak grid pricing events (Fig. 2). In exchange for participation, the treatment group received co-designed and user-tailored energy information and real time alerts, as well as a $US 6 flexible demand monthly payment. Each FlexBox contained a switch to interrupt power to connected appliances and sensors measuring fridge or freezer internal temperature, room temperature and humidity, fridge door activity and fridge energy and power consumption. We monitored household and business power consumption at the electric service panel and used a GSM modem for data transmission and switch actuation. See de Leon Barido et al. [2] for further sensor network and Flexbox details.

The intervention had three features: Monthly reports, real time energy alerts and a demand flexibility program that included a US$6/month payment. Monthly reports were co-designed with participants and provided (i) Nicaragua's monthly electricity generation by resource, (ii) the user's current and historical monthly values for: average hourly consumption (total and fridge only), weekly consumption (total and fridge only), and monthly total consumption and (iii) relationships between: ambient temperature and consumption (household and fridge), fridge door openings and fridge consumption, and fridge internal temperature and consumption. For monthly real-time energy alerts, users set a consumption goal for the upcoming month and texted it to our cloud server, which then sent SMS energy alerts to the user as various energy consumption thresholds were crossed (e.g., "Careful! You have reached 90% of your monthly energy budget!"). Demand flexibility could be programmed by users (e.g. off in specified hours of the day) and by our servers on days with high forecasted wholesale electricity prices. Users were notified of flexible demand events lasting from one to three hours one day in advance and were able to opt out any time before (by sending a text message), or during a flexible demand event by switching outlets on a power strip provided by the project.

The FlexBox allowed us to continuously collect key parameters for monitoring energy consumption and the state of participants' thermostatically controlled loads (TCLs), fridges and refrigerators [2]. For example, the sensor network presented evidence to suggest that the temperature inside households and micro-enterprises was higher than outside ambient temperatures during the hottest part of the days due to the use of non-reflective infrastructure materials that would capture heat and provide no insulation [2]. This led to the energy consumption of TCLs to vary across our sample depending on ambient temperature (a characteristic that is not taken into account in most thermal models). The duty cycle (the ration of time it takes for a refrigerator to travers its dead-band in an on state vs. total time in compressor on and off states) was also found to fluctuate during the way (a parameter that is kept constant in most thermal models). Sensor data presented evidence that diverges significantly from previous TCL modeling assumptions that have been published elsewhere. The data distribution of key TCL thermal parameters included ambient temperature (mean: 30 °C, standard deviation: 3 °C), dead-band width (mean: 9 °C, sd: 4 °C), temperature set point (min: −20 °C, max: 5 °C), duty cycle (mean: 0.52, min: 0.1–max: 0.9), coefficient of performance (0.01–0.03), and efficiency performance index (mean: 1.2, sd: 2.4). See [2] for a more in depth analysis of retrieved sensor data and key TCL parameters.

Sensor baseline data was collected from July 2015 to January 2016, during which there was no interaction with the participants. From January 2016 to July 2016 there was a co-design period where we worked with the treatment group (roughly once per month) to develop clear and useful information snippets (text and figures) for the monthly paper reports they would receive, as well as to ensure that the real-time SMS energy alerts were clear and understandable by everyone. The intervention (monthly energy reports, flexible demand and real-time text-messaging) began in July 2016 and lasted until December 2016. No project participants left the project once the demand flexibility intervention began. Further intervention details are provided in the SI.

2.3. Analysis

Given the balanced outcomes of our treatment and control group participants, we use Bayesian Inference for inter-participant and group comparisons. The approach is robust for two groups and small samples, handles outliers, and provides complete distributions of credible values for group means and standard deviations (and their difference), effect size, and the normality of the data [44,45]. Thus, Bayesian Inference estimates five parameters: means of treatment and control (μ_1 and μ_2), standard deviations of treatment and control (σ_1 and σ_2), and the normality of the data between treatment and control (ν) [57,58].

Bayesian inference is desirable for our analysis as it is robust for small samples, and leads to reallocation of credibility toward parameter values that can consistently describe the observed data [58]. In this

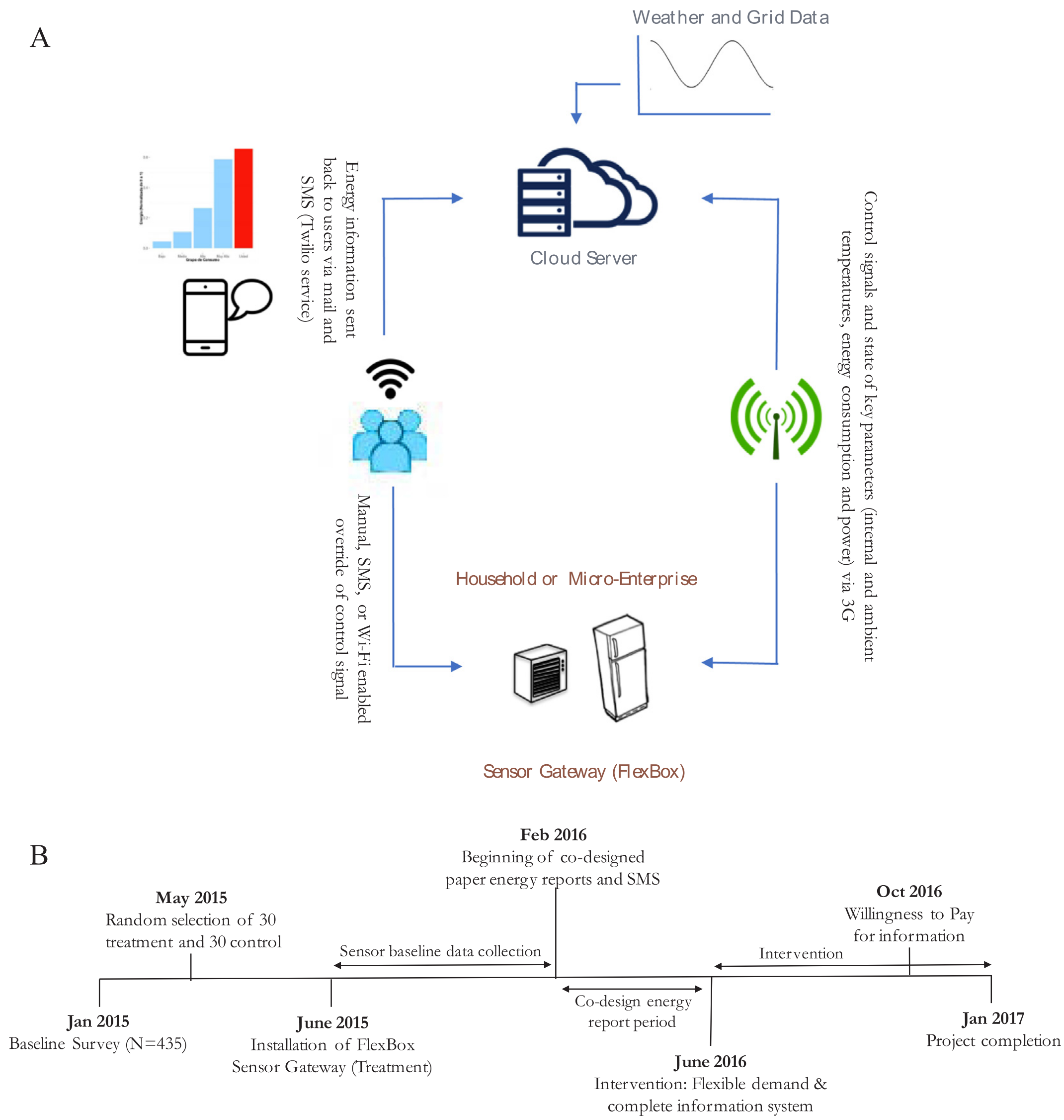

Fig. 2. Intervention [A] and Timeline [B]: [A] The diagram depicts how key parameter data is transmitted to and from households and thermostatically controlled loads (TCLs) via a GSM to a cloud server. The cloud server collects all participant data, evaluates dispatch center day ahead prices and schedules peak price events; it also sends energy limit alerts tailored to each participant. Data is aggregated and monthly reports are sent to each participant. The user may override control signals at any time manually, via SMS. [B] The timeline depicts the schedule and steps of our project implementation, beginning in January 2015 and Finishing in January 2017.

analysis, we estimate three parameter values: (*A*) pre- vs. post-implementation monthly energy consumption (e.g., August 2015–June 2016 vs July–December 2016), (*B*) month-by-month differences during the intervention period (e.g., comparing energy differences between August and September 2016), and *(C)* annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016). The analysis begins with a distribution of credible parameter values that contain previous knowledge without *any newly collected experiment data* (a prior distribution), and the reallocation of credibility is provided by Baye's rule and applying it to parameters and data [58]:

$$\underbrace{p(\mu_1, \sigma_1, \mu_2, \sigma_2, \nu|D)}_{\text{posterior}} = \underbrace{p(D|\mu_1, \sigma_1, \mu_2, \sigma_2, \nu)}_{\text{likelihood}} \times \underbrace{p(\mu_1, \sigma_1, \mu_2, \sigma_2, \nu)}_{\text{prior}} / \underbrace{p(D)}_{\text{evidence}}$$

This suggests that the posterior credibility of our estimated parameters (μ_1, μ_2, σ_1, σ_2) is the likelihood (*t* distribution) times our prior distribution, divided by the new evidence *D* (y_{ii} observed from treatment and control groups) [58]. The posterior distribution is then approximated by using Markov Chain Montercarlo (MCMC), without explicitly computing *p*(*D*). The result is thousands of representative parameter values that are summarized graphically by a histogram (Fig. 3 and Supplemental Information) that are used to estimate mean, mode, standard deviation, and credible differences between treatment and control [44,45].

Here, we build a prior distribution using both our baseline survey estimates (N = 435), and an extended literature review of behavioral energy efficiency intervention and results (see SI) [25–28,30,31,46–48]. We use a broad informative prior (rather than a Bayesian non-informative prior) because there is a large sample of evidence from which we can draw to create a distribution of where we think the most credible parameter estimates lie. For this, we performed an extended literature review and summary of over 30 different intervention types, and over 60 papers [59–62], Our summary suggests that the average reduction due to behavioral energy efficiency (across regions, incomes and study types) is of 10.5% with a standard deviation reduction of 11.1%. The mean and standard deviation of the standard deviation across studies is of 11% and 8% respectively.

When assessing the posterior distribution, the high-density interval (HDI) and the region of practical equivalence (ROPE) help determine

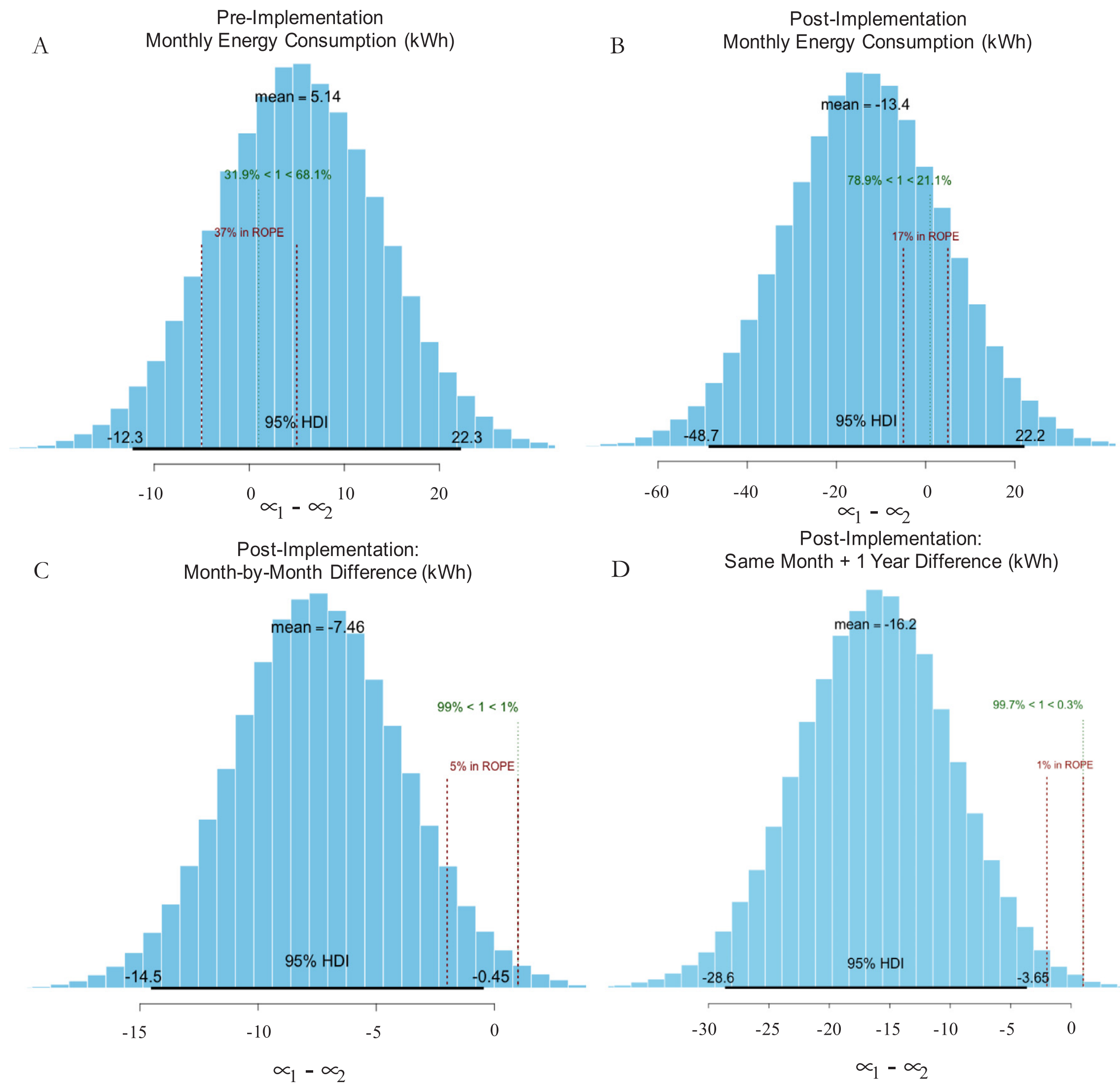

Fig. 3. Bayesian Posterior Estimates Treatment (μ_1) vs. Control (μ_2): [A] Pre-implementation monthly energy consumption (kWh/month), [B] post-intervention monthly energy consumption (kWh/month), [C] month-by-month differences (kWh/month) during the intervention period (e.g., comparing energy difference between August and September 2016) and [D] annual differences (kWh/month) between the same months one year afterwards (e.g., August 2015 vs. August 2016). Black line on x-axis represents the 95% high density interval (HDI), and the red line represents the regional of practical equivalence (ROPE). Median temperature was 30.6 °C in 2015 (sd: 14.5 °C) vs 31.2 °C in 2016 (sd: 15.1 °C), median temperature pre- vs. post intervention months was 31.5 °C in (sd: 14.8 °C) and 30.4 °C 2016 (sd: 15.1 °C) respectively. We highlight year-to-year temperature comparisons, having [D] as our most robust result. The treatment group experiences energy reductions, despite a small increase in ambient temperature (measured by a weather station). Details are discussed in the text and the full Bayesian parameter estimation is provided in the SI. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the credibility of an observed result. The HDI is a 95% density interval where the bulk of the most credible values fall, and ROPE represents parameter sizes that may be deemed negligibly different from the null. In our analysis, we use a ROPE ranging between −2% and 2% (representing group comparisons and the Hawthorne effect) [25,26,59], representing a small reduction, no change, or a slight increase in energy consumption. Results within the HDI and outside ROPE are deemed credible.

We evaluate three different results: (A) pre- vs. post-implementation monthly energy consumption (e.g., August 2015–June 2016 vs July–December 2016), (B) month-by-month differences during the intervention period (e.g., comparing energy differences between August and September 2016), and (C) annual differences between the same months one year afterwards (e.g., August 2015 vs. August 2016). Users are compared to themselves during and at these three different time points to control for number of appliances, household characteristics that affect ambient temperature (e.g., roof and wall type, presence of sky lights), people in household, education, and other baseline characteristics. The comparison in (C) controls for seasonal variations in consumption and federal holidays that affect both weather and behavioral patterns, and is thus our most robust comparison. For flexible demand, we use Bayesian estimation to identify credible differences in refrigerator and freezer energy consumption pre-vs. post-implementation (all hours), and a subset of peak pricing hour events. The SI includes full Bayesian estimation results. Our analysis uses the R statistical programming language [63], the MCMC sampling lag called JAGS [64], and the BEST program for Bayesian means tests in R [44,45].

3. Results and discussion

3.1. Magnitude and uncertainty of behavioral energy efficiency, and flexible demand participation

We use three different measurements to evaluate the effect of our intervention on total energy consumption: (A) post-intervention monthly energy consumption (e.g., August 2015–June 2016 vs. July–December 2016), (B) month-by-month differences during the intervention period (e.g., July vs. August 2016), and (C) differences between the same months in consecutive years (e.g., August 2015 vs. August 2016). The latter controls for both seasonal consumption variation and federal holidays (e.g., Independence Day), with each participant in the treatment and control group being compared with itself one year ago for every month during the intervention period. We compare differences in treatment and control for (A), (B), and (C) using Bayesian estimation and as described in the methods and SI.

We observe the treatment group reducing its total household or small-business energy consumption relative to the control group in all these comparisons, by (A) 13.4 kWh (6%), (B) 7.46 kWh (4%), and (C) 16.2 kWh (9%) respectively (Fig. 3). For post-intervention and month-by-month comparisons, however, our high-density interval (HDI) falls over zero and within the region of practical equivalence (ROPE) suggesting that our results are not credibly different from zero or from values with a significant effect size. For month-annual differences, however, both zero and ROPE are fully outside the HDI suggesting that our results are credibly different from each other and zero. We consider the latter to be the most robust result as it controls for several unobserved factors such as variation in seasonal consumption, federal holidays, within household variability (e.g., behavior, number of appliances), and compares both groups to each other.

Peak prices for flexible demand events were identified one day in advance; events lasted up to three hours (see SI for details). Project participants were opted-into the flexible demand events (with ability to withdraw at any given time), and participated an average of 40 min for every hour of a peak pricing event, (median: 53 min, sd: 20 min) or 70% of the time of every event (median: 88%, sd: 34%) (Fig. 4). Pooling together all hours, there was no credible difference between pre- and post-intervention fridge energy consumption (mean difference Wh: 0.301, sd difference Wh: 20) (Fig. 5A). However, there was a large usage reduction during flexible demand event hours (mean reduction post-intervention Wh: 78.3, sd: 48.2) (Fig. 5B and C).

Based on these results we estimate that if one third of the population (2 million people) received paper reports and energy alerts, Nicaragua could save $US 29 million in wholesale energy costs annually (using average prices), and if this same population participated in flexible demand they could save $US 18 million annually (using differences between peak and off-peak prices). Using actual generation emissions from Nicaragua's grid in this scenario, behavioral energy efficiency could save over 6 million metric tons of CO_2eq annually (using average monthly emissions) and flexible demand would avoid over 3 million metric tons of CO_{2eq} (using peak prices hourly average emissions). Details in SI.

3.2. Social co-benefits and the effect of scarcity

For tracking improvements related to energy literacy, we measured the accuracy of perceived vs. actual energy consumption ($US and kWh) at baseline, intervention, midline, and endline. At baseline, the treatment group had a slightly larger overestimate of their perceived energy costs relative to the control group (median: $US 7 vs. $US 5, respectively). When the intervention began, and likely due to the co-design of the energy information mechanisms, the treatment group had improved its ability to recall its actual consumption within an error $US 2 and largely maintained this improved accuracy throughout the midline (error: $US 3 treatment vs. $US 4 control) and endline surveys (error: $US 1 treatment vs $US 3 control). Although both groups increased their accuracy throughout the pilot, the treatment group had a greater improvement in accuracy of $US 6 against a $US 2 improvement by the control. The treatment group also significantly improved the accuracy of recalling their actual energy consumption (kWh) from a baseline underestimate of 30 kWh, to a mean endline underestimate of 14 kWh (median: 0 kWh, sd: 118 kWh). The control group, on the other hand switched from an underestimate of 30 kWh to an overestimate of 20 kWh (median: 6 kWh, sd: 117 kWh). During the final survey, we used two additional metrics to evaluate whether increased attention to energy bill data permeated to other non-previously surveyed metrics: accuracy at recalling the unit cost of energy, and monthly water expenditures. On average, the treatment group had almost a perfect grasp of the unit cost of energy (mean error: $US 0/kWh, median error: $US 0/kWh, sd: $US 0.06/kWh), while the control group had a mean error of $US 0.5/kWh (median error: $US 0.07/kWh, sd: $US 0.99/kWh), which is 2.5 times higher than the actual unit cost of energy. With regards to water expenditures, the treatment group had, on average, a $US 2/month underestimate of their water bill (median: $US 12/month, sd: $US 101/month), while the control group had a $US 56/month overestimate (median: $US 9.74 month, sd: $US 155/month).

Identified co-benefits through surveys and interviews include information spillover, user empowerment, and the potential for high-resolution information to reduce energy-bill induced stress. Some project participants reported that they forwarded energy information to others (extended family and friends), suggesting that the recorded information benefits could be an underestimate, as those others might have also reduced energy consumption in response. In our sample, home and small business energy management was performed mostly by women, several of whom reported that post-intervention they received new respect for their financial and energy management ideas. Women would use information to highlight management strategies that were being successful including limiting consumption (e.g. televisions only in certain hours, fans only during the day), and scheduling some energy-consuming activities such as washing once a week or bi-weekly. Research elsewhere, however, has found that interventions to support behavioral energy efficiency can negatively impact household power (and gender) dynamics, with men suggesting to reduce the use of common gender specific appliances (e.g., hair dryers) and placing the workload of energy management primarily on women [51,52,65,66]. Though limiting use of comfort appliances such as fans could have negative side-effects (e.g., heat stress), these issues were not brought up by participants.

Our intervention, however, was unable to reduce the user's perceived high stress of energy bills. At baseline, the most common feeling amongst treatment and control groups was that electricity was "very hard to pay" (1: easy to pay, 2: more or less hard to pay, 3: very hard to pay, 4: extremely hard to pay). At the end of the study, stress remained the same and was unaffected by flexible demand payments, more controlled scheduling, information, or actual reductions in consumption. Furthermore, although energy reports included suggestions and advice on a variety of efficiency retrofits, the participants implemented none. Reasons for failure to neither save, nor spend money on retrofits included the continued reoccurrence of immediate pressing needs (e.g., energy bill, education, health), perceptions that flexible demand payments were too small to be saved (i.e., it was better to use them for immediate needs), lack of awareness about how to purchase, retrieve and install new appliances, lack of transportation and time, and perceived high cost of new appliances. When participants were asked if they would forgo payments if someone else purchased and installed efficient appliances for them, 85% answered "yes", with participants willing to exchange one payment month or all future payments to receive help in long term energy efficiency retrofits.

Spending new income on pressing needs rather than making investments in the future, and inability to act (or choosing not to) to resolve constant stressors are well explained by the psychology of scarcity [67]. In scarcity, tunneling is a behavior that might help solve an immediate primary problem, but a heightened focus on immediacy can make one short sighted, leaving less attention for other less pressing issues that are recurrently neglected [67]. Although our participants had good intentions (e.g., saving energy now), they were unable to create and follow a long run savings plan. Our surveys indicated that

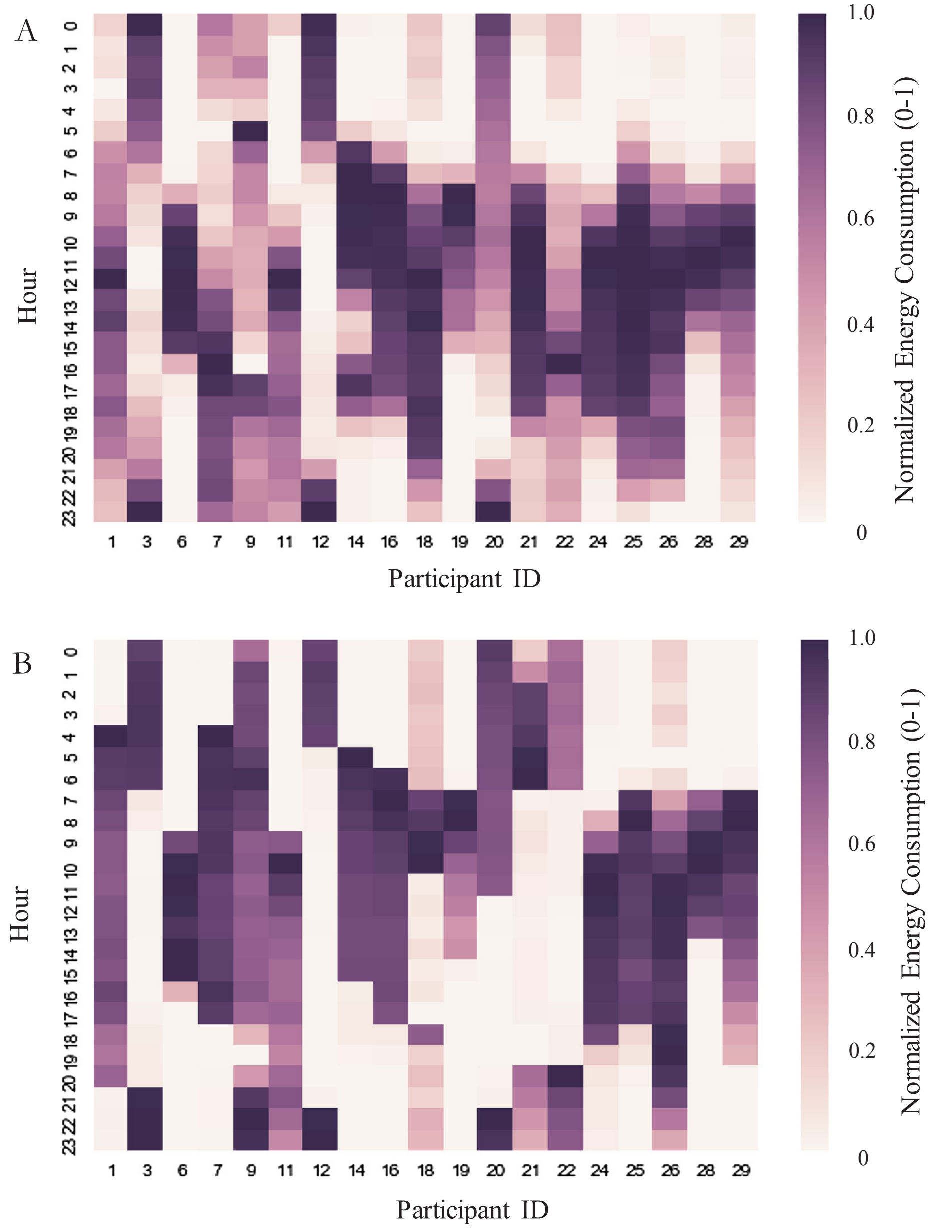

Fig. 4. Median Normalized Energy Consumption (0–1) Pre-and Post-Implementation: [A] and [B] depict pre- vs. post-intervention hourly energy consumption by Participant ID. [B] Post-intervention daily fridge energy consumption is more concentrated in regular daily intervals than in pre-intervention [A]. One can see that the colors and values in [B] start and stop at specific hours, while the colors and values in [A] start and stop in non-scheduled time intervals. We present normalized energy consumption by participant ID to avoid unique hourly energy values that would skew the data, and hence data representation, in the heat map. Full results are presented in the SI.

saving energy involved diligent work where one missed text-message, an unexpected visitor, or a sick child would impede saving energy plans. Despite real energy savings and small cash infusions, the lack of slack (mental and financial) and constant external shocks (temporal and financial) caused actions consistent with the psychology of scarcity [67]. Participants highlighted that their greatest perceived benefit was bill stability, which presumably reduced financial shocks to their household budget [67].

3.3. An estimate to the value of energy information

To determine the value of energy information, we offered a willingness to pay 'information bidding game' to the treatment group, after which participants would either keep information or cash as reward for their flexible demand contributions. Our enumerators carried with them a bag with pieces of paper that had numbers between 25 and 200 written down in each of them in increments of 25 Cordobas (approximately US$0.90). If participants bid a number that was lower than the piece of paper drawn from the bag, they would lose the information and keep receiving the same payment as before. If they bid a number that was equal or higher to the paper drawn from the bag, they would keep the information, and keep receiving a smaller payment (the difference between their flexible demand payment, and their bid). After doing one practice round of bidding, the actual game was played. Out of 20 participants, only two participants bid zero, suggesting that they would rather keep the money than the information. For the rest of the participants, the mean bidding value was $US 4 (median: $US 3.4, sd: $US 1.9), with 10 of them winning the bid, and eight of them losing the bid. This suggests that participants were willing to lose two-thirds of their payment, and continue participating in flexible demand, as long as they kept receiving high-resolution information. Non-zero bids suggest that most participants were willing to gamble their payments in exchange for information. Rationale for keeping the information included the opportunity to pursue long-term energy savings, increase understanding of the household budget, education, and knowledge. Money, our participants mentioned, would simply leave them too fast. While our participants had little value for energy information at the beginning of the study, by the end of the study they were willing to give up $US 4/month to keep it.

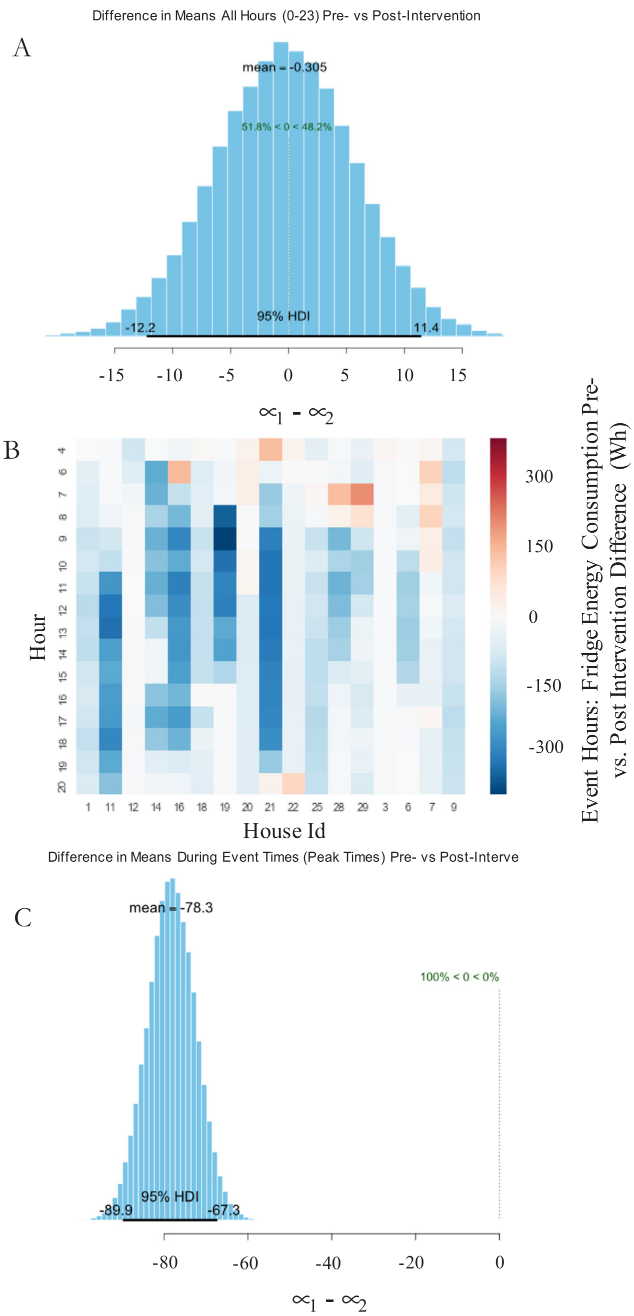

Fig. 5. Bayesian Estimation Results Pre- vs. Post Flexible Demand Intervention: Mean Differences of Pre- vs. Post Intervention Fridge Energy Consumption: [A] Posterior distribution of mean differences pre- vs post-intervention for all hours (0–23), [B] Differences pre-vs post intervention for all hours by participant id (differences in Wh), and [C] Posterior distribution of mean differences within a subset of hours in which there were peak price events. [A] suggests that there is no difference between fridge energy consumption pre- vs. post intervention, and [C] suggests that there was a large credible reduction post-intervention during peak pricing event times.

3.4. Bottom-up and top-down challenges and opportunities

Our research shows that information systems provide multiple benefits beyond their immediately intended goals in low-carbon, resource constrained environments. First, this work has demonstrated that flexible demand interventions can be incredibly successful if they consider inherent behavioral and social characteristics of end-users. This was exemplified by turning the high-resolution data collected for automation and control of flexible loads (e.g., freezers and refrigerators), into high-resolution real-time feedback that led to important behavior change and energy efficiency savings. Equally important were the derived co-benefits from our implementation. Energy literacy, knowledge creation, empowerment and budget management all emerged as co-benefits beyond the immediate energy, environmental and cost savings of our program. At the same time, there are multiple challenges for energy efficiency and flexible demand services in ‘real world’ settings like Managua, and services that do not provide a suite of enabling products will unlikely receive popular end-user support.

The results and lessons learned from our implementation suggest that there are important design elements that may lead to the success or failure of future applications of tandem behavioral energy efficiency and flexible demand programs. Three key elements for a successful implementation include: *(1)* High resolution interaction, co-design and good customer service, *(2)* understanding and support of user intrinsic motivations, and *(3)* creation of new locally relevant business models. In communities with little top-down support for energy efficiency, or waste management, as our demonstration project suggests, the combination of *(1)*, *(2)* and *(3)* can lead to high end-user engagement, positive interactions with the local community, increased persistence, and the creation of new models of end-user engagement that are not dependent on top-down stakeholders (e.g., governments, utilities). These opportunities, however, are only capitalized if they are thought about from program design, as it is necessary to continuously collect data to validate improvements or hypotheses to be explored. In our implementation, *(1)*, *(2)*, and *(3)* were manifested in the form of *(1)* co-design of information systems with users so that feedback mechanisms would be immediately useful and easily understood (only variables that users deemed important were provided to them), *(2)* encouraging program participation by mainly focusing on energy independence and monetary savings, and *(3)* identifying all the barriers that users faced to achieve their desired energy efficiency goals (e.g., access to finance, inefficient appliances, and needed household retrofits) and providing information for end-users to access solutions that could reduce these barriers (e.g., access to sustainable financing for new appliances and retrofits).

Design flaws that may jeopardize future energy efficiency and flexible demand implementations (small pilot projects or large scale deployments) include not collecting prior knowledge of household, business or community dynamics (e.g., budget preferences, consumption patterns, budgetary goals and restrictions), having little prior knowledge of end-user behavior, and no data or understanding of the local dynamics regarding the psychology of scarcity. These design flaws can lead to poorly designed mechanisms to overcome the energy efficiency gap (e.g., requesting access to a savings account to provide financing, when 49% of adults in Latin America do not have access to traditional financial services), rebound effects (e.g., users increasing their energy consumption after implementation of an efficiency pilot) [10], and lack of deep and permanent benefits for project participants. For example, in our pilot, not having designed a final services program in parallel to our flexible demand and behavioral energy efficiency intervention meant that our participants were not able to make long-term investments towards their home, business, or budget. Future successful programs would reduce budget uncertainty and instability, reduce the time required to learn about energy efficiency, provide transport to buy efficient appliances (and discard old ones), and simplify paperwork, among many other challenges that end-users commonly face.

There are also important top-down challenges to scale energy efficiency and flexible demand projects in resource constrained environments. Because there is no utility de-coupling (splitting the utility’s earnings from its sales) in most (if not all) countries of the rising south, efficiency and flexible demand interventions at scale would generate a loss and hence not be palatable to most utilities. A flexible demand strategy that would arguably allow a utility to increase revenue through

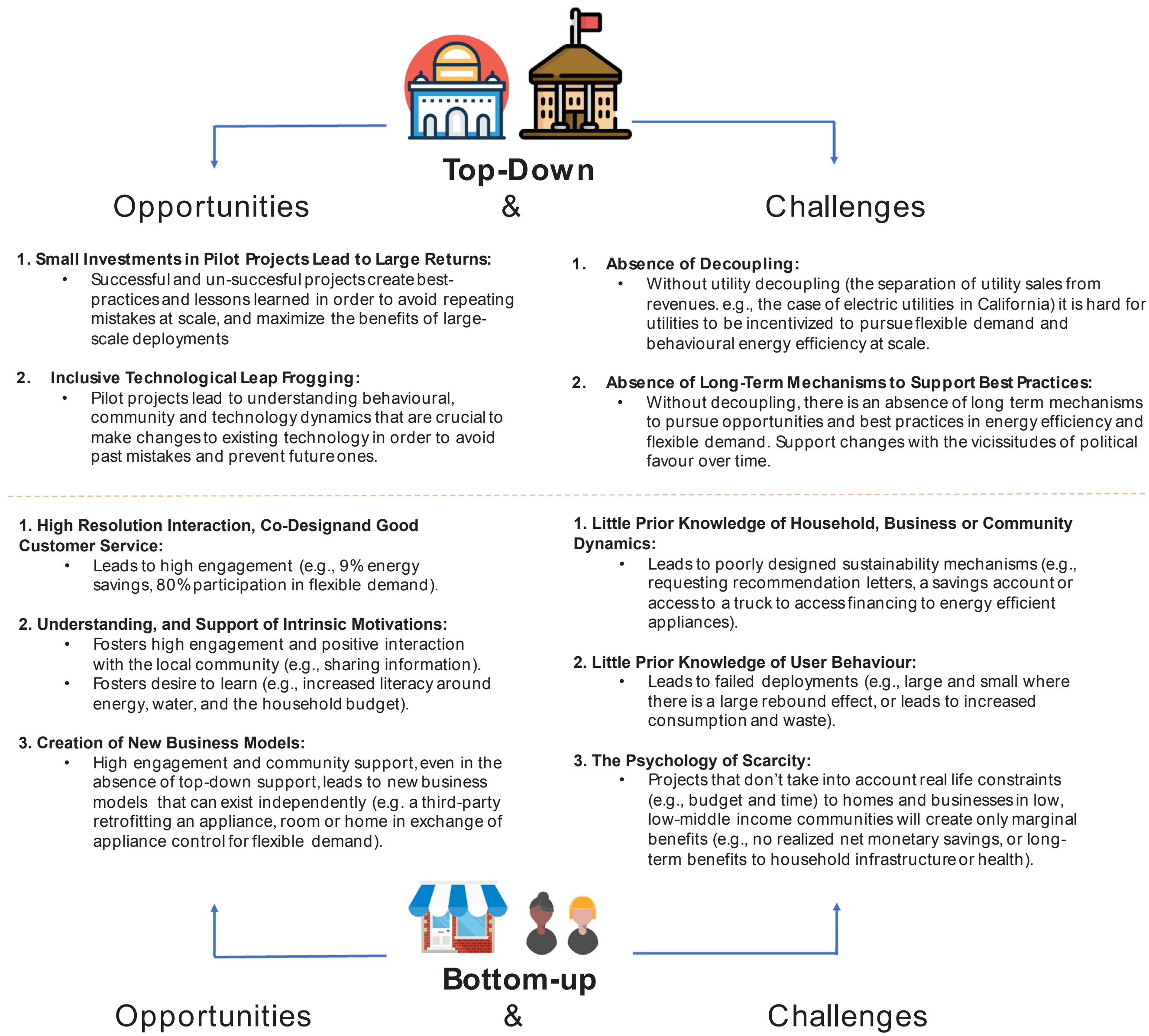

Fig. 6. Bottom-up and top-down opportunities and challenges for flexible demand and behavioral energy efficiency in data-limited low-carbon resource constrained environments.

the purchase of cheaper energy, for example, would be rejected as the utility would be required by a regulator to reduce near-future rates due to their purchase of cheaper energy. The absence of financial mechanisms or structures to incentivize utilities to participate in large-scale and effective energy efficiency and flexible demand means that support for this important resource dwindles depending on political favor and interest. Thus, and faced with serious top-down implementation barriers, user-focused strategies are crucial for behavioral, energy efficiency, and smart city interventions to be successfully scaled.

To develop solutions that succeed at the local level, city governments, utilities, and development banks must embrace the role of cost-effective pilots and demonstrations [68]. Designing top-down systems and solutions is expensive and ineffective if solutions are not adopted, if the results are far smaller than originally intended (or in the opposite direction) [10], or if the approach is missing key design elements. Recruiting entrepreneurs and local developers to re-imagine existing business models and technologies in local contexts, and piloting these innovations, is crucial to scaling energy efficiency, and socially inclusive smart city solutions. If well implemented, pilot projects can lead to understanding behavioral community and technology dynamics that are crucial to make changes to existing technology, and future large scale programs, to avoid past mistakes and prevent future ones. Cities and neighborhoods that champion these small steps and pilot initiatives like likely reap the benefits of better use of funds, and deeper and more widespread benefits towards local-participants (Fig. 6).

4. Conclusions, implications and limitations

In this paper, we presented the results from Latin America's first pilot of micro-level (households and micro-enterprises) demand-side management and behavioral energy efficiency in low-income neighborhoods of Managua, Nicaragua. Previous studies evaluating these two strategies often explored them separately, and further, they usually investigated issues related to behavior, technology, and opportunities for social co-benefits in isolation. Despite a large potential for behavioral energy efficiency and demand-side management in low, low-middle income communities, real-world pilot programs remain scant.

We used a randomized experiment in which thirty participants (households and micro-enterprises) received a wireless sensor gateway that enabled flexible demand of their refrigerators and freezers, and provided them with co-designed high-resolution energy information. Another thirty participants were part of a control group. The treatment-group reduced their energy consumption by nine percent relative to the control, and participated extensively in peak-shaving flexible demand. Increased energy literacy, improved financial management and user empowerment were also identified as intervention co-benefits. We found that improved access to energy information was more important than cash when incentivizing flexible demand participation, and documented the multiple barriers to scale flexible demand and energy efficiency strategies, including bottom-up (e.g., appliance financing) and top-down (e.g., decoupling) challenges as well as ways to overcome them. As more low, low-middle income countries transition away from fossil fuels, interventions such as this one will become increasingly necessary and attractive.

Data availability

All code and data are available from the corresponding author upon request or by direct download via GitHub (https://github.com/diegoleonbarido/flexbox_dree_pub.git).

Acknowledgements

We would like to thank the support of Javier Rosa, who was a collaborator in the design and implementation of the FlexBox [2], Eric Brewer for his continued thoughtful insights and support, and the Technology and Infrastructure for Emerging Regions group at UC Berkeley for technical and lab assistance. We would like to acknowledge the support of Jae Bin and Emerald Ferreira-Yang during the piloting phase and implementation of the technology at UC Berkeley, and of Odaly Molina for the ground implementation in Managua. This research was kindly supported by a National Geographic Energy Challenge Grant, UC Berkeley's Development Impact Lab, and the Inter-American Development Bank IDEAS competition.

Author contributions

D.P.D.L.B conceived the study, designed and led the implementation of the field pilot, performed the post-implementation analysis, and wrote the manuscript. S.S provided field support and feedback on the manuscript. D.C and D.M.K provided intellectual input, contributed to the manuscript development, and supervised the research project.

Conflict of interests

The authors report no competing interests.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2018.06.115.

References

[1] REN21. Renewables 2017: global status report; 2017. [Online]. Available: http://www.ren21.net/wp-content/uploads/2017/06/17-8399_GSR_2017_Full_Report_0621_Opt.pdf%0Ahttp://dx.doi.org/10.1016/j.rser.2016.10.049%0Ahttp://www.ren21.net/status-of-renewables/global-status-report/.
[2] de Leon Barido D Ponce, Suffian S, Rosa J, Brewer E, Kammen DM. Enabling micro-level demand-side grid flexiblity in resource constrained environments. In: Proc second int conf internet-of-things des implement, no. Section II; 2017. p. 233–45.
[3] Peters GP, et al. Key indicators to track current progress and future ambition of the Paris Agreement. Nat Clim Chang 2017;7(118).
[4] Bouton Shannon, Creyts J, Kiely T, Livingston J, Nauclér T. Energy efficiency: a compelling global resource. McKinsey Sustain. Resour Prod. 2010:1–74.
[5] International Energy Agency (IEA) and the World Bank. Sustainable energy for all 2017—progress toward sustainable energy; 2017.
[6] World Energy Council; 2016. [Online]. Available: https://www.worldenergy.org/ [accessed: 15-Aug-2014].
[7] International Energy Agency (IEA). Energy efficiency market report 2016; 2016. [Online]. Available: www.1e.com/energycampaign/.../Server_Energy_and_Efficiency_Report_2009.pdf.
[8] Allcott H, Greenstone M. Is there an energy efficiency gap? Hunt Allcott and Michael Greenstone is there an energy efficiency gap? J. Econ. Perspect. 2012;26(July):38.
[9] Fowlie M, Greenstone M, Wolfram CD. Do energy efficiency investments deliver? Evidence from the weatherization assistance program. SSRN Electron J 2015.
[10] Davis LW, Fuchs A, Gertler PJ. Cash for coolers. NBER Work Pap 18044 2012.
[11] Muhssin MT, Cipcigan LM, Sabah S, Assi Z. Potential of demand side response aggregation for the stabilization of the grids frequency. Appl Energy 2018;220(December 2017):643–56.
[12] Wang J, Zhong H, Ma Z, Xia Q, Kang C. Review and prospect of integrated demand response in the multi-energy system. Appl Energy 2017;202(51537005):772–82.
[13] Callaway DS, Hiskens IA. Achieving controllability of electric loads. In: Proc IEEE, vol. 99, no. 1; 2010.
[14] Keep TM, Sifuentes FE, Auslander DM, Callaway DS. Using load switches to control aggregated electricity demand for load following and regulation. In: IEEE power energy soc gen meet; 2011. p. 1–7.
[15] Koch S, Mathieu JL, Callaway DS. Modeling and control of aggregated heterogeneous thermostatically controlled loads for ancillary services. In: Proc 17th power syst comput conf; 2011.
[16] Mathieu JL, Kamgarpour M, Lygeros J, Andersson G, Callaway DS. Arbitraging intraday wholesale energy market prices with aggregations of thermostatic loads. IEEE Trans Power Syst 2015;30(2):763–72.
[17] Kwag HG, Kim JO. Reliability modeling of demand response considering uncertainty of customer behavior. Appl Energy 2014;122:24–33.
[18] Zeng B, Wu G, Wang J, Zhang J, Zeng M. Impact of behavior-driven demand response on supply adequacy in smart distribution systems. Appl Energy 2017;202:125–37.
[19] Rahmani-Andebili M. Scheduling deferrable appliances and energy resources of a smart home applying multi-time scale stochastic model predictive control. Sustain Cities Soc 2017;32(January):338–47.
[20] Rahmani-andebili M, Shen H. Cooperative distributed energy scheduling for smart homes applying stochastic model predictive control. In: Cooperative distributed energy scheduling for smart homes applying stochastic model predictive control; 2017. p. 1–6.
[21] Taneja J, Lutz K, Culler D. The impact of flexible loads in increasingly renewable grids. In: 2013 IEEE int conf smart grid commun. SmartGridComm 2013, no. October; 2013. p. 265–70.
[22] Koch S, Zima M, Andersson G. Active coordination of thermal household appliances for load management purposes. In: IFAC proc; 2009. p. 149–54.
[23] Lawrence Berkeley National Laboratory. OpenADR specifications (version 1.0). Calif Energy Comm 2009(April):214.
[24] Lanzisera S, Weber AR, Liao A, Pajak D, Meier AK. Communicating power supplies: bringing the internet to the ubiquitous energy gateways of electronic devices. IEEE Internet Things J 2014;1(2):153–60.
[25] Kornbluth K, Cook J, Erickson P. A more renewable-friendly electrical grid: thermal storage refrigeration for demand response in california and Denmark. Smart Grid Renew Energy 2012;2012(November):1–8.
[26] Lakshmanan V, Gudmand-Hoyer K, Marinelli M, Kosek AM, Norgard P. Energy shift estimation of demand response activation on refrigerators – a field test study. In: Proc univ power eng conf; 2014.
[27] Shen B, Ghatikar G, Ni CC, Martin P, Wikler G. Addressing energy demand through demand response : international experiences and practices; 2012. [Online]. Available: https://www.osti.gov/servlets/purl/1212423.
[28] Graziano M, Energy V. Cloudfridge: a cloud-based control system for commercial refrigeration systems. In: ACEEE summer study on energy efficiency in buildings; 2014. p. 285–93.
[29] Nilsson A, Bergstad CJ, Thuvander L, Andersson D, Andersson K, Meiling P. Effects of continuous feedback on households' electricity consumption: potentials and barriers. Appl Energy 2014;122:17–23.
[30] Schot J, Kanger L, Verbong G. The roles of users in shaping transitions to new energy systems. Nat Energy 2016;1(5):16054.
[31] Allcott H, Mullainathan S. Behavior and energy policy. Science (80-.) 2010;327(5970):1204–5.
[32] Sovacool BK, Kivimaa P, Hielscher S, Jenkins K. Vulnerability and resistance in the United Kingdom's smart meter transition. Energy Policy 2017;109(August):767–81.
[33] Chen H, Long R, Niu W, Feng Q, Yang R. How does individual low-carbon consumption behavior occurα – an analysis based on attitude process. Appl Energy 2014;116:376–86.
[34] Allcott H. Social norms and energy conservation. J Public Econ 2011;95(9–10):1082–95.
[35] Boudet H, Ardoin NM, Flora J, Armel KC, Desai M, Robinson TN. Effects of a behaviour change intervention for Girl Scouts on child and parent energy-saving behaviours. Nat Energy 2016;1(8):16091.
[36] Asensio OI, Delmas MA. Nonprice incentives and energy conservation. Proc Natl Acad Sci 2015;112(6):E510–5.
[37] Ecker F, Hahnel UJJ, Spada H. Promoting decentralized sustainable energy systems in different supply scenarios: the role of autarky aspiration. Front Energy Res 2017;5(July).
[38] Naeem A, Shabbir ALI, Hassan NUL, Member S, Tushar W. Understanding customer

behavior in multi-tier demand response management program. IEEE Access 2015.
[39] Gromet DM, Kunreuther H, Larrick RP. Political ideology affects energy-efficiency attitudes and choices. Proc Natl Acad Sci 2013;110(23):9314–9.
[40] Sudarshan A. Nudges in the marketplace: the response of household electricity consumption to information and monetary incentives. J Econ Behav Organ 2017;134(September 2015):320–35.
[41] Bager S, Mundaca L. Energy research & social science making 'Smart Meters' smarter? Insights from a behavioural economics pilot fi eld experiment in Copenhagen, Denmark. Energy Res Soc Sci 2017;28(December 2016):68–76.
[42] Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy 2016;1(4):16032.
[43] Goulden M, Bedwell B, Rennick-Egglestone S, Rodden T, Spence A. Smart grids, smart users? the role of the user in demand side management. Energy Res Soc Sci 2014;2:21–9.
[44] . B, B., Murray Goulden AS. Correspondence: power to the people. Nat. Clim. Chang. 2014;4(8).
[45] van Renssen S. People power to the rescue. Nat Clim Chang 2014;4(6):417–9.
[46] Duarte R, Feng K, Hubacek K, Sánchez-Chóliz J, Sarasa C, Sun L. Modeling the carbon consequences of pro-environmental consumer behavior. Appl Energy 2016;184:1207–16.
[47] Pothitou M, Hanna RF, Chalvatzis KJ. Environmental knowledge, pro-environmental behaviour and energy savings in households: an empirical study. Appl Energy 2016;184:1217–29.
[48] Attari SZ, DeKay ML, Davidson CI, Bruine de Bruin W. Public perceptions of energy consumption and savings. Proc Natl Acad Sci 2010;107(37):16054–9.
[49] Doman L. EIA projects 28% increase in world energy use by 2040. Energy Information Administration; 2017. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=32912 [accessed: 11-Feb-2018].
[50] Rao ND, Ummel K. White goods for white people? Drivers of electric appliance growth in emerging economies. Energy Res Soc Sci 2017;27:106–16.
[51] Broto VC, et al. A research agenda for a people-centred approach to energy access in the urbanizing global south. Nat Energy 2017;2(10):776–9.
[52] Marquis C. This is advanced energy: behavioral energy efficiency. Advanced Energy Economy; 2016. [Online]. Available: https://blog.aee.net/this-is-advanced-energy-behavioral-energy-efficiency [accessed: 02-Jun-2018].
[53] Bronski P, et al. The economics of demand flexibility: how 'Flexiwatts' create quantifiable value for customers and the grid. Rocky Mt. Inst. 2015(August):79.
[54] de Leon Barido D Ponce, Johnston J, Moncada M, Callaway D, Kammen D. Evidence and future scenarios of a low-carbon energy transition in Central America: a case study in Nicaragua. Environ. Res. Lett. 2015;10:1–11.
[55] WB. World Bank development indicators; 2016. [Online]. Available: https://data.worldbank.org/data-catalog/world-development-indicators [accessed: 15-Aug-2014].
[56] University of Gothemberg. Quality of governance initiative; 2016. [Online]. Available: http://qog.pol.gu.se/ [accessed: 15-Aug-2014].
[57] Kruschke JK. Doing Bayesian data analysis. First New York: Elsevier; 2015.
[58] Kruschke JK. Bayesian estimation supersedes the t test. J Exp Psychol Gen 2013;142(2):573–603.
[59] Schwartz D, Fischhoff B, Krishnamurti T, Sowell F. The Hawthorne effect and energy awareness. Proc Natl Acad Sci USA 2013;110(38):15242–6.
[60] Mazur-stommen S, Farley K. ACEEE field guide to utility-run behavior programs. American Council for an Energy-Efficient Economy; 2013. p. 43.
[61] Abrahamse W, Steg L, Vlek C, Rothengatter T. A review of intervention studies aimed at household energy conservation. J Environ Psychol 2005;25(3):273–91.
[62] Ehrhardt-martinez AK, Donnelly KA. Advanced metering initiatives and residential feedback programs: a meta-review for household electricity-saving opportunities. Energy 2010;123(6):128.
[63] Team RDC. R: A language and environment for statistical computing; 2011. [Online]. Available: https://www.r-project.org/ [accessed: 11-Feb-2018].
[64] Plummer M. JAGS: a program for analysis of Bayesian graphical models using Gibbs sampling. In: Proceedings of the 3rd international workshop on distributed statistical computing; 2003.
[65] Carlsson-Kanyama A, Lindén AL. Energy efficiency in residences-challenges for women and men in the North. Energy Policy 2007;35(4):2163–72.
[66] Elnakat A, Gomez JD. Energy engenderment: an industrialized perspective assessing the importance of engaging women in residential energy consumption management. Energy Policy 2015;82(1):166–77.
[67] Mullainathan Sendhil, Shafir E. Scarcity: why having too little means so much. First New York: Time Books, Henry Holt & Company LLC; 2013.
[68] Fairbrother C, Guccione L, Henchen M, Teixeira A. Pathways for innovation: the role of pilots and demonstrations in reinventing the utility business model; 2017.