Energy and Buildings 134 (2017) 223–233

Contents lists available at ScienceDirect

Energy and Buildings

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

Interaction effects of building technology and resident behavior on energy consumption in residential buildings

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ARTICLE INFO

Article history:
Received 12 June 2016
Received in revised form 30 August 2016
Accepted 28 October 2016
Available online 2 November 2016

Keywords:
Energy efficiency
High-performance housing
Building construction technology
Building systems
Human-environmental interaction

ABSTRACT

Buildings account for a significant portion of energy consumption and carbon emissions around the world and increasingly scholars and practitioners are re-thinking strategies that mitigate use. This paper reports an empirical study aimed at identifying the relationship between building technology and resident behavior and the joint effects on energy consumption in residential buildings. Unlike previous work that isolated effects of technology or behavior on energy consumption, this study investigates their interactions. The researchers collected technical and behavioral data from more than 300 residential units and performed data analysis using energy simulation and multivariate regression techniques. Results identify the interaction effects between building technology and resident behavior and provide quantifiable evidence supporting the hypothesis that "building technology and resident behaviors interact with each other and ultimately affect home energy consumption." Findings indicate four important resident behaviors that directly correlate to energy consumption and two that indirectly correlate to energy consumption. The research also indicates that only 42% of technological advances directly contribute to home energy efficiency, suggesting that the achievable impact on energy savings depends on both technical advances and behavioral plasticity.

1. Introduction

Buildings account for a significant portion of energy consumption and carbon emissions around the world. In the past decade, the U.S. government and industry initiatives have catalyzed green building technologies to improve building energy efficiency. The U.S. aims to reduce 40% of the energy use for space conditioning and water heating in residential buildings by 2025. However, total U.S. energy consumed by residential and commercial buildings in 2015 remained the largest portion at 40% which was equivalent to 39 quadrillion British thermal units (BTU) or $416 billion U.S. dollars [1]. As a result, it is necessary for scholars and practitioners to re-think strategies adopted for years in the U.S. that largely focus on the research and development of advanced building systems and products.

Buildings present a complex sociotechnical system that links society, occupants and the environment [2]. Humans spend roughly 90% of their lives in a commercial or residential building. The nexus of building performance, people's behavior and the environment can be observed all around us, yet there is little focus on measurable building performance in the literature or technologies available to easily collect, synthesize and report building performance information [3]. As a result, minimal published quantifiable evidence is available to identify the impacts of resident behaviors on energy consumption. Uncovering the nature of the relationship between buildings and occupants presents an opportunity to positively impact owners, managers, the lives of current and future building occupants and to promote environmental sustainability.

This paper reports an empirical study aimed at identifying the relationship between building technology and resident behavior and the joint effects on energy consumption in residential buildings. Unlike previous studies that isolated effects of technology or behavior on consumption, this work also studies their interaction. The work's central hypothesis is that "building technology and resident behaviors interact with each other and ultimately affect home energy consumption." As illustrated in Fig. 1, the hypothesis can be interpreted as the combination of relationships A + B + C. Therefore, the presented work has two specific objectives: first, to determine

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http://dx.doi.org/10.1016/j.enbuild.2016.10.049
0378-7788/

whether the interaction effects on home energy consumption exist; second, to identify how the interactions affect home energy consumption.

The structure of the article is as follows. First, the background section provides fundamental information on three key concepts of the research (i.e., energy consumption, building technology, and resident behavior). Then, the data and methods sections explain variables, the sample, and analytic approaches used in the research. At the end, results describe analysis, findings and discuss the implications for better understanding energy consumption and its relationships with building technology and resident behaviors.

2. Background

2.1. Home energy consumption

The U.S. Department of Energy (DOE) reports that the housing stock has been increasing energy efficiency since 1980 [4]. Houses built most recently are 14% more energy efficient (EE) than homes built 30 years ago and 40 percent more EE than homes built 60 years ago [4]. With respect to energy consumption, in 2015, all residential buildings consumed 21.15 quadrillion BTUs of energy.

The DOE estimates that the typical household spends approximately 8–14% of their income on energy expenditures. Of this, a third typically is consumed by energy demands for heating and cooling needs [5,6]. This indicates that for the typical America household, heating and cooling cost consume approximate 3–5% of their gross annual income. This percentage is not insignificant when considering the rising housing cost burden. Today, more than one-in-three American homeowners and one-in-two renters are considered to be cost burdened. It is estimated that 12 million renters and homeowners dedicate more than half of their annual incomes to housing expenses.

Residential energy consumption is measured by utility companies, utilizing both analog and digital meters typically installed on the exterior of the residential unit. Energy consumption measurement is recorded by the utility company, compared to the previous month's consumption and utilized to develop a monthly consumption data record. The result is a combination of monthly consumption data, distribution, transmission, tax and service charges used to produce a monthly energy bill that is sent to the occupant for their previous month's service; often referred to as the billing cycle. The billing cycle timeline and lag between occupant behavior and energy consumption feedback provided by the bill data is a critical component in this work.

2.2. Green building technology

Green building technology refers to the collection of advanced technologies and products [3] to building design and construction that allows the reduction of overall energy use and carbon emissions. Evidence suggests that the efficiency and efficacy of building technology, for example, space conditioning systems, used to maintain occupant thermal comfort during both heating and cooling seasons, has a considerable impact on residential energy consumption.

As a result, the implementation of green building technology is on the rise globally [7,8] since it is closely related to the goals of EE and sustainable development [9]. High-performance buildings are becoming the norm throughout the international architectural, engineering, and construction (AEC) industry. Based on the World Green Building Trends survey [10], 51% of the participated architects, engineers, contractors, owners, and consultants committed to incorporating sustainability into more than 60 percent of their work by 2015. The survey also identified energy saving as the top environmental reason for embracing green building technologies. More than 32,000 homes have been constructed using energy-efficiency building technologies within last four years in the U.S. housing market [11]. With green building becoming a critical part of the AEC industry, new green building technologies across design and construction are being developed to keep up with the escalating shift to sustainability. New technologies range from the use of renewable energy resources to smart appliances. Some examples of the state-of-art building technology are biodegradable materials, low-emittance windows, electrochromic smart glass, green insulation, geothermal heating, and improved photovoltaic panels. These technologies greatly decrease carbon footprint yet are not necessarily easy to embrace and adopt. For example, a homeowner's perception of increased initial costs associated with the use of these technologies is a barrier in the green market [12] even though research shows that the investment in green building technologies may yield decreased future energy bills using a life-cycle perspective [13,14].

2.3. Resident behavior

Resident behavior (or occupant behavior) and its consideration as part of the overall development process, and specifically with building systems, is critical to understanding residential energy consumption [15]. In this work, resident behavior refers to actions that contain a direct and/or indirect influence on energy use in buildings [16]. These actions can be divided into three categories: time-related usage, environment- related modes, and quantitatively described behavior. Existing research has established the effect of resident behavior on home energy use. For example, a three-year living lab study of home energy use behavior found that the "energy literacy" from occupants may impact the domestic electricity consumption [17]. Another in-house data analysis on the energy use for space and water heating also confirmed that occupant characteristics and behavior significantly affect energy use at 4.2% [18].

Literature asserts that some resident behaviors considerably affect home energy use. Thermostat set points is an important and widely used factor when trying to understand resident behavior's impact on energy consumption. For example, summer and winter thermostat set points were critical in understanding the performance of residential housing since they indirectly reflect performance of the heating, ventilation and air-conditioning (HVAC) unit and the building's thermal enclosure performance [19]. Humidity setting is another important resident behavior. Zain et al. [20] focused on the nexus of humidity and occupant comfort and energy performance, suggesting it is critical to understand different thermal comfort behavior of human needs for people in different climate conditions. Some non-space-conditioning behaviors also posit important indirect impact on energy use. For example, Ouyang and Hokao [21] claimed the impact of natural ventilation, by opening/closing windows and using fans, on better thermal comfort. Parker [22] noted that the length of showers and the frequency of showers were correlated with cooler weather; therefore, domestic water heating increasingly contributed to energy consumption loads in the sample. The use of appliances such as dishwashers, clothes washers and dryers has been discussed in literature as resident behavior as well [22–24]. Moreover, it has been noted that educating occupants on EE may be the next frontier for high-performance buildings [19]. Studies [21,25] suggested that education improved behavior toward a more energy efficient lifestyle provided it was: given frequently; over long periods of time; with appliances broken out; presented in clear, appealing ways; computerized, interactive tools were most successful in helping occupants.

Literature review shows that most studies investigated the effects of either occupants or technologies. Nevertheless, there is

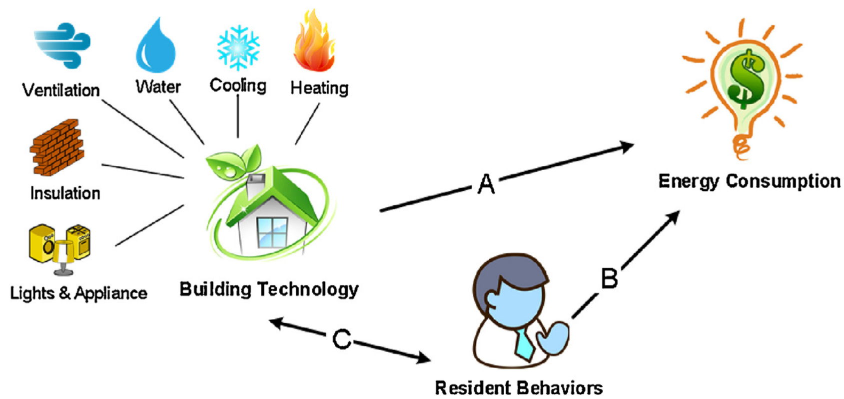

Fig. 1. Associations of key concepts: building technology, resident behavior, and energy consumption.

little research focusing on the interaction effects of building technology and occupant behavior and their joint impacts on the energy use. To close the gap, the presented work explored such interaction effects using empirical data and quantitative methods.

3. Data

3.1. Variables

Table 1 lists 14 variables that were used in this study. The variables represent the study's three primary concepts: energy consumption, building technology, and resident behavior. The authors used these variables in computational analysis with a goal of identifying relationships among the three concepts. Specifically, the authors selected (1) observed annual energy consumption (*ECo*) to measure realistic home energy usage; (2) simulated annual energy consumption (*ECs*) and the HERS score to measure building technology; and (3) 11 variables to measure resident behaviors (for example, thermostat set points). Secondary analysis places observed energy use as the response variable (i.e., dependent variable) and the other 13 variables serve as the predictor variables (i.e., independent variables). The simulated energy use is an estimation computed through energy modeling of which the details are described later in this section. Resident behavioral variables result from the team's condensed literature review characterizing them as highly relevant to energy usage. For example, the humidity setting and comfort setting, as part of the home HVAC system, are the thermostat levels selected by occupants. The variable "education/training on building systems" measures if an occupant received education or professional training to gain the knowledge of home energy savings. This information was collected from the occupants' self-reported survey. Mathematically, the three variables that measure energy use are presented in a scale of continuous values while the 11 variables that measure resident behavior are in a scale of categorical or ordinal values.

As listed in Table 2, the researchers input 24 technical parameters of building technology into an industry-standard energy model to compute simulated energy use (*ECs*). The model complies with 2009 International Energy Conservation Code (IECC) [31,32]. The computed energy use incorporates a building's technology including design/construction, heating and cooling system, hot water, ventilation, insulation, lighting and appliances. The authors utilized REM/Rate software to perform energy simulation. The team also incorporated local climate data that are available for cities and towns throughout North America into the energy simulation. The site specific weather data were derived from ASHRAE Standard 90.1 under the site location menu. REM/Rate software has been widely adopted in energy auditing practice [31–33] and is thus recognized as appropriate for home energy analysis.

The variable *HERS* presents the energy rating of a home's energy efficiency. The HERS Index is a nationally recognized scoring system for measuring a home's energy performance. Based on the results of field testing and energy modeling, an energy rated home receives a HERS Index Score. A score relates the home to the average standard new construction American home. A score of 100 is equal to standard new construction for 2009 International Residential Code (IRC), the latest version when projects incorporated in the study were begun. Lower scores indicate a home performing better than the standard American home. A zero on the HERS index is given to a home demonstrating a net energy demand of zero. The HERS Index Score can be CAFE standards, a sort of mile per gallon rating for houses. It provides prospective buyers and homeowners insight into how the home ranks in terms of energy efficiency [34].

Table 1
Summary of variables for data analysis.

Concept	Variable	Description	Value	Literature
Energy consumption	*ECo*	Observed annual energy use from utility bills	Continuous, in kWh	[4,13,27]
Building technology	*ECs*	Computed annual energy use from energy simulation	Continuous, in kWh	[28,29]
	HERS	The Home Energy Rating System index	Continuous, in point	[29,30]
Resident behavior	*ST*	Temperature setting in thermostat during summer	Ordinal: <68F (20C);68-72F(22C);72-75F(24C);>75F	[16,22,25]
	WT	Temperature setting in thermostat during winter	Ordinal: <68F; 68-72F; 72-75F(24C); >75F	[22,25]
	WS	Season when opening windows	Categorical: Spring; Summer; Fall; Winter	[20]
	FU	Use of fan(s) for ventilation	Categorical: Yes; No	[22]
	HU	Humidity setting	Ordinal: Low; Medium; High	[21]
	SL	Length of showers	Ordinal: Short; Medium; Long	[23,31]
	DW	Frequency of the use of dishwasher	Ordinal: None; Sometimes; Often	[22,24]
	WD	Frequency of the use of washer and dryer in house	Ordinal: None; Sometimes; Often	[22,31]
	CS	Comfort setting during summer	Ordinal: Low; Medium; High	[21]
	CW	Comfort setting during winter	Ordinal: Low; Medium; High	[21]
	ED	Education/training on building systems and energy	Categorical: Yes; No	[22,26,31]

Table 2
Summary of technical parameters for energy simulation.

Technology	Parameter	Description
Design & construction	Size	Continuous number in square feet or cubic feet.
	Number of bedrooms	Continuous number in count
	House type	Categories: apartment; multiple family; townhouse; duplex
	Foundation type	Categorical: slab; above conditioned space; conditioned basement
Heating & cooling	Heat pump fuel	Categorical: electric; gas
	Heating seasonal performance factor	Air-source heat pump heating efficiency
	Seasonal energy efficiency ratio	Air-source heat pump cooling seasonal efficiency
Water	Water heater type	Conventional storage; Heat pump; On demand; Solar
	Water heater energy factor	Gallons of heated water per fuel per day
	Water heater tank size	In gallons
Ventilation	Duct leakage	Air flow in cubic foot per minute (CFM)
	Ventilation system type	Categories: exhaust; Supply; Balanced; Air cycler
	Ventilation system air flow	Continuous number in cubic foot per minute (CFM)
Insulation	R-value	R-values of ceiling, sealed attic, slabs, and above grade walls
	U-value	U-value of windows
	Solar heat gain coefficient	Solar heat gain coefficient (SHGC) of windows
	Infiltration rate	Infiltration rates of heating and cooling
Lights & appliance	Interior lighting	Interior lighting percentage
	Exterior lighting	Exterior lighting percentage
	Refrigerator energy	Energy per year
	Dishwasher energy factor	Dishwasher energy factor in cycles/kWh
	Range and Oven	Type of gas or electric
	Clothes dryer factor	Clothes dryer energy factor in pounds/kWh
	Ceiling fan factor	Ceiling fan energy factor in cfm/Watt

Table 3
Summary of sample home units.

Location	Project type	Utility records	Technical records	Behavioral records	Complete records
Chesapeake City	Family	31	33	33	31
Richmond City	Senior	23	22	23	22
Richmond City	Family	29	30	36	28
Orange Town	Family	18	20	21	17
Wytheville Town	Family	12	24	14	12
Lynchburg City	Senior/Disability	13	15	16	13
Virginia Beach City	Family	21	23	24	21
Hampton City	Family	9	7	12	7
Arlington City	Family	3	0	6	0
Pulaski Town	Senior	17	18	18	16
King George County	Senior/Disability	14	24	15	14
Arlington County	Family	5	5	3	3
Petersburg City	Senior	25	25	20	20
Christiansburg Town	Family	20	14	9	4
Scottsville Town	Senior	19	13	8	7
Total		259	273	258	215

It is noteworthy to explain that variables in this study are not all in similar units, which makes it difficult to assess relative importance. In addressing this problem, the authors mathematically converted the variables of continuous values (e.g., the energy use and HERS score) into standardized scores (e.g., variables of *ECo*, *ECs*, and *HERS* in Table 1) through a process of standardization. The standardized variable presents a standard deviation from the original variable above or below the mean [35]. In other words, a positive standardized score indicates a datum above the mean while a negative one indicates below the mean. Standardization is a useful tool for making regression models more meaningful and is often used to facilitate comparability of the relative importance of predictor variables [36,37]. Thus, the researchers used standardized variables in the regression analysis for computational purposes.

3.2. Data collection

The researchers conducted multiple site visits to collect data in 2014 and 2015. We collected three types of empirical data that are represented in three categories of variables (see Table 1). Specifically, the three types of variable data are: (1) utility records of the unit's energy consumption, (2) technical records of the building unit (HERS certificate), and (3) surveys of resident behavior. Utility records (i.e., utility bills or often locally termed "light bills") were collected through onsite signed releases and a partnership with Wegowise, an on-line utility tracking platform. Technical records were collected during site visits with collaboration from property managers. These records were measured and documented by certified professionals when homes were built or renovated. Behavioral records were collected through a hand-written survey onsite with residents.

Surveying many units in person is a difficult task. The survey team coordinated with property managers to hold meetings of residents for collecting survey data in person or email them the link to the survey. Since many residents did not show up for these meetings where data were meant to be collected, members of the survey team went into the developments and knocked on doors, asking people randomly to answer the survey and sign releases. Approximately 50% of all surveys were collected in this manner. When on-site collection processes did not work as planned, property managers were also asked to anonymously collect surveys left for residents. These surveys collected by property managers constituted approximately 10% of all surveys collected. To increase the validity of survey, most questions were designed to ask the annually average behavior and some other questions were season based (e.g., the temperature setting). It is important to note that the data

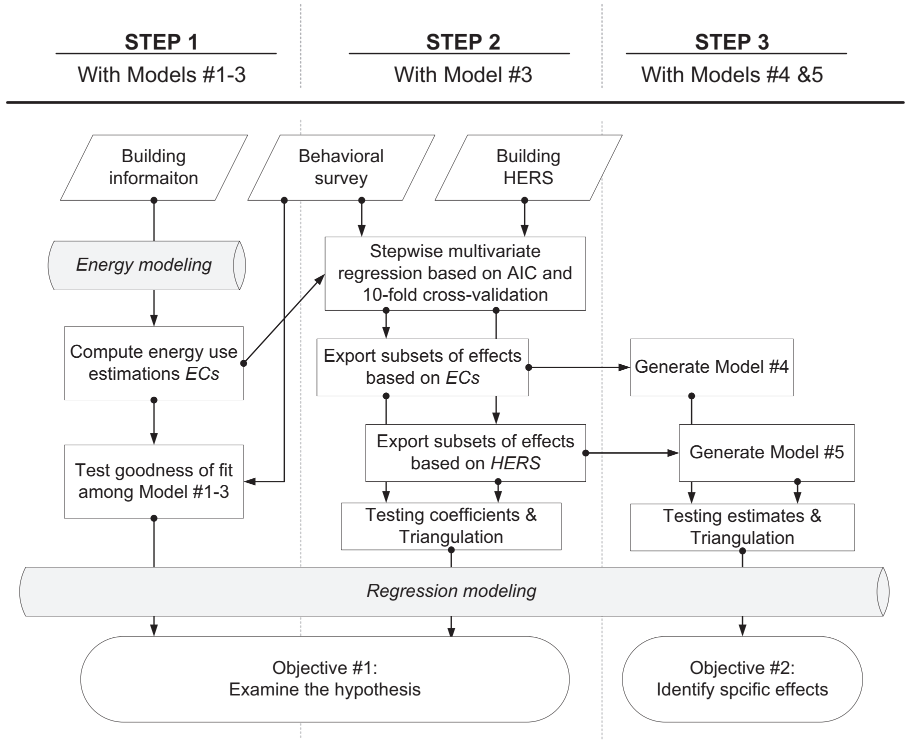

Fig. 2. Flow chart for research objectives and methodology.

collection plan was designed and processed to protect the human subjects of participants under the researchers' Institutional Review Board (IRB) policies.

The criteria for sample selection included the building's geographical location, application of green building technologies, and sustainable construction practices. Ideal samples should cover the entire geography of the state. The sample developments needed to be built or renovated after 2009, which ensures the availability of recent green building technologies during construction. The samples were also required to be EarthCraft Virginia certified green buildings after constructed.

Table 3 summarizes the sample of units and records collected for this research. The initial sample in this study was 312 multifamily residential units across the State of Virginia. The units included both new constructed and renovated residential buildings. New construction project units are located in the counties or cities of Arlington, Hampton, King George, Lynchburg, Petersburg, and Wytheville. Renovated project units are located in the counties or cities of Abingdon, Arlington, Chesapeake, Christiansburg, Orange, Richmond, Scottsville and Virginia Beach. Because of missing data or data unavailability, the number of complete records across all categories (utility records by unit over a continuous 12 months, technical records and complete resident behavior survey) is less than the initial sample size.

4. Methods

Fig. 2 displays the overall method and process for data analysis. The figure also illustrates the associations among specific analysis steps, analytical methods, expected results, and the corresponding research objectives. The data analysis includes three specific steps of which Step 1 and 2 address Objective #1 and Step 3 addresses Objective #2. The two research objectives are previously explained in the Introduction section. Specifically, the three analysis steps are as follows:

Step 1: The authors examined the goodness-of-fit of three regression models (Mode #1–3) to address Objective #1 exploring the optimal interpretation of home energy consumption. Model #1 represents only the direct impact of building technology on energy consumption. Model #2 represents both direct impacts of building technology and resident behavior on energy consumption. In addition to Model #2, Model #3 adds interactions between building technology and resident behaviors. The regression equations of Models #1–3 are described in the following Eqs. (1)–(3), respectively.

$$\text{Model}\,\#1: Y = \beta_a T + \varepsilon \tag{1}$$

$$\text{Model}\,\#2: Y = \beta_a T + \beta_b B + \varepsilon \tag{2}$$

$$\text{Model}\,\#3: Y = \beta_a T + \beta_b B + \beta_c TB + \varepsilon \tag{3}$$

where Y represents the energy consumption variable, T represents the building technology vector, B represents the resident behavior vector (refer to Table 1), β is the corresponding regression coefficient, and ε is the error item.

Step 2: The researchers conducted stepwise regression to select the best model [38,39]. All the variables listed in Table 1 were used in the stepwise analysis. Stepwise regression is an automatic analytic technique in model building that identifies a useful subset of predictors [40]. The technique requires two significance levels: one for adding variables and one for removing variables. In other words, it combines forward and backward selection techniques. The process systematically adds the most significant variable or removes the least significant variable during each step. Stepwise regression is modified during forward selection as it checks all candidate variables in the model to compute if the significance is reduced below the designated tolerance level in very step. As a result, all non-significant variables can be removed from the model one after another. The cutoff probability for *adding* variables is less than the cutoff probability for *removing* variables so that the procedure does not get into an infinite loop.

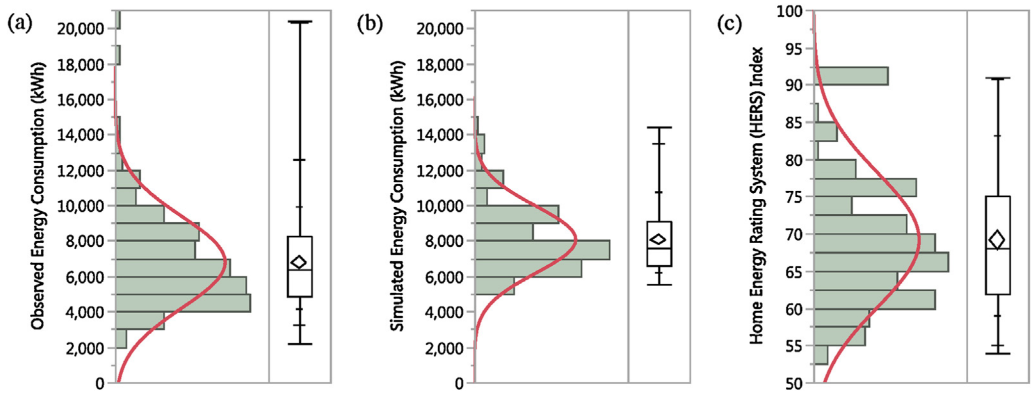

Fig. 3. Histograms and Quantile Plots for the (a) Observed Energy Consumption (*ECo*), (b) Simulated Energy Consumption (*ECs*) and (c) HERS Index (*HERS*).

Table 4
Summary of fit testing for Model #1, 2, and 3.

	Model #1	Model #2	Model #3
R Square	0.064	0.323	0.462
Adj. R Square	0.060	0.234	0.303
RMSE	0.970	0.875	0.835
Mean of Response	<0.001	<0.001	<0.001
N	207	207	207

Step 3: The research team then generated Model #4 and Model #5 to identify which particular resident behaviors significantly correlated to home energy consumption. The researchers used subsets of effects (i.e., the predictors) resulting from the stepwise regression analysis to build Model #4 and #5. The subsets of predictors were determined during the model selection using measures of the Akaike information criterion (AIC) and the 10-fold cross-validation. These measures examine model robustness and confirm the accuracy of model estimates.

It is important to note that the authors applied a triangulation strategy to increase validity and reliability. There is a limitation of the introduced methods that rely upon the assumptions of occupant in energy modeling. In the simulation, this work used the default program settings which are based on the average records for a typical American home. Since the simulation's focus is on the building design and technology, the adoption of the same average settings would help tease out noises from varying occupants. To further mitigate such limitation, the researchers adopted three specific triangulation applications (see Fig. 2). They are: (1) two analysis approaches (the modeling test and stepwise regression) to validate results for Objective #1; (2) two variables (i.e., *ECs* and *HERS* index) in parallel to validate results of stepwise regression; and (3) two measures (the AIC and cross-validation) to validate the subsets of effects.

5. Results

5.1. Descriptive analysis

Fig. 3 describes the distributions of (a) observed energy consumption, (b) simulated energy consumption, and (c) HERS index. The average observed annual energy use is 6777.4 kWh and its standard deviation is 2587.1. The average computed annual energy use is 8055.7 kWh and its standard deviation is 1891.4. *T*-test results on the difference between the observed energy use and computed energy use show that the difference is significant at a 99% level of confidence ($t = 6.59$, $p < 0.001$). This finding indicates that the actual home energy consumption is 1278.3 kWh on average less than the technology-based estimation (simulation) for each home unit. Results also indicate the coefficient between the observation and estimation equals 0.25 or low correlation and suggest the existence of other factors, other than technology, that effect observed, actual energy consumption.

The quantile plot in Fig. 3c shows that the median HERS index is 68 with a range from 54 to 91. This finding validates quality for our sample since all home units ($N = 207$) in the analysis are qualified green buildings (HERS < 100).

5.2. Linear regression model comparison

Table 4 lists the comparison of goodness of fit among the regression models #1–3. Results show that the representativeness of Model #1 is very low (*R*-Square = 0.064), suggesting that building technology factors only are insufficient to explain actual energy consumption. Results also show improved representativeness in Models #2 and 3 (*R*-Square = 0.323 and 0.462) and indicate the importance of resident behavior as a factor in explaining home energy usage. Therefore, findings strongly suggest that resident behavior impacts energy consumption and the interaction between technology and behavior exists as well. To test the reliability of these findings, the authors triangulated stepwise multivariate regression analysis in the next section.

Fig. 4 exhibits the actual and predicted residuals in the whole model leverage plot for Models #1–3. The plots provide a visual indication of whether the test of interest is significant by testing all effects. A model can be inferred as significant at 5% level when confidence curves cross the horizontal line at the mean of the response. Results indicate that all the three models satisfy all the assumptions of correlations ($p < 0.001$) including normality, independence, linearity, and homoscedasticity. In other words, none of the three models contain concerns relative to influential points or multicollinearity.

5.3. Stepwise multivariate regression

Fig. 5 shows the results of model fit test in stepwise multivariate regression. The purpose of the test was to select the subset of effects for the best model based on Model #3 (see Eq. (3)). Mathematically, the lowest AIC and the highest 10-fold $R^2$from 10-fold cross validation represent the best model. As a result, when building technology was calculated by *ECs* (Fig. 5a, Model #4), the best model was obtained when the number of parameters equaled 16. Mathematically, the parameters present variable levels in the computation. In such model, the AIC reached the bottom at 529.0 and the 10-fold R^2 reached its peak at 0.224. Similarly, when building technology was calculated by *HERS* (Fig. 5b, Model #5), the best model was selected when the number of parameters was 14 and

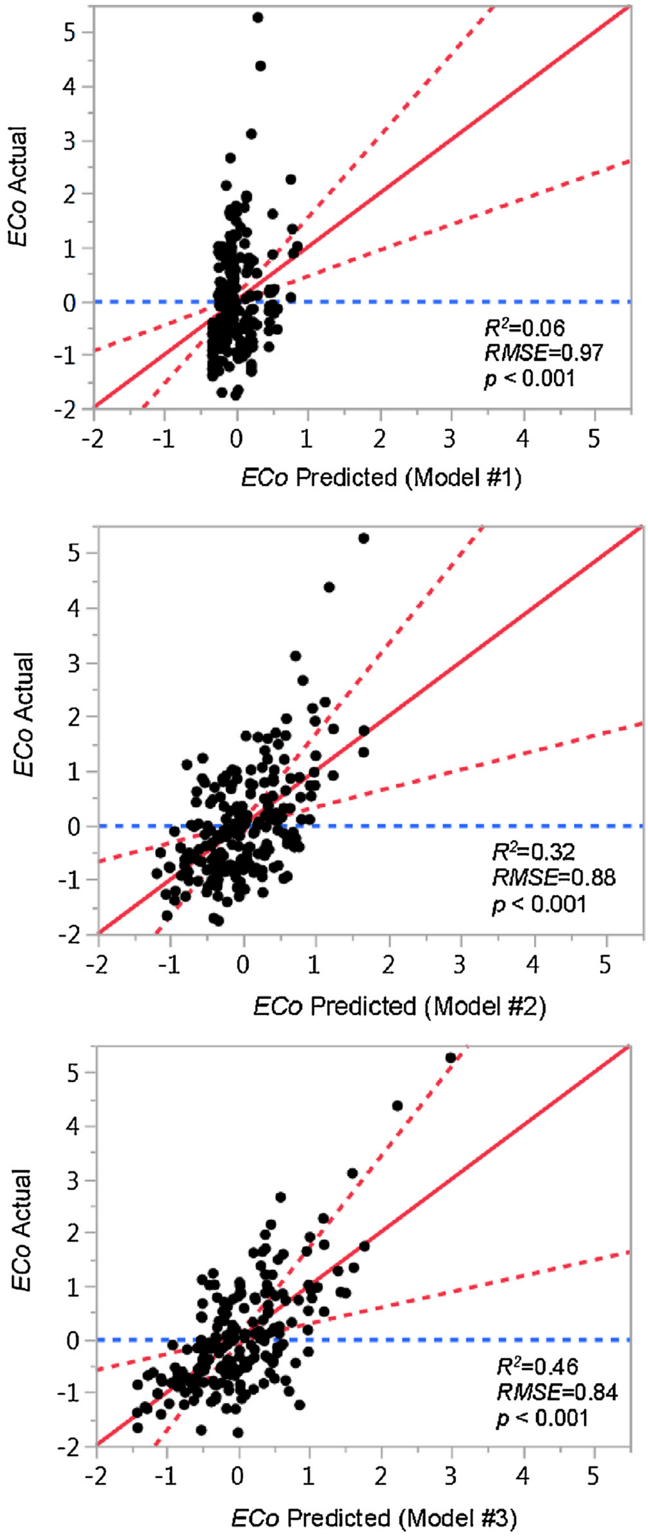

Fig. 4. The Whole Model Leverage Plots for Models #1–3.

contained a minimum AIC of 535.1 and the maximum 10-fold R^2 of 0.158.

Table 5 presents the subsets of effects based on the selected two models. These effects present the variables left in the model in the case of the stepwise analysis. Results from stepwise regression confirm the existence of both main effects and interaction effects from the resident behavior towards home energy consumption. Specifically, in Model #4, results identified behavioral factors *ST* (summer temperature setting), *WT* (winter temperature setting), *HU* (humidity setting), *DW* (dishwasher usage), *WD* (washer/dryer usage), and *ED* (education on building systems) that contain main effects, and factors *ST*, *WT*, *HU*, and *ED* that contain interaction effects with building technology. Likewise, in Model #5, results identified *ST*, *WT*, *HU*, *SL* (shower length), *WD*, and *ED* as main effects, and *ST*, *WT*, *SL*, and *ED* as interaction effects. It is noteworthy that both models confirm four important resident behaviors that indicate temperature settings (winter/summer), humidity setting, and knowledge of building systems. Therefore, the analysis provides quantifiable evidence supporting the hypothesis that "building technology and resident behaviors interact with each other and ultimately affect home energy consumption."

5.4. *Effects of resident behaviors*

To further explore the effects of variability in resident behaviors on home energy consumption, the researchers placed the identified subsets of effects into the regression models and analyzed their standardized coefficients. Through this process, Models #4 and #5 were described in the form of Eqs. (4) and (5) as follows:

$$\text{Model \#4}: EC_o = \beta_a * EC_s + \beta_b * (ST + WT + HU + DW + WD + ED) + \beta_c * EC_s * (ST + WT + HU + ED) + \varepsilon \tag{4}$$

$$\text{Model \#5}: EC_o = \beta_a * HERS + \beta_b * (ST + WT + HU + SL + WD + ED) + \beta_c * HERS * (ST + WT + SL + ED) + \varepsilon \tag{5}$$

It is important to validate the assumptions and conditions for any regression model. Fig. 6 presents results from such validation (i.e., the normal distribution test of the error terms). Results indicate that the plots are approximately linear within the confidence curves, which validates the assumptions and conditions for Models #4 and #5.

Table 6 lists coefficients (β) of all identified effects from Model #4. The model demonstrates goodness of fit (lack of fit *Sig.* = 0.27) and representativeness (Max R^2 = 0.97). Results identified five direct effects in explaining energy consumption: (1) 41.5% of building unit's technology capacity directly contributes to overall energy consumption (β = 0.415, *Sig.* <0.001) with all behavioral variables held constant [41]; (2) the summer temperature set points lower than 75F (24C) increases energy use (β = 0.232, *Sig.* = 0.037); (3) winter temperature set points lower than 75F (24C) decreases energy use (β = −0.162, *Sig.* = 0.048); (4) less or no use of washer and dryer at home decreases energy use (β = −0.347, *Sig.* < 0.001); and (5) the resident's knowledge on building systems decreases the energy use (β = −0.166, *Sig.* = 0.001). Moreover, results also identified four interaction effects between technology and behaviors: (1) the summer temperature set points of lower than 72F (22C) leverages the green technology's performance (β = −0.145, *Sig.* = 0.024); (2) the winter temperature set points lower than 68F (20C) leverages the green technology's performance (β = −0.417, *Sig.* = 0.002); (3) the low humidity setting compared to medium hinders the green technology's performance (β = 0.287, *Sig.* = 0.001); and (4) the resident's knowledge on building systems leverages the green technology's performance (β = −0.210, *Sig.* = 0.003).

Similarly, Table 7 lists coefficients of identified effects from Model #5. The model shows good model fit (lack of fit *Sig.* = 0.30) and representativeness (Max R^2 = 0.95). Results identified four direct effects and two indirect effects. The identified direct effects are: (1) the summer temperature set points lower than 75F (24C) increases energy use (β = 0.635, *Sig.* = 0.023); (2) the winter temperature set points lower than 75F (24C) decreases energy use

Table 5
Subsets of effects from stepwise regression model fitting.

	Main effect	Interaction effect	SSE	DFE	RMSE	R^2	Cp	P	AIC
Model #4	*ST, WT, HU, DW, WD, ED*	*ST, WT, HU, ED*	130.4	191	0.83	0.37	12.19	16	529.0
Model #5	*ST, WT, HU, SL, WD, ED*	*ST, WT, SL, ED*	137.4	193	0.84	0.33	−1.47	14	535.1

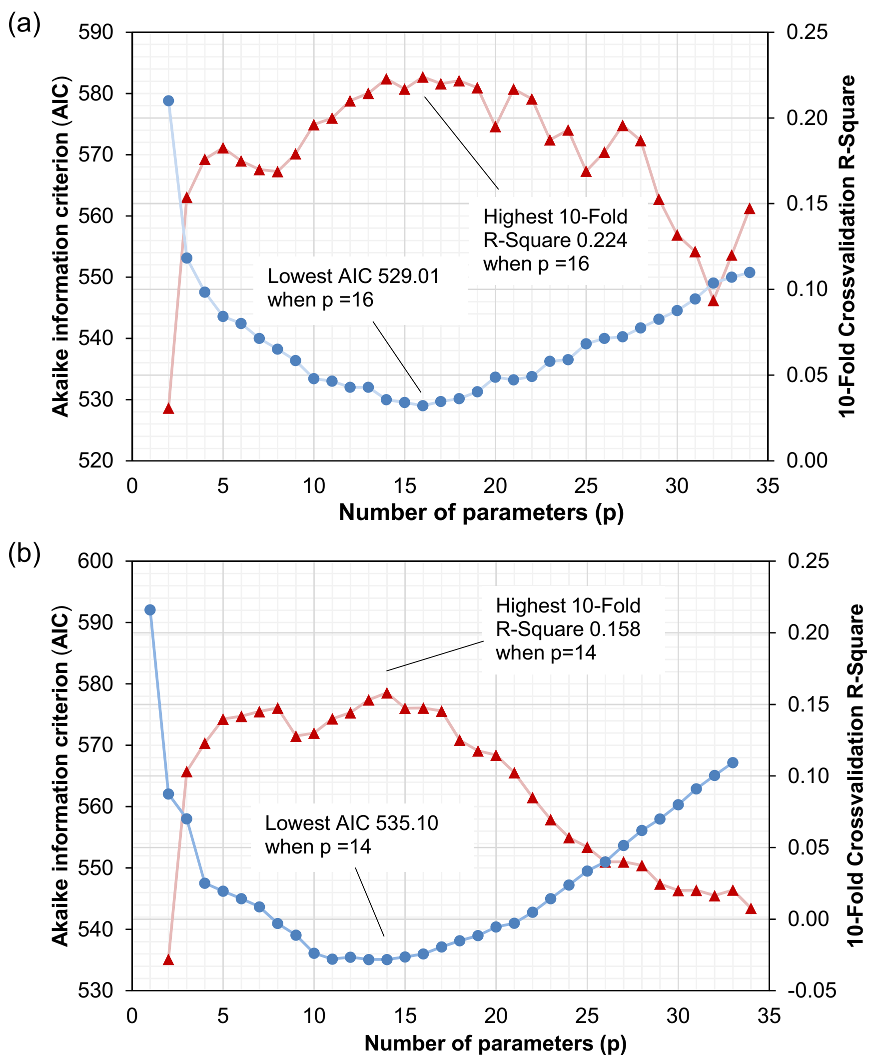

Fig. 5. Results of Stepwise Regression Model fits where building technology is presented in (a) Computed Energy Consumption and (b) HERS index.

Table 6
Results of identified effects from Model #4.

Effect	Variable	Levels	Std β	Std Err	*t*	*Sig*
Main	*ECs*		0.415	0.097	4.30	<0.001**
	ST	(≤75F | >75F)	0.232	0.111	2.10	0.037*
	WT	(≤75F | >75F)	−0.162	0.082	−1.99	0.048*
	WD	(Low & Medium | High)	−0.347	0.063	−5.46	<0.001**
	ED	(Yes | No)	−0.166	0.064	−2.61	0.001**
Interaction	*ECs***ST*	(≤72F | 72-75F)	−0.145	0.064	−2.28	0.024*
	*ECs***WT*	(≤68F | 68-72F)	−0.417	0.130	−3.21	0.002**
	*ECs***HU*	(Low | Medium)	0.287	0.083	3.46	0.001**
	*ECs***ED*	(Yes | No)	−0.210	0.070	−2.99	0.003**
Lack of fit	*F* = 1.382 (*Sig* = 0.273)					
Max R^2	0.971					

* Significant at 95%.
** Significant at 99%.

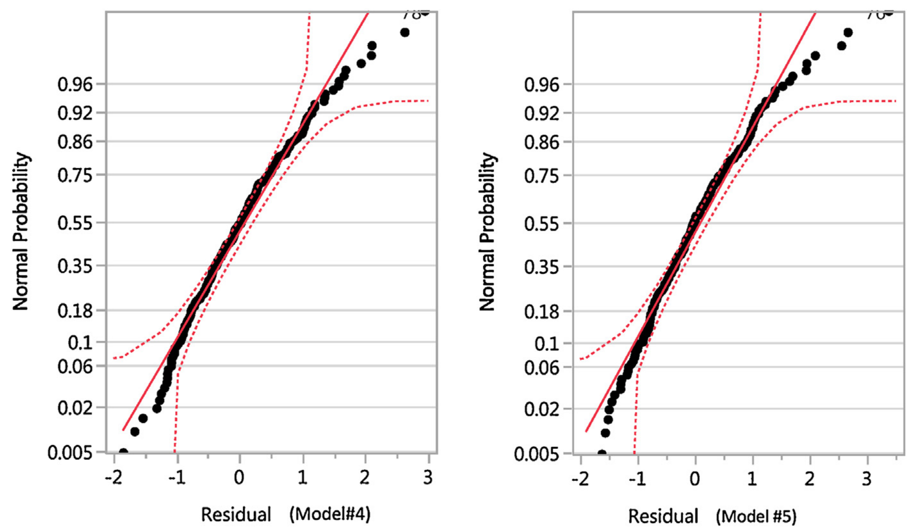

Fig. 6. Normal probability plots of residuals for Models #4 and #5.

Table 7
Results of identified effects from Model #5.

Effect	Variable	Levels	Std β	Std Err	t	*Sig*
Main	*ST*	(≤75F | >75F)	0.635	0.277	2.29	0.023*
	WT	(≤75F | >75F)	−0.433	0.183	−2.36	0.019*
	WD	(Medium | High)	−0.988	0.286	−3.45	0.001**
	ED	(Yes | No)	−0.161	0.072	−2.24	0.026*
Interaction	*HERS*WT*	(≤68F | 68-72F)	−0.631	0.290	−2.18	0.031*
	*HERS*ED*	(Yes | No)	−0.257	0.080	−3.21	0.002**
Lack of fit	F = 1.915 (*Sig* = 0.295)					
Max R^2	0.948					

* Significant at 95%.
** Significant at 99%.

($\beta = -0.433$, *Sig.* = 0.019); (3) less use of washer and dryer decreases energy use ($\beta = -0.988$, *Sig.* = 0.001); and (4) the resident's knowledge on building systems decreases the energy use ($\beta = -0.161$, *Sig.* = 0.026). The two identified indirect effects are: (1) the winter temperature set points lower than 68F (20C) leverages the green building technology's performance ($\beta = -0.631$, *Sig.* = 0.031); and (2) the resident's knowledge on building systems leverages the green technology's performance ($\beta = -0.257$, *Sig.* = 0.002).

6. Discussion and conclusion

In the U.S., 21.7% of energy was consumed by residential buildings [1]. To mitigate the energy use and reduce carbon emissions, the nation has endeavored huge efforts in the research and development of advanced building technology in the past decade. Unlike previous research, this study posits a strategy for energy use reduction through a systems perspective that focuses on the interaction effects between human and technology. The researchers collected technical and behavioral records from more than 300 residential units and their energy consumption across a whole year; and then analyzed the data using multivariate regression techniques. Data analysis provides quantifiable evidence supporting the hypothesis that "building technology and resident behaviors interact with each other and ultimately affect home energy consumption." Specifically, results identified four direct correlates between resident behavior and home energy use: temperature settings (winter/summer), use of a washer and dryer, and knowledge about building systems. Results also identified two indirect correlates (increasing the effect) between technology and behavior: temperature settings specifically during winter and the knowledge about building systems.

Our findings suggest that technological advances in building systems only directly contribute to 42% of energy efficiency. In other words, occupant habits could not take advantage of more than 50 percent of energy efficiency potential that a green building allows. The finding explains, to some extent, why the energy use in buildings remains the same as years ago, given the technological advances in architectural, mechanical, and electrical systems. From a systems perspective, a home is a tiny sociotechnical system [42] in which energy savings require the collective efforts of humans, technologies, management, and the environment. Consequently, both technical advances and behavioral plasticity contain achievable impacts on energy efficiency in buildings.

The work has identified the interaction effects that enable a better interpretation of the underlying relationships among occupants, technologies, and energy use. In scientific studies, the concept of interaction effects are often easy to understand yet the precise meaning is apparently difficult to interpret [43]. In this study, the interaction effects indicate a joint effort from human and technology on the energy use. Occupant behavior and building technology are like two legs without either of which the journey toward energy efficiency would not be possible. Moreover, within such joint effort, the effect of either human or technology depends on the other's particular level/value. In other words, the effect of the same level of technology varies for different occupant and vice versa. It is obvious that a higher level of green building technology would lead to less energy use; however, when considering the interaction with resident behavior, the most advanced technologies might not necessarily be the optimal option for all occupants. It should be noticed that the identified interaction effects are mutual rather than one-way. That means behavior can impact the technology's performance and on the other hand the performance influences occupant behavior as well. For example, during the onsite visits, some participants pointed that "if the heating does not quickly warm the house in winter, I often increase the thermostat temperature set point to make it working quickly," or "if the AC is not working in a fast manner, I will turn on the fan at the same time." Therefore, all of the interactions would jointly affect the home energy use.

The findings yield three practical implications for energy efficiency and global energy use. First, clear and valid information to homeowners and renters regarding building technology and energy savings delivered by housing stakeholders is increasingly important. Home builders, remodelers, contractors, realtors, specialty contractors, retrofit auditors, and mortgage lenders could be credible sources to deliver such information: a green building provides energy saving potential and the actual energy use also largely depends on resident behaviors. Second, energy saving programs, for example tax incentives, should include shared energy monitoring systems to collect behavioral feedback [44]. Behavior-integrated programs and policies will be more impactful on energy conservation. This reflects a big scope of human-energy integration that calls for improved manipulation of individual factors driving energy use at the household level [45]. Third, energy assessment tools and practices should incorporate occupant use patterns to provide more accuracy; and consequently, improved accuracy may positively influence the success of home energy retrofit decisions.

Some limitations and related extension of the present study deserve attention. One technical point is that the identified resident behaviors are subject to the geographical patterns and demographics. The data used in this study only cover buildings located in the warm climate zone and thus the results do not necessarily represent behaviors for residents living in the cold climate zone. In future research, regional and national-level samples are needed, covering varying climate zones. Another noteworthy point is that design and construction costs should be present in the model. The revised model may uncover deeper insight into the relationship between financial savings during planning versus operations and the direct and indirect correlates with occupant behavioral, which allows urban planners and developers more accurate prediction and decision making.

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