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Factors Driving Consumer Involvement in Energy Consumption and Energy-Efficient Purchasing Behavior: Evidence from Korean Residential Buildings

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Abstract: The recent rapid transition in energy markets and technological advances in demand-side interventions has renewed attention on consumer behavior. A rich literature on potential factors affecting residential energy use or green technology adoption has highlighted the need to better understand the fundamental causes of consumer heterogeneity in buildings' energy-related behavior. Unresolved questions such as which consumers are most likely to opt into demand-side management programs and what factors might explain the wide variation in behavioral responses to such programs make it difficult for policy-makers to develop cost-effective energy efficiency or demand response programs for residential buildings. This study extends the literature on involvement theory and energy-related behavior by proposing a holistic construct of household energy involvement (HEI) to represent consumers' personal level of interest in energy services. Based on a survey of 5487 Korean households, it finds that HEI has a stronger association with consumer values, such as preferences for indoor thermal comfort and automation, than with socioeconomic or housing characteristics and demonstrates HEI's potential as a reliable, integrated predictor of both energy consumption and energy-efficient purchases. The study illuminates the multifaceted influences that shape energy-related behavior in residential buildings and offers new tools to help utility regulators identify and profile viable market segments, improve the cost-effectiveness of their programs, and eventually promote urban sustainability.

Keywords: residential energy consumption; household energy involvement; buildings' energy efficiency; sustainability assessment; market segmentation; purchasing behavior

1. Introduction

In many parts of the world, the retail sector of the energy industry is witnessing a rapid transition characterized by the entrance of multiple electricity service providers offering alternative energy service products and energy efficiency contracts for residential buildings. In some advanced economies, households can now choose from a suite of energy pricing and service arrangements offered by multiple electricity service providers in the same service territory. This market transition is also being facilitated by recent advances in the collection and analysis of disaggregated energy-use data that will allow providers to obtain personalized real-time, appliance-level feedback and thus further tap the benefits of energy efficiency and changes in households' energy-consumption behavior.

These changes in the market and technological advances in demand-side interventions have highlighted the need to better understand the energy-related behaviors of consumers in residential buildings [1–3]. More broadly, the social determinants of the adoption and use of green technologies have taken on new importance as many policy instruments and associated public resources have begun to be implemented toward a vision of the decarbonized smart city. Although numerous pilot programs in the United States and Europe have assessed the impact of various pecuniary (e.g., dynamic pricing plans, demand response contracts) and nonpecuniary interventions (e.g., information programs and feedback) on household energy consumption, unresolved policy-level questions include who is likely to opt into demand-side management programs, what might explain the wide variation in behavioral responses to such programs, and how to effectively approach individual consumers in a cost-effective manner.

To answer these questions, many previous studies have explored the influence of such key variables as sociodemographic and housing characteristics, social ties or peer influences, and attitudinal or perceptual factors on individuals' energy-related decisions regarding the purchase of energy durables [4–8] and energy consumption (e.g., [9,10]). Although these approaches have usefully identified numerous influences on energy use and purchasing behavior, their findings have provided limited guidance in the development of effective demand-side management programs for residential buildings.

The primary cause of this gap in our understanding of consumer behavior is the absence of a holistic theoretical construct linking commonly identified factors in energy-related behavior and their consequences. Jensen [11], for example, has found that even households with similar sociodemographic and residential conditions differ as much as 700% in their energy consumption and that environmentally conscious attitudes do not necessarily lead to energy conservation. Edelson and Olsen [12] also reported that households actually increased their consumption of heating fuel after installing better home insulation. Given the complexity of energy consumers' decision-making process, it has been difficult for policy-makers to develop cost-effective energy efficiency or demand response programs and for energy-related businesses to prioritize product development activities that will meet differentiated consumer needs and preferences.

To fill this lack in the research, we draw on involvement theory to propose a new construct—household energy involvement (HEI)—to help explain consumer heterogeneity in buildings' energy-related behavior. HEI is defined as an intrinsic state or motivation reflecting the degree of a consumer's sense of personal relevance or interest in energy use or in energy services such as heating and cooling, lighting, cooking, and water heating. Our study investigates what makes households feel more or less involved in decision-making regarding their daily energy consumption and purchases of energy durables and how such an understanding might help explain their residential energy consumption. Based on a survey of 5487 Korean households, our study develops two types of HEI, identifies their key drivers, and evaluates their association with such performances as energy use and energy-efficient purchases in residential buildings.

This study contributes to current knowledge in two ways, first by using the lens of involvement theory in the marketing literature to help uncover the connection between personality and consumer behavior [13]. By including the critical dimension of personal characteristics, such as a household's preference for indoor thermal comfort or automation, the proposed holistic HEI model reveals that these factors are strongly associated with the level of energy involvement and that higher involvement may lead to energy conservation and/or energy durables purchases. These findings thus help explain the ambiguous or inconsistent findings of previous studies on the causes of energy behavior. Second, the study develops and validates the proposed HEI model and attendant HEI measure based on extensive data collected from a large number of households, thereby providing practical guidance and tools that utility regulators can employ to improve the cost-effectiveness of their programs for residential buildings and energy enterprises can use as an alternative criterion for market segmentation.

Section 2 introduces the theoretical background of the study, followed by an elaboration of its proposed framework and research methods in Section 3. The data and results are presented in Sections 4 and 5, respectively, and Section 6 considers their implications for policy-makers and energy service enterprises.

2. Theoretical Background

2.1. The Involvement Literature

Marketing researchers first began investigating the hypothetical influence of involvement on consumers' decision-making processes in the 1980s. Involvement has been defined as "a state of motivation, arousal or interest" that is "driven by current external variables ... and past internal variables" and whose "consequents are types of searching, processing and decision making" (p. 217 of [14]). Involvement demands a certain amount of effort from the customer, whether in the form of time, cognitive or social activity, or financial costs [15]. As Zaichkowsky has noted, "when we are involved, we pay attention, perceive importance and behave in a different manner than when we are not involved" ([16], p. 12). The same study found that prominent product attributes such as price were not necessarily indicators of high or low involvement, as demonstrated by the involvement score of laundry detergents being higher than that of TVs in the responses of mostly middle-aged females.

Previous studies have identified three general types of factors that influence involvement. *Personal factors* refer to an individual's value system and unique experiences [16], social roles [17], and personality traits, self-concepts, or needs that lead to interest in a product. *Physical factors* include product attributes that distinguish the product from others or serve one's particular interests (e.g., brand, price, dependence on the product, and symbolic value). *Situational factors* refer to events or circumstances (e.g., hot weather) that temporarily increase the relevance of or interest in a product [18]. As Bloch and Richins [17] have shown, consumer involvement in a product can manifest itself in various ways, including participation in information searches, written or word-of-mouth product evaluations, and purchases to meet customers' needs or interests.

In this study of residential energy use, we predicted that higher involvement in energy services would lead to such observable behavioral changes as efforts to reduce energy bills or replace old appliances with more energy-efficient ones. We define HEI as an intrinsic state that manifests in increased attention to managing daily energy usage and/or to purchasing energy-using durables. Although previous involvement studies have focused on non-repeated purchases of expensive durables (e.g., automobiles, cameras) considered relatively high-involvement items, we know little about to what extent consumers might express involvement in repeated or ongoing purchases of low-salience items. A few empirical studies have investigated this in repeated purchase items, including food [19] and laundry detergent [20], but to the best of our knowledge, no research has been conducted on consumer involvement with energy services. Our study thus extends the involvement literature by expanding its application to repeated and frequently purchased utility services that do not carry explicit price tags.

Further, we employed the k-means clustering method to segment the households by the two types of HEI (usage-related and purchase-related HEI) to test whether the consequences of energy behavior are distinguishable by group, thereby improving the usefulness of our model and the HEI measure for developing customized marketing strategies by utilities, energy service providers, and green technology producers. In recent years, energy researchers have employed diverse methods of clustering to analyze market segmentation by utilizing the fine-grained data of load patterns from smart meters. Rajabi et al. [21], for example, assessed various clustering techniques, including k-means for electrical load pattern segmentation, and Lee et al. [22] performed a clustering analysis of load patterns to segment residential consumers for an effective demand response program.

2.2. Energy Behavioral Studies

With increasing awareness of energy efficiency as a cost-effective carbon mitigation option and the recent restructuring of the energy industry, the fields of energy and environmental management have showed renewed interest in consumer behavior. A scientific basis for assessing the impact of demand-side energy policies has been provided by a proliferation of electricity demand response and energy-efficiency pilot programs attempting to leverage different behavioral interventions—price incentives, information feedback, and control technology installations [23–25]. The results of such programs suggest that such behavioral interventions can result in sizeable energy savings.

Despite their generally positive results, these programs have yielded widely divergent electricity savings. A meta-analysis of 70 such studies found that their savings ranged from 4% to 14% [1], too wide a gap to be useful for planning purposes, and some studies discovered that residential electricity savings lasted only several weeks or months [26,27]. Furthermore, these findings do not offer insight into the multifaceted nature of energy-related behavior or explain which or why customers sign up for alternative electricity tariffs [28], suggesting that a more reliable, longer-term indicator is necessary to capture energy customers' practices, lifestyle choices, and intrinsic consumption patterns [29].

Such field experiences highlight the need to better understand the fundamentals of residential energy behavior. In addition, a surge of studies on the diffusion of sustainable technology (e.g., smart meter, home automation, and renewable energy) has recognized the importance of the social aspect of technology, i.e., people's role in the adoption and use of technologies [30–32]. To that end, a wide range of energy behavioral studies have explored drivers behind the adoption of green technology or residential energy behavior. For example, several studies have tested the effects of such theoretical constructs as social networks or norms (e.g., [6,33,34]) and socioeconomic or demographic characteristics (e.g., [4,5]) on the adoption of energy durables. The effects of attitudinal factors such as environmental concerns and of housing characteristics such as home ownership and types of buildings have also been examined [9,10,35,36]. Studies on perceptual variables such as the "perceived relative advantage" of solar PV [7] and "perceived behavioral control" in the context of smart grids [8] have provided insight into the value of personal preference or sociopsychological factors.

While these fragmented approaches have produced an extensive list of factors contributing to heterogeneity in energy use and purchasing behavior, they have not given adequate attention to different empirical contexts [11] or provided theoretical explanations, especially regarding the role of socioeconomic or demographic factors. Examinations of the sociodemographic factors and housing characteristics of residential consumers have offered limited or sometimes inconsistent explanations for wide variances in household energy consumption or responses to various pecuniary and nonpecuniary behavioral interventions. As Raaij and Verhallen [37] have observed, a wide range of internal and external characteristics and intervening factors interact with one another and influence individuals' energy-related behavior. We therefore draw on involvement theory to propose an individual-level construct of HEI to provide a holistic theory that can fill gaps in our understanding of the possible antecedents of consumer behavior and their impact. Our study proposes an integrative theoretical model that encompasses diverse potential determinants of behavior and validates a multidimensional framework and attendant HEI measure based on the analysis of primary data from 5487 households.

3. Research Method

3.1. Conceptual Framework

Our model extends the framework proposed by Bloch and Richins [17] and Raaij and Verhallen [37] to establish key constructs and variables suitable to represent energy use and decisions regarding the purchase of energy-using durables (Figure 1). Bloch and Richins' framework classified the sources of involvement into three dimensions: *product* (physical), *consumer* (personal), and *situational* (external). The influence of the product dimension is limited in the case of energy services, however, which currently offer no symbolic interest (e.g., brands) and little differentiation in quality, performance, and price for given individual households. (Perhaps the only relevant product variable would be perceived product importance, which can also fall into the consumer category as an attitudinal attribute.) In contrast, the consumer dimension, also referred to as personal traits and values, is particularly relevant for the purposes of our study. In line with the literature on involvement and energy behavior, our framework splits the consumer dimension into two distinct subcategories: *consumer socioeconomic* factors and *consumer value and preference* factors. Consumer values and preference factors may include various personal traits (e.g., tolerance for discomfort) and attitudinal factors (e.g., environmental concern). Lastly, the situational sources of involvement encompass a range of housing conditions (i.e., *housing characteristics* such as dwelling size, heating systems, and year built) that would influence residential energy consumption and energy durables purchasing behavior.

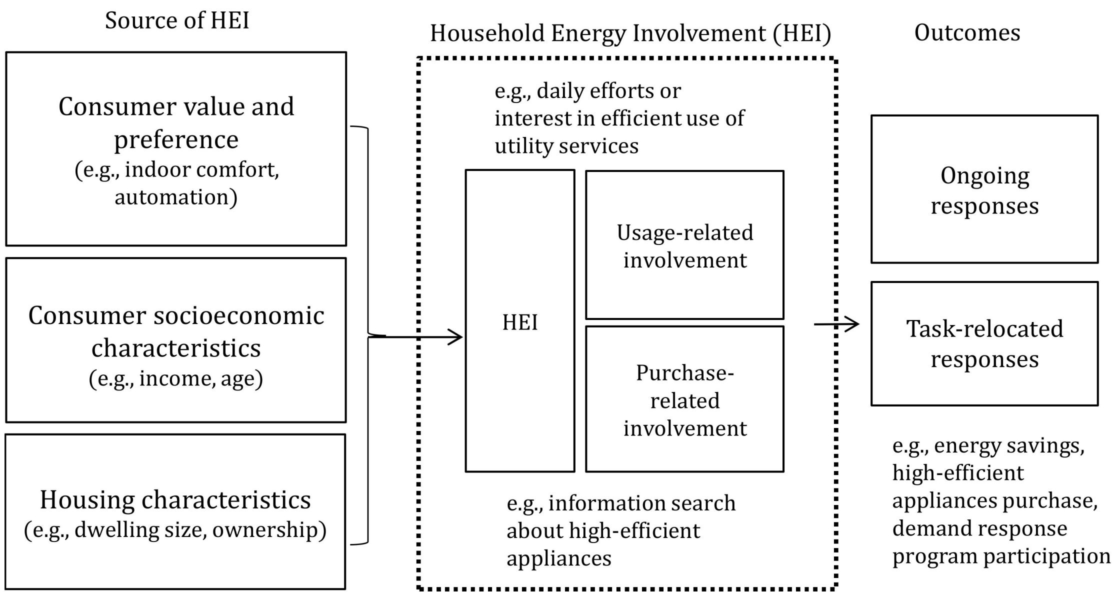

Figure 1. Conceptual Model of the Study.

3.2. Variables and Measurement

This section explains the variables in our conceptual model and their measurements, which are summarized in Table 1.

Table 1. Summary of the Model Variables.

Classification	Variable	Definition (Units)
Consumer Values & Preferences (including attitudinal factors)	*Tolerance*	Ordinal stated willingness to forego personal thermal comfort to save energy bills
	Automation	Ordinal stated willingness to invest in indoor heating/cooling automation systems compared to technologies requiring manual operation
	Receptivity	Ordinal stated tendency of adopting new technologies or unfamiliar practices
	Environmental Concern	Ordinal stated degree to which the respondent is conscious of natural environment and eco-friendly in goods purchases
	Energy Knowledge	Ordinal stated knowledge or awareness of the electricity rate structures and the environmental impact of energy consumption
	Importance	Ordinal stated importance of electricity or gas services for sustaining everyday life

Table 1. *Cont.*

Classification	Variable	Definition (Units)
Socioeconomic Characteristics	*Income*	Interval variable for the household's average monthly gross income, inclusive of other non-salary incomes; choice among ten equally spaced income ranges in increasing order (1: below 1 million KRW, 2: above 1 million KRW and below 2 million KRW, 10: above 9 million KRW)
	Gender	Categorical variable indicating the respondent's gender (1: male, 2: female)
	Age	Interval variable indicating the respondent's age group; choice among seven equally spaced age groups in increasing order (1: below twentieth, 2: in twentieth, 7: above seventieth)
	Job	Categorical variable indicating current occupation; choice among nine items (1: housewife, 2: office worker, 9: unemployed)
	Education	Categorical and ordinal variable indicating the respondent's educational experience; choice among five items in increasing order (1: primary education, 2: secondary education, 5: master's degree or above)
	Household Size	Continuous variable indicating the size of the household, ranging from one to seven in our sample
Housing Characteristics	*Ownership*	Categorical variable indicating the type of house ownership (1: owned, 2: rented, 3: public housing)
	Heat	Categorical variable indicating the type of heating system (1: individual heating, 2: central heating, 3: district heating)
	Dwelling Size	Interval variable for the house's floor area for exclusive use; choice among seven equally spaced ranges in increasing order (1: below 10 pyeong (3.3 m^2), 2: above 10 pyeong and below 20 pyeong, 7: above 60 pyeong)
	House Type	Categorical variable indicating house type (1: single detached house, 2: townhouse, 3: apartment house, 4: others)
	Year Built	Interval variable indicating the year the housing was built; choice among eight equally spaced ranges in increasing order (1: before 1970, 2: from 1970 to 1979, 8: after 2010)
Household Energy Involvement (HEI)	*HEI_Use*	Ordinal variable indicating usage-related HEI as measured by the level of household interest or attention to efficient energy uses; choice among seven-point Likert scale items in increasing order
	HEI_Pur	Ordinal variable indicating purchase-related involvement as measured by the level of household involvement in investing in particular energy-efficient appliances or home energy retrofits
Outcomes	*Energy consumption (log ECOSTS)*	Sum of median values taken from the primary ordinal variables of monthly energy bills by season and by energy types; primary monthly energy bill ranges determined by billing groups of different marginal prices
	LED Purchase	Dummy variable indicating the household's respective purchase of energy-using durables, such as LEDs (Light-Emitting Diodes), programmable thermostats, high-performance windows, and high-efficiency boilers

3.2.1. Consumer Values and Preferences Variables

To examine the role of consumer values and preferences in explaining HEI, we measured the participating households' *tolerance* (willingness to forego personal thermal comfort to save energy bills), *automation* (preference for or willingness to invest in automating an indoor environment), and *receptivity* (preference for new technologies or practices), as in earlier energy behavioral studies (e.g., [23,37]). We also measured attitudinal variables including *environmental concern* (e.g., [5,10]) and *energy knowledge* (e.g., [37]).

3.2.2. Socioeconomic and Housing Characteristics Variables

Our model captures the potential influence of demographic and socioeconomic attributes on HEI, following previous studies (e.g., [9,13,37]). The socioeconomic and demographic variables considered in our model include household income, gender, age, education level, occupation, and household size and composition. As in the literature regarding energy demand (e.g., [5,36]), detailed information about housing characteristics—dwelling size, house type, heating system type, construction year, and ownership type—is also included in this category.

3.2.3. HEI Variables

To quantify the degree of HEI, we propose and validate a new scheme theoretically grounded in the involvement literature. Most previous involvement studies employed measurements suited to consumer durables (e.g., cameras, automobiles) and often based on a composite index of consumer interests or perceived attractiveness of products or brands (e.g., [18,38]), which may not be directly applicable to energy services that involve frequent consumption and non-product-specific characteristics. Through multiple rounds of content and construct analysis, we carefully developed HEI measurements using two criteria. First, the constructs should represent key anchor points of involvement (e.g., interest, relevance, and attention or management efforts such as information search and extended problem-solving behavior), as suggested by the existing literature. Second, the statements generated to tap the underlying concept should be appropriate for assessing the propensity to carefully consider energy services.

Our selected HEI measurements include two types of HEI constructs, usage-related HEI and purchase-related HEI, which are treated separately to compare or distinguish the level of households' involvement in daily energy-use practices or particular energy-efficient appliance purchases [37]. Abstaining from asking normative, value-laden questions, we generated multiple 7-point Likert scale items to evaluate the extent to which households were involved in specific energy-relevant behavior.

3.2.4. Energy Consumption Variables

As indications of the behavioral outcomes of HEI, we asked households to estimate their monthly average energy bills for 3 months—October for spring/fall, August for summer, and January for winter—as the households' actual energy use information was not available from the utility service providers for privacy reasons. The households' reported monthly energy bills were comparable to the national estimate and appeared to be generally reliable.

3.2.5. Appliance Purchase Variables

The energy-efficient durables selected for inclusion in this study were based on the list of high-efficiency appliances developed by KEA (Korea Energy Agency) [39], which includes LED lamps, high-efficiency boilers, energy-efficient windows, high-performance insulation, and programmable thermostats. To limit potential endogeneity issues, we required the owners of these durables to indicate whether they had purchased or installed the durables themselves after moving in. Our logistic regression model for appliance purchase behavior employs only the sample households that indicated active adoption or non-adoption of the energy-efficient durables and excludes those who replied that the durables had already been installed before moving in.

3.3. HEI Measurements

To establish content validity, we first asked six academic researchers and graduate students in the areas of energy economics and behavior to examine an initial pool of measurements from the perspective of how well the chosen items represented the defined HEI. Further, we pretested ten households not included in our sample before implementing the pilot survey and revised the HEI statements and other questions to reflect that feedback. Next, we treated the chosen 26 items to assess HEI in the pilot survey of 354 households, and as a result of construct validity analysis dropped 6 items showing low reliability and convergent performance. Lastly, based on the results of our main survey, we conducted the reliability and factor analysis and re-examined the contents. As a result, we additionally dropped 4 more items with factor loadings lower than 0.50 [18,40] and employed 16 involvement proxies at the end. Three of the four items dropped in the final round turned out to be the questions in reverse order designed to test the reliability of responses. Cronbach's Alpha of the HEI measurements show around 0.8 ~ 0.9 on average and individually, indicating high internal consistency, and an exploratory factor analysis (principle component) confirms the one-factor dimension of the HEI construct. Table 2 displays the final 16 measurement items selected for quantifying HEI. The results of the measurement reliability and factor loadings are summarized in Table S1.

Table 2. Household Energy Involvement Measurement Items.

<table>
<tr><th colspan="3">Anchor Points of the Measurement Scale</th></tr>
<tr><td colspan="3">1. Interests and consciousness in energy use at home
2. Efforts in attention and information searching, either routinized or triggered
3. Willingness to invest in energy-efficient appliances and home energy improvement
4. Active consideration of energy efficiency when purchasing home energy equipment</td></tr>
<tr><td colspan="3">Scaling: 7-point Likert scale</td></tr>
<tr><td colspan="3">1 Strongly unlikely, 2 Very unlikely, 3 Unlikely, 4 Neutral, 5 Likely, 6 Very likely, 7 Strongly likely</td></tr>
<tr><td>Types (No. of Items)</td><td>List of Measurement Items</td><td>Coefficient Alpha (std)</td></tr>
<tr><td>Usage-Related HEI (11)</td><td>I ask around or find information on my own to minimize energy bills while still remaining comfortable indoors.
I teach my family members to pay attention to not wasting energy at home.
I make efficient use of indoor lighting (e.g., turning off the lighting in vacant rooms).
When using electronic devices, I tend to search for ways to save energy (e.g., set my computers in the power-saving mode).
I carefully examine my monthly home energy bills.
Using energy efficiently and without unnecessary waste in my home is one of my main concerns.
I normally turn off a power strip when not using the items plugged into it.
Especially in the summer and winter, I pay attention to operating the air-conditioner or the heating system according to when many family members are at home.
I tend to be concerned about the sudden increases in electricity costs due to the increasing block tariff rates when using a lot of electricity.
In the winter, I try to reduce heat loss from the windows by improving the insulation, such as using thick curtains or attaching weather strips.
When appliances or devices are not in use, I try to avoid the unnecessary use of energy (e.g., unplugging my TV or computer from the outlet).</td><td>0.872</td></tr>
<tr><td>Purchase-Related HEI (5)</td><td>I have seriously considered replacing energy-intensive lighting fixtures with more efficient ones (e.g., LED bulbs).
I take energy ratings information into serious account when purchasing home appliances.
I tend to hesitate to buy electric appliances for fear of excessive electricity bills.
I take factors that affect heating and cooling costs (e.g., a southern exposure, double windows, type of heating system, age of building) into serious consideration when purchasing or renting a house.
I have considered purchasing high-efficiency energy equipment (e.g., certified products, solar water heaters, high-efficiency boilers, insulating windows) to reduce energy costs.</td><td>0.795</td></tr>
</table>

3.4. Survey Design

To collect information on the energy-use involvement and behavior of the households, we conducted an internet-based survey that asked questions about a range of household-level information, such as the participants' values, preferences, and socioeconomic and housing characteristics. Respondents were limited to the head of household or the spouse who was primarily responsible for paying energy bills and who was thus expected to engage in energy decisions more often than other household members. To ensure the representativeness of the survey sample, we employed the entire pool of sample frames managed by an online survey company (SKTillion, with more than 500,000 active members).

A standard two-stage survey procedure was performed—a pilot survey of 354 households in March followed by the main survey of 5133 households in May 2015. We undertook the survey in spring rather than the summer or winter season so that any unintended effects of extreme weather on household energy behavior would not be introduced. As the pilot indicated a modest sample selection bias and miscommunication issues, we performed a stratified sampling procedure and revised questionnaires for the main survey [40–42]. Each of the recruited samples in the main survey received an email asking them to fill out a Qualtrics-based online questionnaire that included screening questions (e.g., whether the respondent was a household head or a spouse) and dummy questions (e.g., questions with the same answers listed in different orders). After eliminating responses that failed to pass the eligibility criterion or at least one of the dummy questions, we obtained the effective responses of 3245 households for the analysis, or about 63% of the main survey respondents. Overall, the final sample used for our analysis was highly representative of Korean households in terms of key socioeconomic and demographic attributes.

4. Data

4.1. Sample Distributions

Among the final sample of 3245 households, 49.8% of the respondents were male and 50.2% were female. Household income (Figure 2) and jobs also showed distributions similar to those of the population at large. The average monthly gross income of the sample was 4.61 million KRW (approximately 4000 USD), which is comparable to the national average of 4.26 million KRW reported by the National Statistical Office in 2014. Office workers constituted 42.6% of the respondents, followed by workers in other jobs (31.5%), housewives (22.6%), and unemployed (3.3%). The range of ages among the respondents, from 30 to 60, represents Korean demographics well, although those over 70 were under-represented because of their limited participation in the online survey pool (Figure 3). The most frequent household size was four (41.5%), and the size of the dwellings ranged from 66.1 to 99.1 m^2 (38.5%), which is consistent with Korean national statistics. With regard to the type of dwelling, apartments accounted for the largest proportion (63%), followed by townhouses (21%) and single-family dwellings (13%).

With regard to the selected proxy for household energy consumption, the households' average reported monthly energy bills were about 116,300 KRW (about 101 USD) and accounted for about 2.6% of the households' average gross income, which is slightly lower than, but comparable to, the national estimate of 3.3% [43]. We also asked the respondents to indicate the reliability of their provided information so that we could better consider uncertainty when analyzing the results. The information about household-level monthly energy bills appeared to be generally reliable, as more than 70% indicated the top two items ("certain" or "energy bills checked") on the 5-point Likert scale question about information reliability. Furthermore, the results for the entire effective sample and for the subsample, excluding those admitting their information might be modestly or very unreliable, showed similar results.

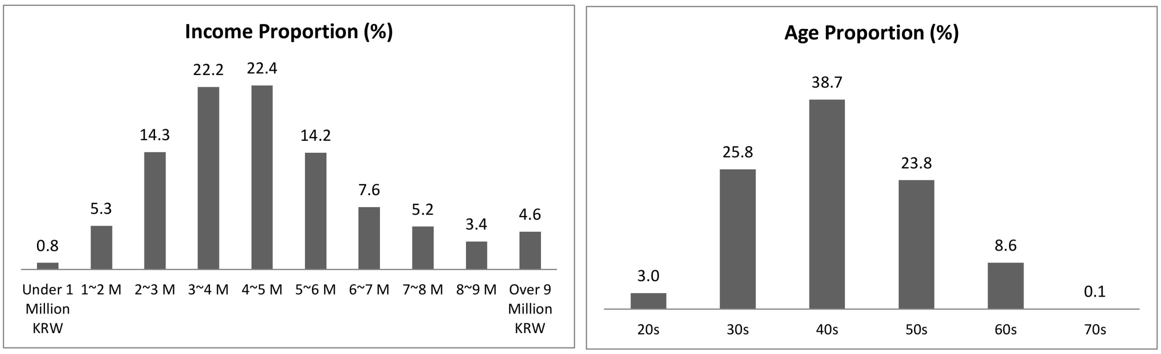

Figure 2. Sample Distribution of Income and Age.

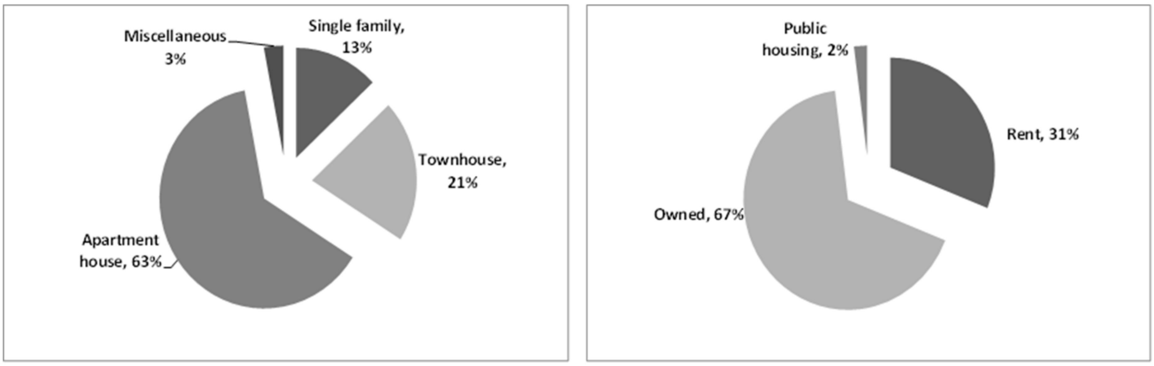

Figure 3. Sample Distribution of Housing Types and Ownership.

4.2. Estimation

Given that the outcomes of HEI are ordinal in nature, we employed ordered probit models to identify the determinants of HEI, assuming that the residuals are normally distributed. The models are given as follows:

$$HEI\_use_i = \alpha_0 + XAi' + XBi' + X\Gamma i' + \varepsilon_{ui} \tag{1}$$

$$HEI\_pur_i = \beta_0 + XAi' + XBi' + X\Gamma i' + \varepsilon_{pi} \tag{2}$$

where *HEI_use* and *HEI_pur* are specified as the dependent variables, which are ordinal variables indicating usage-related HEI and purchase-related HEI of individual households i respectively; XAi' refers to the consumer values and preference variables of individual households i (*Tolerance, Automation, Receptivity, Environmental Concern, Energy Knowledge*, and *Importance*); and XBi' and $X\Gamma i'$ are the contributions from the socioeconomic and demographic variables and home characteristics variables, respectively. Specifically, the socioeconomic/demographic variables included *Income, Gender, Age, Job, Education*, and *Household Size*, and the home characteristic variables included *Ownership, Heat, Dwelling Size, House Type*, and *Year Built*.

Another set of regression models related the HEI with their possible outcomes—i.e., energy consumption and appliance purchase behavior—with all other controlled variables. For the analysis of energy-efficient appliance purchases, we used a standard binary logistic model. Descriptive statistics and bivariate correlations of the estimation models are shown in Table S2. The models are given by

$$Energy\ Use_i = \gamma_0 + \gamma_1\ HEI\_Use_i + X\omega' + \varepsilon_i \tag{3}$$

$$Energy\ Use_i = \theta_0 + \theta_1\ HEI\_Pur_i + X\omega' + \upsilon_i \tag{4}$$

$$logit(P_i) = \delta_0 + \delta_1 HEI\_Use_i + X\omega' + \lambda_i \tag{5}$$

$$logit(P_i) = \lambda_0 + \lambda_1 HEI\_Pur_i + X\omega' + \varphi_i \quad (6)$$

where $Energy\ Use_i$ is the log-transformed energy costs of individual households i and $logit(P_i)$ is the logit transformation of the probabiltiy of purchasing the appliance (odds), *HEI_use* and *HEI_pur* are the independent variables, $X\omega'$ are the contributions from the sociodemographic and house characteristics variables listed above and in Table 1. $\varepsilon\ and\ \upsilon$, $\lambda\ and\ \varphi$ are the error terms following the normal distribution assumptions and the extreme value distribution of the standard logit model, respectively.

With regard to consumer segmentation by HEI (5.3 *Additional analysis*), we employed the *k*-means clustering method to segment the residential energy consumers who participated. Our nonhierarchical clustering approach assigned the samples to a pre-defined number (*k*) of subsample clusters according to key criteria measures that we considered important in characterizing consumer behavior. In principle, these clusters are formed in a way that maximizes the average distance between the clusters (dispersion) while minimizing the average distance within the clusters (compactness).

We chose the two types of HEI as the criteria measures, because HEI is both closely associated with consumer values and preference variables and a significant predictor of performances such as household energy consumption and energy-efficient appliance purchases. In addition, we confirmed that the base case with three groups divided by households' HEI shows a better performance of division ratio, which is calculated by average distance between groups divided by average distance within groups, than those of alternative cases. We tested alternative models adopting other combinations of source variables that are found to be significant in the first regression models with a different number of clusters to compare the results with the base case of adopting HEI criteria with three groups. We found that the base model adopting two types of HEI divided by three groups showed the highest performance.

5. Results and Discussions

5.1. Main Sources of HEI

Our multidimensional analysis of HEI indicates that the consumer values and preferences attributes are strong explanatory factors for HEI, in contrast to the models consisting of sociodemographic and housing characteristics (HModels 1 and 3 in Table 3), which exhibit very little explanatory power. We performed the multivariate regression analysis as well and found that the results were similar overall to those of the ordered probit models in Table 3. The results suggest that personal traits and preferences, such as willingness to forego personal thermal comfort to save energy bills (*Tolerance*) and values (e.g., *Environmental concern*, *Importance*), are critical factors in forming households' intrinsic state of motivation or increased attention to managing energy usage, as the higher the levels of those factors, the higher the household's usage and purchase-related energy involvement.

Table 3. Source of HEI.

Ordered Probit Estimation VARIABLES	**HModel 1** ***HEI_Use***	**HModel 2** ***HEI_Use***	**HModel 3** ***HEI_Pur***	**HModel 4** ***HEI_Pur***
Values and Preferences:				
Automation		0.0131		0.133 ***
		(0.0153)		(0.0155)
Receptivity		0.0505 ***		0.0941 ***
		(0.0179)		(0.0180)
Tolerance		0.487 ***		0.416 ***
		(0.0218)		(0.0217)
EnvironmentalConcern		0.303 ***		0.350 ***
		(0.0234)		(0.0237)
EnergyKnowledge		0.382 ***		0.330 ***
		(0.0240)		(0.0240)
Importance		0.260 ***		0.105 ***
		(0.0224)		(0.0223)

Table 3. *Cont.*

Ordered Probit Estimation VARIABLES	**HModel 1** ***HEI_Use***	**HModel 2** ***HEI_Use***	**HModel 3** ***HEI_Pur***	**HModel 4** ***HEI_Pur***
Socioeconomic and Housing Characteristics:				
Income	−0.00397	−0.0416 ***	0.00102	−0.0432 ***
	(0.0101)	(0.0103)	(0.0101)	(0.0103)
Gender (female)	0.278 ***	0.413 ***	0.0696 *	0.168 ***
	(0.0366)	(0.0377)	(0.0365)	(0.0376)
Age	0.0709 ***	−0.0429 **	0.0820 ***	−0.0175
	(0.0195)	(0.0198)	(0.0195)	(0.0199)
Ownership (rented)	0.00713	−0.0163	−0.0804 *	−0.112 ***
	(0.0421)	(0.0422)	(0.0422)	(0.0424)
Ownership (public rented)	−0.0314	−0.0812	0.0562	0.00758
	(0.122)	(0.122)	(0.122)	(0.122)
Heating (central)	−0.250 ***	−0.207 ***	−0.144 **	−0.0845
	(0.0705)	(0.0707)	(0.0706)	(0.0709)
Heating (district)	−0.0536	−0.0365	0.000747	0.0580
	(0.0521)	(0.0522)	(0.0521)	(0.0524)
Dwelling size	−0.00427	−0.0344	0.0709 ***	0.0508 **
	(0.0210)	(0.0211)	(0.0210)	(0.0212)
House type (townhouse)	−0.00888	−0.00721	0.00662	0.0209
	(0.0653)	(0.0655)	(0.0655)	(0.0658)
House type (apartment)	0.0503	−0.00246	−0.000600	−0.0492
	(0.0573)	(0.0575)	(0.0575)	(0.0578)
House type (others)	−0.157	−0.229 *	−0.00805	−0.0431
	(0.117)	(0.118)	(0.118)	(0.118)
Year built	−0.00833	−0.00976	−0.0317 ***	−0.0387 ***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Observations	3,245	3,245	3,245	3,245
Pseudo R^2	0.003	0.089	0.003	0.103
Log pseudolikelihood	−11334.44	−10361.26	−9171.78	−8253.59

Note: The results of multiple constants are not displayed in the table. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In contrast, the results for consumer socioeconomic and housing characteristics in our conceptual framework (Figure 1) imply that external or situational factors are probably less important in determining consumers' HEI than are their personal values and preferences. Except for *Gender,* which consistently showed statistical significance for both types of HEI, the results regarding such key socioeconomic variables as *income* and *age* changed in the fuller models (HModels 2 and 4), perhaps suggesting a partial reason for the mixed results shown in previous studies examining sociodemographic influences on energy use.

Note, however, that not all the value and preference variables present statistical significance for both types of HEI (*HEI_Use*, *HEI_Pur*), which provides empirical support for their separate treatment [37]. For example, *automation* and *receptivity*, which were expected to drive the disposition to invest in energy-efficient appliances, are found to be statistically significant only for the purchase-related HEI *(HEI_Pur).* That is, households exhibiting strong preferences for *automation* and *receptivity* favor managing energy bills by investing in efficient energy-using technologies, but not by engaging in daily energy-conscious activities. We also performed an OLS regression analysis for the sources of the HEI model. Although the coefficients of the various parameters become small in the regression estimation, the conclusions remain the same as those of the ordered probit estimation.

5.2. HEI and Outcomes

Next, we analyzed whether the HEI construct is linked to behavioral outcomes as predicted by our conceptual framework. We find that both usage-related and purchase-related HEI are negatively correlated with energy consumption (bills) at a 1% level of significance, meaning that households with higher HEI are likely to consume less energy (EModels 1 and 2 in Table 4). Since our earlier analysis showed that values and preference attributes are the main determinants of HEI, we utilized the HEI as a composite index (explanatory variable), substituting various values and preference variables in order to examine the direct relationship between HEI and energy use. Overall, the results regarding socioeconomic and home characteristics as control variables in the analysis of HEI outcome support the results of prior studies: households with higher-income residents, larger size, and older structures were likely to consume more energy.

Table 4. Analysis of Response to HEI (Energy Consumption and LED Purchase).

Variables	**EModel 1** *Energy Consumption*	**EModel 2** *Energy Consumption*	**PModel 1** *LED Purchase*	**PModel 2** *LED Purchase*
HEI_Use	−0.0705 ***		0.0921 **	
	(0.0109)		(0.0406)	
HEI_Pur		−0.0578 ***		0.206 ***
		(0.01000)		(0.0396)
Socioeconomic and Housing Characteristics:				
Income	0.0215 ***	0.0218 ***	0.0880 ***	0.0851 ***
	(0.00497)	(0.00495)	(0.0227)	(0.0229)
Gender (female)	−0.0159	−0.0266	−0.556 ***	−0.594 ***
	(0.0173)	(0.0172)	(0.0843)	(0.0827)
Age	0.0269 ***	0.0274 ***	−0.197 ***	−0.254 ***
	(0.00949)	(0.00951)	(0.0411)	(0.0407)
Ownership (renter)	−0.0145	−0.0183	−0.773 ***	−0.809 ***
	(0.0197)	(0.0197)	(0.1000)	(0.0997)
Ownership (public)	−0.0956	−0.0911	−0.887 **	−0.930 ***
	(0.0603)	(0.0601)	(0.356)	(0.357)
Heating (central)	−0.174 ***	−0.167 ***	−0.120 ***	−0.133 ***
	(0.0380)	(0.0379)	(0.0244)	(0.0242)
Heating (district)	−0.230 ***	−0.227 ***	0.0195	0.0186
	(0.0256)	(0.0255)	(0.160)	(0.160)
Dwelling size	0.0833 ***	0.0865 ***	0.0392	0.0439
	(0.0113)	(0.0113)	(0.121)	(0.121)
House type (townhouse)	0.0420	0.0432	0.231 ***	0.210 ***
	(0.0302)	(0.0303)	(0.0489)	(0.0492)
House type (apartment)	−0.0838 ***	−0.0860 ***	−0.420 ***	−0.481***
	(0.0277)	(0.0278)	(0.146)	(0.146)
House type (studios)	−0.0186	−0.0101	−0.410 ***	−0.446 ***
	(0.0573)	(0.0571)	(0.125)	(0.124)
Year built	−0.00444	−0.00547	−0.165	−0.238
	(0.00539)	(0.00540)	(0.283)	(0.284)
Family size	0.120 ***	0.121 ***	−0.0479	−0.0782 **
	(0.00895)	(0.00894)	(0.0388)	(0.0388)
Constant	10.98 ***	10.89 ***		
	(0.0882)	(0.0829)		
Observations	3,237	3,237	2,968	2,968
R-squared/Loglikelihood	0.187	0.186	−1772.65	−1761.51

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Table 4 (PModel), which summarizes the results of the case of LEDs, one of the four types of energy-efficient appliances examined, indicates that HEI is positively associated with the probability of purchasing LED lamps. The results show that purchase-related HEI has a much bigger impact on LED purchases than does usage-related HEI, which is marginally significant with 95% confidence. For the other three types of durables analyzed, however, only the coefficients of purchase-related HEI for energy durables purchases remain significant, with 99% confidence for all cases.

Results show that LED purchases are also influenced by a number of socioeconomic and housing characteristics: *income*, *age*, *gender*, *ownership*, *heating systems*, and *house type*. Although males are shown to be more likely to purchase LEDs than females, no gender effects are found in energy consumption. Similarly, we find that house owners are more likely to purchase LEDs, whereas ownership shows no effect on energy bills, supporting "the split incentives" issue for renters [30]. For the other three appliances, some of the variables showed different results (e.g., the gender effect disappeared in high-efficiency boiler purchases). These varied results regarding the type of outcome or features of energy durables suggest limitations in generalizing the effects of socioeconomic or housing environment factors on energy behavior.

5.3. Additional Analysis: Consumer Segmentation by HEI

Lastly, we utilized the HEI measure to divide the households into segments to see whether systematic differences among those segments might suggest a new process for identifying viable market segments. We employed the *k*-means clustering method to segment the residential energy consumers in the sample into three groups distinguishable by their level of HEI. Among the total number of 3245 households, the share of high (1)-, medium (2)-, and low (3)-HEI segment was 30.8%, 45.7%, and 23.6%, respectively, and the low-HEI group contained relatively bigger variations and outliers than the other two groups (Figure 4).

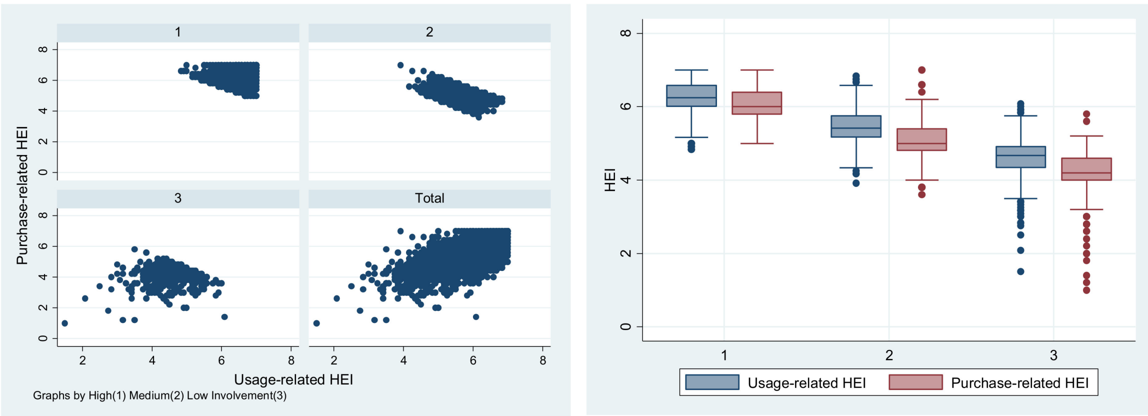

Figure 4. Descriptive Statistics of the Segments.

The pairwise comparison tests for the divided segments show that all *values and preference* variables differ significantly between all jointly pairwise combinations with 99% confidence, whereas commonly identifiable socioeconomic and/or housing characteristics do not (Table 5). Strikingly, some key socioeconomic and household characteristics, such as *household income*, *education*, and *family size*, are not significantly different among the groups, which suggests a possible need to review marketing practices that heavily rely on such commonly identifiable consumer information. Our results are in line with Jensen's findings of high variance in residential energy consumption, even among households with similar demographic and building conditions [11], and imply that the failure to take value and preference factors into account may help explain previous mixed results regarding socioeconomic or demographic influences on energy consumption.

Table 5. Values and Preferences, Socioeconomic and Housing Characteristics by Segment.

	High INV(1)	Medium INV(2)	Low INV(3)	(2) vs (1)	(3) vs (1)	(3) vs (2)
Automation	4.573	4.246	3.966	−0.326 ***	−0.607 ***	−0.280 ***
	(1.566)	(1.130)	(1.012)	(0.051)	(0.060)	(0.055)
Receptivity	4.844	4.423	4.115	−0.420 ***	−0.729 ***	−0.308 ***
	(1.265)	(1.044)	(0.981)	(0.045)	(0.053)	(0.049)
Tolerance	5.782	5.040	4.492	−0.742 ***	−1.289 ***	−0.547 ***
	(0.874)	(0.779)	(0.822)	(0.033)	(0.039)	(0.036)
Environmental Concern	5.274	4.559	4.045	−0.715 ***	−1.228 ***	−0.513 ***
	(0.886)	(0.768)	(0.829)	(0.033)	(0.039)	(0.036)
Energy Knowledge	5.016	4.435	3.878	−0.580 ***	−1.137 ***	−0.556 ***
	(0.873)	(0.779)	(0.757)	(0.032)	(0.038)	(0.035)
Importance	5.673	5.442	5.217	−0.230 ***	−0.455 ***	−0.224 ***
	(0.803)	(0.772)	(0.829)	(0.032)	(0.038)	(0.035)
Income	5.169	5.133	5.010	−0.036	−0.159	−0.122
	(2.058)	(1.966)	(1.974)	(0.081)	(0.095)	(0.088)
Gender	1.538	1.493	1.473	−0.045 *	−0.065 **	−0.019
	(0.498)	(0.500)	(0.500)	(0.020)	(0.024)	(0.022)
Age	4.223	4.073	3.970	−0.151 ***	-0.254 ***	−0.103 *
	(0.995)	(0.959)	(0.970)	(0.039)	(0.046)	(0.043)
Education	3.530	3.592	3.525	0.062	−0.005	−0.067
	(0.980)	(0.940)	(0.959)	(0.039)	(0.046)	(0.042)
Ownership	1.318	1.355	1.377	0.037	0.059*	0.022
	(0.515)	−0.519	(0.536)	(0.021)	(0.025)	(0.023)
Dwelling Size	3.528	3.412	3.375	−0.116 **	−0.153 **	−0.037
	(1.043)	(1.030)	(1.071)	(0.042)	(0.050)	(0.046)
Year Built	5.325	5.500	5.542	0.175 *	0.218 *	0.042
	(1.783)	(1.700)	(1.717)	(0.070)	(0.083)	(0.077)
Family Size	3.482	3.490	3.405	0.008	-0.077	−0.085
	(1.054)	(1.051)	(1.091)	(0.043)	(0.051)	(0.047)

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results also confirm that the segments are distinguishable by the performances examined: the high-HEI segment consistently appeared to use less energy (Table 6) and be more likely to purchase energy-efficient appliances than the other two groups (Table 7). The difference between the high-HEI and the low-HEI segment is particularly evident at the significance level of 1%, whereas the difference between the high-HEI and the medium-HEI, or between the medium-HEI and the low-HEI segment, remains relatively small, with its significance level varying with season.

Table 6. Household Energy Bills and Differences by Segment.

	High INV(1)	Medium INV(2)	Low INV(3)	(1)–(2)	(1)–(3)	(2)–(3)
Monthly Avg.	95,291	99,509	104,135	4218 *	8844 ***	4626 *
	(46,708)	(46,475)	(47,952)	(1923)	(2254)	(2089)
Winter	129,881	135,486	138,715	5605 *	8833 **	3229
	(63,366)	(63,067)	(64,744)	(2606)	(3055)	(2831)
Summer	77,397	81,104	86,724	3707	9326 ***	5619 **
	(46,011)	(45,672)	(47,088)	(1891)	(2217)	(2054)

Note: The monthly energy bills are the mean value of each group, and the currency is the Korean Won (KRW). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. Share of Purchasing Energy-Efficient Durables by Segment. (Unit: %)

	High INV(1)	Medium INV(2)	Low INV(3)
LED	39.5	28.9	20.7
Programmable Thermostat	20.2	14.4	9.0
High-efficiency Boiler	23.1	17.5	13.5
High-performance Window	17.0	9.6	5.2

6. Conclusions

To examine what makes consumers become more or less involved in their daily use of energy or relevant purchase decisions in residential buildings and what the consequences of HEI might be, we employed a holistic involvement framework and analyzed the energy behavior of 5487 Korean households and found a tight coupling among consumer values and preferences, HEI, and actual buildings' energy-related behaviors. We identified value and preference attributes as the most critical dimensions or elements affecting the level of HEI and demonstrated that their inclusion provides greater explanatory power than models consisting of sociodemographic and housing characteristics only. The results also demonstrate HEI's potential as a reliable, integrated predictor of both energy consumption and the purchase of energy-efficient durables in residential buildings: the higher the level of HEI, the lower the use of energy and the higher the probability of purchasing energy-efficient appliances. These findings are confirmed by the results of market segmentation by individual levels of HEI.

This study contributes to current knowledge in several ways. First, the proposed holistic theoretical construct linking multidimensional factors influencing individual energy behavior and its consequences provides a potential explanation for the mixed and inconsistent results reported in the previous literature on the causes of energy behavior in residential buildings. Second, unlike previous studies, which often regard households as one group and evaluate various instruments (e.g., financial incentives, information feedback) to support the adoption and use of green technologies in general, our study identifies key driving factors of consumer heterogeneity under a holistic framework, proposing a method applicable to differentiated energy markets. Third, our study extends the marketing literature to consumer involvement to the area of repeated and frequently purchased utility services, which have been regarded as low-involvement products and understudied.

Our study thereby offers practical guidance and tools to policy-makers and demand-side management businesses. Managers in utility companies or electricity service providers can utilize the lens of involvement to assess and segment the heterogeneous residential buildings market, distinguishing between subgroups with similar values and preferences, such as those with a greater tolerance for thermal discomfort or a higher interest in automation. Specifically, our analysis of the source of HEI implies a potential difference between consumers who prefer manual control, as indicated by usage-related HEI over automatic adjustments, as indicated by purchase-related HEI. While some preference variables, such as tolerance, energy knowledge, and perceived importance, remain significant for both types of HEI, some, such as automation, are significant only for purchase-related HEI. Also worthy of note is that the receptivity (to new things) has a positive association with both HEI types, and the magnitude is greater for the purchase-related HEI.

In particular, our finding of marginal or little difference in some representative socioeconomic or household-specific attributes challenges previous marketing practices that rely heavily on commonly identifiable information (e.g., age, gender, education). Although our results highlight the importance of values and preferences in understanding residential energy behavior, it may be infeasible or inefficient for program managers to assess various components of those factors in practice. Our analysis showing the close association between those attributes and the level of HEI, however, suggests that managers may be able to utilize the HEI measure without necessarily evaluating the various values and preferences of individual consumers, as the HEI is a composite index or process output of the interaction of multifaceted sources driven by those values and preferences. Decision-makers thus may be able to improve the cost-effectiveness of their marketing or demand-response programs through targeting and offering customized messages or recommendations, such as providing rebate programs for energy-efficient durables to the group with high purchase-related HEI or offering education programs to the group with low HEI to increase the level of energy knowledge or perceived importance. Further, policy-makers or program managers could also employ the HEI measure as a complementary performance indicator to capture the behavioral performance of various energy-efficiency campaigns and public awareness programs in the long run.

Our study has several limitations and a few caveats regarding the interpretations of these results and their implications for future research. First, given that involvement has been understood to be influenced by situational factors (e.g., seasons, events such as a move) and external variables (e.g., cultural and social norms, degree of market liberalization), the absolute level of HEI may differ by time or region. As the focus of our study was on the relative level of HEI, not on its absolute level, we performed the survey in spring to avoid any unintended temporary effects of extreme weather on household energy consumption behavior, and the sample households to which the survey was administered were well distributed across regions in Korea. Nonetheless, the external validity of our findings may not hold for households in other countries with different weather conditions.

Second, our integrative HEI model and findings highlight critical aspects of consumers' heterogeneity, such as their internal values and preferences that drive their fundamental level of interests and attendant efforts in energy use. Although our model is not intended to uncover all the possible drivers of HEI, the explanatory power for the sources of HEI seems rather small, which suggests the possibility of missing some other significant variables. This gap may have to do with the complex mechanism of individuals' energy-related behavior, in which a wide range of internal and external variables interact with one another [37]. Continued development of a holistic yet parsimonious HEI model and attendant measurements (e.g., whether the key variables of values and preferences are exhaustive and valid) would be highly valued.

Third, although we analyzed such physical aspects of residential conditions as dwelling size and year built, we did not consider other elements in buildings' design that may collectively determine Indoor Environmental Quality (IEQ), which encompasses air quality, thermal comfort, lighting, and ergonomics. Given that our HEI measure does not concern all of these aspects, HEI-predicted energy consumption may reveal systematic differences from real energy consumption. Future research may examine how our HEI measure can be augmented or alleviated with other aspects of the quality of buildings' design. In addition, given that many buildings do not perform as planned, investigating the relationship between HEI and its behavioral outcomes in a dynamic setting may offer an important avenue for future research. In particular, learning from Post Occupancy Evaluation (POE) [44], which is the process of obtaining feedback on a building's performance in use, may help explain how HEI can increase or decrease over time for individual households.

Lastly, thanks to the abundant electrical real-time data now available from smart meters, several efforts have been made to apply various machine-learning techniques for clustering residential energy consumers (e.g., [21,22]). Identifying the load patterns of households can help us better understand consumers' lifestyles and practices in daily or timely use of energy and thereby improve the performance of energy efficiency and/or demand response programs. Yet the possibility that the automation systems in smart grids may also lead to frustration and passivity [32] also seems an important avenue for future research. Furthermore, as Liu et al. [31] have noted, the diffusion of smart grids raises serious privacy concerns that must be taken into consideration by researchers and service providers employing this rich source of data. Together, these concerns and the results of this study suggest that researchers and practitioners should be cautious about approaching the study of residential consumers based on consequential data alone. A complementary approach that encompasses both fundamental and measurable criteria of consumer characteristics and data on fine-grained load patterns of residential buildings is thus encouraged for future research.

Supplementary Materials: The following are available online at http://www.mdpi.com/2071-1050/12/14/5573/s1, Table S1. Household Energy Involvement Measurement Reliability and Factor Loadings; Table S2. Descriptive Statistics and Correlations of Variables.

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