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Discriminant effects of consumer electronics use-phase attributes on household energy prediction

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ABSTRACT

The aim of this study is to provide a better understanding of the heterogeneities in user-product relationships and their consequences regarding the household energy predictions. Several supervised and unsupervised machine learning algorithms have been applied to a comprehensive data set of residential energy consumptions collected by the US Energy Information Association. The results of the analyses reveal that, while the heterogeneities in the use-phase of consumer electronics could skew their environmental assessment results, they do not possess the same discriminant influences on the household electricity consumption compared to certain socio-demographics or usage of home appliances. Various cross-comparisons among product features and use-phase behaviors have been made and the most important predictors of the residential electricity consumption based on the data have been introduced. Product-level and user-level discussions on the findings have also been provided.

1. Introduction

Environmental assessment techniques usually suffer from uncertainties in the dynamics or heterogeneities of the systems undergoing analysis (Reap et al., 2008a). One of the most important contributors to such uncertainties is the consumer behavior. This can be problematic for consumer electronics for which the usage phase, which is governed by the consumer behavior, plays a pivotal role in contributing to the environmental impacts. For instance, a review of Life Cycle Assessment (LCA) studies about consumer electronics reveals a substantial discrepancy in the results of the environmental assessments, particularly for personal computers (Raihanian Mashhadi and Behdad, 2017a). This discordance is believed to originate from the difference in assumptions regarding the usage mixes (Teehan and Kandlikar, 2012).

The uncertainties and the lack of insight about the consumers' interactions with their electronics and home appliances are not limited to the LCA domain. It has been shown that significant heterogeneity is present in time-use patterns of watching TV (Sekar et al., 2016) that can favor population-specific energy intervention policies targeting TV energy consumption. On the other hand, most of the energy intervention policies implemented during the last decade have been incompetent at capturing the consumer behavior effects. For example, time-of-use tariffs have been reported to create rebound effects (Torriti, 2012), increasing the actual electricity consumption while aiming at reducing its costs. Moreover, there are still certain limitations regarding the effectiveness of feedback for behavioral change with respect to energy consumption (Wilson et al., 2015). Smart feedback devices have also been shown to be only effective when they target consumer behavior by creating comparative norms; while even then, they may motivate some users to increase their consumption (Schultz et al., 2015, 2007).

The importance of considering consumers' behavior and their interactions with electric or electronic products in designing energy intervention policies or conducting LCA studies is undeniable. However, further investigation is required to provide insight into the important behaviors, design features or user-product interactions. Several questions can be asked about the extent to which use-phase attributes matter with respect to the environmental assessment or the household electricity prediction. For instance, if the misconceptions regarding user behavior can skew the results of LCA, as a result of energy consumption miscalculations, what specific behaviors are more important to target? Does only the daily time of use matter or are charging behavior and power management after use also of equal importance? What is the role of product design? Moreover, looking at the big picture, how important can the accumulation of these effects be to create larger trends contributing to the total household energy consumption?

While previous efforts have been made to identify the determinants of the household energy consumption (e.g., see (Kavousian et al., 2013; Hori et al., 2013; Ekholm et al., 2010)), they usually focus on socioeconomic properties of households (Hori et al., 2013), appliances stock-ups (Kavousian et al., 2013) and simple considerations of consumer

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behavior (Ek and Söderholm, 2010), ignoring product-specific data including design features and consumer-product interactions. The present study strives to further explore the impact of consumer-product interactions on household energy predictions. This study also builds upon previous efforts to identify key factors of the household energy consumption by applying various supervised and unsupervised learning algorithms on the extensive and comprehensive dataset of the US Residential Energy Consumption Survey (U.S. Energy Information Administration, 2013a) that includes socio-demographics, users' behavior, product features and corresponding energy consumptions.

The rest of the paper is structured as follows. The second section provides a brief presentation of previous findings of the household electricity determinants and solutions to improve sustainable behavior regarding electricity consumption. The third section presents the data under study and the analyses that have been conducted. The fourth section provides a discussion on the findings of the study with respect to the energy policy and design considerations. Finally, the fifth section concludes the paper.

2. Background: importance of the use-phase attributes

It has been previously shown that the discrepancies in the results of LCA studies on personal computers mostly originate from the assumptions with respect to the use-phase attributes (Raihanian Mashhadi and Behdad, 2017a; Teehan and Kandlikar, 2012). While several efforts have been made to fortify LCA with simulation techniques (Miller et al., 2013; Bichraoui-Draper et al., 2015; Raihanian Mashhadi and Behdad, 2017b), which help capture heterogeneities and dynamics in the targeted systems, yet a holistic understanding of important use-phase attributes, including users' behaviors and design features, is critical for both policy makers and LCA practitioners. Consumers' use-phase behavior may play a major role in LCA of products whose usage cycle is a fundamental contributor to emissions (Daae and Boks, 2015). For a review of LCA limitations in handling uncertainties and heterogeneous systems, the reader is referred to (Reap et al., 2008b, 2008a). Moreover, for more details on the discordance in LCA results of consumer electronics, the reader may refer to (Raihanian Mashhadi and Behdad, 2017a; Teehan and Kandlikar, 2012). Despite the fact that the role of consumer behavior is acknowledged in the accuracy of the personal computer environmental assessment results, more clarification is required to identify the critical behaviors.

In addition, consumer behavior has shown to drastically affect household energy consumption (Swan and Ugursal, 2009; Seryak and Kissock, 2003). For example, it has been shown that not only the occupant behavior is substantially heterogeneous, but it also can skew the household energy consumption by 100% (Seryak and Kissock, 2003). Sekar et al. (2016) depicted that while the heavy TV watchers account for less than 15% of the population they contribute to more than 30% of the TV energy consumption. Telenko and Seepersad (2010) showed that the amount of electricity consumption of an electric kettle in its usage cycle is determined by the habitual characteristics of its users. Since, the contribution of the residential sector to the national energy consumption is significant (e.g., in the US the residential sector accounts for about 25% of the national energy consumption while in some countries this proportion is up to 50% (Saidur et al., 2007)), such behavioral considerations should not be neglected, particularly, because recent studies on the US population reveal that people tend to spend more time at home (Sekar et al.). The future energy policies should be more focused on tiered interventions.

2.1. Determinants of residential electricity consumption

Due to the importance of household electricity consumption prediction, both from the supply and the sustainable consumption perspectives, several studies have been carried out to identify the predictors of residential electricity consumption. Moll et al. (2008) conducted an analysis on the determinants of household energy use across the EU and reported that while the energy requirements were similar among the countries they studied, the determinants of energy requirement within countries were household expenditure and size. Similarly, Maréchal (2009) has recognized that social and cultural differences contribute to the differences in the consumption level across countries that are similar in income level. Tukker et al. (2010) presented a summary of insights learned from the literature about the determining variables related to the household consumption and the generated environmental impacts. Income level, household size, location and social and cultural differences were among the key factors. Sahakian and Steinberger (2011) studied household energy consumption in the context of air-conditioning in an urban megalopolis in Southeast Asia. They have highlighted the distinctions in the choice structures regarding space cooling and sustainable consumption among the different socio-economic groups.

More recent studies have also focused on appliances stock-ups and usages, as well as social interactions, as determinants of electricity consumption. Kavousian et al.(2013) claimed that in addition to weather, location and floor area, the number of refrigerators, entertainment devices and high-consumption appliances are determinants of electricity consumption. Hori et al. (2013) emphasized the linkage between social interactions and energy-saving behaviors. The knowledge gained from such studies may be used in Design for Sustainable Behavior (DfSB) frameworks. While such studies strive to incorporate social-psychological theories into sustainable design frameworks aiming to motivate consumers toward more sustainable behaviors (Tang and Bhamra, 2012; Strömberg et al., 2015; Cor and Zwolinski, 2015), they need to overcome certain challenges and limitations. For instance, Kuijer and Bakker (2015) discuss how such efforts may become product or behavior isolated and fade in the actual larger trends.

Among the previous efforts focused on residential electricity consumption analysis and demand modelling, some have studied various versions of the Residential Energy Consumption Survey (RECS) which is being used in this study. For instance, Kaza (2010) used a quantile regression approach on the RECS data and explored the effect of housing size and type, neighborhood and family characteristics. Heiple and Sailor (2008) used RECS data related to Houston, Texas for building energy profiling at spatial scales. Min et al. (2010) used regression analysis of RECS data and focused on fuel type, urban and rural households and regions. However, none of these studies focused heavily on appliances ownership, usage context, and product-user interactions. For a review of residential energy consumption predictions, the reader may refer to (Fumo and Rafe Biswas, 2015; Kavgic et al., 2010).

While the above-mentioned studies are extremely informative about the determinants of the residential energy consumption, they usually exert a high-level approach and do not provide much information at the *product-level* or about the user-product interactions. In a recent study, Hicks (2017) highlighted such effects by suggesting that the actual lifetime of the multifunctional devices determines whether or not they can improve energy consumption compared to single-use devices. Our study builds upon the current literature on household energy consumption, with the aim of providing more insights on the impact of various *product features* and different types of *user-product interactions* with a focus on consumer electronics and appliances. In the first step, a comprehensive analysis of the US household electricity consumption determinants is conducted to identify the major predictors, as well as the extent to which consumer electronics and home appliances use-phase attributes affect electricity consumption. Then, the study explores the relationship between different use-phase attributes of personal computers and their energy consumption, in order to identify the features and the behaviors that shape the personal computers usage cycle energy consumption.

3. Analysis of energy consumption

This section focuses on a two-stage analysis of the household energy consumption determinants. First, we analyze the total household energy consumption in order to find the critical features and strong predictors that should be prioritized in any product or policy design process. Second, we investigate the extent to which PC use-phase attributes can affect PC energy consumption. Such analysis is motivated by the disagreements in the LCA literature about the assumptions related to the PC energy consumption during the usage phase.

3.1. Dataset

The 2009 Residential Energy Consumption Survey (RECS) (U.S. Energy Information Administration, 2013b) data, collected by the US Energy Information Administration (EIA), have been used. The data have been imputed and have been provided in a comma-separated format by the EIA (U.S. Energy Information Administration, 2013a). EIA conducts similar survey studies every few years in order to develop energy end-use models. The survey includes socio-demographics, users' behaviors, and product design features and represents the US population.

3.2. Analysis of the total energy consumption of the household

Table 1 compares the effects of some product categories on the total electricity consumption of households (*KWH*) and presents the definition of variables and subcategories within each variable. The figure on the rightmost column illustrates the average energy consumption per each subcategory, in addition to the 95% confidence interval around the mean. As can be seen, households using separate freezers, dishwashers, dryers, televisions, computers and rechargeable devices use electricity significantly more than the groups that do not use such products.

Moreover, Fig. 1 depicts the average (with 95% confidence interval) of the total electricity consumption among households based on the age of the second household member and yearly income. Interestingly, a direct relationship between electricity and annual income is observed. Moreover, the figure suggests that the highest energy consumption occurs in households whose second member's age falls between 40 and 54 years old (*AGEHHMEMCAT2* = 9, 10 and 11). Also, single-member households (*AGEHHMEMCAT2* = −2) have a significantly lower energy consumption level compared to the rest of the categories. A more comprehensive comparison of energy consumption among different product users', as well as sociodemographic groups, is presented in the Supplementary document.

A consumer segmentation study has been conducted using all the variables of the RECS data. A partitioning around medoids (Maechler, 2017) algorithm using Gower's dissimilarity (Gower, 1971) matrix has been applied to the same data to account for the mixed type variables. The cluster analysis (Fig. 2) using average silhouette width (Rousseeuw, 1987) favored for two clusters in the data set. However, the separation based on the average silhouette width results is weak (average silhouette width = 0.14). Fig. 2 depicts the clustering results for various k (k = 2,3,4,5).

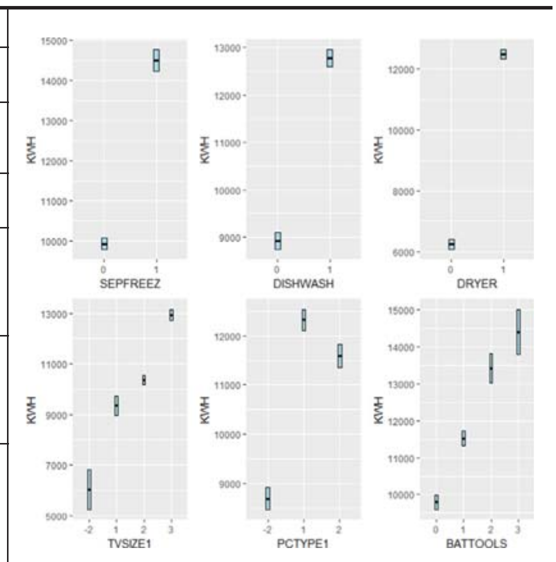
The important question to answer is that what consumer behaviors, product categories, and product designs strongly determine a household's total energy consumption? In order to answer this question, we utilize the variable set provided in the RECS 2009 survey (total 489 variables excluding the variables that are related to other energy sources) and the total actual electricity consumption of the household (*KWH*) that EIA reports based on the data from the electricity bills. The impact of different product categories has been investigated.

A Least Absolute Shrinkage and Selection Operator (LASSO) regression analysis have been carried out using all the variables to identify the important predictors of the total electricity consumption (*KWH*). *LASSO regression* (Tibshirani, 1996) is a shrinkage and variable selection algorithm for a linear regression that uses l1-regularization on the predictor coefficients. It can be used in regression cases in which a large number of attributes exist, in order to find the strong predictors in the model. *LASSO regression* is usually superior to ordinary least squares (OLS) estimates due to two reasons (Tibshirani, 1996). First, by shrinking the coefficients it compensates some bias to improve the large variance in OLS. Second, it is more interpretable because of the shrinkage of the coefficients to zero which automatically performs the subset selection of variables that needs to be done prior to any type of regression prediction. This is particularly critical in cases with large sets of predictors (here 489 variables).

Hyper-parameter tuning has been done to adjust the regularization parameter of the LASSO regression model (λ). Moreover, in order to deal with the categorical variables in the LASSO model, dummy variables were created for different levels. In addition, the variables were

Table 1
Comparison of households' energy consumption with respect to the usage of different products.

Variable	Definition	Code	Code Definition
SEPFREEZ	Separate freezer used	0 1	No Yes
DISHWASH	Dishwasher used	0 1	No Yes
DRYER	Clothes dryer used in home	0 1	No Yes
TVSIZE1	Size of most-used TV	1 2 3 -2	20 inches or less Between 21 and 26 inches 37 inches or more Not Applicable
PCTYPE1	Most-used computer - desktop or laptop	1 2 -2	Desktop Laptop Not Applicable
BATTOOLS	Number of rechargeable tools and appliances used	0 1 2 3	0 1 to 3 4 to 8 More than 8



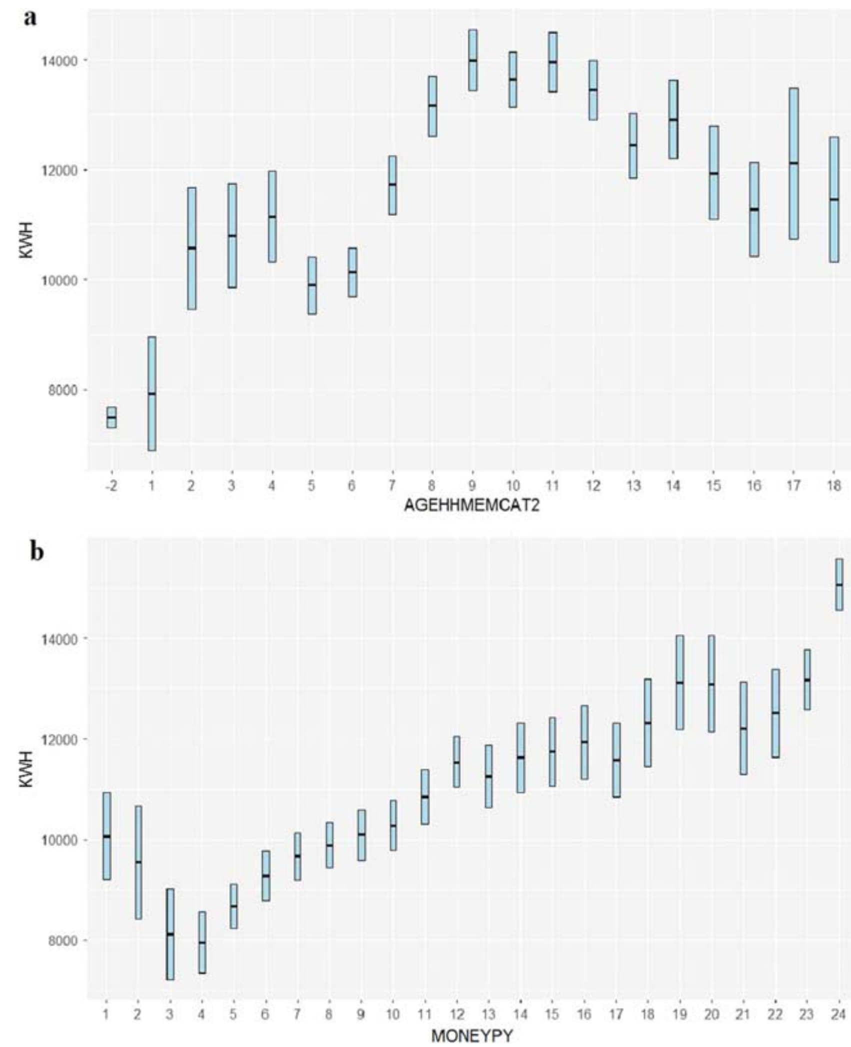


Fig. 1. Energy consumption per age of the second household member (a) and the annual income of the household (b).

centered and scaled for the LASSO model, so that the cross-variable comparisons would be accurate.

Table 2 represents the variables of the model with the highest absolute value of coefficients. Note that certain specific categories of the explanatory variables could be found to be important. For example, *FUELHEAT.5* = 1 denotes *FUELHEAT* = *5*, which means the main space heating fuel is electricity.

3.3. Analysis of the heterogeneities in the PC energy consumption

It has been mentioned that previous LCA studies of PC do not agree on the assumptions related to the electricity consumption. Moreover, the results of our analysis on the determinants of the households' electricity consumption, presented in the previous section, highlights the importance of consumers' behavior and their interactions with appliances. Therefore, an analysis of the extent to which such interactions shape PC energy consumption could provide insight to improve the corresponding assumptions in LCA. In order to estimate the PC electricity consumption, we have considered the variable *KWHOTH*, which is the EIA's estimation of the households' energy consumption for purposes excluding water and space heating and air-conditioning, to reflect the energy consumption of personal computers. In order to investigate the extent to which use-phase attributes contribute to the PC energy consumption, regression analyses have been done on 33 variables representing socio-demographics and ownership and usage of computers and their peripherals as predictors, and *KWHOTH* as the dependent variable. A description of the variables included in the study can be found in the Supplementary document (Table S1). Since the regression R^2 has found to be relatively low, two other regression algorithms, *decision tree* and *random forest*, have been utilized in order to provide insight via cross-comparison between the results of different regression models. *Decision tree* models have previously performed successfully for energy consumption predictions, producing interpretable results (Tso and Yau, 2007). Growing the decision trees tend to split the predictors with respect to the output variable. The tree then should be pruned based on optimizing a complexity parameter in order to minimize overfitting. To further develop the decision tree model, *random forest regression* has been used (Liaw and Wiener, 2002). Random forest models improve the generalization error of the regular decision tree models via bootstrapping samples and growing multiple trees, while only allowing m out of p ($m < p$) predictors to be used in each tree. This technique results in de-correlating the individual trees and building a strong regressor out of several weak models. Hyper-parameter tuning has been done for the complexity parameter of the regression tree model (C_P) (Fig. S1), predictor selection of the random forest regression model (m_{try}) (Fig. S2) and the regularization parameter of the LASSO regression model (λ). Table 3 summarizes the performance of the three models and the important variables suggested by each of them.

A closer look at Table 3 suggests that although the regression analyses identified the significant variables among the variable set we considered, the developed models do not provide high levels of

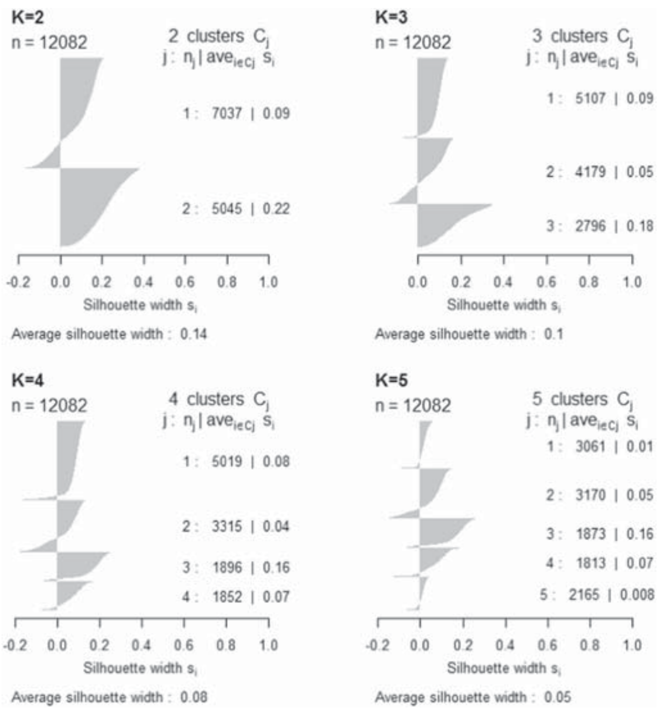


Fig. 2. Cluster analysis results on the total electricity consumption data. Silhouette analysis suggests 2 clusters.

Table 2
Summary of important variables introduced based on the LASSO regression model considering all the variables in the survey and KWH as the target variable.

Variable	Coefficient	Definition
FUELHEAT.5	1308.66	Main space heating fuel is electricity
TOTCSQFT	993.65	Total cooled square footage
FUELH2O.5	932.64	Fuel used by main water heater is electricity
SWIMPOOL.1	715.65	Swimming pool present
PELLIGHT.3	495.16	Electricity used for lighting and other appliances is paid for some other way rather than by the household or included in rent
DRYRFUEL.5	475.03	Fuel used by clothes dryer is electricity
REPORTABLE_DOMAIN.26	− 421.21	Household in California
UR.R	413.85	Household in rural areas
NCOMBATH	379.47	Number of full bathrooms
TVCOLOR	376.09	Number of televisions used
NUMTHERM	365.02	Number of thermostats
NOUTLGTNT	364.86	Number of outdoor lights left on all night
AGEHHMEMCAT2. − 2	− 349.35	Household contains one member
USECENAC.3	331.57	Central air conditioner turned on just about all summer
REGIONC.1	− 327.38	Household in northeast census region
USENG.0	316.99	Natural gas not used in home
SEPFREEZ.0	− 314.24	Separate freezers not used in home
TOTROOMS	310.40	Total number of rooms in the housing unit
FUELPOOL.5	309.56	Fuel used for heating swimming pool is electricity
PERMELEC.0	− 294.25	Built-in electric units not used for secondary space heating
NHSLDMEM	288.59	Number of Household members
R^2 = 0.651		

predictability (low R^2). This is not surprising, however. The target variable used in the model, *KWHOTH*, is the EIA estimation of electricity consumption for purposes other than water and space heating and air-conditioning. Therefore, while being the closest estimate to the PC electricity consumption provided by the data set, it also includes the energy consumption of all the consumer electronics and home appliances. In should be noted that the aim of the above-mentioned analysis has been to identify the important variables that contribute to PC energy consumption (relative to the rest of variables considered in the model), aiming to highlight the heterogeneities that should be considered when estimating the environmental impacts of personal computers usage phase electricity consumption.

All three models agree on the significance of demographics (age category), usage of computer peripherals (printers) and the number of devices used (number of PCs). Other demographic features, such as income, or device-related behaviors, such as usage time or power management choices, seem to be somewhat important regarding the energy consumption. The importance of such attributes raises the question of consumer heterogeneity and the extent to which it can affect consumer electronics energy consumption estimations. If the energy consumption of (and therefore the results of LCA) of personal computers are dependent on the users' profiles and their behaviors during the usage phase, are we dealing with the same behaviors throughout the population, or do different segments show drastically different behaviors? To answer this question, a consumer segmentation study has been carried out. Similar to the previous case, partitioning around medoids (Maechler, 2017) algorithm using Gower's dissimilarity (Gower, 1971) matrix has been used. As presented in Fig. 3, the cluster analysis suggests two clusters (K = 2) to group the data. Note that the separation is stronger (average silhouette width = 0.33 vs. 0.14) in this case compared to the case in which we considered all the variables (Fig. 2).

To further visualize the cluster analysis, Self-Organizing Maps (SOM) have been utilized. SOMs are useful tools for dimensionality reductions and investigating patterns in data. The algorithm uses an underlying artificial neural network to map the data points from a higher dimensional space to a two-dimensional grid, such that the positions and the distances on the map represent statistical relationships between the points (Kohonen, 1998). Using the SOM the correlation of variables and the relationships among variables and clusters can be visualized.

Fig. 4 illustrates two distinct groups of observations. The top left corner of the grid represents the consumers with lower income levels, relatively lower education levels, lower number of household members and less usage of personal computers. On the other hand, the bottom right corner of the grid refers to those with higher income levels, higher education, more personal computer usage and more electricity consumption. The bottom figure represents the result of a hierarchical clustering on the SOM projection, which also groups the observations into two distinct clusters. Another interesting observation is the fact that users with lower PC usage levels use mostly older devices (*PCTYPE1* = *2* which refers to desktop and *Monitor1* = *2* which refers to CRT monitors) that are more energy intensive. This compensating effect may have prevented the groups to become more distinct with respect to energy consumption.

4. Discussion

4.1. User-level attributes and user-product interactions

The review of the results of the analyses presented in the previous section reveals fruitful insights. Investigating the relationship between personal computers use-phase attributes and the corresponding electricity consumption category (*KWHOTH*) identified the significance of heterogeneity in consumer behavior on the PC electricity consumption profile. The regression analysis suggests that users' demographic properties, as well as specific habits regarding usage of the device, such as the number of devices owned, usage of peripherals (printers), daily usage and power management behaviors, have significant effects on the

Table 3
Summary of important variables introduced based on three regression models for the PC energy consumption.

Variable	LASSO	Regression Tree	Random Forest[a]	Variable Definition
NHSLDMEM	X		X	Number of household members
AGEHHMEMCAT3	X	X	X	Age category of third household member
MONEYPY	X		X	2009 gross household income
HHAGE	X		X	Age of householder
FAX	X			Separate fax machine used
INWIRELESS	X			Wireless internet in home
PCTYPE1	X			Most-used computer - desktop or laptop
PCONOFF1	X			Turn off most-used computer when not in use
AGEHHMEMCAT4	X		X	Age category of fourth household member
PCPRINT	X	X	X	Number of printers used
EDUCATION	X		X	Highest education completed by householder
NHSLDMEM	X			Number of household members
AGEHHMEMCAT2	X	X	X	Age category of second household member
NUMPC	X	X	X	Number of computers used
PCTYPE2		X		Second most-used computer, desktop or laptop
TIMEON1			X	Daily usage of most-used computer
TIMEON2			X	Daily usage of second most-used computer
EMPLOYHH			X	Employment status of householder
MONITOR1			X	Monitor type of most-used computer
PCONOFF2			X	Turn off second most-used computer when not in use
TIMEON3			X	Daily usage of third most-used computer
R^2	0.288	0.218	0.274	

[a] Top variables based on the increase in the node purity.

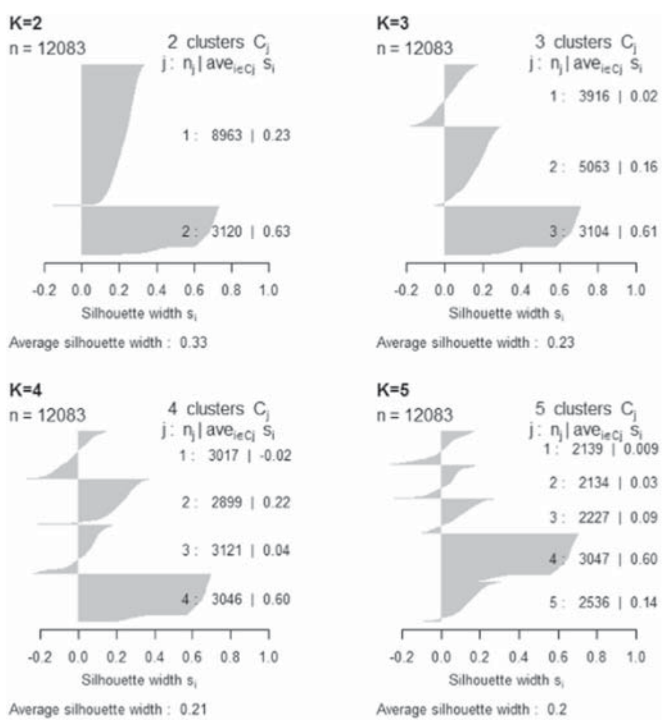


Fig. 3. Cluster analysis results on the PC data. Silhouette analysis suggest 2 clusters.

electricity consumption. The importance of such observations is highlighted by the cluster analysis, as it suggests that while studying personal computer usage, two distinct groups of users are present in the population. One group refers to the average users of personal computers and the other group reflects the segment who intensively use them. This observed heterogeneity in the PC usage behavior could be particularly critical for LCA practitioners. Since the majority of the discrepancy in the LCA results of personal computers originate from the use-mix assumptions (Raihanian Mashhadi and Behdad, 2017a), it is pivotal to consider the appropriate usage profile of the target population while conducting environmental assessment studies.

The SOM heatmaps (Fig. 4) indicate the spectrum of users. The top left corner of the grid represents the first group, while the bottom right corner of the grid represents the second group. Comparison of the heatmaps illustrates that the more intensive users own more devices (*NUMPC*) and have higher values for PC usage time (*TIMEON1* and *TIMEON2*), while showing more responsible energy management behavior (*PCONOFF1&2*) and the usage of more energy efficient devices (*PCTYPE1&2*). Note that, in the heatmaps, *PCONOFF = 1* means not applicable, *PCONOFF = 2* means no turning off the PC after usage and *PCONOFF = 3* indicates turning off the PC after usage. Therefore, the bottom right corner contains more users that actually turn off their devices after usage, compared to the top right, the bottom left and the top left (which also contains households that do not have a computer at all) corners. Similarly, *PCTYPE1&2* = 1 means not applicable, *PCTYPE1 &2* = 2 means desktop computer and *PCTYPE1&2* = 3 means laptop computer. Also, *MONITOR1* = 1 refers to not applicable, *MONITOR*1 = 2 refers to CRT monitor, and *MOITOR*1 = 3 refers to LCD monitor. Therefore, the intensive users actually utilize more energy efficient devices. This behavior compensates for the energy consumption and prevents the groups from showing more drastic differences in their KWOTH.

However, the first part of the analysis highlights the other side of the coin, particularly from the policy-making stand point. While it was shown that when conducting LCA, use-phase attributes should be considered to estimate the PC energy consumption during usage cycle, personal computers may not be major role players in contribution to the total electricity consumption of households, regardless of their high frequency of usage. First of all, the consumer segmentation study on the whole feature set indicates that the separation is much weaker than only considering PC attributes while suggesting two clusters as the optimal number of groups. This proposes that consumers' usage behavior of different devices may be completely opposite across different product categories. Meaning that, users may show intensive unsustainable behavior using one product category while displaying substantial sustainable behavior among others. Consideration of this phenomena is crucial with respect to designing energy intervention policies, because entailing a certain consumer behavior type may cause strong rebound effects on other usage profiles. Designing product-specific energy intervention policies should be considered when targeting household energy consumption. These rebound effects have been major challenges of providing effective energy intervention policies (Torriti,

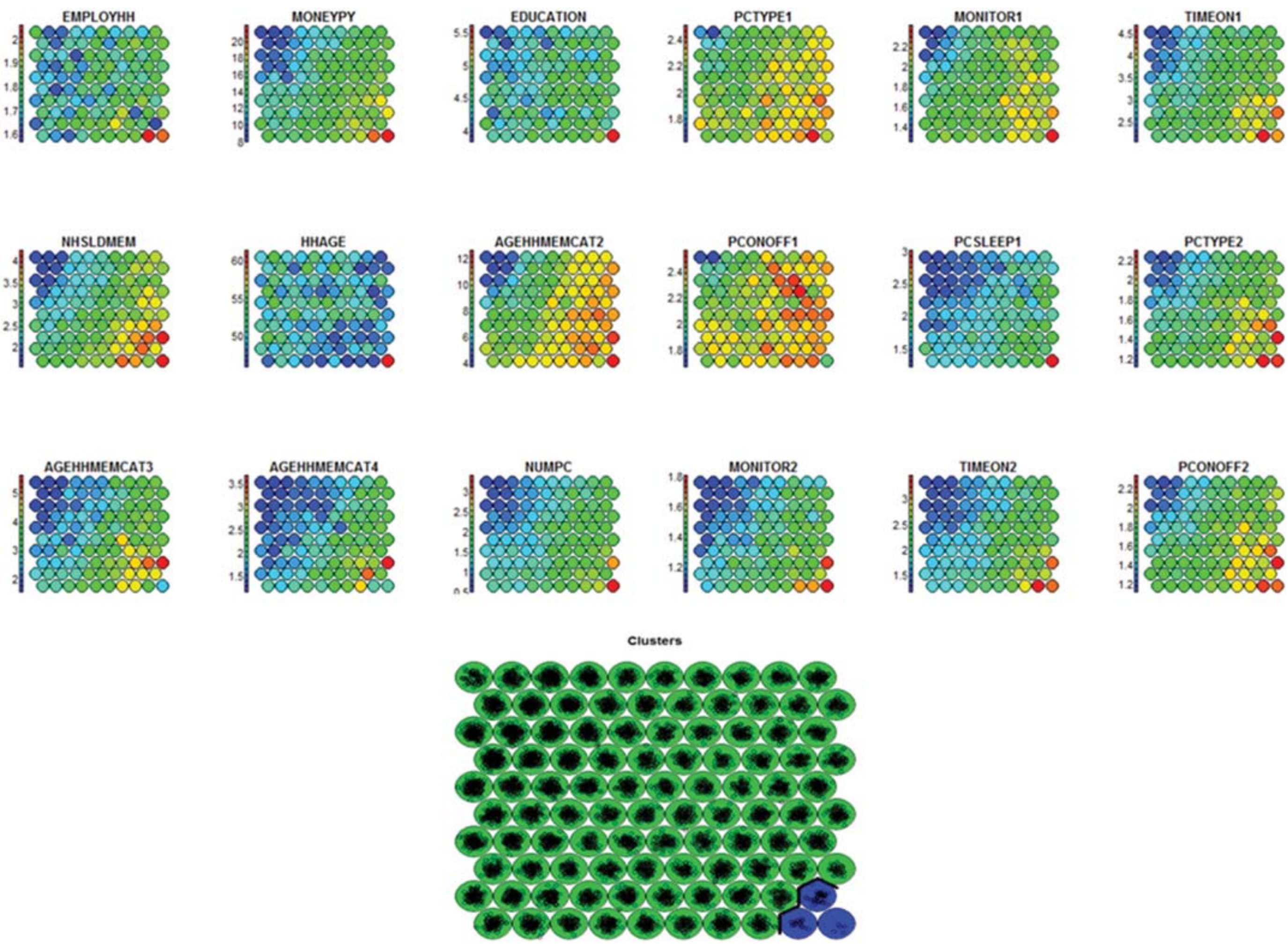


Fig. 4. SOM heatmaps of the variables in the PC energy consumption model (* variables definitions are provided in Table 1 and Table S2).

2012).

When designing energy intervention policies under budget constraints, it is critical to paint a clear view of the major predictors of household energy consumption in order to prioritize target behaviors. Table 2 summarizes the most important variables of the LASSO regression model on the total electricity consumption. A majority of the total energy consumption consists of the electricity consumed for heating water and space, as well as for air conditioning. Interestingly, in line with the previous findings (Tukker et al., 2010), location plays a pivotal role in the total energy consumption as well. Variables related to the location of the household being in California or the northeast census region were found to have negative effects on energy consumption, which may again emphasize the effect of weather conditions and the lack of need for air conditioning. Moreover, the presence of a swimming pool, the fact that the household is located in rural areas, as well as the size of the household (both physical size of the house and the number of members) increase the probability of showing significant increases in the total energy consumption. However, urban households showing a lower electricity consumption may also be reflective of the fact that urban households are usually smaller compared to their rural counterparts (Tukker et al., 2010).

Moreover, the effect of consumer behavior and the rebound effects cannot be stressed enough. Based on the variable importance information provided by Table 2, those households that are not responsible to pay for the electricity they use in their dwellings are more prone to consume more electricity, regardless of whether the dwelling is owned or rented. Also, while many large and energy-intensive home appliances like refrigerators were not found to have significant discriminant effects on the energy consumption – probably because most people use them in the same way and therefore, they have the same level of influence on the energy consumption of all households – leaving outside lightings on, which is another representation of consumer behavior, was found to be significantly important.

4.2. Product-level attributes

Returning to the effect of consumer electronics, Table 2 suggests that some of the home appliances are significantly more important compared to the rest of the electric or electronics devices that the household uses. Particularly, the number of television sets a household owns or whether or not a household uses separate freezers seem to have a significant discriminant effect on the level of electricity consumption. This is especially crucial from the policy point of view, as it has been shown that TV watching behavior may be completely segregated. Therefore, energy intervention policies aiming at promoting sustainable behavior with respect to watching television (Sekar et al., 2016) need to take into account the difference between different user types.

A cross comparison of electricity consumption among users with respect to their product features and usage behaviors has been presented in the Supplementary document (Figs. S4-S17). Some distinctions between electricity consumption of households that use certain features can be observed. For instance, households that use larger refrigerators, frost-free refrigerators or refrigerators with through-the-door water or ice capability consume more electricity on average (Fig.

S4). On the other hand, those who use products with two doors and freezer above the refrigerator relatively consume less electricity compared to users of the other refrigerator types (Fig. S4). For appliances like dishwashers, clothes washers and dryers, the usage behavior and the frequency of use are the most important factors (Fig. S8-S10). Interestingly, for most of the home appliances, the age of the device does not seem to have a major effect on the electricity consumption, unless the device is significantly old and probably not being used frequently.

A comparison between different charging behaviors (Fig. S17) also suggests substantial electricity consumption consequences, which highlights the effect of standby energy consumption (Gram-Hanssen, 2010). Furthermore, consumers' unawareness about green design polices should also be highlighted. While energy intervention policies, such as product labeling, have been introduced (Burgess and Nye, 2008) to ameliorate energy consumption, the responses in our study do not show a difference in energy consumption of households using products with Energy Star labeling compared to users of devices without them, as most of the respondents refused to answer or were unaware of the responses to questions regarding the Energy Star labeling.

Despite the fact that most of the results of the analyses favor more importance of consumer behavior compared to the product design (from the energy consumption standpoint, the way that people use their appliances seems to be more important than the technology or the design features of the products), fruitful design insights can still be achieved. The categorical variables in the RECS dataset have been converted to a binary transaction matrix in order to conduct association rule mining. Association rule mining has been previously shown to be useful in appliance association detection (Singh and Yassine, 2017). Table 4 summarizes the top informative rules related to televisions. The first rule is related to the daily watching times and is reflective of the population groups that spend extensive time periods watching TV. Meaning that those who watch TV more than 10 h per day during week days (*TVONWD1 = 5*) would also spend the same amount of time watching TV during weekends (*TVONWE1 = 5*). Two design related observations can be made. First, there is a correlation between the TV size and the TV technology. Meaning that most of the smaller sets (20 in. or less) are standard tube TVs, while most of the larger screens are related to more recent TV technologies such as plasma and projection. It is not clear whether this is due to manufacturers' policy to manufacture larger screens or is a matter of consumer preferences. Nonetheless, this has critical environmental impacts. In other words, the environmental benefits achieved by the more energy efficient technologies may be compensated by producing larger screens. Moreover, the mined rules also reveal a strong relationship between dependent products. In other words, it can be seen that users of smaller sets most likely would not use TV peripherals, such as audio systems or video players. This also suggests that the usage of consumer electronics are entangled and a comprehensive environmental impact assessment of them requires a holistic consideration of related devices.

Table 4
Association rule mining results of variables related to TV usage.

Rules	Support	Confidence	Lift	Count
{TVONWD1 = 5} = > {TVONWE1 = 5}	0.100315	0.826739	5.004342	1212
{TVSIZE1 = 1} = > {TVTYPE1 = 1}	0.082933	0.800319	1.853097	1002
{TVSIZE1 = 1} = > {DVR1 = 0}	0.085251	0.822684	1.419749	1030
{TVSIZE1 = 1} = > {PLAYSTA1 = 0}	0.090962	0.877796	1.216091	1099
{TVSIZE1 = 1} = > {TVAUDIOSYS1 = 0}	0.100066	0.965655	1.2104	1209
{TVTYPE1 = 3} = > {TVSIZE1 = 3}	0.071677	0.817753	1.962281	866
{TVTYPE1 = 4} = > {TVSIZE1 = 3}	0.044364	0.976321	2.342782	536

Variable	Variable Definition	Codes	Codes Definition
TVSIZE1	Size of most-used TV	1	20 in. or less
		2	Between 21 and 26 in.
		3	37 in. or more
		-2	Not Applicable
TVTYPE1	Display type of most-used TV	1	Standard Tube
		2	LCD
		3	Plasma
		4	Projection
		5	LED
		-2	Not Applicable
TVONWD1	Most-used TV usage on weekdays	1	Less than 1 h
		2	1 to 3 h
		3	3 to 6 h
		4	6 to 10 h
		5	More than 10 h
		-2	Not Applicable
TVONWE1	Most-used TV usage on weekends	1	Less than 1 h
		2	1 to 3 h
		3	3 to 6 h
		4	6 to 10 h
		5	More than 10 h
		-2	Not Applicable
DVR1	Separate DVR connected to the most-used TV	0	No
		1	Yes
		-2	Not Applicable
PLAYSTA1	Video game console connected to the most-used TV	0	No
		1	Yes
		-2	Not Applicable
TVAUDIOSYS1	Home theater system connected to the most-used TV	0	No
		1	Yes
		-2	Not Applicable

5. Conclusion and policy implications

The impact of consumer behavior and the heterogeneities and the uncertainties it imposes on the energy consumption predictions have been irrefutable in the literature. However, there are still many unanswered questions in these domains that should be addressed.

While most of the previous studies have focused on socio-demographics, this paper aims at providing more insights about consumer electronics and the users' interactions with them. Table 5 summarizes the findings of this study. Our study shows that while the difference in consumer behavior and the design features of consumer electronics can significantly influence their electricity consumption estimates (and therefore, their environmental assessment results), regardless of their frequency of use, their energy consumption may be faded away in larger trends while studying household electricity consumption. However, in addition to the socio-demographics, usage of certain home appliances such as TVs and freezers may play a pivotal role in discriminating a household electricity consumption compared to the others. On the other hand, the usage of such devices is substantially heterogeneous across the consumers' population. For instance, targeting certain clusters of TV watchers for energy intervention policies, instead of all average users, can drastically improve electricity consumption (Sekar et al., 2016). Our study shows that TV ownership is one of the important determinants of household energy consumption, therefore, targeted energy policy design, tiered interventions, and tiered communication methods not only can improve the TV electricity consumption but it also can improve the total household energy consumption.

Moreover, comparison of different design features among such products suggests that certain pro-environmental design decisions may actually lose impact as a result of contradicting design polices or consumer preferences. For instance, our results depict that the users' of the more efficient TV technologies are also the owners of TV sets with significantly larger screens. This factor can cancel the energy savings

Table 5
Summary of findings and their energy consumption implications.

Finding	Energy Consumption Implication
Importance of customer behavior	• Consumers' electronic products usage behavior is heterogeneous. This segregation should be considered when assessing environmental impacts of the target product. • However, the degree to which this segregation influences household energy consumption depends on the product category.
Difference in consumer behavior across different product families	• Consumers could conduct contradicting energy consumption behavior across different product categories. They may show intensive unsustainable behavior using one product category, while displaying substantial sustainable behavior among others. • Designing product-specific energy intervention policies should be considered when targeting household energy consumption.
Important home appliances	• Within the electric and electronic product categories, ownership of some of the home appliances, such as TV sets and separate Freezers, have the most discriminating effect on the household energy consumption. • This is especially crucial from the policy point of view, as it has been shown that TV watching behavior (and therefore the corresponding energy consumption) is completely segregated.
Difference in heterogeneity level of different appliances usage	• The heterogeneity in the usage of different products is not the same. While TV watching behavior is significantly segregated, this may not be true for other products such as refrigerators.
Product interdependency	• Ownership of many home entertainment devices is dependent. Therefore, this dependency should be considered in the design of any energy intervention policy targeting this product category.
Product design conflictions	• Users of the more efficient TV technologies are also the owners of TV sets with significantly larger screens. It is not clear though whether this is a design policy (newer TVs are produced larger) or a matter of consumer preferences (people purchase larger TVs if they are willing to pay for newer technologies).
Lack of consumer awareness	• Households are unaware of energy efficiency labels such as the Energy Star program and therefore, probably are not motivated to purchase appliances with more efficient energy labels.
Data scarcity	• Detailed electricity consumption data for actual household home appliances is not publically available. • Such data will help to design idiosyncratic policies for each household.

achieved due to the advancements in the technology of the TV. It is not clear though whether this is a design policy (newer TVs are produced larger) or a matter of consumer preferences (people purchase larger TVs if they are willing to pay for newer technologies). Also, users of larger TVs tend to own more home entertainment devices. This has a clear message for the policy makers that the intervention policies regarding the home appliances, and particularly, home entertainments should not be made in a vacuum and without consideration of the related devices as their usage is dependent.

Moreover, the lack of consumer awareness about their product efficiency features, as well as the rebound effects corresponding to the product and policy designs should be further investigated. Our analysis shows that a significant number of households are unaware of efficiency labels such as the Energy Star program and therefore, probably are not motivated to purchase appliances with more efficient energy labels. Therefore, we suggest more efforts being made toward energy consumption awareness education. The result of this study could benefit both LCA practitioners and product/policy designers to utilize a clearer understanding of use-product relationships and their effects on energy consumption.

Future work should also investigate the role of multifunctional products in changing the user-product interactions and their corresponding energy consumptions. Moreover, future RECS surveys may be utilized in order to investigate the consumers' usage profiles and their likelihood of adopting different energy intervention policies such as smart meters. Note that, currently, the detailed electricity consumption data for actual household home appliances is not publically available. Independent surveys or the smart-meters data can be used to increase the accuracy of household energy estimates in the future. Such data will help designing not just tiered energy policies but idiosyncratic policies for each household.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.enpol.2018.03.059.

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