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Behavioral patterns and profiles of electricity consumption in dutch dwellings

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ABSTRACT

In EU member states, the consumption of electricity per dwelling has remained more or less constant, although the consumption of large appliances has decreased considerably in the last 2 decades. This stabilization is caused by the increased ownership, usage and consumption levels of Information, Communication and Entertainment (ICE) appliances. This paper aims to analyze electrical appliance use in the Dutch housing stock, and identify behavioral patterns and profiles of electricity consumption. The analysis is conducted by applying descriptive, correlation, and exploratory factor analyses on data collected from 323 dwellings in two neighborhoods in the Netherlands. Our results show that behavioral patterns could be found based on actual occupant behavior of lighting and appliance use, especially depending on household activities like cooking, (personal) cleaning, etc. Behavioral profiles could be determined based on household and dwelling characteristics, i.e. household size, income, education, dwelling type, age, hours of working outside. The 4 profiles set up in this research are explained as 'family,'' techie,' 'comforty,' and 'conscious.' These profiles showed statistically significantly differences in terms of their electricity consumption levels.

1. Introduction

Residential buildings consume 23% of the electricity in the Netherlands [1]. ODYSSEE-MURE project reports that, in European Union (EU) countries, although the consumption of large appliances has decreased considerably between 2000 and 2012 (Fig. 1 (left)), increasing ownership and use of appliances and larger homes push the electricity consumption up by about 0.4% per year, per household [2]. Household electricity consumption in the Netherlands has followed a similar pattern to the one of EU (Fig. 1 (center) and (right)). While the efficiencies of washing machine, dryer, dish washer, refrigerator, and freezer have immensely improved and their use remained similar, thus reducing their overall electricity consumption; the ownership, usage time and power of computer, printer, TV, DVD, and other personal electronic devices, electric oven, microwave oven, kettle, and similar have gone up, thus increasing their overall electricity consumption [3].

These statistics point to the importance of the influence of occupants' ownership and use of lighting and appliances, and systems on the electricity consumption in dwellings. Several studies have claimed that households can achieve more energy savings by changing occupant behavior [4–8]. Therefore, it is important to analyze the share of occupant behavior in energy consumption in detail. More research on the issue is needed; however, there are several reasons to why this is difficult, some of which are the retrospective methods of data collection by the energy companies, the assumed usage patterns of systems and appliances in most calculation tools, the uncertainties in collecting and analyzing data, the issues of energy performance gap [9].

In existing research, behavioral factors related to heating energy consumption have been identified, as well as the household and dwelling characteristics that are related to these behavioral factors [10–12]. The studies point to the potential of energy consumption reduction, if energy efficiency policies are articulated according to different household profiles [10,13]. The ability to make accurate predictions of the electricity usage of households is an important issue not only for policy but also for energy companies, and will become even more important with the emergence of smart electricity grids [9].

In the Netherlands, various studies have been conducted with the aim of identifying behavioral patterns related to higher levels of heating energy consumption and/or to energy-saving attitudes, however there is no such study for electricity consumption behav-

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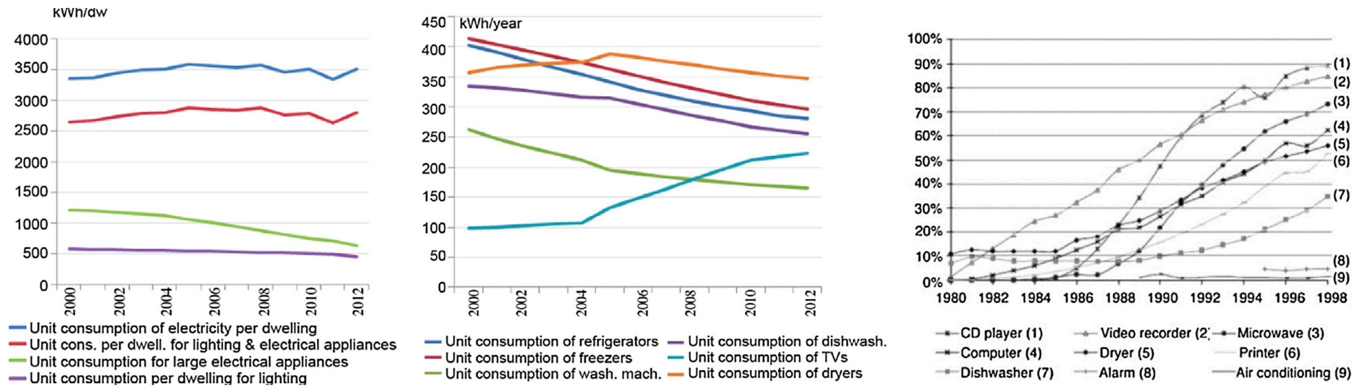

Fig 1. Average electricity consumption per dwelling in EU (left), Electricity consumption of large electric appliances and TV (middle), Ownership of appliances in the Netherlands (right).

ior. Our work contributes to the literature by providing detailed information about electricity consumption behavior, and by determining the patterns and profiles of users. Existing research suggests that occupant behavior is more visible in newer than in older dwellings [12]. Accordingly, our sample might be appropriate to study energy consumption behavior, because our data is collected on dwellings built after 1995. In addition, it seems that electricity consumption behavior relates far less to the physical characteristics of a house compared to that of heating energy consumption, therefore routines of electrical appliance use might provide us with more articulated insights into occupant behavior. This research could contribute to the efforts, such as Wright's [14], that focus on encouraging individuals and households towards more energy efficient behavior.

In our previous paper [9], we reported on the variance in the total electricity consumption and researched the determinants of it in dwellings in the Netherlands. We found that using the parameters of duration of use of general, hobby, food, and cleaning appliances, household size, gas consumption, years of residence, number of bedrooms, dwelling type, number of showers, dryers, washing machine loads, and outside working hours, we could explain 58% of the variance in electricity consumption. In this paper, we use the same sample and data we used in our former work. Our first aim is to further analyze the behavioral aspects of household electricity consumption in the Netherlands. For this, we statistically define behavioral patterns and profiles of lighting and electrical appliance usage in relation to electricity consumption. Further, we identify the household and building characteristics, along with clues about lifestyles and attitudes, which provide the evidence to build behavioral profiles.

Our data is collected by a survey from 323 dwellings in the Netherlands on [1] appliance ownership, [2] presence in rooms, [3] activities of cooking, shower and bath, cleaning, [4] household composition and dwelling characteristics. Existing research focuses either on behavioral patterns using the first three groups of data, or on behavioral profiles using the last group of data. Our second aim is to link the patterns and profiles using the behavioral factors as a common denominator, found by factor analysis, which could help to better define occupant behavior in calculations and/or simulation programs.

2. Literature and research questions

Behavioral patterns and profiles have been defined with household characteristics [15–17], variables related to lifestyle [10,16–19], variables related to values, motivations, attitudes [11,20–23], and variables related mainly to routines and habits [24–26].

Abreu et al. [27] adopted a profile recognition method to identify user profiles of electricity consumption. The electricity consumption data was collected with 15 min intervals from 15 houses over a period ranging from 3 months to 1 year. Clusters were then created using profile recognition over this quantitative data. Households completed questionnaires to self-report their daily routines, and the usage profiles that were obtained with this 'qualitative' data were compared with the 'quantitative' clusters for validation. The study showed that approximately 80% of household electricity use can be explained through repeated daily routines.

Widen et al. [28] produced load profiles over 5 existing time-use data sets collected in Sweden in 1996, 2006, and 2007. The number of people included in the surveys varied from 13 to 431 in 5 to 139 households. The activities of people were reported next to measurements of electricity and hot water consumption. The data resolution varied from 5 min to 60 min. The activity profiles created with reported data were compared to the ones with measured data. The results showed that household behavior profiles regarding cooking, washing, lighting, TV, PC and audio use could be modeled using time-use data of electricity consumption. However, hot water consumption was not successfully modeled. It was clear that electricity consumption was closely related to occupancy and the grouping of appliances according to specific activities, and this could be a good way to modelling electricity consumption.

Coleman et al. [29] monitored 14 households in the UK between March 2008 and August 2009. The dwellings were selected by snowball sampling, and they had over 220 individual appliances. This research found that usage profiles varied widely between households in both size and make-up, and the average (mean) household electricity consumption from ICE (information, communication and entertainment) appliances equated to around 23% of average whole house electricity consumption (median 18%). Of this, standby power modes accounted for 11.5 kWh, which was around 30% of ICE appliance consumption and around 7% of average whole house electricity consumption. Coleman et al. found that desktop computers and televisions were the appliances that consumed the most electricity, with most of their consumption occurring during the active power mode. Audio appliances, printers, and other play and record equipment were significant end-uses, largely due to standby consumption. In one of the households, computers that were continuously active and connected to the internet were also found to be responsible for a large portion of the sample's electricity consumption.

O'Doherty et al. [30] analyzed the determinants of domestic electrical appliance ownership in the Irish housing stock. A survey conducted in 2001 and 2002 on 40,000 houses revealed that newer and more expensive houses had more appliances, but also more Energy Saving Appliances (ESA). Years spent at the same address

Table 1
Appliance use: Ownership and duration (minutes per day).

CONTINUOUSLY USED APPLIANCES

App	M	Max	Min	SD
Internet (wireless router)	1	3	0	.56
Telephone	1	8	0	1.13
Fridge	1	2	0	.35
Freezer	1	2	0	.56

CLEANING APPLIANCES

App		M	Max	Min	SD
Dryer	N	1	1	0	.47
	D	19	130	0	28.18
Iron	N	1	3	0	.27
	D	17	150	0	23.78
Vacuum cleaner	N	1	3	0	.39
	D	16	90	0	23.85
Wash. machine	N	1	1	0	.18
	D	50	90	0	D

FOOD PREPARATION APPLIANCES

App		M	Max	Min	SD
Coffee machine	N	1	3	0	.47
	D	32	840	0	76.10
Toaster	N	1	2	0	.53
	D	3	85	0	7.11
Electric grill	N	1	2	0	.46
	D	14	255	0	23.77
Microwave oven	N	1	2	0	.36
	D	10	85	0	13.51
Water heater	N	1	2	0	.35
	D	13	85	0	14.54
Cooker hood	N	1	2	0	.42
	D	30	180	0	32.84
Dishwasher	N	1	2	0	.43
	D	42	240	0	45.33

ICE APPLIANCES

App		M	Max	Min	SD
TV	N	2	6	0	.89
	D	238	900	0	161.87
PC	N	1	5	0	.82
	D	153	2880	0	309.12
Laptop	N	1	6	0	1.08
	D	190	3060	0	369.92
Stereo	N	1	4	0	1.07
	D	104	720	0	147.9
DVD player	N	1	3	0	.68
	D	21	360	0	40.92

(N: number of appliance; D: duration of use; M: mean; SD: Standard Deviation).

decreased the ownership of ESA. Likewise, householders under the age of 40 had the most appliances but also the most ESA. Dwellings located in dense urban areas had more ESA. Lastly, more suburban, terraced houses had the least ESA. O'Doherty et al.'s groups were determined based on household and dwelling characteristics together, however no relationship was researched between these groups and electricity use.

Genjo et al. [31] used cluster analysis to group 505 Japanese households in 1996. This research did not necessarily try to identify the specific characteristics of the groups according to their electricity consumption, but some distinct findings of their research were that the possession of electrical appliances was a reflection of residents' lifestyle, larger and multi-function appliances were popular among Japanese households, and economic affluence had a strong influence in grouping the households according to appliance use and electricity consumption.

In the Netherlands, research on behavioral profiles regarding energy consumption focus on heating energy. Even if this research is only on electricity consumption, it is insightful to see and compare ours' to the studies that analyzed heating energy consumption in terms of the household characteristics, behavioral factors, patterns and profiles. Raaij and Verhallen [10] identified 5 profiles of energy behavior among 145 households in the Netherlands: Conservers (higher education, smaller household size), Spenders, Cool, Warm (oldest group) and Average. They found no differences regarding income and employment parameters. The research of Groot et al. [16] and Paauw et al. [17] developed 4 profiles of energy consumption: convenience/ease (comfort important, no interest in economic savings, energy, or the environment (EEE)); conscious (comfort important, interest in savings for EEE), cost (awareness of economy and hence energy and the environment); and climate/environment (concern for EEE). Raaij [10], Groot [16] and Paauw's [17] work found statistically significant differences in energy consumption among their groups. Vringer et al.'s work [23] grouped households in the Netherlands according to income, age, education and household size. Guerra Santin's research [12] revealed 5 groups (spenders, comfort, affluent-cold, conscious-warm, conscious-cold) according to the use of heating and ventilation systems, household appliances, household and dwelling characteristics. She did not find statistically significant differences between the behavioral profiles and patterns in terms of energy consumption.

Table 2
Specific appliances owned by a percentage of households.

Appliance name	Number of households	Percentage of households in the sample
Electrical cooker	107 houses	36%
Gas furnace	92 houses	31%
Induction cooker	87 houses	30%
Solarium	24 houses	8%
Jacuzzi	8 houses	3%
Sauna	5 houses	2%
Waterbed	13 houses	4%
Aquarium	10 houses	3%
Terrarium	13 houses	4%
Close-in-Boiler	28 houses	9%
Extra heating	14 houses	5%
Ventilator	45 houses	15%
Air Conditioning	13 houses	4%
Video camera	64 houses	21%
Video games	60 houses	21%
Home cinema	80 houses	27%
Hard disc recorder	69 houses	23%
Video recorder	98 houses	33%
Other appliances	33 houses	20%

Existing research on behavioral patterns of electricity consumption focus on parameters related to 'attitude,' 'motivation,' 'lifestyle,' 'household composition,' 'appliance possession,' 'household and building characteristics.' Methodologically, behavioral patterns and profiles are produced either using continuous data on actual behavior (for example [32–34]) or by clustering behavioral profiles based on cross-sectional data about household characteristics (for example [12]), and some by combining both (for example [27–29]). In existing research, relationships between behavioral patterns, and household and building characteristics have rarely been investigated. Our work contributes to the literature by [1] using (partially) continuous data on actual behavior as well as household and dwelling characteristics, [2] driving behavioral factors, patterns, and profiles, and linking them to each other as well as looking for their relationship with electricity consumption.

There are several studies that focus on identifying the behavioral patterns and profiles for heating energy consumption, but none on electricity consumption behavior in Dutch housing stock. Determining behavioral profiles could lead to more accurate prediction of electricity consumption in dwellings, better planning for the targeted energy saving measures, and helping energy companies for more precise calculations.

3. Methodology

3.1. Research framework and methods

In this paper, we defined occupant behavior as the presence in a space, the use of lighting and appliances, and the activities at home that directly cause electricity consumption. Figs. 2 and 3 display the research framework and methodology. We started with an analysis of the appliance use in the database. Through a descriptive analysis, we reported the maximum, minimum and mean levels of ownership and use of appliances in the database (Section 4.1, Table 1). Secondly, we researched the effect of occupant behavior on electricity consumption in the database, through correlation analysis between the behavioral, household and dwelling characteristics, occupant presence, electricity consumption (Section 4.2, Table 3).

In step three, we conducted exploratory factor analysis to determine the factors underlying behavior of electricity consumption (Section 4.3, Table 4, Fig. 4). Behavioral factors are clusters of variables that constitute the drivers of behavior. Following the factor analysis, the household variables were dichotomized according to their scores for each behavioral factor (below the mean = 0, above the mean = 1), which meant that each household had a '0' or '1' score for each factor, and each household had a string composed of '0's or '1's. Categorizing the households according to the common strings, the behavioral patterns were defined (Section 4.3, Table 5, Fig. 5).

In step four, the behavioral factors were used in correlation analysis, in order to find out the relationship between behavioral factors and household and dwelling characteristics. The households were distributed into groups based on the correlation outputs, these groups were the user profiles (Section 4.4, Tables 6 and 7, Fig. 6). Lastly, we looked for the relationship between the behavioral factors, patterns and the behavioral profiles (Section 4.5, Fig. 7). Following, the relationship between behavioral patterns, profiles and energy consumption was determined (Section 4.6, Fig. 8).

3.2. Data: explanation of data, outliers, transformed variables

The study data was collected via a survey in two districts (Wateringse Veld and Leidsche Rijn) in the Netherlands only in the Winter of 2008. The database of 323 cases covered a range of topics in the form of a questionnaire, with regard to household characteristics (size, composition, years of residence in the dwelling, changes in household composition in the previous year), individual characteristics (age, education, occupation, hours spent outside the home), economic characteristics (income, ownership, electricity tariff), presence (number of people and duration of occupation in each room), dwelling characteristics (type, number of rooms, function of rooms), appliance use (number of domestic appliances, number of appliances in the living room, standby appliances, chargers, duration of use, appliance labels, sizes), and lighting devices (number, type).

3.2.1. Outliers

Outliers were analyzed and variable frequencies were checked to see how many of the variables could be used for statistical analysis. Out of the 323 cases in the database, the electricity consumption data for seven were exceptionally high, probably because the occupants did not actually record the electricity consumption in the past year but wrote the meter reading. Twelve questionnaires were returned blank. These 19 cases were therefore excluded from the database, leaving a final sample size of 304.

3.2.2. Missing data

Some of the data in the database were insufficient to be included in the statistical analysis, hence were not included, namely:

- The number of weeks when nobody is at home;
- Whether the electricity and gas meters were checked regularly
- Appliance labels

3.2.3. Transformed variables

The 'electricity tariff' can take two values in the Netherlands: [1] single tariff consumption – one daytime and evening rate on weekdays and weekends [2], double tariff consumption – two different rates, one for during the day and another for evenings, nights and weekends. The electricity consumption data obtained from the survey were based on kWh values. Some cases had single tariff consumption records (9%), and some had double records (91%). To obtain a final variable for electricity consumption, a check was performed to determine whether a single or double electricity tariff made a difference. No significant correlation was found, so the single and the double tariff recordings were computed to one electricity consumption category.

The respondents retrospectively reported their hourly presence at home and in different rooms, during the week. This data was transformed into total hourly presence in rooms during the morning, the day, the evening, the night and all day.

In terms of the number of appliances owned, and the duration of use of the appliances, we conducted two transformations. First, in order to obtain a total figure of duration of use, we multiplied the number of appliances in the house with the duration of use of each. Secondly, we added up the total duration of use of appliances per function of group. We created 4 groups with functions of 'Information Communication Entertainment (ICE)', 'Cleaning', 'Food preparation' and 'Continuously used' appliances (Table 1).

Following, the results of the study are reported in 4 Sections: 1. Descriptive analysis on appliance ownership and use; (2) the impact of occupant behavior on electricity consumption; (3) behavioral factors, patterns, and profiles of electricity consumption; as well as (4) the relationship among them.

4. Results

4.1. Appliance use behavior

The mean, maximum and minimum number of each appliance in the sample, and their duration of use (minutes per day) were reported and categorized in 4 groups, i.e. 'Information Communication Entertainment (ICE)', 'Cleaning', 'Food preparation' and 'Continuously used' appliances (Table 1). On average, there were 21 appliances in a house and 5 of these appliances were in the living room. The average electricity consumption in our sample was 3058.57 kWh/year.

On average, there was a fridge, a freezer, a wireless internet router, and a telephone that worked continuously in each house. As for cleaning appliances, a dishwasher and a dryer, a vacuum cleaner and an iron were used in each house in the sample. ICE appliances

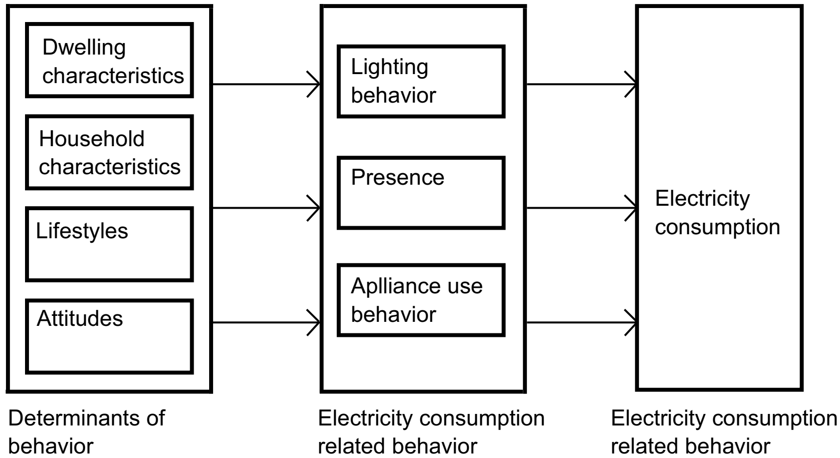

Fig. 2. Research framework.

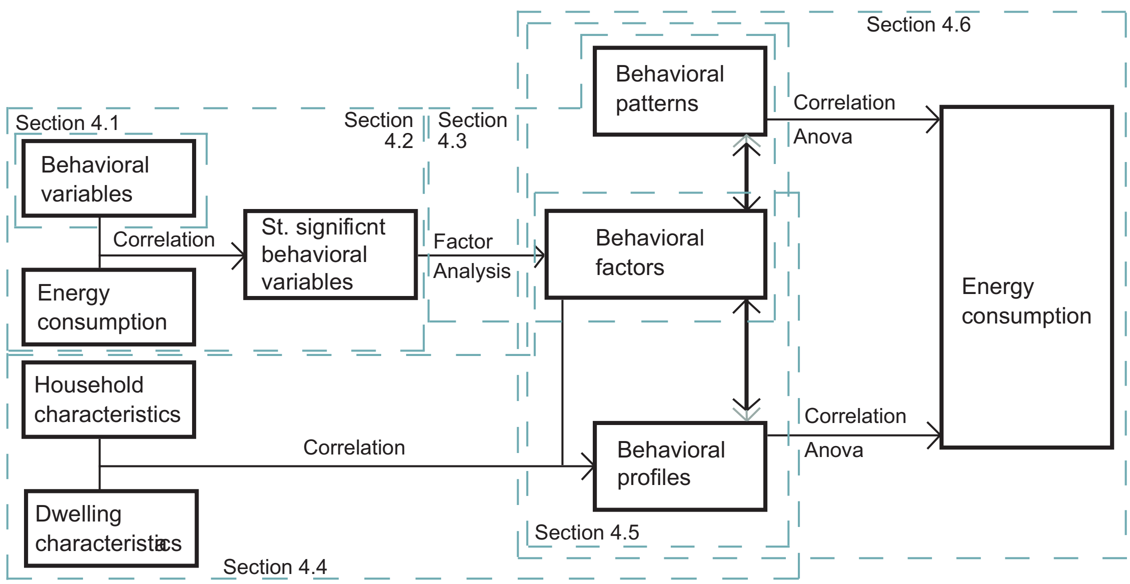

Fig. 3. Research methodology.

were 2 TVs, a PC, a laptop, a DVD player, and a music player. Lastly, a dishwasher, a microwave oven, a toaster, a grill, a water heater, a coffee maker, and an exhaust hood created the set of food preparation appliances present in each house on average, in our sample. Except for continuously used, all the appliance groups we set up refer to a specific function/activity in the house. Besides, only 'food preparation' appliances is a category that relate to a specific room (kitchen) in the house.

Some of the houses also owned specific appliances. The ownership and/or the use of these appliances were not high enough, so we did not include them in the factor analysis. The number of appliances they possessed were reported in Table 2.

4.2. Effects of occupant behavior, household and building characteristics on electricity consumption

Correlation analyses were carried out to determine the relationship between occupant behavior and electricity consumption (Table 3). The first set of variables considered were the use of household appliances. ICE (Information-Communication-Entertainment) appliances appeared to have the most significant influence on electricity consumption ($r = 0.98^{***}$), which was followed by the total duration of use of household cleaning ($r = 0.13^{**}$), food preparation ($r = 0.09^{*}$) and continuously used ($r = 0.02^{*}$) appliances. In the survey, respondents were also asked to report their behavior on the weekly use of appliances, and the total use particularly in the living room, however these variables did not seem to be correlated to electricity consumption, hence they were omitted from the analysis.

Secondly, the influence of the use of stand-by and battery charged appliances, and the ownership of energy saving, non-energy saving lamps, and PV/solar panels were analyzed. The most significant impact on electricity consumption was by halogen lamps ($r = 0.17^{**}$). The use of battery charged ($r = 0.22^{*}$), and stand-by ($r = 0.15^{*}$) appliances had a positive influence on electricity consumption, while energy saving lamps ($r = -0.04^{*}$), and PV/solar panels had a negative one. The ownership of PV/solar panels did not, in fact, significantly correlate with electricity consumption, however this parameter was included in the factor analysis, to set up behavioral patterns and profiles.

The use of mechanical ventilation was not found to be correlated with electricity consumption, but the use of shower ($r = 0.23^{**}$),

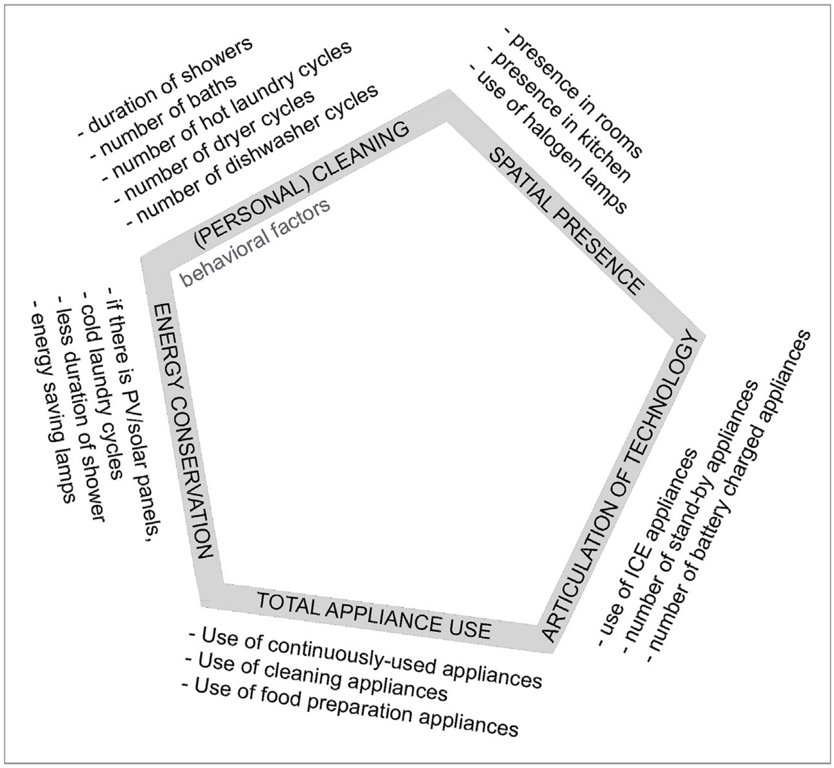

Fig. 4. Behavioral factors and the variables that determine these factors.

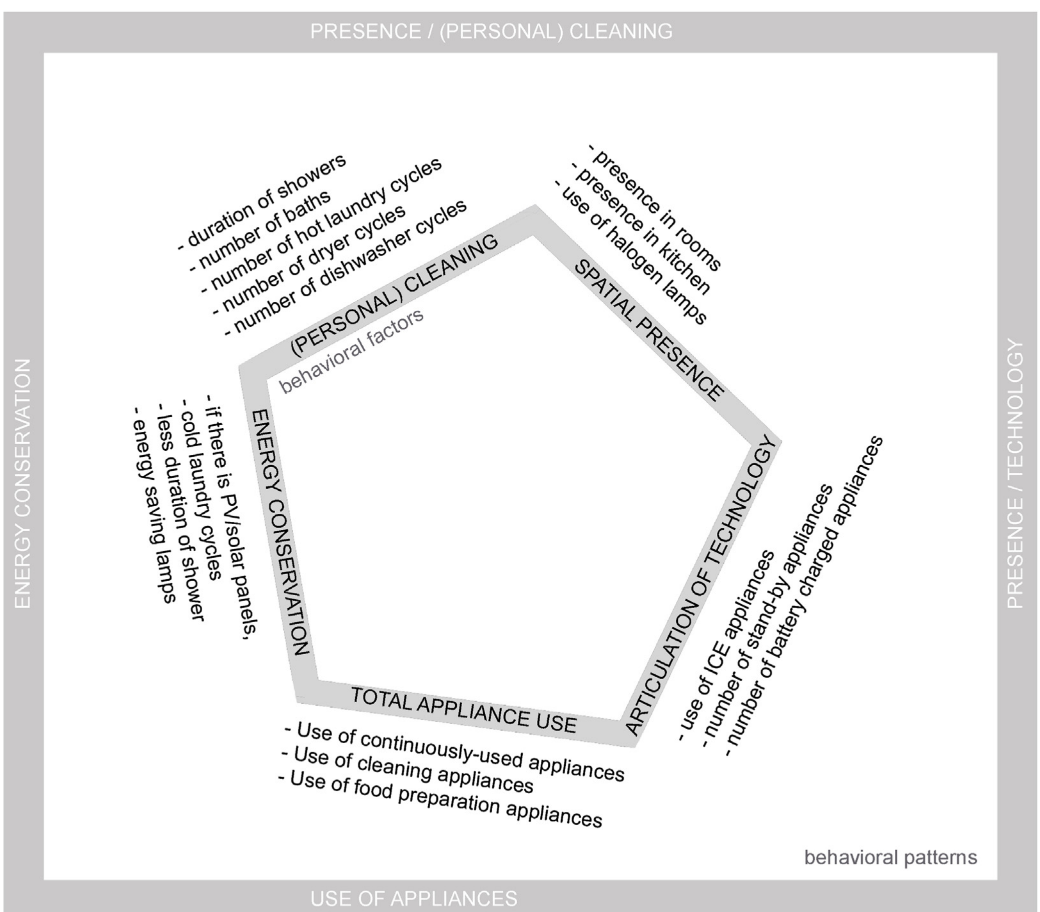

Fig. 5. Behavioral factors and behavioral patterns.

Table 3
Descriptive and correlation analysis of household and dwelling characteristics, occupant behavior and electricity consumption.

Variable		Definition	Number of cases	Mean and Standard Deviation	Correlation Electricity Consumption
Household appliances	Continuously used	Total daily duration of use of continuously used appliances	H: 118 L: 164	M: 4895.58 SD: 2414.45	0.02* N: 282
	Food preparation	Total daily duration of use of food preparation appliances	H: 107 L: 175	M: 238.77 SD: 176.26	0.09* N: 282
	Household cleaning	Total daily duration of use of household cleaning appliances	H: 99 L: 183	M: 116.98 SD: 105.88	0.13** N: 282
	ICE	Total daily duration of use of ICE appliances	H: 89 L: 193	M: 1457.92 SD: 1376.59	0.98*** N: 282
	Stand-by	Total number of stand-by mode of appliances	H: 120 L: 174	M: 2.75 SD: 3.06	0.15* N: 294
	Battery charged	Total duration of battery charged appliances	H: 65 L: 239	M: 67.5 SD: 140.11	0.22* N: 304
	Energy saving lamps	Number of energy saving lamps	H: 104 L: 190	M: 5.89 SD: 6.05	−0.04* N: 294
	Halogen lamps	Number of halogen lamps	H: 117 L: 177	M: 14.52 SD: 10.07	0.17** N: 294
	PV/Solar panel	Presence of PV or solar panels	Y: 46 N: 248	M: 0.15 SD: 0.36	−0.79 (r:0.23) N: 294
	Hot wash cycles	Total weekly number hot laundry cycles	H: 62 L: 230	M: 0.94 SD: 1.50	0.19** N: 292
	Showers	Total weekly duration of showers in the household	H: 122 L: 182	M: 139.21 SD: 135.28	0.23** N: 304
	Bath	Total weekly number of baths in the household	H: 90 L: 214	M: 1.33 SD: 2.59	0.14* N: 304
Presence	Room 1	Total hours of presence in room 1 (weekdays/all day)	H: 167 L: 109	M: 13.61 SD: 5.35	0.22* N: 294
	Room 2	Total hours of presence in room 2 (weekdays/all day)	H: 111 L: 165	M: 5.18 SD: 4.08	0.31* N: 294
	Room 3	Total hours of presence in room 3 (weekdays/during the day)	H: 20 L: 259	M: 0.97 SD: 0.20	0.12* N: 294
	Living room-Kitchen	Total hours of presence in living room-kitchen (weekdays/morning)	H: 85 L: 188	M: 2.52 SD: 2.11	0.21** N: 294
	Bathroom	Total hours of presence in bathroom (weekdays/morning)	H: 91 L: 182	M: 1.28 SD: 1.17	0.18** N: 294
Household characteristics	Household size	Household size	H: 115 L: 183	M: 2.53 SD: 1.17	0.38** N: 301
	Years of residence	Years of residence in the same house	H: 151 L: 136	M: 5.38 SD: 3.13	−0.16* N: 287
	Age	Presence of age group 6–65 in the household	Y: 214 N: 84	M: 3.00 SD: 0.75	−0.72* N: 298
	Income	Monthly household income	H: 171 L: 113	M: 3.99 SD: 1.04	0.13* N: 284
	Education	A member of the household has university or higher education	Y: 32 N: 270	M: 5.46 SD: 2.03	−0.03 (r:0.22) N: 302
	Working outside	Hours spent outside the house	H: 178 L: 124	M: 23.60 SD: 14.03	0.97 (r:0.13) N: 302
Dwel. C.	Dwelling type	Type of dwelling (corner/self-standing house, top floor apartm.)	Y: 46 N: 255	M: 2.95 SD: 1.05	−0.23* N: 301
	Bedrooms	Number of bedrooms	H: 85 L: 218	M: 1.84 SD: 0.97	0.26** N: 303

Notes on cases and abbreviations:
H: Number of cases that have higher value than the mean value.
L: Number of cases that have lower value than the mean value.
Y: Number of cases that have positive response to the question.
N: Number of cases that have negative response to the question.
Household income: H means higher (L for Lower) than 56 000 Euros.
Age: Mean value of age groups in the sample is "16–65 years old." However, for categorizing households in terms of electricity consumption, we expanded the group to (1) '6–65 years old;' and (2) 'children and elderly.'
Dwelling type: The mean value of 2.95 means row house is the common typology. For categorizing households in terms of electricity consumption in our analysis, we re-categorized this variable according to how much the dwelling might be receiving day light. Thus, we created two groups (1) corner, or self-standing houses, or top floor flats; and (2) row house, or ground or middle level houses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

bath ($r = 0.14^*$) and the number of hot laundry cycles ($r = 0.19^{**}$) were. Showers were calculated in terms of the total duration of showers per week in the household, and bath in terms of total number of them per week in the household.

Presence in rooms (other than the living room) were positively correlated with electricity consumption. The correlation analysis showed that the presence in room 1 ($r = 0.22^*$) and room 2 ($r = 0.31^*$) all day, room 3 ($r = 0.12^*$) during the day, and living room/kitchen

Table 4
Factor scores and communalities (principle components analysis).

Variables	Components' factor scores					Communalities
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
Continuously used	0.588					0.677
Food preparation	0.509					0.527
Cleaning	0.468					0.645
ICE		0.721				0.631
Stand-by		0.493				0.525
Battery chargers		0.624				0.676
Energy saving lamps					0.429	0.704
Halogen lamps			0.530			0.754
PV/Solar panel					0.515	0.552
Hot wash cycles				0.448		0.755
Dryer				0.522		0.742
Dishwasher				0.562		0.677
Showers				0.577	0.325	0.695
Bath				0.432		0.589
Room 1			0.487			0.491
Room 2			0.660			0.573
Room 3			0.406			0.602
Living room-Kitchen			0.617			0.605
Bathroom			0.657			0.617

Rotation method: Varimax with Kaiser Normalization (for more explanation on the rotation method, see reference 35).
Factor scores < 0.4 are suppressed.

Table 5
Distributions of cases (N) and strings according to factors, and Derivation of behavioral patterns.

Name of pattern	Factor 1 Total appliance use	Factor 2 Articulation of technology	Factor 3 Spatial Presence	Factor 4 (Personal) Cleaning	Factor 5 Energy conservation	Number of cases that constitute a string
1. Appliance use	1 1 1	1 0 1	0 1 0	1 0 1	1 0 0	21 24 23
2. Presence/ Technology	1 1 1 1	1 1 1 1	1 1 0 0	1 0 1 0	0 1 0 0	25 22 26 21
3. Presence/ (Personal) Cleaning	1 1 1 1	1 0 1 0	1 1 1 1	1 1 1 1	0 1 0 0	19 23 18 22
4. Energy conservation	1 1	0 1	0 1	0 0	1 1	18 20

Table 6
Correlations between household and dwelling characteristics and behavioral factors.

Household and dwelling characteristics		Factor Score 1	Factor Score 2	Factor Score 3	Factor Score 4	Factor Score 5
		Total appliance use	Articulation of technology	Presence	(Personal) Cleaning	Energy Conservation
Dwelling type (corner/ free-stand/top floor)	Pearson Correlation	−0.18	−0.07	–	−0.03	−0.04
	Significance (2-tailed)	0.03	0.38	–	0.05	0.05
Number of bedrooms (other than living room)	Pearson Correlation	−0.17	0.31	–	0.08	0.10
	Significance (2-tailed)	0.06	0.00	–	0.03	0.24
Years of residence in the same house	Pearson Correlation	0.01	−0.03	–	0.00	0.03
	Significance (2-tailed)	0.93	0.68	–	0.92	0.70
Household size	Pearson Correlation	−0.16	0.36	–	0.17	−0.11
	Significance (2-tailed)	0.05	0.06	–	0.02	0.02
Presence of children or elderly	Pearson Correlation	0.13	−0.19	–	0.14	0.04
	Significance (2-tailed)	0.15	0.09	–	0.01	0.60
Education level (highest level in the household)	Pearson Correlation	−0.01	0.01	–	−0.10	−0.03
	Significance (2-tailed)	0.89	0.05	–	0.26	0.04
Hours spent outside the house for work	Pearson Correlation	0.09	0.10	–	0.08	−0.05
	Significance (2-tailed)	0.31	0.03	–	0.02	0.05
Income level	Pearson Correlation	−0.50	0.11	–	0.09	−0.01
	Significance (2-tailed)	0.05	0.02	–	0.04	0.90

Table 7
Behavioral factors and behavioral profiles.

Factor	Name of Factor	Correlated Household/Dwelling variable
Factor 1	Total appliance use	- (Older couple) - Middle-ground floor dwelling - Lower income - More work outside - Household size (<2)
Factor 2	Articulation of technology	- Number of bedrooms - Work at home - Higher income - Household size (=>2)
Factor 3	Spatial presence	–
Factor 4	(Personal) Cleaning	- Number of bedrooms (>2) - Household size (>2) - Work at home - Higher income - Young household
Factor 5	Energy conservation	- University education - Household size (<2) - Work outside - Corner/top floor house

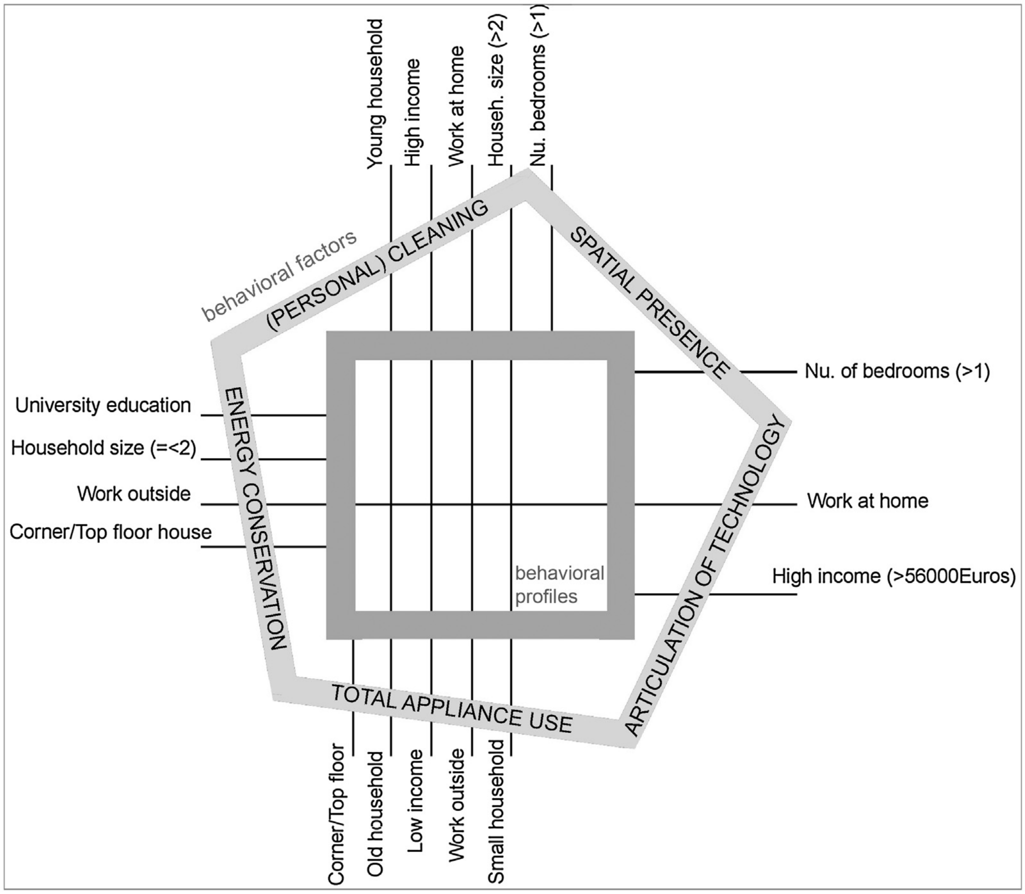

Fig. 6. Household/dwelling characteristics, behavioral factors, and profiles.

(r = 0.21**) and bathroom (r = 0.18**) in the morning were positively and significantly correlated with electricity consumption.

4.3. Behavioral factors and patterns

A factor can be described with its measured variables and their relative importance to that factor [35]. The relationship among different variables in a database can be described using factor analysis, by exploring the factors that help to identify the related behaviors. We used exploratory factor analysis to identify behavioral factors underlying electricity consumption. We used the variables that were significantly correlated to electricity consumption (Table 3). However, some of the variables that were not significantly correlated to electricity consumption were still included in the analysis, considering that they might reveal further about the behavioral patterns.

Accordingly, 19 variables were used for the factor analysis. To start with, we checked if the factor analysis was suitable for our sample: The correlation significance and the coefficient values were checked between the different variables. Majority of the significance values were smaller than 0.05 and coefficient values were lower than 0.9, which meant that there was reasonable factorability, hence none of the variables were eliminated from the analysis. The determinant value was 0.00239, which was greater than 0.00001, therefore multicollinearity was not a problem for the data. Next, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, and Bartlett's test of sphericity were controlled. The KMO value was 0.73, and Bartlett's test was highly significant ($p < 0.000$) showing that factor analysis was appropriate to analyze our sample. Our sample size was greater than 250, we had less than 30 variables, and most of their communalities after extraction were around 0.7, as well as their average communality was 0.67 (which was greater than 0.6), therefore we retained all factors that have Eigen values above 1 (See [35] for a definition, and more explanation on KMO measure, Bartlett's test of sphericity, and Eigen value in factor analysis).

Based on each variable's primary score on each factor, the factor scores were created for the factors. Table 4 displayed the analysis results in terms of the variables defining each of the five factors, as well as the factor loading matrix and their communalities. The initial Eigen values, i.e. degree of variation in the total sample created by each factor, displayed that the first factor explained 16.29% of the variance in electricity consumption, the second 15.23%, the third 13.79%, the fourth 9.00%, and the fifth 7.84%, creating a cumulative of 62.15%. Factors 6–19 were able to explain around 3–4% of the variance each. Accordingly, the first 5 factors were chosen to use further in the study. These factors were named as: 'total appliance use,' 'articulation of technology,' 'spatial presence,' '(personal) cleaning behavior' and 'energy conservation' (Fig. 4).

Accordingly, Factor 1 was merely about the total duration of appliance use in the dwelling and comprised of the continuously used, food preparation, and cleaning appliances. Factor 2 was about the use of Information, Communication and Entertainment (ICE) appliances, and the use of stand by and battery charged appliances. This factor implied a more technology and device oriented lifestyle, as well as home-office working preferences. Factor 3 related to the presence of the occupants in the rooms, in the kitchen/living room and the bathroom, and the intensive use of halogen lamps. Factor 3 pointed to the relationship between spatial use at home and electricity consumption. Halogen lamps emphasized the less

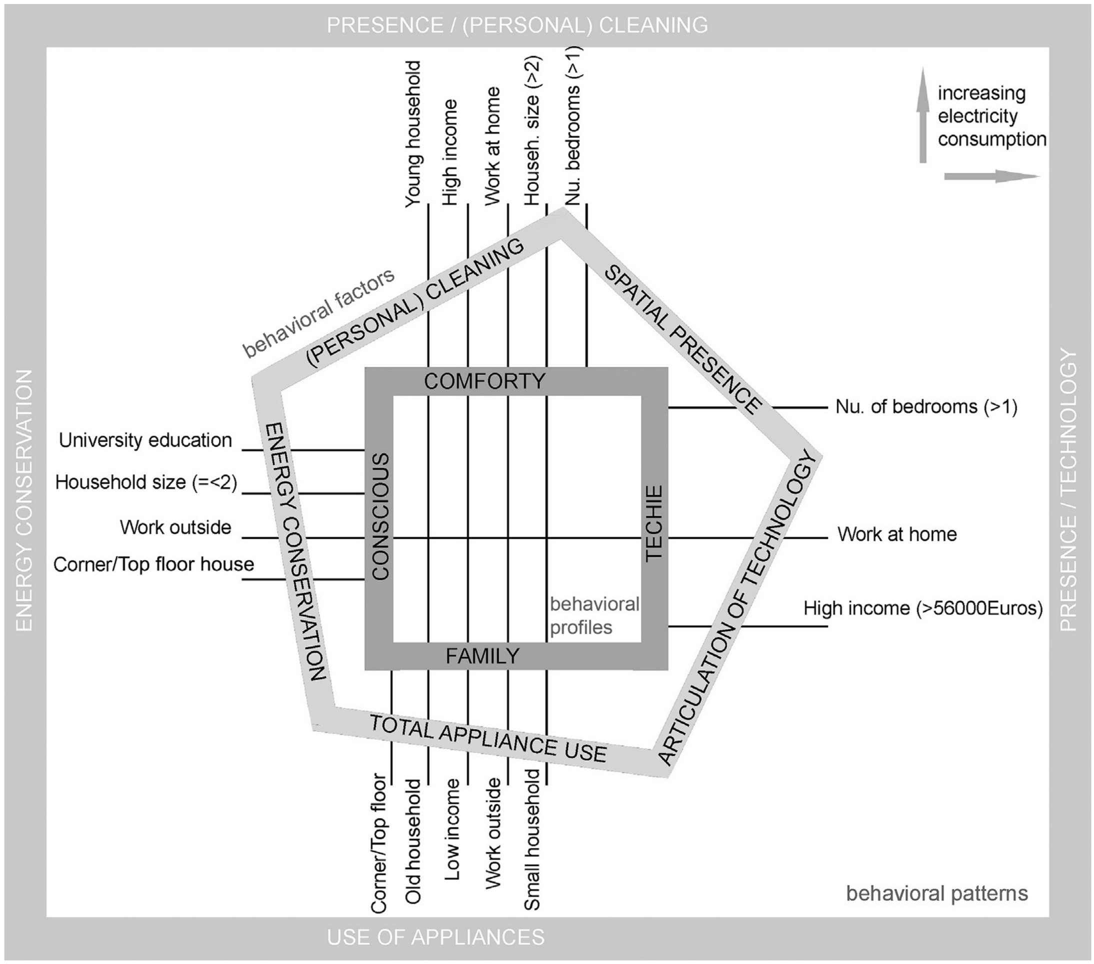

Fig. 7. Relationships found between household/dwelling characteristics, behavioral factors, patterns, and profiles.
Notes: Outer square/Edges = behavioral patterns. Center pentagon/Edges = behavioral factors. Inner square/Edges = behavioral profiles. Lines = household/dwelling characteristics (to the bottom and left characteristics that are related with less electricity consumption; to the top and right characteristics that are related with more electricity consumption are distributed.)

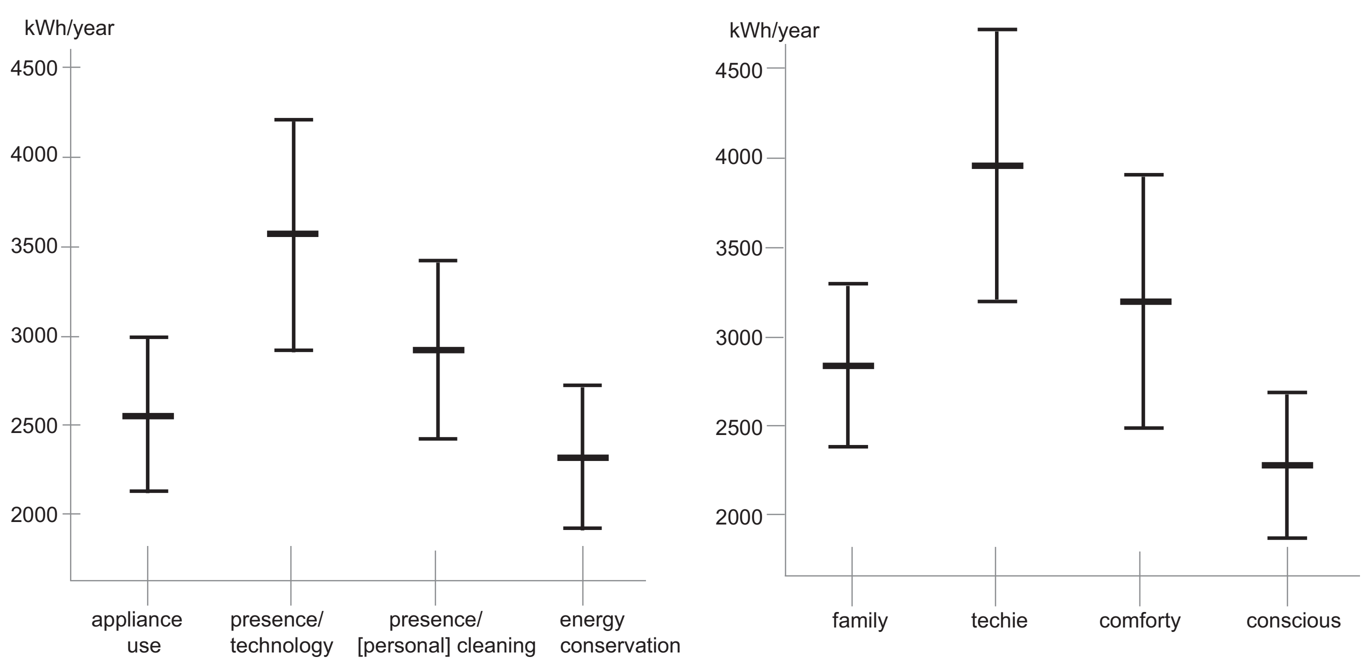

Fig. 8. Mean and 95% Confidence Interval (CI) for electricity consumption in kWh/year for each behavioral pattern (left) and for each behavioral profile (right).

energy conscious attitude against everyday life. Factor 4 related to the intensive laundry and personal cleaning habits. The number of hot washes, the use of dryer and dishwasher, as well as the duration of showers, and the number of baths point to the significance of the influence of cleaning habits on electricity consumption. Factor 3 and 4 also hinted at the relationship between occupant comfort and electricity consumption. Factor 5 related to less use of electricity. The variables that defined this factor were the ownership of PV/solar panels, energy saving lamps, and the laundry habits, where the ownership of PV/solar panels, energy saving lamps, as well as the decreasing number of dryer and hot washing cycles had a negative influence on electricity consumption.

To determine the behavioral patterns, first we dichotomized the factor scores of the cases in our sample. We did this by comparing each case's factor score to the sample's mean factor score obtained from the factor analysis (if above = 1, if below = 0). Then we repeated it for the five factors. Through this, the five dichotomous scores for each case in the sample, i.e. each household, created a string. The clustering of all strings revealed thirteen categories (Table 5).

Afterwards, these categories were clustered once more, according to the correlation between the behavioral variables that compose the factors and electricity consumption (see Table 3 for the correlation analysis). Eventually, thirteen strings were organized into 4 patterns (Fig. 5): Pattern 1: (Appliance use), Pattern 2: (Presence/Technology oriented), Pattern 3: (Presence/Comfort oriented), Pattern 4: (Energy conservation). Table 5 showed the behavioral patterns, the factors, and the distributions of the strings for each behavioral pattern and factor.

4.4. Behavioral factors and profiles:Household and building characteristics related to behavioral factors

In order to determine the behavioral profiles in the sample, we analyzed the behavioral factors in terms of their correlation to the household and building characteristics. (Table 6). We saw that spatial presence was not attached to a certain household and/or dwelling characteristic, however it complemented profile 2 and 3.

Analyzing Table 6, we found the household profiles of 'family,' 'techie,' 'comforty,' and 'conscious,' which were explained further within the descriptions of the profiles in the next paragraphs, and in Table 7, Fig. 6.

The results showed that the households that had high correlation values for factor 1: 'appliance use' were mostly young couples, except the few cases of the elderly. These households had the average behavior, both in terms of ownership and usage of continuously used, food preparation and cleaning appliances. They lived on ground or middle floor apartment or row house, which influence the natural light level in the house (hence the electricity consumption). The households had slightly lower income in some cases, compared to the other profiles. We called this profile as 'family.'

The household variables that related to factor 2: 'articulation of technology' had higher education level, higher income level, and in some cases, lower hours of working outside. Variables related to household composition did not appear correlated with this factor, but this profile had young single or couple household. One or both members of the household probably had a flexible working schedule, and possibly freelancing and/or working at home. The higher education and less hours of working outside was potentially related to the higher use of ICE appliances, stand-by and battery charged appliances. This household type was also related to factor 3 'spatial presence,' i.e. bedroom 3 (label 3 refers to the extra bedroom, or extra function of the bedroom other than sleeping) and bathroom. The use of bedroom 3 during the day confirmed working at home or home-office configuration. The use of bathroom in the morning might be related to shower and other personal cleaning behavior, however the factor of 'personal cleaning' was not found correlated with this profile. We named this profile as 'techie.' This group also had the largest number of hard disc recorders, video cameras and video recorders, which were not included in the analysis because of their small amount in the sample.

The variables which were related to Factor 4 ((personal) cleaning behavior), were dwelling typology (corner or freestanding), number of bedrooms, and a household profile of higher income level, bigger household size, and less hours of working outside. This group lived in larger houses with more than one bedroom, one or more children, and possibly one of the parents or both parents-part time stayed at home. This group came forward with its intensive use of appliances that related to dwelling and/or household cleaning, i.e. duration of showers, number of baths, dishwasher use, number of hot laundry cycles and dryer loads. In addition to Factor 4, this group was also related to Factor 3, presence in bedroom 1 and 2, which complemented the correlation with the variables of the number of bedrooms and working less hours outside, and presence in living room and kitchen. This group also used more halogen lamps, which points to less interest in energy saving. We named this group 'comforty.' This group had the largest ownership of induction and electricity cooker, waterbed and air conditioning, video games and home cinema, which were not normally included in the analysis because of their relatively small number in the entire sample.

This household profile related to Factor 5 'energy conservers,' which meant more use of energy saving lamps, and ownership of PV and/or solar panels, however these parameters did not appear significantly correlated with the factor. The household profile had less use of shower compared to other profiles, and it used less of dryer and hot laundry cycles, which related to Factor 4 '(personal) cleaning behavior.' This household profile had higher education level, worked more hours outside the house, had smaller household size, and lived in top floor apartment or corner house in some cases. The profile did not include a significantly correlated income parameter, but it had more income than profile 'family,' and less income than profile 'techie' and 'comforty.' We called this group as 'conscious.'

4.5. Relationships between behavioral patterns, profiles, and factors

Fig. 7 showed how the behavioral factors, patterns, profiles, and characteristics were related to each other. The behavioral patterns formed the outer layer, the behavioral factors formed the middle pentagon, and the behavioral profiles the inner square. The outer square represented the behavioral patterns. As top and right meant more use of electricity, the left and bottom meant less use of electricity. The middle pentagon showed the behavioral factors, i.e. total appliance use, articulation of technology, (personal) cleaning, and energy conservation. The behavioral patterns and factors seemed to be consistent, except for the factor 'presence,' which appeared both within (personal) cleaning and technology patterns. When electricity consumption and underlying behavioral factors are considered, the patterns of 'presence/technology' and 'energy conservation' seemed to oppose, as well as ' (personal) cleaning' and 'use of appliances.'

Household profiles of 'conscious' and 'techie' seemed to oppose, when the household and dwelling characteristics related to the behavioral factors were taken into account. For instance, conservers worked more hours outside compared to techies, and seemed to live in dwellings that get more day light. Techies had more household income. Both groups had high education, although only for conservers this variable was significantly correlated with the behavioral factors. Similarly, 'comforty' and 'family' opposed with each other. 'Comforty' was of younger households, who had higher income and higher number of children, spent more time at home and had bigger houses. 'Family' was older, smaller in household size and income, and spent less hours at home in general.

4.6. Relationships between behavioral patterns, behavioral profiles, and electricity use

The correlation analysis between behavioral factors and electricity consumption revealed that factor 1 (appliance use) was correlated with electricity consumption $r = 0.11$, $p < 0.05$; factor 2 (articulation of technology) by $r = 0.35$, $p < 0.00$; factor 3 (presence) was not significantly correlated with electricity consumption ($r = 0.14$, $p < 0.15$); factor 4 (personal) cleaning by $r = 0.37$, $p < 0.00$; and factor 5 (energy conservation) was significantly correlated with electricity consumption ($r = 0.13$, $p < 0.05$). These factors were used to define behavioral patterns.

For determining the differences in electricity consumption for each behavioral pattern, we conducted a one-way Anova test, where we found statistically significant differences ($r = 0.17$, $p = 0.02$). Both the statistically significant differences among behavioral patterns, and the similarities between our results with those of the literature showed that our research might be used further for research on electricity consumption and occupant behavior. Fig. 8 showed the energy consumption for each behavioral pattern (left).

Following, we looked at the behavioral profiles in relation to electricity consumption (Fig. 8 (right)). 'Family' had a high score for appliance use, 'techie' (technology oriented singles/couples who also worked at home) had a high score for articulation of technology and presence, 'comforty' (large families with high preference for comfort, showers, baths, dryer, etc.) had a high score for presence and (personal) cleaning, and 'conscious' (singles or couples with high education and working outside) for energy conservation (PVs, energy saving lamps, etc.). We found statistically significant differences among the four profiles in terms of electricity consumption ($r = 0.19$, $p = 0.02$).

5. Discussion

In this paper, we aimed to analyze in detail the behavioral aspects of household electricity consumption in the Netherlands. In this section, we present a discussion [1] on the appliance ownership, use and daily life; [2] on the results of factor analysis, i.e. the behavioral factors, patterns and profiles, and their relationship with electricity consumption; [3] on the comparison of our results with the existing research; and [4] on methodology.

5.1. Appliance ownership, use and daily life

In terms of ownership of appliances, every household owning a dryer, a separate freezer, and 6 battery charged appliances is a remarkable result. Presence in rooms/at home tells us about the times of the day that the appliances are used. In general, it could be said that most appliances, except for ICE are used in the morning (07:00–09:00), and the evening (18:00–20:00).

In our sample, every household has on average 2 TVs, 1 desktop computer, 1 laptop, 1 stereo system and 1 DVD player. Some households have 1 TV and 1 laptop per person. The total daily hours spent watching TV is 4 h on average, PC use per day is approximately 2 and a half hours, and laptop use 3 h. This suggests how central TVs and computers are to our lives. TVs are the most important electricity consumers at home, the energy efficiency of which haven't been improved as well as the other appliances. When we think of this together with the number of battery charged appliances, we could say the possession and use of ICE appliances will be very important for policy efforts in reducing electricity consumption in future.

As for cleaning appliances, a dryer is used 2 times per week and a washing machine 5 times. These numbers show that almost every item of clothing is worn only once before it is washed. When this is considered together with the 17 min use of the iron per day and the once or twice showers per person per day, it tells us about the occupations and/or the intense cleaning and comfort preferences of the households.

In terms of food preparation appliances per household (on average), the fact that there is a freezer in continuous use tells us about food storing/eating habits. Perhaps less fresh food is being consumed and/or households might always be preserving food for winter/summer. The grill and microwave oven being used 24 min in total per day suggests that the main meals consist of easy-to-prepare food. Lastly, a dishwasher is used 42 min per day on average, which means that either the dishwasher is used on the quick cycle every day, or the long cycle nearly 4 times a week.

5.2. Behavioral Factors/Patterns/Profiles

Using exploratory factor analysis, we found the behavioral factors as total appliance use, articulation of technology, spatial presence, (personal) cleaning behavior, and energy conservation. In consistence with the behavioral factors we found the 4 behavioral patterns as the use of appliances, presence/(personal cleaning), presence/technology, energy conservation. Following, the household and dwelling characteristics were included in the analysis, and the behavioral profiles were revealed as 'family', 'techie', 'comforty', and 'consciouss'.

Here we saw that the behavioral factor of spatial presence appeared in two behavioral patterns, i.e. cleaning and technology. While the use of ICE appliances created enough factor score to relate to a separate behavioral factor and pattern, the behavioral factor of presence appeared in two different behavioral patterns ((personal) cleaning and technology). The positive or negative behaviors of (personal) cleaning and use of halogen or energy saving lights also lead to two different patterns ((personal) cleaning and energy conservation).

By defining household characteristics in relation to behavioral factors, and the relationship between behavioral factors and patterns, one could determine the associated behavioral factors and behavioral patterns of a household. For instance, if a household is part of the 'techie' profile, we could expect a high score for 'articulation of technology' and 'presence at home,' which means working/being present high hours in the rooms, and using a lot of technological devices, including ICE appliances, stand-by, and battery charged appliances.

The higher or lower values of household size, income, education, working outside, number of bedrooms, and dwelling type were found to be related to different behavioral factors. For instance, the 'comforty' profile had bigger household size, higher income and number of bedrooms compared to 'family,' while it had lower working outside hours. The 'conscious' profile was found to have more hours of working outside, smaller household size, and higher education, compared to 'techie,' and was found to live in a house that gets more day light. The profile 'conscious' didn't necessarily correlate to income, but it had more income than profile 'family,' less income than 'comforty.' In our sample, considering the electricity consumption, the behavioral profiles did not relate to particular household stereotypes such as single, couple, elderly, etc., but to variables such as working hours, household size, education, and income.

5.3. Comparison with literature

Our results were similar to those of Widen et al. [28]: Electricity consumption is closely related to occupants' presence. Besides, appliance use based on specific activities like cooking, washing, lighting, TV and PC use could be a good way to model occupant behavior and electricity consumption, and the related profiles. In our research, we found that the use of ICE appliances (articulation of technology) determined a behavioral pattern on its own. Coleman et al.'s research [29] also pointed to the significance of ICE appliances: "computers and TVs during the active power mode, and audio appliances, printers, and other play and record equipment during standby consumption are significant end-users (23% of electricity consumption).Äccording to O'Doherty et al. [30] householders under the age of 40 had the most appliances but also the most energy saving appliances (ESA). In our sample, the two groups had the most number of appliances were young singles, couples or families, which complied with the results of O'Doherty et al. Lastly, Genjo et al.'s [31] analysis found that economic affluence had a strong influence in grouping the households according to electricity consumption. Income was one of the household characteristics that we used to determine the behavioral profiles, as well.

In the Netherlands, the research on behavioral profiles regarding energy consumption focus on heating energy, but still they are insightful to compare to our work in terms of their findings. Raaij and Verhallen [10] identified 5 profiles of energy behavior as conservers, spenders, cool, warm and average, and the related household characteristics as household size, education, and age. Groot et al. and Paauw et al. [16,17] developed 4 behavioral profiles based on comfort, interest in energy savings, and awareness of economy. Vringer [23] grouped households in the Netherlands according to income, age, education and household size. Lastly, Guerra Santin's research [12] revealed 5 groups according to the use of heating and ventilation systems, household appliances, household and dwelling characteristics. The variables of household size, education, age, comfort, and income were also those that we used in setting up the behavioral profiles in our sample. We didn't look into behavioral attitudes like interest in energy saving or awareness of economy. In terms of the profiles defined, 'conservers,' 'family,' and 'comforty' are the behavioral profiles found in literature, and visible in our results, as well. It might be interesting to look deeper into these profiles, since they might reveal more about the common underlying aspects of behavior that relate to similar electricity and heating energy consumption behaviors.

5.4. Methodology

Technological advances and decreasing hardware prices enable new research to utilize smart meters and other continuous data collection methods (for instance [32–34]). Research that works with this kind of data uses analysis tools like profile recognition (for instance [27]), time use analysis and load modeling [28,36], eigen decomposition (for instance [37]) and Markov chains (for instance [38]). Our research employed data collected by a questionnaire, therefore most of the data is cross-sectional, except for the behavioral data (presence, use of appliances and systems) that was collected based on a weekly calendar. In this kind of methodology, collected cross-sectional data on behavior is modelled by tools like cluster (based on cases) and factor analysis (based on variables). In this research, we worked with factor analysis. Further research could combine these two methodologies, confirming each other's results, as well as providing more insight into occupant behavior and electricity consumption relationship.

In terms of the limitations of this research, because our data is collected with a questionnaire, even if the questions on presence and behavior are detailed on a weekly basis, respondents might have filled in the information based on remembering their habits, but not actual behavior. This could be discussed as a limitation on the one hand, and as a successful approach on the other hand [24–26]. Secondly, our data is collected from two Venex neighborhoods (satellite towns) in the Netherlands, where education and economical levels of households are quite homogenous. Even if the representation of these characteristics in our sample is in line with the Dutch averages, the homogenous distribution of the variables be the reason for them to come up as not-significant determinants of occupant behavior. Thirdly, the influence of Hawthorne effect [39] must be mentioned, where the survey respondents' awareness of the goal of the survey might have directed them to fill-in the questionnaire different than the reality.

6. Conclusions and future work

This research aimed to analyze in detail the appliance use in the Dutch housing stock, and define behavioral patterns and profiles of electricity consumption. We analyzed survey data collected from 323 dwellings in the Netherlands on appliance ownership and use; presence; cleaning; household and dwelling characteristics.

First, a descriptive analysis was conducted on the variables related to ownership of appliances, their use, presence, and household and dwelling characteristics, and electricity consumption. We created 4 groups with 'ICE', 'Cleaning', 'Food preparation' and 'Continuously used' appliances. As a second step, correlation analysis was conducted to see the relationship between variables related to occupant behavior and electricity consumption. The outputs of this analysis were used to realize a factor analysis revealing the underlying factors of behavior. Accordingly, we found total appliance use, articulation of technology, presence, (personal) cleaning, and energy conservation as the behavioral factors of electricity consumption. Afterwards, based on the behavioral factors, we defined the behavioral patterns (appliance use, technology/presence, (personal) cleaning/presence, energy conservation). Lastly, we looked for correlations between behavioral factors and household, and dwelling characteristics, from which we found the behavioral profiles (family, techie, comforty, conscious). In the next step, we considered the relationship between behavioral factors, patterns, profiles and electricity consumption. We found statistically significant correlations between different behavioral patterns, as well as between different behavioral profiles in relation to electricity consumption.

In the Netherlands, relationships between behavioral patterns, household and building characteristics in relation to electricity consumption have hardly been investigated. Our work adds to the research by using actual behavior data as well as household and dwelling characteristics, and by driving behavioral factors, patterns, and profiles, and linking them to each other as well as looking for their relationship with electricity consumption.

Determining behavioral profiles could lead to more accurate prediction of electricity consumption in dwellings, as well as planning the targeted energy saving measures, and helping energy companies for better calculations. Considering that occupant behavior might be more visible in the newer dwellings, and that behavior might be revealed more precisely by analyzing 'electricity' consumption, this research might provide more detailed and articulated input on occupant behavior to research and policy, which focus on motivating/encouraging individuals' and households' towards more energy efficient behavior.

In terms of future work, we could think of the following directions:

- Every household owning 1 wireless internet router in continuous use and 6 battery charged appliances should be researched further in terms of a mobile 24/7 lifestyle and the addiction to being 'connected'.
- Existing studies showed that large part of household energy use can be explained through repeated daily routines. As follow up work, the causes of daily routines of behavior that are related to electricity consumption should be researched further.

- In relation to the point above, collecting and analyzing longitudinal data on behavior is necessary to confirm the findings from cross-sectional data to overcome methodological limitations.
- Personal cleaning behavior appeared to be an important factor both in the patterns and profiles in this research, which suggests a comfort related aspect of energy consumption. This aspect needs to be investigated in terms of the motivations, frequencies, and consequences of the particular behavior.
- Further research is also needed on the actual household appliance inventory, their powers and energy ratings in much larger samples. This research could be extended by specifically investigating the use of ICE appliances, food preparation (especially freezer, dishwasher) and (personal) cleaning (use of shower and bath, use of dryer and washing machine) based on specific activities like cooking, cleaning, or hobbies. In addition, the stand-by and on/off functions and battery charged appliances must be studied more in detail.

Understanding the occupant behavior will be even more important in future for efficiency of electricity use. Findings from this research could help improving design of objects, systems and architectural design in order to reduce energy consumption by occupants at home.

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