From energy behaviours to lifestyles: Contribution of behavioural archetypes to the description of energy consumption patterns in the residential sector

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Abstract

Many studies emphasise that household energy behaviour is a key determinant of domestic energy consumption, but few highlight the fact that they are fundamentally associated with lifestyle and housing context. Existing studies that address this issue perform clustering but use only restricted datasets and rarely describe the associated households and housings. In this study, we develop an original methodology to construct behavioural archetypes from qualitative and quantitative variable, opening up perspectives for a wider and more transparent use of survey data. The clustering is performed with 35 variables describing hygiene, food, heating, lighting and leisure practices and housing occupation. Seven homogeneous archetypes of domestic behaviours were constructed from a database describing 1363 households in the Ile de France region. The analysis of the related household profiles shows that the behavioural archetypes are related to specific housing contexts and energy consumption levels. The work also invites to stand back from the variables usually mobilized, such as income or tenure status, and used for the conception of targeted policies. In particular, the work highlights the value of the household life cycle in constructing a typology suitable for policy makers. Finally, this work opens up avenues for the construction of archetypal energy consumption models.

Highlights

- The segmentation of households according to their residential behaviour is explored
- The methodology makes use of mixed data and promotes comparability
- 7 behavioural archetypes are derived from 35 variables and the associated households are described
- These refer to particular associations of households, housing, and energy consumption
- Household income and composition are strongly related to behaviour

Keywords: Energy behaviour, Residential, Energy, Behavioural archetypes, Lifestyles, Energy policy

Word count (excluding title, author names and affiliations, keywords, abbreviations, table/figure captions, acknowledgements, and references) :7428 words

Nomenclature

Symbols	
K_1	Number of clusters of variables
K_2	Number of clusters of behaviours
Abbreviations	
ARI	Adjusted Rand Index
FEC	Final Energy Consumption
LED	Light Emitting Diode
AHC	Agglomerative Hierarchical Clustering
HCPC	Hierarchical Clustering on Principal Components

SV	Synthetic Variable

1 Introduction

According to 2018 estimates by the Intergovernmental Panel on Climate Change, the remaining carbon budget for a 66% probability of limiting global warming to 1.5°C is around 420 $GtCO_2$, while current annual emissions stand at 42 ± 3 $GtCO_2$ [1]. As of 2019, annual CO_2 emissions generated by buildings had risen to around 10 $GtCO_2$ [2]. Reducing the carbon intensity of buildings and promoting sustainable energy use are therefore major instruments for governments to mitigate the impacts of climate change. In addition to technical measures to retrofit buildings and replace inefficient appliances, governments and businesses will need to support behavioural change [3].

Indeed, aside from building and household characteristics [3], [4], the literature points to behaviours as major explanatory factors in domestic energy consumption [5]–[9]. In particular, it shows that the energy savings associated with behaviour change alone could reach 20% of household energy consumption [9]. However, the links between buildings, behaviours, inhabitants and energy remain to be explored, since energy models do not simulate domestic energy consumption accurately, a phenomenon known as the “energy performance gap” [10]. This lack of knowledge jeopardises our ability to achieve the full potential for energy savings and greenhouse gas reduction. The known sources of error are multiple and include of course imperfect physical models of the buildings, the systems, and the environment [10] but also an insufficient understanding of the diversity and the dynamics of the practices of inhabitants in their dwellings [8]. The latter issue has received considerable attention in recent decades, with many studies devoted to understanding and modelling residential energy behaviour [11].

A large body of work has focused on the description [12], [13] of the factors that determine energy-related behaviour [14], [15] and the quantification of their effect on residential energy consumption [9], [16]. Quantitative and qualitative research has provided a sound basis for the identification of behavioural determinants that can be categorised into socio-economic characteristics of households [4], [17], technical and environmental characteristics [18], [19], psychological [20], and cultural factors [21]–[23]. From our point of view, the field research carried out by the human sciences is particularly interesting because it has provided new perspectives for articulating the complex set of determinants of energy behaviour. Ethnographic studies have shown that household energy behaviour is fundamentally related to the way in which households live in their homes [18], [19], [24]. Moreover, several authors have pointed out that inhabitants are generally not aware of their energy consumption and that it is much more a matter of habits and behavioural tactics than of reasoning [12], [24]. Lastly, the conceptual frameworks proposed by Van Raaij [23], Lutzenhiser [21] and Stephenson [22] emphasise that energy behaviour is influenced by the interactions between cognitive norms, energy practices and material culture.

In this respect, it is clear that simplistic behavioural scenarios will not be sufficient to understand and simulate actual household energy consumption. However, it is not possible to collect behavioural data from all households, which means that modelling work has to be carried out. Among the different modelling strategies, three approaches can be distinguished: stochastic models [25]–[27], multi-agent models [28], and archetypes [29]–[31]. Stochastic models reproduce the diversity of behaviours collected by national time-use surveys or with the help of activity diaries. Examples are the work of Vorger [26] and Richardson [27] who used a markovian approach to model behaviour and estimate building energy consumption. However, this kind of approach has several shortcomings. While guaranteeing plausible behaviours at each moment, it does not question the coherence of the whole sequence and of the activities of members of the same household. These studies do not therefore examine the inhabitant's rationale behind the behaviours, nor the links with the households and housing where they emerge. Multi-agent models offer an interesting alternative modelling framework in which each entity (physical system or individual) perceives and interacts with the environment [28]. This approach, whose calibration is data-intensive, makes it possible to study emergent phenomena in complex systems and, in particular, to test behavioural hypotheses, simulate energy consumptions or evaluate the performance of home automation systems [32]. Lastly, the construction of behavioural archetypes makes use of data from surveys [33], sensors [34], [35], or daily diaries [31] and allows for multivariate analyses of behaviour by categorisation. Ben and Steemers [33] conducted a literature review of studies that have constructed archetypes from behavioural variables [35]–[39]. Our position is that this type of approach offers a good balance between reproducing data and hypothesising about behaviour. It allows both a description and a detailed understanding of behaviour and opens the way to the inductive formulation of hypotheses on the logics at work and of tailor-made solutions [37], and can support simulation and decision making [40].

The construction of archetypes is a key issue in our research. In a previous study, Lévy and Belaïd [3] used a factorial analysis coupled with a hierarchical ascending classification on data describing the energy types and consumption of French households. They showed that the clusters that describe energy modes actually refer to specific household and housing structures. However, this work did not make it possible to determine whether these consumption patterns were associated with specific behaviours, which we propose to study in this article with the help of behavioural archetypes. This is in line with the research question pursued by Ben and Steemers who pointed out that few studies have investigated the link between behavioural archetypes and the characteristics of the households and dwellings where they emerge.

2 Research framework

As an introduction to the state of the art of existing behavioural archetypes, it is important to differentiate between studies that focus on a target use (e.g. heating practices, window use, eating practices) - referred to here as types of behaviour- and those that focus on a set of uses - referred to here as behavioural archetypes. The former are often associated with research that seeks to explain the emergence of pro-environmental behaviours [41]. The first known cross-sectional segmentation is that of Van Raaij, who in 1983 differentiated 145 Dutch households according to 17 self-reported behaviours for heat regulation and ventilation in the home. The clustering was done in two steps: first he assigned scores to each household through factor analysis, then he manually segmented the households into 5 clusters according to the dichotomised scores. The clusters were denoted “conservers”, “spenders”, “cool”, “warm”, and “average”. Ben and Steemers [33] later did the same with 78 households, focusing on space occupancy, heating habits and appliance use, allowing them to create 5 behavioural archetypes (“active spenders”, “conscious occupiers”, “average users”, “conservers” and “inactive user”). Guerra Santin [35] conducted cluster analysis on a set of 313 households in the Netherlands for which she had variables describing heating, occupancy, ventilation and appliance use. This article stands out for the richness of the behavioural variables manipulated. She identified 5 clusters denoted "Spenders", "Affluent-cool", "Conscious-warm", "Comfort" and "Convenience-cool". Sütterlin [37] employed cross-sectional behavioural variables (associated with hygiene, heating, food and mobility) but focused mainly on curtailment behaviour. The segmentation, likewise performed by tandem analysis, also included attitudinal, belief and normative variables. In the end, she identified six consumer segments among 1292 Swiss households, namely “idealistic”, “selfless inconsequent”, “thrifty”, “materialistic”, “convenience-oriented indifferent”, and “problem-aware well-being-oriented”. Finally, Zhang [39] proposed 3 dimensions of behaviour (energy efficiency of the property; greenness of behaviour; daytime occupation) to identify 8 behavioural archetypes in the UK. His research made it possible to propose measures for local energy policy design. These studies highlighted clusters of behaviour, identifying processes that were sometimes energy-consuming, sometimes energy-saving, or complex behaviour sets combining, for example, high heating temperatures and regulation behaviour.

This literature review allowed us to identify four gaps that we wish to contribute to filling. First, to our knowledge, (i) no existing work has simultaneously used behavioural variables describing hygiene, food, lighting, heating, leisure, and occupation practices, all of which are known to be determinants of energy consumption. In addition, research works sometimes do not make explicit what the variables refer to, which limits both the interpretation and reproducibility. Furthermore, (ii) most of the behavioural classification work has used limited data sets and none seems to have been carried out in France. Also, (iii) most of the studies process data manually [42] or use hierarchical ascendant classification on principal components (HCPC) on categorical data only [37], which generates loss of information or even bias by categorisation of quantitative variables [43]. Finally, (iv) among the articles that have studied domestic behaviour by archetypes, only a few have analysed households, energy consumption and associated dwellings by correlation [33], [35], [36].

The scientific contribution of the present study is threefold. Firstly, we propose an original methodology to construct behavioural archetypes from qualitative and quantitative data, by employing an advanced variable classification methodology presented in [44]. This method improves the stability of the results: the elimination of the categorisation stage allows the dimension of the data matrix not to increase. It also limits the introduction of bias associated with thresholding. It also limits the introduction of associated biases. Secondly, we present 7 archetypes of behaviour for a French region. The computation is based on the classification of a rich dataset of 35 behaviour variables that cover a large panel of domestic behaviours. Thirdly, we show through an advanced statistical study of households, dwellings, and energy consumption that these homogeneous sets of behaviours refer to particular housing situations.

3 Data & methodology

This section presents the data used for the computation and the methodology used to compute and analyse the Synthetic Variables (SV) and behavioural archetypes (Figure 1).

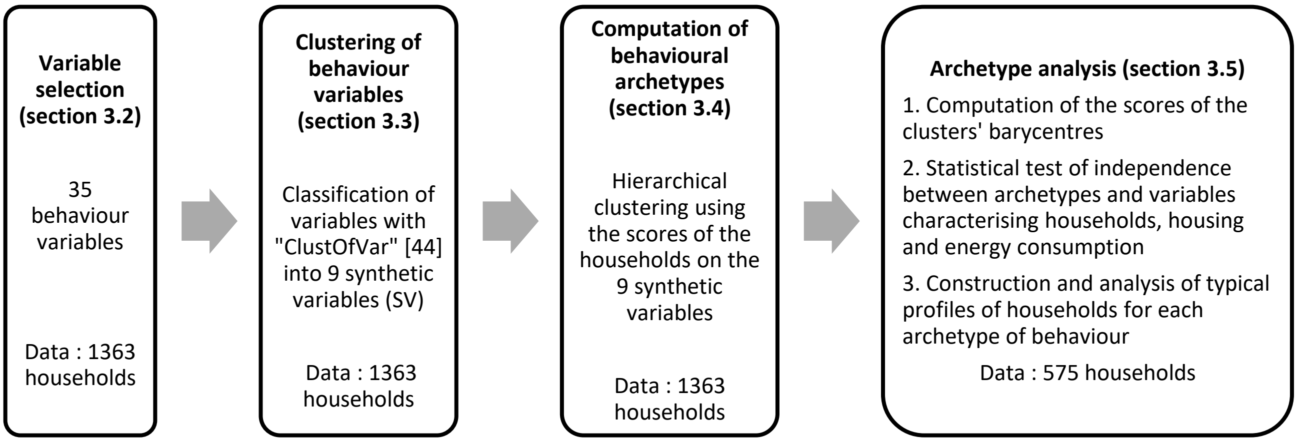


Figure 1: Methodology of the work

3.1 Presentation of the dataset

The data used for the study are those of the ENERGIHAB project, funded by the French National Research Agency [45]. The dataset consists of a phone survey conducted in 2010 with 1950 households in the Île-de-France region. The questionnaire consisted of 362 questions and generally took less than an hour to complete. The questions concern behaviour, energy consumption, and households and dwellings characteristics. The survey was used by Bourgeois and Pellegrino [46] to construct three behavioural indicators and to study the spatial distribution of energy related behaviours. It has also fed into research on the modelling of heat flows in an urban environment [15]. These data were recently used by Belaïd in [47] to examine the key drivers of household environmental attitudes and energy-saving behavior. The households interviewed were selected to ensure that heterogeneous household and housing profiles were represented. This means that the proportions of the behavioural archetypes constructed are not representative of what might have been observed in Île-de-France in 2010. Variables were constructed from the responses to the questionnaires. In this study we used thirty-five behavioural variables, nineteen of them qualitative and sixteen quantitative, which are described in section 3.2. The selection of behavioural variables is based on the work of Bourgeois et al. [46] and describes equipment, use, and regulation. After selecting the variables, only those households for which we have complete data were kept, giving a table of 1363 households described with 35 variables.

In the last part of the study (see section 4.3.3), we study the links between behavioural archetypes, the associated households and the dwellings and their energy consumption. To this end, 20 additional variables were used, 6 of which characterise households, 11 their dwellings, and 3 their final energy consumption. For these 20 variables, 575 out of the 1363 households provided valid responses. A list of the variables and basic statistics are provided in Appendix 8.4. It is important to note that final energy consumption is broken down into three variables: total annual energy, total annual energy per unit area and total annual energy per capita. These three variables were estimated from consumption data reported in euros, in kWh for electricity and in m^3 of gas.

3.2 Variable selection

The development of archetypes depends greatly on the nature and the selection of the variables [48]. As described in section 2, several papers have developed archetypes, but many of them selected behaviours in a single consumption area (e.g. heating, food, hygiene, etc.) or behaviours relating to the most energy-intensive practices such as heating temperatures, heating regulation, window opening frequency or duration of presence. In this study we drew on the current state of the art to select the variables that best describe residential lifestyles. 35 behavioural variables selected by the ENERGIHAB project team were evaluated [46]. These variables cover a wide range of consumption categories [49], [50] in the home. These are as follows: Food (F), Hygiene (H), Lighting (LI), Thermal Comfort (TC), Work & Leisure (WL). Variables relating to housing occupancy (OCC) were also taken into account as they have been identified in the literature as being very significant in describing residential behaviours [51]. For the sake of clarity, we also classified each of the variables according to the following three dimensions: equipment (EQ), usage (US), and regulation (REG) [46]. The complete list of behavioural variables is given in . The variables were named by aggregating the consumption category (F, H, LI, TC, WL, OCC), a suffix describing the behavioural variable (EQ, US, REG) and a number.

Table 1 : List of variables selected for the description of household behaviour. The variables are categorical (C) or numerical (N). Source: ENERGIHAB.

Behaviour variable	Description	Type	Comment
F_EQ1	Number of food facilities	N	From 0 to 10 (mean = 5 facilities)
F_EQ2	Ownership of an individual independent freezer	C	2 modalities
F_US1	Number of meals eaten per week at home	N	Between 0 and 14 (mean = 9.9)
F_US2	Number of days of oven use	N	From 0 to 7 (mean = 2.6 days/week)
F_US3	Number of days of baking tray use	N	From 0 to 7 (mean = 6 days/week)
F_REG1	Number of energy-consuming appliances purchased considering the energy class	N	From 0 to 7 (mean = 1 appliance)
HY_EQ1	Number of hygiene appliances	N	From 0 to 5 (mean = 3.7 appliances)
HY_US1	Number of daily showers per day and per capita	N	From 0 to 4 (mean = 1 shower/day/cap)
HY_US2	Members of the household take baths	C	2 modalities
HY_US3	Number of days of dishwasher use	N	From 0 to 7 (mean = 1.9 days/week)
HY_US4	Number of laundry days at home	N	From 0 to 7 (mean = 3 days/week)
HY_US5	Number of days of dryer use	N	From 0 to 7 (mean = 0.9 days/week)
HY_REG1	Level of water savings	C	2 modalities
HY_REG2	Practice of selective sorting	C	2 modalities
HY_REG3	Use of "green" household products	C	2 modalities
LI_EQ1	Number of lights per square metre living space	N	From 8e-3 to 7e-2 (mean = 1.2e-1 lights/m²)
LI_REG1	Proportion of Light Emitting Diode (LED) lamps	C	3 modalities
LI_REG2	Presence of halogen lamps	C	2 modalities
LI_REG3	Lamp regulation level for unoccupied rooms	C	2 modalities
TC_EQ1	Ownership of a backup heating system	C	2 modalities
TC_US1	Declared average heating temperature in winter	N	From 14°C to 38°C (mean: 20.3 °C)
TC_US2	Number of days per week of home ventilation	N	From 0 to 7 (mean = 5.9 days/week)
TC_US3	Air vents sometimes blocked	C	2 modalities
TC_US4	Open windows to refresh rooms	C	2 modalities
TC_REG1	Type of clothing during the heating period	C	3 modalities
TC_REG2	Reduction of temperature at night or during absence	C	2 modalities
TC_REG3	Number of unheated spaces during winter	N	From 0 to 5 spaces (mean: 0.35)
TC_REG4	Heating turned off when opening windows	C	2 modalities
WL_EQ1	Number of televisions, personal computers, game consoles and IT devices	N	From 0 to 12 (mean: 3.5)
WL_US1	Average daily hours of use of main television set	N	From 0 to 8h (mean: 2.5h)
WL_US2	Average daily hours of use of main personal computers	N	From 0 to 8h (mean: 1.8h)
WL_REG1	Level of regulation of unused screens	C	3 modalities
OCC1	Level of presence during the weekends	C	3 modalities
OCC2	Frequency of departures on vacation	C	3 modalities
OCC3	Number of days of work away from home	C	3 modalities

3.3 Clustering of behaviour variables

Due to their complexity, residential behaviours are likely to be described in high-dimensional spaces with numerical and categorical variables. A significant amount of work has created categorical variables from quantitative variables by thresholding to form a homogeneous set of categorical variables. This approach has the disadvantage of losing a significant amount of the information contained in the quantitative variables and of increasing the dimension of the problem. An alternative approach is to perform a mixed data factor analysis [52]. This allows the calculation of synthetic scores which are used to perform Agglomerative Hierarchical Clustering (AHC). However, De Soete et al. [53] noted that the space comprising orthogonal principal factors does not always allow adequate representation of taxonomic information. We initially conducted a factor analysis on this mixed-type dataset [52]. However, interpreting the factorial axes constructed by the method proved to be tricky. It was noted that the axes of order greater than 5 grouped variables that were too heterogeneous, which complicated interpretation. This showed that the variance criterion used was not the most appropriate for constructing a new representation space. We therefore adopted the approach taken by Chavent, who used a correlation criterion to construct a synthetic representation space.

The variable classification approach proposed by Chavent [44] offers an alternative for building quantitative variables from a mixture of quantitative and qualitative variables. The clusters of variables are built on a homogeneity criterion (Equation 1) which is defined as the sum of correlation ratios (for qualitative variables) and squared correlations (for quantitative variables) to a synthetic quantitative variable. A synthetic variable (SV) is computed as being the first principal factor computed through a factor analysis of the variables belonging to the cluster. The term "synthetic variable" is taken from Chavent's method for clarity. In addition to providing synthetic variables, this approach enables the proximity of variables to be studied in terms of correlation.

$$H\,(C_k) = \sum_{x_j \in C_k} {r^2}_{x_j, y_k} + \sum_{z_l \in C_k} {r^2}_{z_l, y_k}$$

Equation 1: Homogeneity H of cluster C_k represented by its synthetic quantitative variable $\boldsymbol{y_k}$. $\boldsymbol{x_j}$ denotes the j-th quantitative variable and $\boldsymbol{z_l}$ denotes the l-th column of the full disjunctive table computed on the qualitative variables.

$$d\,(A,B) = H(A) + H(B) - H(A\;U\;B)$$

Equation 2: Dissimilarity d between clusters of variables A and B

The choice of the number of clusters K_1, i.e. the number of SVs, was done in three steps. First, Agglomerative Hierarchical Clustering (AHC) was used to build a hierarchical structure of the variables. The aggregation was computed by minimising the dissimilarity criterion at each step (Equation 2). Second, the evolution of the height of the tree was visualised, computed as the accumulation of dissimilarities, as a function of the number of clusters of variables. A first estimate of the optimal number K_1 was done by choosing the one for which the decrease in height between clusters $K_1 - 1$ and K_1 was much larger than that between clusters K_1 and $K_1 + 1$. Lastly, we studied the stability of this choice by comparing the results of the same clustering operation on 100 random subsets of households, a process called "bootstrapping". The stability is summarised in the Adjusted Rand Index (ARI) which measures the recurrence of the association between the variables. In this case the ARI criterion measures the persistence of associations between the variables. All computations were performed using the *ClustOfVar* R package [54]. Another example of the classification of variables using the same methodology can be found in [55].

3.4 Computation of behavioural archetypes

Household clusters are constructed by AHC from the variables after centering and reduction. The distance between two households is computed as the Euclidean distance between their normalised coordinates on the SV. The aggregation criterion for the hierarchical classification is Ward's criterion [56].

The choice of the number K_2 of household clusters was performed iteratively to obtain homogeneous and interpretable clusters. First, we plotted the intra-cluster inertia gains as a function of the partitioning level. To satisfy the homogeneity criterion, we chose the number K_2 of clusters for which the decrease in intra-cluster inertia between $K_2 - 1$ and K_2 clusters was much larger than that between K_2 and $K_2 + 1$ clusters. To meet the interpretability criterion, we observed the distributions of behaviour, housing characteristics and household profiles represented in the K_2 clusters.

3.5 Behaviour archetype analysis

The analysis of the clustering results was done in three steps. Firstly, the coordinates of the barycentres of the archetypes were calculated. A Student test was performed on the coordinates of the cluster's barycentres to identify the SV that best characterise the built clusters. By using the definition of the SV (see Appendix 8.1), the barycentres can be qualitatively described. The homogeneity of the constructed clusters is examined by calculating the average distance of households from the barycentre of their archetype (see section 4.3.1).

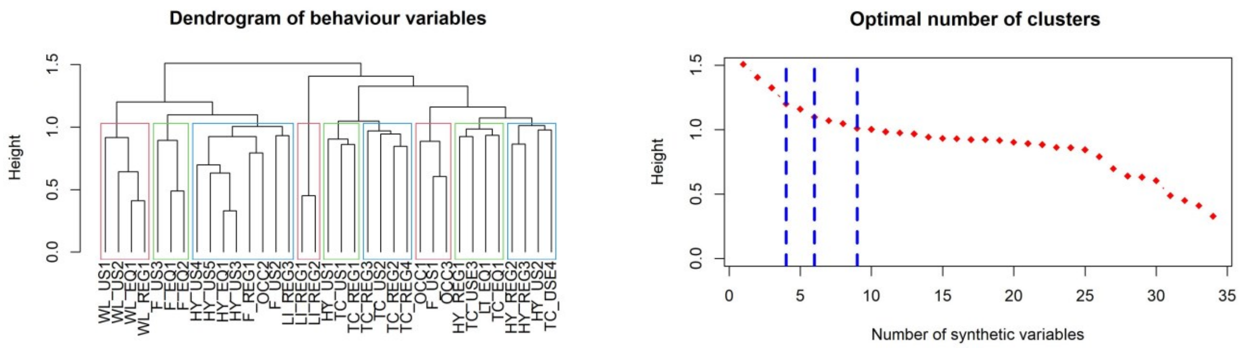
Secondly, a statistical test of independence was performed to check whether the behavioural archetypes and 20 variables characterising households, dwellings and energy uses (see section 4.3.2) are independent. For qualitative variables the test performed was a Chi-square test. For quantitative variables, the p-value was calculated by ANOVA and corresponds to the risk of rejecting the hypothesis of equality of means between the archetypes. Due to insufficient data, only households that consume gas and/or electricity were considered for this step. The energy intensities were computed as final energy (in kWh_{FE}) as they aim to represent energy consumption as a service. It should be stressed that consumption data are self-reported and based on bills and therefore suffer from imprecision. A 1984 study by Warriner [57] estimated that this error could be between 10.5% and 29.3% depending on the type of energy and the use of household receipts. Only energy consumption between 20 kWh_{FE}/m^2 and 1000 kWh_{FE}/m^2 was considered correct, corresponding to 575 of the 1363 households. The distribution of households and dwellings was similar in this subset, which allowed the analysis to be pursued.

Finally, typical profiles were constructed for each archetype. To do this, we performed a factor analysis coupled with a hierarchical ascending classification on each set of households associated with the archetypes. This calculation allows us to describe the links between households, dwellings, and the archetype and to make assumptions about the underlying consumption logic (see section 4.3.2).

4 Results and discussion

4.1 Clustering of variables

The clustering of variables produces a hierarchical classification of the behaviour variables (Figure 2A). We identified three values of K_1 for which a sharp increase in cluster homogeneity was observed (Figure 2B). Clustering with K_1 greater than 25 could be interesting because it could produce more homogeneous clusters. However, this would not fulfil the parsimony principle. Selection between the three values (K_1= 4, 6 and 9) was made by observing the stability and interpretability of the clusters. Since, we observed that the Adjusted Rand Index (ARI) increased with K_1 ($ARI_{K1=4}$ = 38%, $ARI_{K1=6}$ = 45%, $ARI_{K1=9}$ = 49%), K_1=9 was selected so as to keep a variable clustering that depends less on the dataset. Second, we found that clustering with K_1=4 or K_1= 6 produced clusters that mix behaviours for which no simple method of simultaneous interpretation could be found in the literature. The clusters of variables with K_1=9 are presented in Table 2. A table listing the coordinates and the correlations used for the interpretation and naming of the SV is provided in the Appendix (see 8.1). The homogeneity and interpretability of the clusters are discussed in the next paragraph.



(A) Dendrogram of behaviour variables. The height of a cluster C= AUB is defined as h(C)= d(A, B)

(B) Evolution of height as a function of the number of variable clusters.

Figure 2: Classification of behaviour variables. Source: secondary processing of ENERGIHAB data.

*Table 2 : Synthesis of the variable clusters obtained with K1=9. Each cluster is associated with a synthetic quantitative variable (SV). The contribution of the variables to the synthetic variable is given in brackets. * denotes variables that are too poorly c*

Synthetic variable	SV1	SV2	SV3	SV4	SV5	SV6	SV7	SV8	SV9
Interpretation of the SV	Food equipment	Presence at home	Hygiene equipment and use	Restriction level	Heating requirement	Heating regulation	Leisure demand	Green gestures	Type of lamps
Number of variables (Number of degrees of freedom)	3 (3)	3 (6)	8 (10)	4 (6)	3 (6)	4 (5)	4 (5)	4 (8)	2 (5)
% of variance explained by the SV	53.9%	30.2%	29.9%	29.0%	24.7%	31.1%	40.1%	28.8%	51,7%
Variables included (correlation between the variable and the associated SV)	F_EQ1 (0.74) F_EQ2 (0.64)	F_US1 (0.64) OCC3 (0.59)	HY_EQ1 (0.71) HY_US3 (0.62) HY_US5 (0.42)	HY_REG 1 (0.31) TC_US3 (0.3)	TC_US1 (0.44) TC_REG 1 (0.43)	TC_REG 4 (0.47) TC_REG 2 (0.39)	WL_REG 1 (0.72) WL_EQ1 (0.67)	HY_REG 2 (0.56) HY_REG 3 (0.48)	LI_REG2 (0.77) LI_REG1 (0.77)

	F_US3 (0.24)	OCC1 (0.28)	HY_US4 0.40) F_REG1 (0.25) OCC2 (0.18)* F_US2 (0.08)* LI_REG3 (0.02)*	TC_EQ1 (0.28) LI_EQ1 (0.26)	HY_US1 (0.37)	TC_US2 (0.24) TC_REG 3 (0.14)*	WL_US2 (0.48) WL_US1 (0.15)*	HY_US2 (0.06)* TC_USE4 (0.04)*	

It can be seen that SVs aggregate behavioural variables in the same consumption areas, unlike the clusters obtained by a classical HCPC. However, Table 2 shows that 7 variables are weakly correlated with SV as their contribution, defined as the squared correlation with the SV is less than 20%. These variables were therefore not considered for SV interpretation. After identifying the variables that are the most strongly linked to the SV, the SV can be interpreted by positioning the modalities of the qualitative variables on the SV and studying the correlation of the quantitative variables with the SV as done in [55]. These data are provided in appendix 8.1.

After this step, the correlations between the variables were calculated to verify that each SV provided independent information. The correlation coefficients were all below 0.25 in absolute value, except for SVs 1, 3 and 7. The correlation coefficient between SV3 and SV1 was 0.42, between SV3 and SV7 -0.46 and between SV1 and SV7 -0.34. This highlights the fact that the numbers of food, hygiene and leisure facilities are not completely independent, which is confirmed by the proximity of the facility variables in Figure 2. Another investigation looked at the quality of data representation: although the algorithm aims to construct the most strongly correlated variables, it is interesting to observe the percentage of variance synthesised by the constructed variables, which varies between 24.7% and 53.9%. This variation is due to the fact that the SVs group variables that are either very close (e.g. SV1) or rather distant (e.g. SV4).

4.2 Clustering of household behaviours

The clustering of behaviours is based on the hierarchical classification of the scores of each household on the 9 synthetic variables (SV). From the Euclidean distance on the normalized components we built a tree using the Ward criterion (Figure 3). The inter-class inertia is plotted as a function of the number of clusters. Five levels of K_2 were seen as particularly interesting when used for clustering (K_2=2, K_2=4, K_2=7, K_2=10, K_2=13). Choosing K_2=13 could have produced more precise behaviour clusters, but the clusters obtained were not interpretable. As a compromise between cluster homogeneity and parsimony we first chose K_2 = 10, but one cluster comprising around 100 households was explained by only one singular SV, which was not helpful in building explainable clusters. In the end, K_2 =7 was selected.

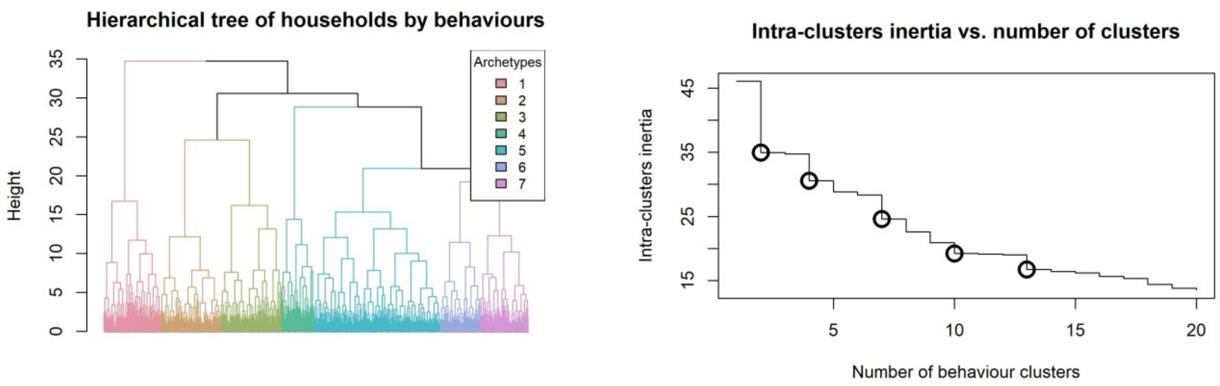


Figure 3: Selection of the number of behaviour clusters. Left: Hierarchical tree of behaviours. Each leaf is associated with one household. Right: Intra-cluster inertia as a function of number of clusters. The circles indicate relevant choices for K_2. Source: Secondary processing of ENERGIHAB data.

To better compare the homogeneity of the clusters, we calculated the mean and standard deviation of the distance distributions to the barycentre of each type. The scores of the barycentres on the SVs of each cluster are given in Appendix 8.2. The resulting clusters are fairly homogeneous. The average distances to the barycentre were between 1.7 and 2.1 except for cluster 5 (average 2.7). Clusters 4, 5 and 7 had a higher dispersion (standard deviation of the distance distribution of 2, 2.7 and 2.1 respectively) than the other clusters (standard deviation around 1.7), and can therefore be interpreted as having lower homogeneity. The average distances to the barycentre can be interpreted in terms of behaviour by observing the position of the modalities on the SV (see Appendix 8.1). In doing so, we noted that each household differs on average from the barycentre, considered as representative of the type, by the modulation of one behaviour in the SV grid. In the rest of the paper, we will focus on the average behaviour of the archetypes, i.e. on the set of behaviours that would be adopted by a household whose coordinates on the SV are those of the barycentre of the households classified within the type. It should be remembered, however, that households grouped within archetypes adopt behaviours that can be seen as modulations of this average behaviour.

4.3 Analysis of the archetypes of domestic practices

4.3.1 Presentation of the archetypes

To facilitate the interpretation of the behavioural archetypes, the coordinates of the barycentre of each class were translated into explicit behaviour. The interpretation of the SV was performed by exploiting the coordinates of the modalities of the qualitative variables on the SVs and the correlations of the quantitative variables with the SVs. The results are presented in Table 3. Only non-zero coordinates (at the risk of 10%) are interpreted. Finally, a name was associated to each type of behaviour according to the salient characteristics (such as temperature level, level of equipment, presence in the home). A colour code was used to highlight the tendency of a behaviour to decrease (green) or increase (red) the final energy consumption.

Table 3 : Interpretation of the scores of the barycentres of the behavioural archetypes. Only scores significantly different from 0 are interpreted. The statistic used is a Student test with a 10% significance level. Behaviours that are generally associated wit

Archetype number	1	2	3	4	5	6	7
Name of the archetype	**Leisure house**	**Economic house**	**Practical cocoon**	**Warm house**	**Pursuit of comfort**	**Frugality house**	**Savings house**
SV1: Food equipment	High	Low	Very high	Average	Low	Very low	Average
SV2: Presence at home	Quite low	Quite low	Very high	Very low	Quite low	High	Very high
SV3: Hygiene equipment and use	High	Low	Very high	High	Average	Very low	Low
SV4: Restriction level	Low	Average	Quite high	Low	Very high	Average	Low
SV5: Heating requirement	Quite high	Very low	Quite low	Very high	Average	Average	Average
SV6: Heating regulation	High	Very high	Low	Low	Average	Low	Low
SV7: Leisure demand	Very high	Low	Very high	High	Average	Very low	Low
SV8: Green gestures	Quite high	High	High	Quite high	Average	Average	Very low
SV9: Lighting equipment	LED always	LED rarely	LED sometimes	LED sometimes	LED often	LED often	LED sometimes
Number of households [for which we have complete household data]	**227 [86]**	**349 [159]**	**251 [106]**	**192 [88]**	**53 [27]**	**198 [75]**	**93 [34]**

These sets of behaviours can be read at first sight by correlation. Recurrent associations between equipment levels (SV1 and SV3) can then be observed for most of the archetypes. Then, one can then look at energy-intensive patterns, combining high levels of equipment and heating needs (archetypes 1 and 4) or, on the contrary, frugal patterns (archetypes 6 and 7) with more restricted demands. However, analysis of the behavioural associations between presence at home, equipment, and heating is not straightforward. In fact, the analysis of behavioural archetypes must be contextualised to reconstruct the processes and therefore the causalities that lead to these sets of behaviours. This requires knowledge of energy consumption, households, and dwellings.

4.3.2 Associations between behaviour types, households, dwellings, and energy consumption

In the previous section, groups of households sharing a relatively similar set of residential behaviours were constructed. We investigated the links between the characteristics of households, dwellings, energy consumption and membership of one or other of the archetypes. A statistical test of independence was performed between the categorical variable describing archetype membership (7 levels) and each of the descriptive variables. The risk - also called p-value, given as a percentage - of being wrong in rejecting the hypothesis of independence of the variable and the archetype is given in Table 4**Erreur ! Source du renvoi introuvable.**. For qualitative variables, the p-value was calculated by the Chi-square test of independence. For quantitative variables, the p-value was calculated by ANOVA and corresponds to the risk of rejecting the hypothesis of equality of means between the archetypes. The calculations were made on R using the *stats* package [58] and on the subset of 575 households for which complete data were collected. The results show a strong linkage of the archetypes to the variables describing households and dwellings. Some variables, however, appear to be unrelated. The socio-professional class, the surface area per person, and the type of energy do not seem to be linked to the behavioural archetypes. Also, it should be noted that final energy consumption is strongly related to the archetypes (see also Figure 4), whereas consumption per m² and per person is not (see also appendix 8.3). This result confirms that the behavioural archetypes essentially refer to household and housing structures of different sizes, which are key drivers of energy consumption. As a corollary, in view of the absence of a significant link between archetypes and consumption per m² and per person, it can also be said that the possible difference in consumption between more or less energy-intensive archetypes is less than the measurement error (between 10 and 30% according to Warriner [57]). This order of magnitude is in line with the estimates found in the literature [9].

Table 4 : Table of p-values from the calculation of independence between archetypes and the descriptive variables. P-value corresponds to the risk of being wrong in rejecting the hypothesis of independence of the variable and the archetype. Levels of significance

Variable	Details	p-value	Significance
Number of household members	6 categories (1, 2, 3, 4, 5, 6 or more persons)	0,05 %	***
Income	5 categories (by quintiles)	0,05 %	***
Composition of the household	5 categories (Couple with child(ren) Childless couple, One-parent family, Single person, Several persons - no family)	0,05 %	***
Socio-professional group of the reference person	5 categories (Employees & Workers, Executives, Farmers & Artisans, Technicians and Associate professionals, No profession)	9,2 %	
Age of the reference person	5 categories (30-39, 40-49, 50-59, 60-69, 70+)	0,05 %	***
Status	3 categories (Active, Unemployed, Retired)	0,05 %	***
Housing surface	6 categories (<30 m², 30-50 m², 50-75 m², 75-100m², 100-150 m², >150 m²)	0,05 %	***
Zone	3 categories (Urban, Peri-urban, Rural)	17,2 %	
Housing type	2 categories (Individual, Collective)	0,05 %	***
Status of occupation	4 categories (Owners, Tenant in public housing, Tenant in the private sector, Free accommodation)	3,1 %	*
Surface per person (m²/person)	Quantitative (12.5-250 m²/p, median 39 m²/p)	10, 7 %	
Electric heating	2 categories (Yes, No)	97,8 %	
Gas heating	2 categories (Yes, No)	89,1 %	
Oil heating	2 categories (Yes, No)	21,0 %	
Date of construction	4 categories (Before 1949, Between 1949-1975, Between 1975-1990, After 1990)	4,4 %	*
Recent refurbishment work	2 categories (Yes, No)	3,0 %	*
Numbers of years of residence	Quantitative (1-86 years, median 14 years)	0,01 %	***
Total final energy consumption	2 categories (Low, High)	0,05%	***
Total final energy consumption per square metre of living space	2 categories (Low, High)	45,0 %	
Total final energy consumption per capita	2 categories (Low, High)	58,9 %	

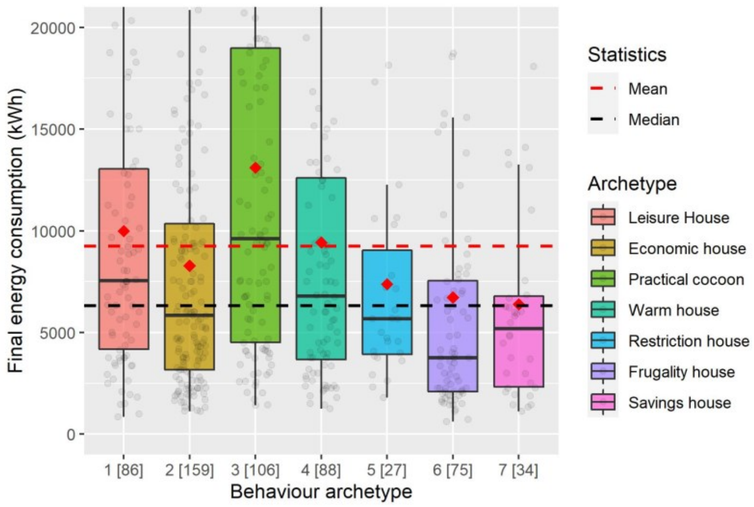


Figure 4: Distributions of total final energy consumption (FEC) per behaviour archetype. The total number of households per type is given in square brackets. Only households using electricity and/or gas are considered. Data source: ENERGIHAB

To develop the discussion further, a statistical test was carried out to test the independence of the consumption distributions among each of the types (20 tests). The results show that there are certain similarities between the archetypes, and that there are four main families of consumption distributions: a first one grouping archetypes 1 and 4, a second one grouping archetypes 2 and 5, a third one grouping archetypes 6 and 7, and a last one grouping archetype 3 alone.

One could think that this proximity questions the interest of archetypes for modelling. On the contrary, we think that this result is interesting because it suggests that similar consumptions (archetypes 1 and 4 for example) can have different causes (size of the household or the dwelling, an energy-consuming behaviour). Further analysis of consumption will therefore require additional modelling work.

4.3.3 Description of typical households and dwellings associated with the behavioural archetypes

In this section, the links between households, dwellings and archetypes are explored. Typical profiles were constructed by HCPC over household and dwelling characteristics. Compared to a correlation analysis, this multivariate method makes it possible to capture the interactions between the characteristics and reflect the heterogeneous situations of households and dwellings in which the same archetypal behaviour is found. An inventory of the typical profiles and the proportion of households represented are given in Table 5.

Table 5: Typical household and dwelling profiles associated with each of the behavioural archetypes. Each profile is representative of a proportion of the households in the archetype, which is shown as a percentage. Data source: secondary processing of ENERGIHA

Behavioural archetype	Typical profiles of households and dwellings *The proportion of households represented by each profile is given in %*
1	**42%** - High-income couple, aged 40-49, with children. They own a single-family house built between 1949 and 1975 in a rural area.
	27% - Middle-income couple in their fifties with children. They own a recent flat of 50 to 75 m² in an urban area.
	15 % - Single elderly person, retired, with average income, owner of a recent flat of 50 to 75 m² in an urban area.
	16% - Retired couple, no children at home, living in a small old house built before 1949 in an urban area.
2	**43%** - Single active person in their fifties with a medium or low income. Owner of a flat of more than 100 m² in an urban area, built before 1949.
	36% - Middle-income couple in their fifties without children, renting a pre-1949 flat in an urban area.
	21% - Middle-income young family with children who own a small recently built house in a suburban area.
3	**48%** - Young couple with children with an average income, owners of a house built before 1975 in a rural area, with a living area of between 75 and 100 m².
	42% - Retired childless couple with average or high incomes, owners of a house built before 1975 in an urban area, with between 75 and 100 m² of living space
	10% - Single retired person with low income, owner of a flat built before 1949 in an urban area, with between 75 and 100 m² of living space
4	**23%** - Couple in their fifties with children, renting collective housing built before 1975 in an urban area
	22% - Couple in their fifties without children, owners of a recent house of over 150 m² in a rural area.
	19% - Single person in her fifties, renting a house built after 1975 with a surface area of almost 75 m² in a rural area.
	18% - Very high income couple without children living in collective housing built after 1975 in an urban area
	14% - Retired couple, without children, living in a small, detached house in an urban area.
	7% - Single person with an average income in their thirties, renting a flat of less than 50 m² in an urban area
5	**26%** - Single person, retired, with a very low income and owner of a 50 m² flat in which she has lived for 40 years.
	26% - Young couple with children, renting a 50-75 m² flat in the suburbs
	22% - High-income couple with children, owners for less than 5 years of a 75 m² flat built between 1949 and 1975 in a rural area.
	19% - Single parent family with a reference person aged between 30 and 40, with very low income. Tenant in public housing.
	7% - Low-income family with children, where the reference person is in his/her 40s and unemployed. Tenant of a single-family house in a rural area.
6	**65%** - Single retired person over 70, renting a collective dwelling, built before 1949 in an urban area
	30% - Middle-income retired couple owning a recent flat in an urban area
	5% - Young, middle-income family with a single-family house built between 1949 and 1975 in an urban area.
7	**43%** - Single retired person, owner occupier of a 75 m² flat in an urban area for more than 40 years.
	27% - Single person, over 60 years old and active. Tenant of a collective dwelling in an urban area.
	21% - Retired couple without children on average or low incomes, living in a single-family home in a rural area.
	9% - Retired couple with one or more children living at home. Owner of a single-family home in an urban area for more than 30 years.

The construction of these typical profiles allows here two things: a better understanding of the archetypes of behaviour through contextualization and a comparison of the segmentation with the literature. The interpretation of behavioural patterns was done with the help of hypotheses based on observations from ethnographic work [18], [24] or larger anthropological and sociological studies [12], [59].

Type 1: Leisure house. This type of behaviour is associated with energy-intensive practices such as extensive equipment for food, hygiene, and leisure, but also high heating demands. As a result, these households consume a significant amount of energy compared to the total sample (median consumption is 21% higher than the sample). A large proportion of the households consists of a very well-off working household with children, owning a fairly old, detached house located in an urban area (Table 5). One can hypothesise that these households are very absent because of their professional activity, and are very well equipped, firstly because of the presence of children, but also because of the absence of financial constraints and perhaps a significant consumer culture.

Type 2: Economic house. In this type, most behaviour is characterised by regulation and moderation, including the level of equipment, and the heating demand. The median final energy consumption (FEC) is therefore lower than the sample median. The most common profile is that of a single low-income owner-occupier in an urban area. The other two profiles tend to be middle-class renters or young owners. It can be hypothesised that these households adopt energy saving practices for economic or cultural reasons.

Type 3: Practical cocoon. This type of behaviour is characterised by very high presence at home, very high equipment and use in all areas (hygiene, food and leisure). As a result, the households associated with this type have a very high total energy consumption (median consumption is 55% higher than the sample). Two typical household profiles are represented. The first is that of young active people with children, with average incomes, and also owners of a large dwelling in a rural area. The second profile is that of retired people (couples or single), owners of a dwelling of more than 100 m² where they have lived for 40 years. These two profiles are particularly interesting because they show that the same energy-intensive behaviour pattern can be adopted by very different households. In the first case, it can be assumed that the households have equipped themselves to meet the needs associated with the presence of children. The high presence at home may be associated with lack of employment, working from home and the presence of children for lunch. A greater number of energy saving actions distinguishes them from families associated with archetype 1. In the second case, it can be assumed that households have kept the equipment they needed before the children left. Also, the strong presence at home can be explained by the fact that people are retired.

Type 4: Warm house. Households of this type have fairly energy-intensive practices: high equipment and use for leisure and hygiene, high heating demand and low thermal regulation. However, these households tend to go out frequently. As a result, their median energy consumption is 24% higher than that of the total sample. For this behavioural archetype, there is greater diversity in the associated household and housing structures, as five typical profiles were constructed (Table 5), although most are middle-income couples in their fifties. It is noticeable that this archetype stands out from the others by a "Very high" value on the SV4 variable ("Heating requirement") and low regulation behaviours. It can be assumed that the common trait of these households is a definition of comfort associated with a higher heating temperature and unregulated consumption.

Type 5: Pursuit of comfort. This type of behaviour is distinguished by the prevalence of both regulation behaviour (low equipment, use of LEDs) and comfort-seeking behaviour (supplementary heating equipment, obstruction of air vents). Households associated with this type have a slightly lower total consumption (median 13% lower) but higher consumption per square metre of living space (median 18% higher), while consumption per person is very low (-35%). It is very interesting to observe that a very wide range of household profiles is associated with this archetypal behaviour. A large proportion of them are single, renters and mostly belong to medium or low socio-economic groups, and another large proportion are families with children. A notable statistic for households in this archetype is that they are more likely to live in urban areas in much smaller dwellings (27 m²/cap versus 37m²/cap on average). As a result, this behavioural archetype reflects highly restrictive behaviour, possibly for financial or contextual reasons (e.g. associated with poor housing quality).

Type 6: Frugality house. This type comprises households with little equipment but with high presence. According to the standard profiles calculated, almost all households of this type are single or retired couples with average or low incomes and living in a flat in an urban area. A reasonable assumption is that these households, for financial or cultural reasons, adopt energy-saving practices.

Type 7: Savings house. Households belonging to this behaviour type share a set of frugal practices such as the use of low-energy lamps and low-energy equipment. This type is very similar to type 6 except for the scarcity of ecological actions. Four typical profiles are associated with this type and describe elderly or unemployed people (12% of the households in the archetype compared to 5% overall). They mainly live alone or as a couple, and in a flat that they own. The frugality which is more prevalent in this generation [42], and financial constraints could also explain this assemblage of behaviours.

The constructed clusters can be compared to a reasonable degree with classifications in the literature. Archetypes 1 and 3 can be compared with Van Raaij's [36] 'spenders' and Ben and Steemers' [33] 'active spenders'. They do, however, allow us to differentiate between retired households with a high presence at home (Archetype 3) and active households with children and a lower home presence (Archetype 1). The 'conservers' of the previous authors coincide with archetypes 6 and 7 but also with archetype 2. Once again, the classification makes it possible to differentiate between heterogeneous situations (single working people with low incomes, retired people or unemployed people etc.). The classification proposed here, as well as the profile analysis, allows for a better understanding of the diversity of contexts in which behaviour emerges.

This behavioural classification goes beyond the findings of Lévy and Belaïd [3] who showed that energy modes were associated with particular household and housing contexts. The present study not only shows that homogeneous sets of behaviours can be constructed but also that these behavioural patterns are associated with particular household and housing contexts. In particular, the household composition, the age of the reference person and the income are decisive variables in the formulation of hypotheses about the emergence of behavioural archetypes. However, it should be noted that archetypes associated with comfort-seeking or deprivation behaviours (archetype 5), or with behaviours reflecting a higher level of thermal comfort (archetype 4), appear to be less related to household and dwelling characteristics than the other archetypes.

Several previous studies have explored the influence of household life cycle on household consumption and behaviour, particularly with respect to energy consumption in the home [3], [60]. This framework was used here to represent a longitudinal profile of the distribution of behavioural archetypes (Figure 5). Households were differentiated according to their income level relative to the median. When interpreting the graph the important thing is to go further in the statistical study and characterize the relationship of each archetype with the variable "age of the reference person". A chi-square test of independence between archetypes shows that the ages of household reference persons are very different overall between them (with a risk of 5%). Two exceptions are archetypes 2 and 7 (people over 50 are over-represented in both) and between archetypes 4 and 5 (these types are significantly less related to the age of the RPs). Several observations can then be made. For income, we confirm that type 1 is more common among the most affluent populations, whereas archetypes 6 and 7 are more common among the less well-off. In terms of age, different longitudinal dynamics are observed according to income. As it stands, it is observed that the most affluent and youngest populations are very present in archetype 2 ("Economic house"). Older households are more present in archetype 1 ("Leisure house") and finally in archetype 3 ("Practical cocoon"). For lower incomes, the dynamics appear more complex: A large proportion of households are attached to archetype 2 ("Economic house"). Younger households tend to be in archetype 6 ('Frugality house'). Households whose reference person is between 40 and 60 years old are in archetype 4 ("Warm House") and finally households further along in the life cycle are in archetype 6 ("Frugality house") or 7 ("Savings house"). On the other hand, some archetypes seem to depend weakly on income and age, such as archetypes 2 and 5. At this stage of the analysis it is difficult to accurately distinguish the mechanisms of emergence of these archetypes. However, it seems reasonable to suggest that other explanatory variables absent from the study (e.g. cultural, geographical, contextual) could help to better visualise and understand their emergence.

These results complement the literature. Where Bourgeois et al. showed the influence of age and family size on the level of equipment, use and regulation [46], we suggest that in fact a set of practices changes during the life cycle of the household. Lastly, on the dynamic aspect and to put our result into perspective, we recall that Moussaoui, in an interview-based study, proposed an explanation for the differentiation of consumption over the life cycle. She suggested that the adoption of behaviours at each stage of the life cycle is associated both with changing needs and with the fact that each generation faces specific energy conditions and therefore develops its own energy culture [42].

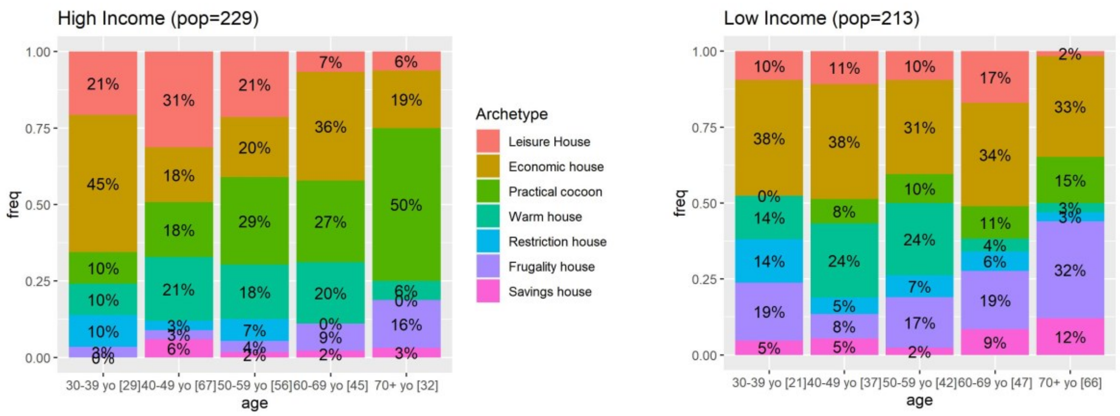


Figure 5: Distribution of behavioural archetypes by age of household reference person. The data correspond to the proportions of the archetypes by age group. The number of households for each age category are given in square brackets. Source : secondary processing of ENERGIHAB data.

The modelling carried out highlights the diversity of determinants that can be associated with households, dwellings, but also with the energy cultures developed and the specific housing contexts. This work opens up modelling perspectives that would make it possible to better understand the emergence dynamics and also, by simulating the associated energy consumption for each profile, to propose tailored solutions to support an overall reduction in energy consumption.

4.4 Limitations

Two major types of criticism can be levelled at the study, on the data used and on the classification strategy. First, the data used in this study date from 2010 and do not include significant developments in digital uses, nor the very recent growth of homeworking, which has changed the habits of certain households. Furthermore, the behavioural and energy consumption data used were collected by a survey, which is subject to reporting bias through lack of information or error. Finally, these data refer to average reported behaviours and may therefore reflect bias in the survey participants' behavioural assessments.

Second, behavioural archetypes are inherently imperfect. Moreover, despite our commitment to describing the diversity of behaviours exhaustively, there is no doubt that other behavioural variables could have been included. In particular, further work could include a more detailed description of digital uses and equipment quality.

In terms of the prospects for developing this research, we feel it important to emphasise that these behavioural archetypes can be used to conduct a static projection of behaviour in a synthetic space. This article does not explore the dynamics between behavioural archetypes. This study was also limited to regional data. Although the distributions of lifestyle and culture have been reported to be similar between Île-de-France and other French regions, significant differences in income, travel patterns and proportions of urban and rural populations suggest the utility of performing the same type of analysis on extended data in order to broaden the results. Another possibility for this study would be to include knowledge and cultural input in order to illustrate the cognitive and normative backgrounds of the households in addition to the material and socioeconomic frameworks we investigated [22].

5 Conclusion

This research makes three contributions. First, it builds seven archetypes from cross-sectional behavioural variables on a large database. Second, the description of the associated households and housings is performed using typical household and housing profiles. Finally, it develops a methodology for classifying behavioural data from qualitative and quantitative data, opening up prospects for a more transparent, comparable, and reproducible use of survey data. To our knowledge, this study is the first to integrate variables simultaneously covering hygiene, food, heating, lighting and leisure practices and housing occupation. The archetypes constructed make it possible to account for the intersecting dynamics in these areas. While the behavioural tendencies towards over-consumption or conservation observed in the literature were also found here [35], [36], [40], the analysis of household profiles and archetypes has highlighted that these behaviours can emerge in specific contexts but in a more complex way than described in the literature. This study provides useful information for public policymakers and modellers. For public authorities, this study based on detailed regional behavioural data shows that behaviour is not only a matter of individual values, beliefs, and attitudes. It is also largely determined by the household's position in its life cycle, its income, and by its housing characteristics. Furthermore, differentiating households according to their behaviour opens the possibility of designing more tailored solutions to support households in reducing their energy consumption. Proposals made in the literature regularly mention the development of financial incentives for renovation operations, the replacement of energy-intensive equipment, or measures to encourage changes in behaviour [33]. These solutions are certainly relevant to the households and behaviours described in this article. Nevertheless, in view of the knowledge that has been accumulated on the influence of the life cycle of households on behaviour and energy consumption [3], it seems important to devise policies that include this perspective. In this view, financial and support measures could focus in particular on the transitions between the stages in the household life cycle since it is at these moments that equipment and residential choices are made and behaviour is reconfigured. However, the details of the policy measures require a more precise simulation of the consumption of each of these profiles, which will be carried out in our future work. For the modellers, the work provided opens up prospects for modelling consumption based on lifestyles. The most common top-down model today is multilinear, and associates variables that are highly correlated, which limits the significance of the coefficients. We will study the integration of the "archetype" variable and study its effect on the accuracy and interpretation of the model. Secondly, the archetypes allow us to design behavioural scenarios for dynamic thermal simulations. In the same way as Ben and Steemers, we want to use these behavioural archetypes and the associated household and dwelling profiles to simulate energy consumption and the effects of retrofitting, behavioural change or automation measures.

This study proposes numerous avenues for further research. First, the robustness of these archetypes needs to be explored, notably by exploiting national databases or even those of other regions and considering recent changes in behaviour resulting from the Covid-19 crisis, which has altered occupancy patterns if not equipment levels and use. Second, the link between these behavioural archetypes and consumption needs to be analysed through several modelling strategies. This would make it possible, for example, to quantify the effect of multiple factors (surface area, number of inhabitants, quality of insulation, etc.) for each archetype. Third, the dynamics between behavioural archetypes have only been touched upon here. Further modelling would provide a better understanding of these dynamics. This work would of course support a fourth type of research, this time concerned with the evolution of these archetypes of behaviour and associated consumption in the future.

6 Acknowledgments

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8 Appendix

8.1 Appendix: Interpretation of the synthetic variables

Table 6 : List of the synthetic variables (SV) and the variables that were used for their construction. Each quantitative variable is described with the correlation coefficient with the associated SV. Each qualitative variable is described by the coordinates of

Synthetic Variable	Behaviour variable	Correlation	Coordinates of modality
SV1 [-2.67; 3.26]	F_EQ1	-0.86	
	F_US3	-0.49	
	F_EQ2=INDFREEZ_N		0.48
	F_EQ2=INDFREEZ_Y		-0.82
SV2 [-1.33;2.30]	F_US1	-0.80	
	OCC3=OCCWE_HIGH		-0.37
	OCC3=OCCWE_LOW		0.78
	OCC3=OCCWE_MID		-0.07
	OCC5=AWAY_EVD		0.63
	OCC5=AWAY_ST		0.25
	OCC5=HOMEBASED		-0.68
SV3 [-3.36; 2.42]	F_US2	-0.28	
	F_REG1	-0.50	
	HY_EQ1	-0.84	
	HY_US3	-0.79	
	HY_US4	-0.65	
	HY_US5	-0.63	
	LI_REG3=REGLUX_N		-0.29
	LI_REG3=REGLUX_Y		0.03
	OCC4=VAC_N		0.41
	OCC4=VAC_OFT		-0.41
	OCC4=VAC_ST		-0.09
SV4 [-1.42;6.07]	LI_EQ1	0.51	
	HY_REG1=WATERSAV_N		-0.20
	HY_REG1=WATERSAV_Y		1.37
	TC_EQ1=AUXHEAT_N		-0.32
	TC_EQ1=AUXHEAT_Y		0.78
	TC_USE3=VENTILBLOCK_N		-0.09
	TC_USE3=VENTILBLOCK_Y		2.72
SV5 [-2.12;5.77]	TC_US1	0.66	
	HY_US1=<1SHOWER		-0.19
	HY_US1==1SHOWER		-0.21
	HY_US1=>1SHOWER		1.46
	TC_REG1=INTERMCLOTH		0.19
	TC_REG1=LIGHTCLOTH		0.90
	TC_REG1=WARMCLOTH		-0.52
SV6 [-1.46; 3.03]	TC_US2	-0.49	
	TC_REG3	0.38	
	TC_REG2=REGULT_N		-0.65
	TC_REG2=REGULT_Y		0.49
	TC_REG4=HEATOFF_N		-0.58
	TC_REG4=HEATOFF_Y		0.65
SV7 [-1.81; 2.89]	WL_EQ1	0.82	
	WL_US1	0.69	
	WL_US2	0.39	
	WL_REG1=SCREENREG_HIGH		0.59
	WL_REG1=SCREENREG_LOW		-0.84
	WL_REG1=SCREENREG_MID		0.20
SV8 [-3.3; 1.8]	HY_US2=BATH_N		-0.05
	HY_US2=BATH_Y		1.12
	HY_REG2=SELECSORT_N		-2.18
	HY_REG2=SELECSORT_Y		0.22
SV9 [-1.82; 0.85]	LI_REG1=LEDBC_ALW		-0.99
	LI_REG1=LEDBC_N		0.68
	LI_REG1=LEDBC_SMT		0.34
	LI_REG2=HALOG_N		-1.28
	LI_REG2=HALOG_Y		0.39

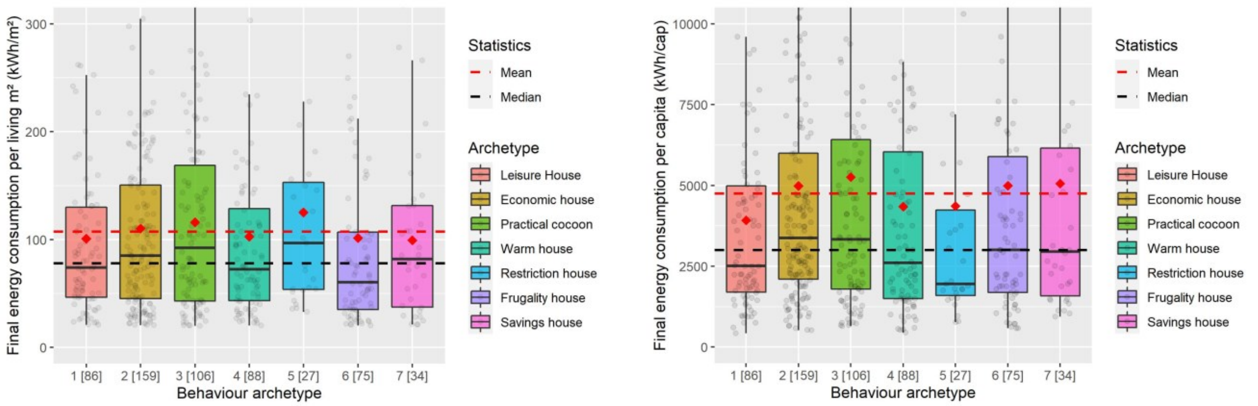
8.2 Appendix: Interpretation of the behaviour clusters

Table 7: Barycenter scores for the 7 archetypes. Only non-zero coefficients (95% confidence interval) are given. By construction, a zero score corresponds to an "average" behaviour.

	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7
Food equipment	-0.41	0.16	-0.62		0.33	0.98	
Presence at home	0.10	0.24	-0.53	0.63	0.34	-0.36	-0.43
Hygiene equipment & use	-0.37	0.28	-0.70	-0.28		0.86	0.41
Restriction level	-0.37		0.15	-0.37	2.72		-0.27
Heating requirement	0.14	-0.47	-0.20	1.04			
Heat regulation	0.12	0.58	-0.30	-0.28		-0.36	-0.33
IT demand	0.60	-0.27	0.51	0.31		-1.00	-0.28
Saving gestures	0.30	0.22	0.18	0.10			-2.37
Lighting equipment	-1.46	0.53	0.45	0.46	-0.57	-0.28	0.33
Food equipment	-0.41	0.16	-0.62		0.33	0.98	

8.3 Appendix: Distributions of energy intensities by behavioural archetype

Table 8 : Distributions of energy intensities by behavioural archetype. Median for the entire dataset is plotted in dashed line. The number of households of each type is shown in square brackets



(A) Final energy consumption per square metre of living space

(B) Final energy consumption per capita

8.4 Appendix: Household and housing characteristics by behavioural archetype

Table 9 : Household and housing characteristics by behavioural archetype

	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Total (%)
Number of persons								
1 pers	15%	43%	9%	25%	33%	64%	62%	33%
2 pers	31%	35%	38%	27%	19%	28%	26%	32%
3 pers	17%	8%	15%	15%	22%	5%	9%	12%
4 pers	24%	10%	23%	23%	15%	1%	0%	15%
5 pers	8%	2%	12%	10%	7%	0%	3%	6%
≥6 pers	3%	1%	3%	0%	4%	1%	0%	2%
Composition of the household								
Childless couple	26%	26%	37%	23%	7%	24%	24%	26%
Couple with child(ren)	52%	19%	47%	42%	41%	5%	12%	32%
One-parent family	6%	6%	6%	9%	15%	4%	0%	6%
Several persons (no family)	1%	4%	1%	1%	4%	3%	3%	2%
Single person	15%	43%	9%	25%	33%	64%	62%	33%
Age of the reference person								

Less than 30 yo	1%	1%	1%	6%	0%	1%	3%	2%
30-39 yo	12%	16%	4%	10%	33%	8%	3%	11%
40-49 yo	37%	21%	22%	32%	15%	8%	18%	23%
50-59 yo	24%	18%	22%	28%	26%	15%	15%	21%
60-69 yo	20%	22%	21%	17%	15%	23%	21%	20%
70+ yo	6%	23%	31%	7%	11%	45%	41%	23%
Socio-professional group								
Employees & Workers	29%	30%	27%	36%	37%	44%	38%	33%
Executives	22%	26%	39%	16%	19%	17%	29%	25%
Farmers & Artisans	6%	7%	6%	6%	0%	5%	3%	6%
Intermediate profession	42%	35%	26%	42%	44%	29%	29%	35%
No profession	1%	2%	2%	0%	0%	4%	0%	2%
Professional status								
Active	74%	58%	41%	80%	63%	27%	26%	55%
Retired	22%	38%	53%	16%	30%	68%	62%	40%
Unemployed	3%	3%	7%	5%	7%	5%	12%	5%
Income								
Income Q1	6%	26%	9%	10%	19%	36%	29%	19%
Income Q2	10%	10%	5%	11%	19%	16%	6%	10%
Income Q3	27%	26%	23%	28%	33%	17%	29%	25%
Income Q4	15%	17%	25%	13%	11%	8%	6%	15%
Income Q5	16%	4%	16%	15%	0%	0%	0%	9%
No response	26%	17%	23%	23%	19%	23%	29%	22%
Surface								
Less than 30m²	0%	2%	0%	3%	4%	4%	3%	2%
Between 30-50m²	7%	16%	3%	10%	26%	29%	24%	14%
Between 50-75m²	21%	33%	12%	19%	30%	28%	38%	25%
Between 75-100m²	26%	21%	24%	24%	30%	27%	21%	24%
Between 100-150m²	31%	26%	46%	32%	11%	12%	15%	28%
More than 150m²	15%	2%	15%	11%	0%	0%	0%	7%
Zone								
Rural area	47%	34%	39%	33%	30%	28%	24%	35%
Urban area	45%	55%	56%	57%	56%	57%	74%	56%
Urban periphery	8%	11%	6%	10%	15%	15%	3%	10%
Type of housing								
Collective housing	38%	60%	37%	56%	78%	71%	71%	55%
Individual housing	62%	40%	63%	44%	22%	29%	29%	45%
Status of occupancy								
Homeowners and first-time buyers	69%	67%	81%	65%	56%	61%	50%	67%
Private housing residents	15%	23%	8%	22%	19%	24%	26%	19%
Public housing residents	16%	11%	10%	14%	26%	15%	24%	14%
Electric heating								
No	63%	62%	62%	66%	56%	65%	65%	63%
Yes	37%	38%	38%	34%	44%	35%	35%	37%
Gas heating								
No	47%	49%	49%	48%	44%	48%	35%	47%
Yes	53%	51%	51%	52%	56%	52%	65%	53%
Oil heating								
No	94%	94%	94%	86%	96%	92%	97%	93%
Yes	6%	6%	6%	14%	4%	8%	3%	7%
Date of construction								
Before 1949	35%	43%	35%	24%	33%	36%	32%	35%
1949-1975	20%	19%	25%	35%	33%	37%	29%	27%
1975-1990	20%	19%	27%	23%	15%	11%	24%	20%
1990+	26%	18%	12%	18%	19%	16%	15%	18%
Recent refurbishment work								
No	23%	15%	19%	16%	22%	35%	21%	20%
Yes	77%	85%	81%	84%	78%	65%	79%	80%
Number of years of residence (years)								
mean [standard deviation]	19 [14]	20 [12]	17 [13]	12[12]	24[19]	12 [10]	25 [16]	19 [14]
Surface per capita (m²/person)								
mean [standard deviation]	48 [25]	45 [31]	46 [35]	44 [30]	52 [26]	32 [14]	50 [20]	47 [29]
Final energy consumption								
High	63%	47%	69%	53%	41%	36%	35%	52%
Low	37%	53%	31%	47%	59%	64%	65%	48%
Final energy consumption per capita								
High	47%	52%	53%	47%	52%	37%	50%	50%
Low	53%	48%	47%	53%	48%	63%	50%	50%
Final energy consumption per m²								
High	47%	55%	54%	45%	41%	48%	44%	49%

Low	53%	45%	46%	55%	59%	52%	56%	51%