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ORIGINAL ARTICLE

Household archetypes and behavioural patterns in UK domestic energy use

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Abstract Variations in household behaviour often lead to a mismatch between actual and estimated energy performance at home. More detailed information on behavioural variables could help in improving the prediction of energy consumption and enabling policy interventions responding to different household groups. This research aims to identify household archetypes and behavioural patterns in order to allow a targeted approach in energy-saving policy and retrofit improvement. It employed a statistical approach to cluster households based on empirical data collected from a household survey in Cambridge, UK. Factor analysis was used to identify behavioural factors. Based on the commonalities of variables under each factor, five factors were defined: (1) main space heating, (2) auxiliary space use, (3) main space use, (4) auxiliary space heating and (5) use of appliances. Statistical pattern analysis was then applied to develop behavioural patterns. These patterns were derived based on their factor scores. Finally, non-parametric correlation analysis was carried out in order to determine the relationship between behavioural factors and the following: household or dwelling characteristics, comfort and energy use for creating household archetypes. After significant correlations were found between behavioural factors and other variables, five archetypes were identified: (1) active spenders, (2) conscious occupiers, (3) average users, (4) conservers and (5) inactive users. Among these archetypes, households with a larger house, higher energy use and more complex household composition tended to have longer hours of main space heating, while larger and more complex households tended to use the main space of their dwellings for longer. Using these archetypes allows for a better integration of occupant behaviour into the technically oriented efficiency paradigm. This tailored approach provides a gateway to developing more effective policies and low energy strategies geared towards specific households.

Keywords Household archetypes · Behavioural patterns · Domestic energy use · Occupant behaviour · Energy policy

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Introduction

Occupants' daily domestic life in housing accounts for more than a quarter of the total energy consumption and carbon dioxide emissions in the UK (Palmer and Cooper 2013). This is one of the most important areas being targeted by the Government for reducing energy usage and increasing climate security (DTI 2007). Occupant behaviour has been demonstrated to have a significant impact on household energy consumption (Steemers and Yun 2009; Gram-Hanssen 2004). Meanwhile, the predicted energy savings associated with energy-efficient technologies frequently exceed actual savings made due to behavioural factors (Stern 1985; Gram-Hanssen et al. 2012; Sunikka-Blank and Galvin 2012). These behavioural factors may be categorised into socio-economic variables (Steemers and Yun 2009; Belaïd 2016), lifestyle groups (Guerra-Santin and Itard 2010) and socio-material configurations (Gram-Hanssen 2010), in which social and material worlds are considered as inextricably entwined (Beaulieu et al. 2016). They may also be explained by a rebound effect relating to higher comfort expectations (Sorrell et al. 2009). Within a socio-technical approach, this is taken further to show how occupant comfort co-evolves with technical systems in a social and cultural context (Shove 2003; Guy 2006).

Occupant behaviour therefore represents an important research area for generating the information needed for the development of energy efficiency interventions and evidence-based energy policy in the residential sector. However, energy consumption is complex. Employing standard and simplistic behavioural profiles in energy modelling leads to a significant discrepancy between actual usage and prediction (Menezes et al. 2012). For energy demand reduction, an approach of incorporating the complexity of behaviour is needed that captures the key determinants of energy performance to allow better evaluation of energy-saving policy programmes and retrofit options. Collecting and employing an exhaustive dataset on occupant behaviour for each household in home energy audits is likely to be unrealistic. Current behavioural modelling using mainly stochastic methods in building simulations addresses behavioural complexity but excludes occupants' socio-demographics and household characteristics which are crucial for identifying specific target groups (Andersen et al. 2016; Gaetani et al. 2016). An alternative is to create an archetype for each significant class of household based on statistical analysis, and then examine different ways of tackling energy efficiency according to the characteristics for that archetype. If the archetypes are carefully selected, this procedure enables a tailored evaluation of the different household types along with their different energy consumption patterns and potentially different responses to energy efficiency interventions. The approach can be applied at a national, regional or local level.

Archetypes are particularly helpful in exploring policy opportunities geared towards different household groups, because they have the potential to support analyses of energy usage trends and patterns at more disaggregate levels (Hughes and Moreno 2013). Moreover, archetypes can be used to make future projections by exploring changes in household behavioural patterns and energy retrofit options while developing priorities for research and development.

In recent decades, an increasing number of studies have been conducted with the aim of determining household archetypes and segmentation, behavioural patterns, occupancy profiles in relation to energy consumption as well as household characteristics (van Raaij and Verhallen 1983; Guerra-Santin 2011; Sütterlin et al. 2011; Zhang et al. 2012; Hughes and Moreno 2013; Poortinga and Darnton 2016). Household archetypes can be defined with household characteristics, lifestyle and behavioural patterns, attitudinal variables and physical characteristics of the dwellings. In what is perhaps the most inclusive development of residential energy consumer archetypes, Zhang et al. (2012) proposed a three-dimensional model and identified eight archetypes: (1) pioneer greens, (2) follower greens, (3) concerned greens, (4) home-stayers, (5) unconscientious wasters, (6) regular wasters, (7) daytime wasters and (8) disengaged wasters. Energy policy and interventions were designed for each of these archetypes that integrated the factors extensively studied in previous research in UK domestic energy use. However, while this study has informed policy regarding the need of a tailored and multidimensional approach, there is little information about the socio-demographic characteristics of these archetypes, making it difficult to determine their applicability in practice and thus the way to employ them for energy demand reduction.

Previous studies have already revealed different statistical approaches to clustering energy consumers and making household archetypes for targeting energy efficiency improvements. Table 1 presents key references on identifying different energy consumer segments, including a brief outline of sample, method and outcome. These studies analysed the interdependencies between occupant behaviour, attitude and energy consumption while developing certain segments or archetypes based on different methods. Nevertheless, as every author analysed data collected with a different set of predetermined parameters, the resulting clusters differ as well. While the above-mentioned studies exemplify research with the aim of identifying consumer typologies and behavioural patterns in general, there is a current

Table 1 Summary of existing research on household clustering and segmentation

Author(s)	Sample size	Date	Location	Data analysis method	User groups
van Raaij and Verhallen (1983)	145	Nov 1976–Nov 1977	Vlaardingen, the Netherlands	Principal component analysis, pattern analysis, discriminant analysis	Conservers, spenders, cool, warm, average
Defra (2008)	378	2007	England	Cluster analysis	Positive greens, waste watchers, concerned consumers, sideline supporters, cautious participants, stalled starters, honestly disengaged
Guerra-Santin (2011)	313	Autumn 2008	Leidsche Rijn in Utrecht and Wateringse Veld in The Hague, the Netherlands	Correlation analysis, strings classification, exploratory factor analysis	Spenders, affluent-cool, conscious–warm, comfort, convenience
Sutterlin et al. (2011)	1292	Nov 2009–Jan 2010	Switzerland	Cluster analysis, correlation analysis	Idealistic energy saver, selfless inconsequent energy saver, thrifty energy saver, materialistic energy consumer, convenience-oriented indifferent energy consumer, problem-aware well-being-oriented energy consumer
Hughes and Moreno (2013)	250	2010–2011	England	Factor analysis, cluster analysis	Profligate potential, thrifty values, lavish lifestyles, modern living, practical considerations, off-peak users, peak-time users
Poortinga and Darnton (2016)	1538	May–Jul 2011	Wales	Cluster analysis	Enthusiasts, pragmatists, aspirers, community focused, commentators, self-reliant

lack of research on developing household archetypes that link household characteristics with behavioural and attitudinal variables. Although, some studies have shown the extent to which occupant behaviour is connected with certain types of socio-technical and psychographic characteristics (Sütterlin et al. 2011; Zhang et al. 2012; Poortinga and Darnton 2016). There has, however, been little work done to develop archetypes that statistically combine occupant behaviour, comfort, energy use, household and dwelling characteristics. The determination of household archetypes with detailed profiles and behavioural patterns would lead to more accurate energy-saving estimations from retrofit and, at the same time, help organisations in the energy industry to make better predictions.

This study aims to develop household archetypes while obtaining greater insight into the relationship between behavioural factors and energy use, comfort, household and dwelling characteristics. In addition, this study aims to determine household archetypes based on behavioural patterns for energy modelling in the next-stage research. In this study, three research questions are addressed:

1. What are the factors underlying behaviour at home?
2. What are the behavioural patterns with regard to occupant activities and space heating?
3. What are the household archetypes with regard to behavioural patterns, comfort, energy use and household characteristics?

Methodology

Data collection

To develop representative household archetypes for energy modelling and policy intervention, a tailored and comprehensive dataset was required. Based on the literature and preliminary studies, a questionnaire was designed that covers the aspects of comfort, behaviour, energy use and household characteristics. The questionnaire was paired with data on building characteristics obtained from the Domestic Energy Performance Certificate Register (DCLG 2014). As energy behaviour is contingent with other behaviour associated with household lifestyle (Guerra-Santin and Itard 2010) and space heating has the greatest impact on energy use (Ben and Steemers 2014), behaviour in this research was defined as the use of space, daily activities and the use of space heating. These behaviours were surveyed in a measurement of hours on a weekly basis, such as the total hours the occupant spent in the bedroom in a typical week. Household characteristics included socio-demographic variables shown to influence energy consumption in previous studies (Steemers and Yun 2009; Guerra-Santin and Itard 2010; Chen et al. 2013): age, tenure type, household size, household type/composition, work-status, occupation, education and household income.

The survey was carried out in Cambridge in spring 2015. Based on the availability of Energy Performance Certificates (EPC) from the EPC register, households were selected using postcodes to ensure that data on the dwellings' physical characteristics could be collected. A total of 400 postcodes were chosen with an intention of having surveyed households equally distributed among five Cambridge postcode districts from CB1 to CB5. The questionnaire containing 24 question sections was created online using Qualtrics Survey Software and printed out for face-to-face and postal surveys. As a complementary option for participants filling in the questionnaire, a link to the online survey was offered. A total of 78 households participated in the surveys, including 55 usable cases (response rate 28%) from face-to-face surveys and 23 usable cases (response rate 12%) from postal surveys. The number of respondents was constrained due to the limited number of households with an EPC available, the non-presence of people at home during the face-to-face survey and the length and detail of the questionnaire. As Cambridge is a more affluent city when compared to other areas within the UK, households with low income and low levels of education were underrepresented.

Data analysis

Following the data collection, the analysis mainly used the SPSS statistical software package to identify the behavioural factors and to further develop household archetypes. Initially, an analysis of the factors underlying behaviour was carried out using factor analysis with the principal component method (Fig. 1a). This was to group similar behavioural variables into dimensions and identify latent variables called factors. Afterwards, behavioural patterns were defined using statistical pattern analysis by dichotomising the factor scores of each case

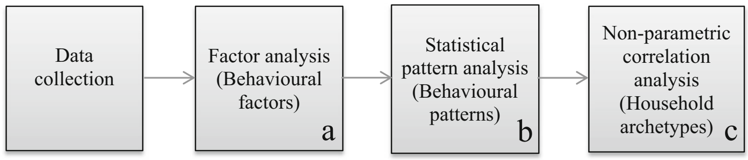

Fig. 1 Methodology. **a** Analysis of the factors underlying behaviour using Factor Analysis with the principal component method. **b** Defining behavioural patterns using statistical pattern analysis by dichotomising the factor scores of each case derived from the previous step and subsequently categorising the cases accordingly. **c** Determining household archetypes based on the relationships between the behavioural factors and the following: household characteristics, energy use, comfort, dwelling characteristics

derived from the previous step and subsequently categorising the cases accordingly (Fig. 1b). This method was performed in the form of a data matrix, classifying data into categories and combining these categories into a set of patterns. van Raaij and Verhallen (1983) and Guerra-Santin (2011) have also used this method to determine residential energy behavioural patterns. Finally, the household archetypes were developed based on the relationships between the behavioural factors and the following: household characteristics, energy use, comfort, dwelling characteristics (Fig. 1c). These relationships were explored using non-parametric correlation analysis. The "Results" section contains a more detailed description of the statistical analyses.

Results

Behavioural factors

Factor analysis was used to identify the underlying factors that explain the relational structure among the observed behavioural variables. The analysis was performed using the SPSS statistical software package with an extraction method using principal component analysis. The behaviour factors (clusters of inter-correlated variables) generated from the analysis were interpreted in such a way to reveal the hidden dimensions of the observed household practices. The interpretation of a factor utilises a descriptive label that comprises selecting a concept reflecting the nature of the variable measured and its relative importance to that factor (Field 2013).

The results are shown in Table 2, which contains factor loadings and communalities of the 32 variables used for the factor analysis. Initially, the analysis was conducted without any pre-setting on the number of components. The result was a rotated component matrix consisting of ten factors accounting for 75.60% of the variance. However, the breaking point of the scree plot was at five or six factors. A close examination of the Initial Eigenvalues of the resulting factors showed that the first factor explained 26.87% of the variance, the second 10.68%, the third 7.44%, the fourth 6.00%, the fifth 5.18% and the sixth to 35th less than 5% each. Thus, extraction of five factors that would account for only 56.18% of the variance was preferred, as this enhances the overview of the matrix considerably. An examination of discriminant validity through the factor correlation matrix showed that correlations between factors were lower than 0.7, and correlation coefficients between a single variable and every other variables were higher than 0.5. Consequently, the factor analysis was carried out again, selecting for the extraction of only five factors. As shown in Table 2, the five columns under 'Components' show the contribution of each variable to its factor. The last column contains extraction communalities, which are estimates of the variance in each variable that is accounted for by the components.

Five behaviour factors are presented in Table 3, namely 'main space heating', 'auxiliary space use', 'main space use', 'auxiliary space heating' and 'use of appliances'. The variables contained in factor 1 indicate a long duration of heating for the main functioning rooms. The variable 'study/office usage', which has a very different nature from other variables comprising this factor, has very low scores in factor loadings and communalities. It was thus considered that this variable would not be included in the naming of the factor. The variables in factor 2 are related more to an extensive usage of auxiliary rooms. The heating durations of conservatory and basement/storage areas were merged into this description, as they were positively correlated with the usage durations of these rooms and had a relatively smaller contribution to this factor. The variables in factor 3 were related to the main space usage

Table 2 Rotated component matrix and communalities for 32 behavioural variables

Behavioural variables	Components					Communalities
	1	2	3	4	5	
Living room heating	0.931					0.869
Bathroom heating	0.906					0.857
Dining room heating	0.901					0.834
Bedroom heating	0.893					0.839
Studying/office heating	0.889					0.814
Kitchen heating	0.884					0.806
Guest room heating	0.873					0.774
Hall heating	0.864					0.774
Master bedroom heating	0.864					0.781
Utility room heating	0.476			0.456		0.676
Study/office usage	0.428					0.32
Conservatory usage		0.899				0.83
Utility room usage		0.791				0.727
Basement/storage areas usage		0.708				0.548
Conservatory heating		0.595		0.672		0.864
Bathroom/toilet usage		0.552	0.419			0.591
Bedroom usage			0.67			0.533
Guest room usage			0.551			0.536
Sleep			0.608			0.411
Dining room usage			0.531			0.454
Exercise			0.548			0.335
Living room usage			0.445	− 0.414		0.464
Social			0.529			0.397
Time spend at home			0.456			0.443
Master bedroom usage						0.43
Kitchen usage						0.258
Cooking					0.732	0.566
Personal hygiene					0.563	0.474
Housework					0.571	0.389
Other places usage					− 0.461	0.29
Other places heating				0.796		0.696
Basement/storage areas heating		0.489		0.715		0.779

Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalisation. Rotation converged in eight iterations. Factor loadings < 0.4 are suppressed

at home. The variables of sleep, exercise and social were merged into this description due to the significant correlation between these three variables and the usage duration of some rooms included in this factor. Factor 4 contains the variables mainly associated with the long heating duration of auxiliary space. Less usage duration of the living room might also indicate less heating duration of some of the main rooms. The relationship between the variables in factor 5 seems to suggest an intensive use of appliances. The fact that no variable was shared between this factor and other factors indicates the independence of appliance-usage behaviour. The variable of 'other places usage' has very low scores in both factor loading and communalities and was thus not considered in the description of this factor.

Table 3 Behavioural factors

Factor	Name of factor	Variables
Factor 1	Main space heating	Living room heating, bathroom heating, dining room heating, bedroom heating, studying/office heating, kitchen heating, guest room heating, hall heating, master bedroom heating, utility room heating, study/office usage
Factor 2	Auxiliary space use	Conservatory usage, utility room usage, basement/storage areas usage, bathroom/toilet usage, conservatory heating, basement/storage areas heating
Factor 3	Main space use	Bathroom/toilet usage, bedroom usage, guest room usage, sleep, dining room usage, exercise, living room usage, social, time spend at home
Factor 4	Auxiliary space heating	Utility room heating, conservatory heating, less living room usage, other places heating, basement/storage areas heating
Factor 5	Use of appliances	Cooking, personal hygiene, housework, less other places usage

Behavioural patterns

Statistical pattern analysis was used to determine behavioural patterns. The first step was to dichotomise the factor scores (component scores) based on whether they lie above or below the mean score for the five factors. Subsequently, binary strings were formed for the 78 respondents, with each containing five dichotomous scores. Theoretically, $2^5 = 32$ binary strings should be obtained after dichotomisation. Nevertheless, only 29 strings were found in the sample due to polarity of certain variables (Table 4). The three missing strings due to polarity were 11,010, 11,001 and 10,110. These strings represented individual patterns with some more similar than others. The strings were then grouped according to their overall scores as very high, high, medium, low and very low. The thresholds were defined based on not only the overall scores but also the score differences between space heating and space use. As a result, five behavioural patterns were defined using interpretation of the common characteristics of the grouped cases, including active spenders, conscious occupiers, average users, conservers and inactive users.

Table 4 shows the behavioural patterns along with the strings categorised for each pattern. The six participants of pattern I have a high score on at least four of the five factors with heating duration of main space and auxiliary space above average—*Active spenders.* People who fall into this category are characterised by their use of more space, longer durations of heating and more use of appliances. The 11 participants of pattern II may be described by an extensive usage of space with a low score on at least one of the heating factors and a high score in at least three of the five factors—*Conscious occupiers.* This group of users tends to stay at home and use various rooms for longer durations, with less heating duration in some rooms. The largest cluster is pattern III with 26 participants. People in this category have a high or low score on two or three of the five factors with a maximum of one high score in either auxiliary space use or main space use—*Average users.* They are semi-active in their use of space, heating and appliances, sharing an average score with the five factors added together. The 10 respondents of pattern IV have a low heating duration in general but have a high score in two of the three non-heating factors—*Conservers*. This type of user is energy conscious with a shorter duration of heating and a longer duration of usage of space and appliances. The 24 participants of pattern V have a high score on only a maximum of one of the five factors—*Inactive users.* Occupants in this category generally have a shorter duration of space usage, heating and appliances compared with average users.

Household archetypes

In this section, correlation analysis was carried out in order to determine the relationship between behavioural patterns and household characteristics alongside comfort and energy use for developing household archetypes. Comfort was measured on a scale of 1 (very dissatisfied) to 7 (very satisfied), while energy use was recorded in the unit of kWh/m^2. Each of the five behavioural patterns produced in the above section formed the basis for the archetypes. The behavioural variables used for the analysis were those created for each behaviour factor in the "Behavioural factors" section, based on factor scores. The results from Spearman's correlation analysis can be found in Table 5.

Table 4 Behavioural patterns with strings classification

Pattern [criteria for classification]	Factor 1 Main space heating	Factor 2 Auxiliary space use	Factor 3 Main space use	Factor 4 Auxiliary space heating	Factor 5 Use of appliances	Number	
Active spenders [4 or 5 high scores, high in F1 and F4]	1	1	1	1	1	2	6
	1	1	1	1	0	2	
	1	0	1	1	1	1	
	1	1	0	1	1	1	
Conscious occupiers [3–4 high scores, high score in F2 and F3]	1	1	1	0	1	2	11
	1	1	1	0	0	2	
	0	1	1	0	1	5	
	0	1	1	1	0	1	
	0	1	1	1	1	1	
Average users [2–3 high scores]	0	0	1	1	1	2	26
	0	0	1	1	0	2	
	0	0	0	1	1	3	
	1	0	0	1	0	2	
	1	0	0	1	1	2	
	1	0	0	0	1	3	
	0	1	0	1	1	2	
	0	1	0	1	0	2	
	1	1	0	0	0	1	
	1	0	1	0	1	6	
	1	0	1	0	0	1	
Conservers [low score in F1 and F4, 2 high scores]	0	0	1	0	1	6	10
	0	1	0	0	1	1	
	0	1	1	0	0	3	
Inactive users [0 or 1 high score]	0	0	1	0	0	2	24
	1	0	0	0	0	5	
	0	1	0	0	0	5	
	0	0	0	1	0	5	
	0	0	0	0	1	2	
	0	0	0	0	0	5	

The results indicated that the households, which scored high for main space heating, were mainly large families with high income living in large modern houses with high energy consumption. In addition, households, which scored high for auxiliary space use, had a low energy use/m^2, indicating a preference for energy conservation in this group. Households with high scores for main space use were mostly large young families with children living in owner-occupied houses. Households that scored high for auxiliary space heating were largely retired people or students living in energy-efficient dwellings. Households with a high score in ‘use of appliances’ were seniors living in semi-detached or detached houses.

Five household archetypes were formed corresponding to the features of behavioural patterns and associated characteristics derived above. The active-spender archetype tends to be large wealthy families living in large modern and energy-efficient houses while consuming high energy. The conscious-occupier archetype is more likely to be large young families with children living in owner-occupied houses that use energy consciously. The average-user archetype could cover a wider range of household types compared to other archetypes; therefore ‘working couples with moderate energy use behaviour’ was selected so as to distinguish it from other groups. The conserver archetype consists of singles or couples with low income, living in small energy-

Table 5 Correlations between behaviour factors, comfort, energy use, household and building characteristics

	Factor 1 Main space heating	Factor 2 Auxiliary space use	Factor 3 Main space use	Factor 4 Auxiliary space heating	Factor 5 Use of appliances
Tenure type			− 0.255*		
Household type	0.303**		0.326**		
Household size			0.378**		
Occupant age			− 0.233*		0.236*
Education level					
Household income	0.241*				
Working status				0.257*	
Occupation					
Environmental impact rating				0.259*	
Energy efficiency rating				0.266*	
Dwelling age	0.260*				
Dwelling type					0.272*
Dwelling orientation					
Floor area	0.310**				
Energy use/m^2	0.297*	− 0.298*			
Energy use	0.449**				
Comfort					
Thermal comfort					

*Correlation is significant at the $P \leq 0.05$ level (two-tailed); **correlation is significant at the $P \leq 0.01$ level (two-tailed)

inefficient houses with reserved energy behaviour and low energy use. The inactive-user archetype is defined as single people with full-time jobs, spending little time at home.

Discussion

This research has identified five different household archetypes to serve as a basis for targeted policy interventions tailored to specific socio-demographic groups regarding domestic energy demand reduction. These are (1) active spenders, (2) conscious occupiers, (3) average users, (4) conservers and (5) inactive users. Each of these archetypes contains specific behavioural patterns linked with household characteristics based on statistical analyses of empirical data. As a basis for determining behavioural patterns, five factors underlying occupant behaviour variables were found: (1) main space heating, (2) auxiliary space use, (3) main space use, (4) auxiliary space heating and (5) use of appliances. Significant correlations were found between the behavioural factors and energy use, household and dwelling characteristics. These correlations contributed to the profiles of the archetypes.

Despite the different clustering bases or criteria that other studies employed, some household archetypes identified in this paper share similarities with the findings of previous research. For instance, the ‘spenders’ and ‘conservers’ described by Raaij and Venhallen (1983) correspond, to some extent, to the ‘active spenders’ and ‘conservers’ identified in this paper. In both cases, the spenders are ‘more often at home’ and ‘more energy consuming’, whereas the conservers have a ‘small household size’ and are ‘less energy consuming’. Furthermore, the spenders identified by Guerra-Santin (2011) and the ‘active spenders’ have similar characteristics, such as ‘use of more space’, ‘more hours of heating’, ‘large household’ and ‘high income’. The ‘lavish lifestyles’, ‘thrifty values’, ‘practical considerations’ and ‘modern living’ described by Hughes and Moreno (2013) also correspond to the active spenders, conservers, ‘conscious occupiers’ and ‘inactive users’ respectively in terms of occupancy, socio-economic status, household composition and energy use.

Different energy efficiency strategies and policy programmes may be appropriate for each of the distinct archetypes. For active spenders, behavioural recommendations (incentives and opportunities) for cutting down their heating and appliance use may be the best strategy, alongside tailored retrofit measures such as boiler and control upgrades for those with low heating system efficiency. In contrast, the inactive users are likely to have little space for behavioural improvement but a limited amount of energy saving might be gained from a mixture of retrofit and behavioural change such as fabric insulation and reducing heating temperatures. Such a balance of behavioural and physical strategies would also benefit average users. On the other hand, retrofit might be the main energy-saving strategy for the conscious occupiers who have relatively desirable energy behaviour that should be reinforced. Similarly, retrofit could be made affordable through government subsidies to allow conservers to improve their energy-inefficient dwellings. When applying an archetype-based approach to target household energy efficiency, a survey on household and dwelling characteristics as well as behavioural patterns can be used to determine which archetype the household belongs to.

The limitation of this research lies primarily in the representativeness of the sample. Firstly, the residents were not randomly selected from a large population, but rather based on the availability of EPCs and willingness to participate in this study. This might have biased the sample. In addition, the sample was also relatively small and is from Cambridge—a city with a unique socio-geographic location in the UK that is not wholly representative of the wider population. Nevertheless, this research does not aim to be exhaustive in typology terms, but rather to provide indications on different ways of reducing energy use by targeting different household groups. Despite the relative small sample size, factor analysis was viable given high community scores, relatively small number of expected factors and low model error (Preacher and MacCallum 2002). Furthermore, the data obtained from questionnaires relied on what people say without triangulation such as monitoring or time-use surveys, and hence could have introduced bias that may undermine the results. However, due to the nature of behavioural uncertainty and complexity, self-reported behaviours were taken at face value to represent approximate behavioural estimation.

The next stage in the analysis will be to test the effect of retrofit options and behavioural measures on each archetype in energy modelling in greater detail. A larger sample size and more comprehensive data of socio-demographic and behavioural variables related to energy use may help to specify the household archetypes in more detail. More accurate information on household behaviour that relies not only on self-reported data but also other validated sources such as monitoring would help to improve the accuracy of the archetypes. An inclusion of attitudinal parameters in household archetypes would be useful for behavioural change recommendations.

Conclusions

As one of the few household archetype studies in the field of domestic energy consumption, this research provides support for the segmentation of behavioural patterns coupled with household profiles. The differentiation of household types is vital for energy policy and retrofit programmes to achieve optimum outcomes. The findings of five distinct household archetypes advance existing user segmentations by linking behavioural factors with household and dwelling characteristics, as well as energy use. This allows policy interventions to be geared towards identifiable groups of households to maximise the impact and effectiveness. It also provides a framework to incorporate occupant behaviour in developing retrofit strategies. By considering households in a disaggregated angle with bottom-up approaches, the optimal intervention for each household archetype could be identified. This will enable the development of tailored, effective policy and energy efficiency strategies.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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