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Contextualising household water consumption patterns in England: A socio-economic and socio-demographic narrative

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ABSTRACT

Water utilities strive to achieve a sustainable reduction in per capita consumption (PCC) by optimising their peak demand management strategies. Socioeconomic (SE) and socio-demographic (SD) characteristics have been proven to correlate with PCC. However, the full extent to which these characteristics underpin peak demand and PCC is yet to be fully understood. Previous work used medium resolution smart meter data from 10,000 households to discover and characterise temporal consumption patterns that underpin peak demand, identifying four distinct clusters of households, namely "Evening Peak" (EP), Late Morning Peak (LM), Early Morning Peak (EM) and Multiple Peak (MP). Using survey results, "Acorn household classification", household occupancy and UK population and household attribute data, this study attempts to draw a correlation between the four clusters and known variables of the participating households. Results have revealed a strong correlation between many endogenous attributes (particularly housing, occupancy, age, number of children and household income) and households' consumption patterns underpinning peak demand. Some 56% of families in privately rented housing show EP characteristics compared with 22% owner-occupiers and 9% social renters. EP households with teenage boys have 37% higher per household consumption (PHC) than average, while EM families with teenage girls use 47% more water in early morning showers than average.

1. Introduction

Due to worsening water stress in England, water companies are required by legislation (Legislation.gov.uk, 2014; Waterwise, 2016) to take a variety of DSM measures to improve water use efficiency and sustainably reduce Per Capita Consumption (PCC). Achieving a sustainable reduction in consumption requires a fundamental understanding of the intricacies of household water demand. Water planners, especially in water-stressed regions, routinely target households with a variety of DSM measures (Browne et al., 2014; Nawaz et al., 2019; Pullinger et al., 2013a). Some of these measures take the form of tariff systems (Fuente, 2019; Lu et al., 2019). Most DSM interventions are predicated upon understanding the underpinning determinants of water demand in the household (Gato Trinidad et al., 2011). Emphasis on understanding daily consumption patterns and their nuanced relationship with peak demand (Beal and Stewart, 2014; Gato-Trinidad and Gan, 2014) continues to reverberate across many studies. This understanding will equip water planners with the crucial knowledge to design, manage and optimise urban water infrastructure (Beal and Stewart, 2014) and DSM strategies. While many studies have helped utilities understand, in a broader sense, the differences in water use perception within the context of household variables such as gender (Tong et al., 2017), there is a shortage of studies linking these variables to several consumption patterns.

The average PCC in the UK currently stands at 140 L per person per day (l/p/d) (Lawson et al., 2018). Water demand in the household sector is a function of both exogenous (environmental) and endogenous (contextual) factors (Abu-Bakar et al., 2021a; Makki et al., 2013, 2015). As such, demand-side management (DSM) strategies and the delivery of targeted intervention (Bennett et al., 2013; Makki et al., 2015) intrinsically depend on the knowledge of the full extent to which these factors influence peak demand and PCC. Many DSM strategies have relied on households' known Socioeconomic (SE) and socio-demographic (SD) variables, such as wealth and occupancy (Fielding et al., 2012; Seimetz et al., 2016). However, water managers often adopt a "one-size-fits-all" approach, which seldom considers the heterogeneity in households' water consumption patterns and how they meticulously correlate with SD and SE attributes.

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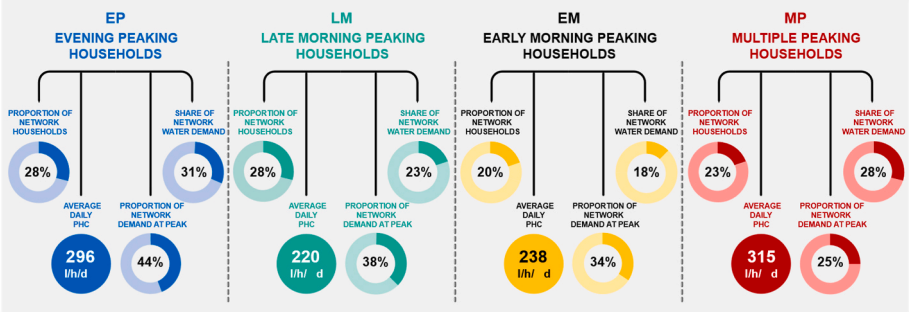


Fig. 1. A summary of the key characteristics of the four clusters from Study A.

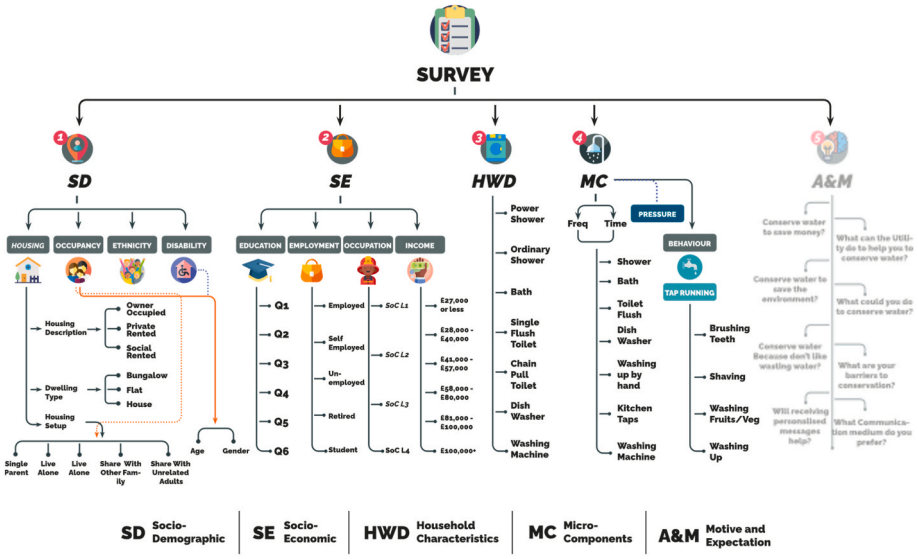


Fig. 2. Graphical illustration of the survey components.

In a recent empirical study (henceforth referred to as Study A), Abu-Bakar et al. (2021b) used medium resolution smart meter data to characterise the consumption behaviours of 10,000 households in England. The study identified four clusters whose significant differences are defined by the distinction in the daily consumption patterns underpinning their peak demand. Some 28% of households in the study belonged to the Evening Peak (EP) cluster, whose consumption at peak (typically between 19:00 and 21:00) constitutes ~44% of the network's total demand. The Late Morning (LM) cluster represents 28% of the network but is responsible for 38% of network demand at peak - typically occurring between 09:00 and 11:00. A third cluster, Early Morning (EM), accounts for 34% of network demand and represents 20% of households. Lastly, the Multiple Peak (MP) cluster, which represents 23% of the network, is characterised by multiple, sporadic peak demand events throughout the day, consuming 25% of network water each time. Fig. 1 illustrates the key attributes of the four clusters. The study is, however, limited by the reliance on medium resolution data from smart meters whose rollout in England is still in its infancy, with the majority of households being either unmetered or still on ordinary meters (Boyle et al., 2013). Household metering across the UK only increased slightly from 49.7% in 2015 to 54.8% in 2019 (equating to ~12.9 million households) (OFWAT, 2020), with universal penetration not likely to be achieved until 2030 (EnvironmentAgency, 2008). Smart meter rollouts are expected to take even longer due to slow uptake within the water sector and low public acceptance (Boyle et al., 2013; Geels et al., 2021). PCC in England is on the rise, steadily increasing from 124 to 156 L per person per day (L/P/D) in 2016 to an average of 132 and 168 L/P/D for metered and unmetered households, respectively (OFWAT, 2020).

Another limitation of Study A is the non-availability of occupancy and other household endogenous data, which made it impossible to calculate PCC (PHC/Occupancy) and challenging to draw a correlation between the various consumption patterns and other household variables to contextualise the results. The aim of this paper, therefore, is two-fold: firstly, to present a contextual narrative of household water consumption behaviour, such as the relationship between different endogenous attributes and PHC, PCC, microcomponents (MC) and households' propensity to conserve water. MC refers to specific water use events, such as showers/clothes washing. As a second objective, this paper uncovers the relationship between household variables and the established patterns of consumption. This may enable water managers to characterise and classify household water consumers without smart meter data. In doing so, this study utilises survey results, "Acorn household classification" and household occupancy data from a representative sample of households from Study A.

The SD and SE focus of this study is a direct response to the need for a better understanding of the factors contributing to indoor water consumption, which will enable the development of better and targeted conservation strategies and a more reliable forecasting model (Cominola et al., 2018b; Fielding et al., 2012; Makki et al., 2013).

1.1. Literature review

Many SD attributes, such as age and gender, have been tested for their significance in affecting water consumption patterns at home (Millock and Nauges, 2010; Pullinger et al., 2013b). Rathnayaka et al. (2014) concluded that such attributes could support utilities' DSM



Fig. 3. Socio-demographic and Socio-economic distribution of survey participants.

strategies to improve demand prediction accuracy. In Abu-Bakar et al.'s (2021a) review of water demand management strategies, the authors argued that DSM instruments that target water users based on their socio-demographic (e.g. age and gender) attributes tend to yield better outcomes than relying on metering alone.

Previous studies (Abu-Bakar et al., 2021a; Koech et al., 2021; Daminato et al., 2021) have emphasised the immense contribution of smart metering to household consumption measurement, pattern recognition and micro-component analysis, offering water planners powerful insights into household water consumption behaviours (Boyle et al., 2013; Nguyen et al., 2018). However, the adoption of smart technologies in the water industry is slow (Ponce Romero et al., 2017), even though many generations of smart meters can produce much higher temporal resolution data than traditional meters. Not only is there a lack of standardisation in smart meters, but the data granularity varies widely among the different technologies (Pericli and Jenkins, 2015).

Traditionally, micro-component analysis is conducted using either flow-trace (from pulse-output smart meters) (Giurco et al., 2008) or sensor-generated outputs. Most flow trace-based approaches utilise Machine Learning (ML) and Artificial Intelligence (AI) techniques to disaggregate high-resolution flow-traced data to micro-component categories (Abu-Bakar et al., 2021a; Cominola et al., 2018a).

Micro-component analysis reveals household water use events such as showering and washing up on temporal and spatial scales. However, it is only possible through the disaggregation of water use, which usually begins with data capture at sub-minute resolution. The use of high-resolution data disaggregation (usually at 5-s intervals) underpins several microcomponent studies (Giurco et al., 2008; Larson et al., 2012; Rathnayaka et al., 2017). Sometimes, micro-component disaggregation is achieved as an add-on capability gained by attaching data loggers or acoustic sensors to water meters (Boyle et al., 2013).

Although disaggregation has many benefits, the process is costly. It requires specialised software-hardware combinations as well as technical expertise, making it unfeasible to integrate into a utility's routine DSM program. This is because most household-scale smart-meters can only record data at longer intervals, sometimes referred to as medium resolution (usually at 15 min to a day), thus limiting their ability to capture microcomponent events (Cominola et al., 2018a).

There is abundant research using medium-resolution smart-meter data (Cheifetz et al., 2017; Cominola et al., 2016, 2019; Koech et al., 2021) to ascertain other water use patterns, offering values alternative to micro-component analysis. There is, however, a gap in the literature for research focusing on a multivariate characterisation of household consumption patterns underpinning peak water demand.

Several studies have linked SD and SE attributes of households to both water consumption behaviours and volumes. The study by Vieira et al.'s (2018) on household water use efficiency found that SD and socio-cultural (SC) characteristics significantly influenced consumption patterns, especially shower frequency and duration.

Homewood and Snowdon (2014) found occupancy and household composition to have the most significant influence on PCC in England and Wales, correlating with previous research (Willis et al., 2013; Beal and Stewart, 2014).

It has been found that household income and educational level positively correlate with consumers' propensity to conserve water, i.e., higher-income families are more likely to install water-saving devices

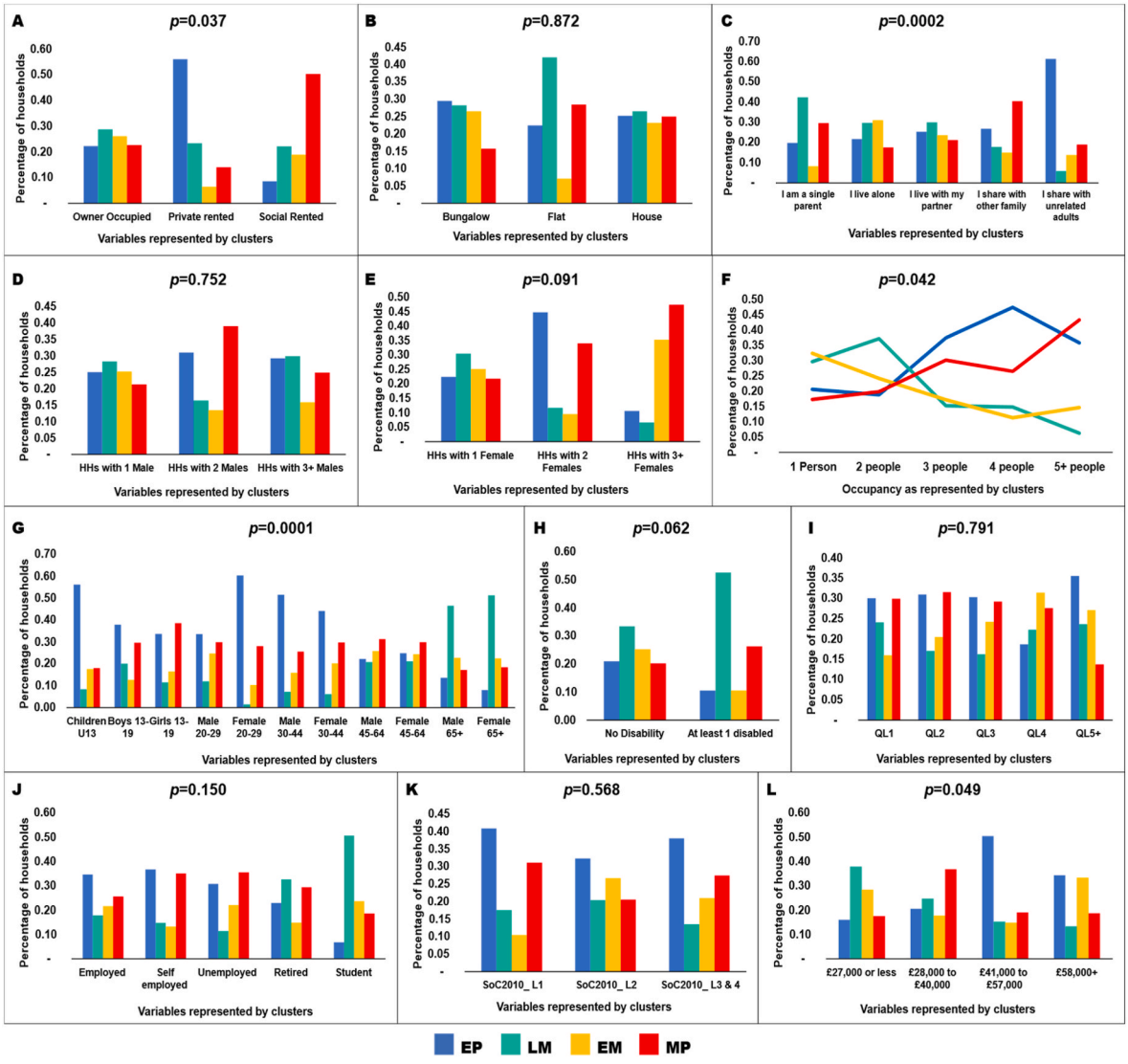


Fig. 4. Illustration of cluster proportion of households under each set of socio-economic and socio-demographic variables. A. Household tenure groups variables; B. Household dwelling types; C. Household composition; D. Number of males in the household; E. Number of females in the household; F. Occupancy. G. Age and gender groups; H. Disability; I. Educational qualifications (QL1: GCSE/O level/NVQ 1 and 2; QL2: A level/AS Level/Level 3 NVQ/Level 3 Diploma/BTEC; QL3: Level 4 and 5 diploma/Level 4 and 5 NVQ/HNC/DipHE/Foundation degree; QL4: Bachelors Degree (eg.,B.A., BSc)/Level 6 Diploma/Level 6 NVQ; QL5+: Masters Degree (e.g., MA, MSc)/Level 7 Diploma/Level 7 NVQ/PGCE; PhD/DPhil/level 8 Diploma); J. Employment; K. Standard Occupational Classification 2010 (SOC2010); L. Household income.

(Makki et al., 2015). Nevertheless, lower-income households tend to engage in more water conservation practices and have much lower PCC than households with higher education and income (Makki et al., 2015; Olmstead and Stavins, 2009). The study by Watson (2017) found that lower-income and single-parent households have a higher PCC and a low willingness to adopt conservation practices, such as installing efficiency devices, due to the difficulties associated with raising their family alone.

A study by Horsburgh et al. (2017) on gender differences in water consumption found a reduction of 17% in per-visit water consumption in women's bathrooms after replacing manual fixtures with automatic ones, compared with an increase of 4.7% in men's bathrooms. Water consumption by women was found to be four times lower in the toilet than at the taps (Horsburgh et al., 2017).

Even though age has been found to be a significant determinant of consumption, the literature is divided on which age group consumes the most. Many studies (Gregory and Leo, 2003; Aprile and Fiorillo, 2017) have concluded that older household occupants engage in water conservation behaviours, while Beal and Stewart (2014) and Willis et al. (2013) argue that pensioners consume more water than the average because they tend to spend more time at home. Studies have consistently found that affluent households with children and teenagers tend to experience more frequent and more prolonged micro-component events, such as showers (Makki et al., 2013, 2015; Beal and Stewart, 2014; Willis et al., 2013; Beal and Stewart, 2014).

Water conservation behaviours are correlated with housing tenure, with house owners more likely than renters to invest in water-efficient devices (Aprile and Fiorillo, 2017; Grafton et al., 2011). Randolph and Troy (2008) measured the water conservation attitudes of householders according to their tenure and building type. They found that 47% of public housing tenants were unready to reduce consumption, as opposed to 28% of private tenants and 37% of outright owners, while 10% of both types thought more could be done.

Developing improved water demand forecasting and management strategies can be enhanced by understanding the factors influencing water use at different spatial and temporal scales (Xenochristou et al., 2020). In addition, the literature strongly recommends incorporating

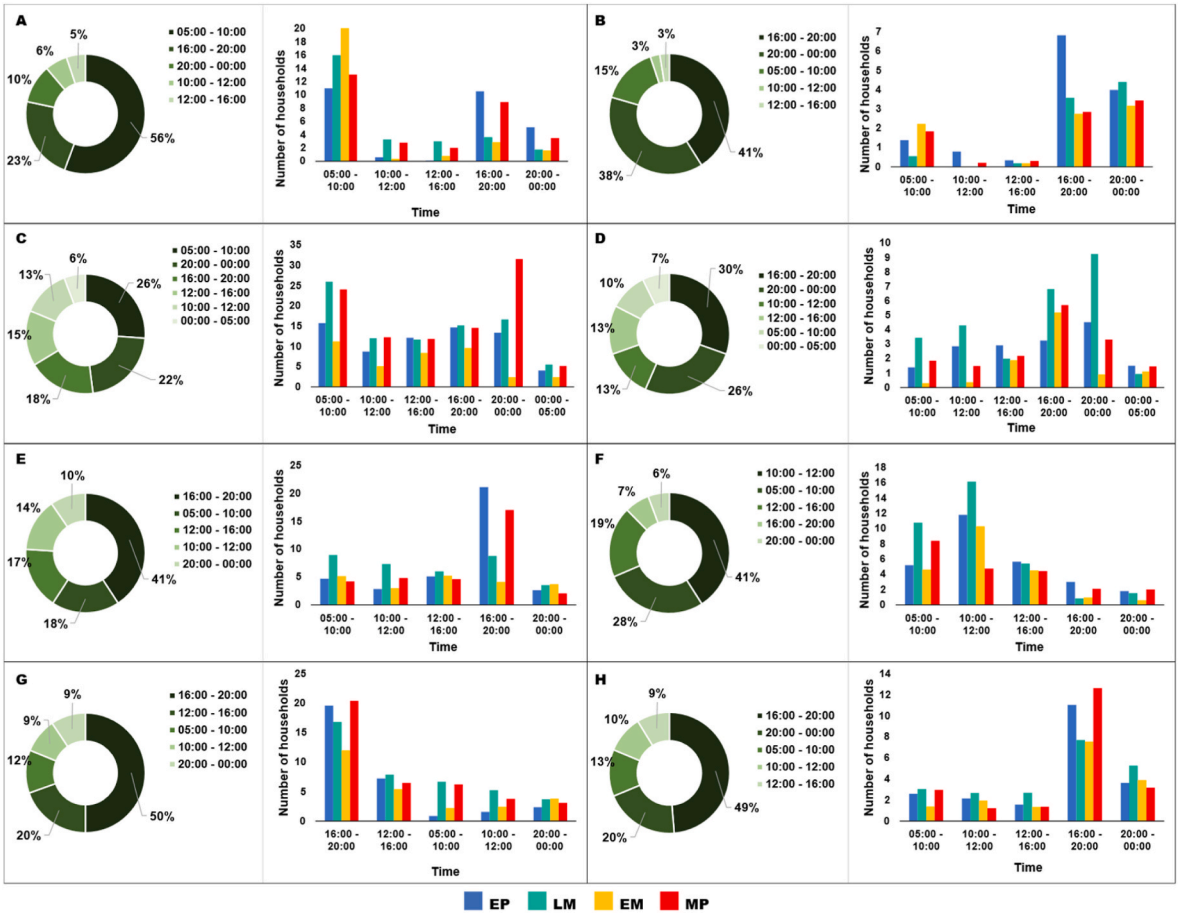


Fig. 5. Illustration of microcomponent times and the proportions of clusters under each microcomponent. A. Shower times; B. Bath times; C. Toilet flushing times; D. Dishwasher use times; E. Hand washing-up times; F. Washing machine use times; G. Kitching taps use times; H. Outdoor water use times.

Table 1
Monthly mean PHC (l/h/d) for surveyed households in their clusters.

Months	EP	LM	EM	MP	Monthly Mean
January	264.56	195.60	237.47	256.10	238.43
February	291.46	212.96	225.59	373.00	275.75
March	274.67	202.83	225.90	360.00	265.85
April	252.10	234.80	213.76	265.14	241.45
May	257.17	236.53	214.00	297.63	251.33
June	279.48	221.76	237.55	373.29	278.02
July	350.00	245.49	220.12	310.00	281.40
August	288.23	240.76	216.48	296.36	260.46
September	275.50	209.00	209.17	320.00	253.42
October	265.81	205.34	204.71	229.07	226.23
November	284.92	201.78	211.51	260.21	239.61
December	268.32	216.44	195.54	373.00	263.32
Mean ($\bar{x}$)	**279.35**	**218.61**	**217.65**	**309.48**	**256.27**
Relative to absolute mean	**109%**	**85%**	**85%**	**121%**	
Standard Deviation (σ)	**24.23**	**16.26**	**11.98**	**49.01**	**16.82**
Standard Error ($\sigma_{\bar{x}}$)	**6.994**	**4.694**	**3.458**	**14.149**	**4.855**
Variance (σ^2)	**586.93**	**264.38**	**143.50**	**2402.16**	**282.80**
Median ($\tilde{\sigma}_{\bar{x}}$)	**275.08**	**214.70**	**215.24**	**303.82**	**256.94**
Min	**252.10**	**195.60**	**195.54**	**229.07**	**229.07**
Max	**350.00**	**245.49**	**237.55**	**373.29**	**373.29**

SD, economic, and DSM strategies into forecasting models (DFID, 2010; Donkor et al., 2014).

2. Materials and methods

The population under study was the 10,000 smart-metered households that participated in Study A, spanning two geographical areas 50 miles apart, consisting of 1034 unique Postcodes across 24 District Metering Areas (DMAs). Machine Learning (ML) approach was used in Study A to cluster and classify hourly data for participating households over a period of 12 months (January–December 2019).This study, however, adopted a data triangulation approach (Denzin, 1978) by combining a consumer survey with Acorn, UK population and household attribute and occupancy datasets. The rationale behind the use of triangulation is that this strengthens the data's veracity and enhances the findings' generalisability. It facilitates comparing and evaluating the insights obtained from the correlation of different comparable variables from different datasets to consumption patterns. For example, it helps address questions such as "how do the influences of the age and occupancy variables obtained from the survey compare to the influences of similar variables from the Acorn, the UK population and household attribute and occupancy datasets"? Results obtained from each data source will allow the consumption patterns to be interrogated robustly for a better understanding of the significance of SD and SE undertones of household water consumption.

Table 2
PHCs of clusters under housing variables.

Variables	EP	LM	EM	MP	p-value	Mean ($\bar{\bar{x}}$)	Std. Dev. (σ)	Standard Error ($\sigma_{\bar{x}}$)	Variance (σ^2)	Median ($\tilde{\bar{x}}$)	Min	Max
Household tenure groups												
Owner Occupier	276.81	230.94	219.49	305.09	**5.7E-07**	**258.08**	**39.94**	**19.97**	**1595.33**	**253.88**	**219.49**	**305.09**
Private rented	281.78	126.17	224.50	212.69		**211.28**	**64.27**	**32.13**	**4130.50**	**218.59**	**126.17**	**281.78**
Social Rented	258.00	216.89	185.95	264.71		**231.39**	**36.94**	**18.47**	**1364.38**	**237.44**	**185.95**	**264.71**
Household dwelling type												
Bungalow	252.53	157.89	156.89	234.79	**1.07E-14**	**200.53**	**50.33**	**25.17**	**2533.22**	**196.34**	**156.89**	**252.53**
Flat	87.13	143.89	137.60	202.30		**142.73**	**47.14**	**23.57**	**2222.23**	**140.75**	**87.13**	**202.30**
House	298.53	242.82	235.70	305.09		**270.54**	**36.33**	**18.17**	**1320.03**	**270.68**	**235.70**	**305.09**
Household composition												
I am a single parent	201.92	222.71	146.75	263.70	**2.84E-59**	**208.77**	**48.67**	**24.33**	**2368.34**	**212.31**	**146.75**	**263.70**
I live alone	149.77	116.20	129.55	166.46		**140.49**	**22.14**	**11.07**	**490.13**	**139.66**	**116.20**	**166.46**
I live with my partner	272.28	242.06	247.08	303.43		**266.21**	**28.11**	**14.06**	**790.38**	**259.68**	**242.06**	**303.43**
I share with other family	370.62	290.52	250.24	269.46		**295.21**	**52.90**	**26.45**	**2798.12**	**279.99**	**250.24**	**370.62**
I share with unrelated adults	429.15	262.25	254.13	523.44		**367.24**	**131.72**	**65.86**	**17349.58**	**345.70**	**254.13**	**523.44**
Occupancy												
1 person	141.10	130.20	136.72	168.10	**7.02E-13**	**144.03**	**16.66**	**8.33**	**277.55**	**138.91**	**130.20**	**168.10**
2 persons	284.57	264.85	230.56	257.76		**259.43**	**22.34**	**11.17**	**499.25**	**261.30**	**230.56**	**284.57**
3 persons	237.67	273.54	273.80	232.88		**254.47**	**22.25**	**11.13**	**495.21**	**255.60**	**232.88**	**273.80**
4 persons	375.92	178.50	261.36	270.43		**271.55**	**80.95**	**40.47**	**6552.21**	**265.90**	**178.50**	**375.92**
5+ persons	424.81	452.33	458.29	498.59		**458.50**	**30.44**	**15.22**	**926.73**	**455.31**	**424.81**	**498.59**

2.1. Hypothesis

2.1.1 The compound null hypothesis in this study (H_0) is that (a) there are no relationships between household variables and patterns of consumption attributable to the four clusters and (b) household variables and the clusters have no bearing on PHC/PCC. The following three hypotheses are therefore proposed, and rigorous statistical tests were performed on the results:

2.1.2 Hypothesis 1 (H_1): There is a direct relationship between all or some household variables and water consumption patterns; these variables can be used to infer the likelihood of households belonging to a particular consumption cluster.

2.1.3 Hypothesis 2 (H_2): Households' daily water consumption is directly influenced by SD and SE variables.

2.2. Consumer survey

A survey questionnaire (Appendix), comprising 31 questions was sent by email to a representative sample of 750 households. All participants also took part in Study A. The survey sought to collect an array of relevant household data under five broad categories, namely, SD, SE, Household water use device ownership (HWD), Micro-components (MC) and Attitudes and Motivations (A&M). The results on A&M are out of this paper's scope and therefore not included.

SD and SE attributes have consistently proven to be important benchmarks for water demand estimation and studying households' MC and PCC variability (Kowalski and Marshallsay, 2005; Nguyen et al., 2013; Wentz et al., 2014). As such, these variables are considered pivotal in this study in determining water consumption behavioural patterns. Under SD, broad-ranging questions were posed on housing, occupancy, ethnicity and disability. Research has linked people's motivation to their propensity to conserve water (Aprile and Fiorillo, 2017; Corral-Verdugo et al., 2002; DEFRA, 2013). This part of the survey aimed to investigate whether endogenous and household cluster attributes either affect people's propensity to conserve water or help determine what motivates them. Fig. 2 illustrates these survey components graphically.

2.3. Occupancy data

Occupancy data for over 9,000 households from Study A participants were obtained to bolster the relatively smaller sample size of the survey data. Occupancy is a significant variable in determining PCC and PHC variations and the intensity of households' water use (Fielding et al., 2012). However, several other factors, such as the age distribution of occupants, must also be considered (Arbués et al., 2010). The occupancy data ranges from single-occupancy households to households with six or more residents.

2.4. Acorn data

2.5 Acorn (CACI, 2014; Parker and Wilby, 2013) is a segmentation model used to classify UK households and Postcodes into different socio-economic categories (Table 5). Acorn classification data formed the third component of the data triangulation. The model classifies household types into 47 distinct sub-categories under six broad categories: Affluent Achievers, Rising Prosperity, Comfortable Communities, Financially Stretched, Urban Adversity and Not Private Households. The Acorn data were obtained for over 9,000 of the same cohort of households in Study A. These data were then matched to households' PHC and occupancy to reinforce the consumer survey results and ascertain their relationship with the clusters, occupancy and PHC/PCC.

2.5. ONS data

UK Population and Household description data at Postcode level were obtained from the Office of National Statistics (ONS, 2021), featuring a variety of population and demographic attributes of households in all 746 postcodes in the study. The attributes include marital status, age, gender, qualification, and household income.

2.6. Statistical analysis

The survey results were processed and analysed using standard statistical tools as follows.

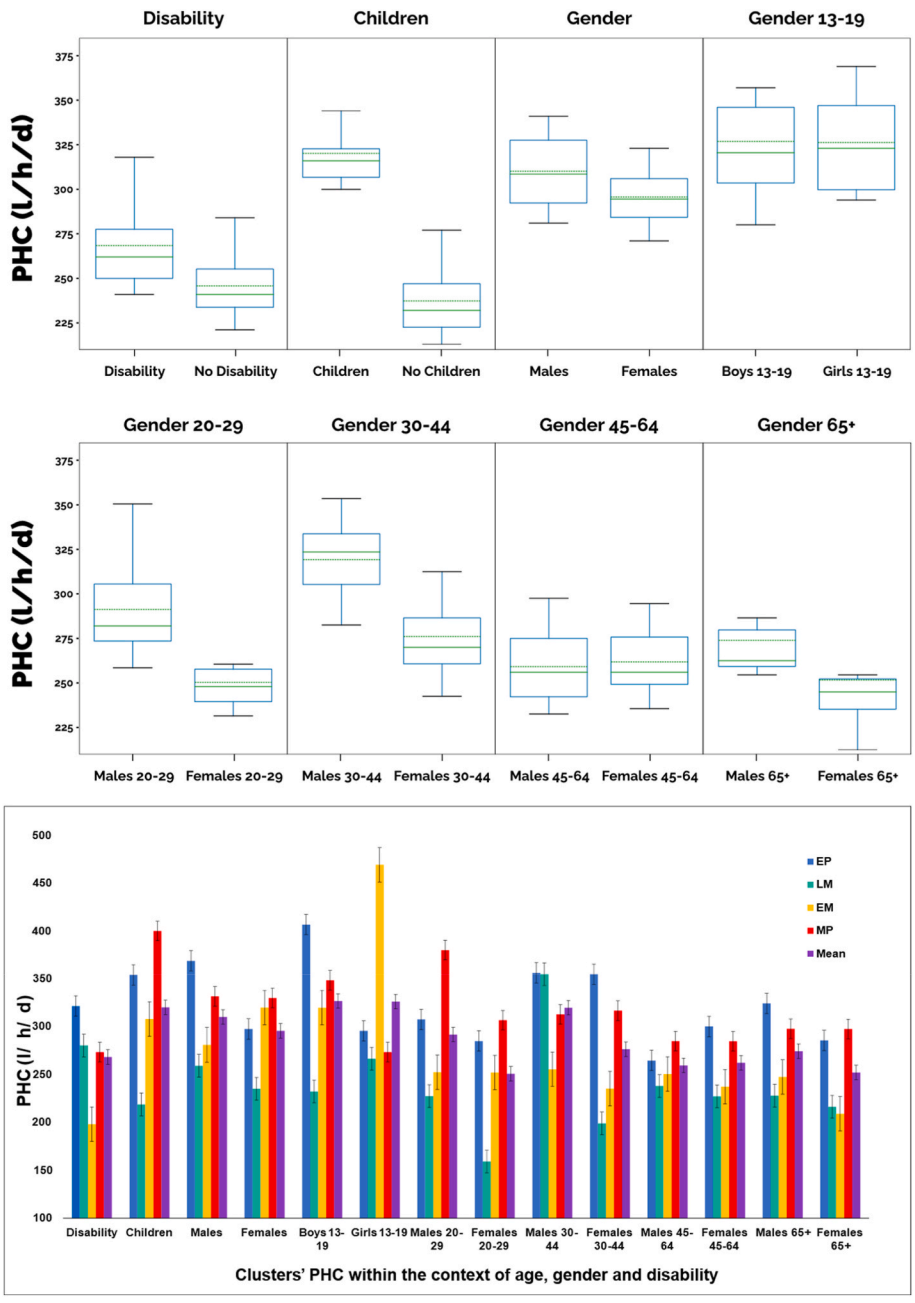


Fig. 6. Consumption according to age, gender and disability. Box plots comparing PHC values between comparable variables (Value at the top of the whisker is the Maximum consumption; bottom of the whisker is the minimum consumption; top bound of the box is the upper quartile value; bottom bound of the box is the lower quartile value; the solid line in the centre of the box is the median; the dashed line in the centre of the box is the mean); Bar plots illustrating Clusters' PHC within the context of age, gender and disability.

2.6.1. Chi-squared (McHugh, 2013) was used to test the statistical significance of the results of various variables distributed across different categories and observations using the following equation

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

where χ^2 is the chi-squared; O_i is the observed value and E_i is the expected value

2.6.2. Fisher's exact test (Shan and Gerstenberger, 2017) was used to determine any random or nonrandom associations between the survey's categorical variables, such as gender, age and disability, where the sample size was too small as follows

$$p = \frac{(a+b)!(c+d)!(a+c)!(b+d)!}{a!b!c!d!n!} \tag{2}$$

where p is the p-value; $a, b, c, d =$ the values in a table and n is the total frequency.

2.6.3. Statistical methods (Allen, 2017) such as standard deviation and variance were used to measure the dispersion of the values within the datasets around the mean values using the following equations

$$sd = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N-1}} \tag{3.1}$$

Where sd is the sample standard deviation; N is the number of observations; x_i is the observed values of a sample item and $\bar{x}$ is the mean value of the observations.

$$S^2 = \frac{\sum (x_i - \bar{x})^2}{n-1} \tag{3.2}$$



Fig. 7. 12-month comparison of PHC between opposing variables within age, gender, and disability context. A. Households with disabled occupants vs no disabled occupants; B. Households with children vs no children; C. Households with males vs females; D. Households with boys aged 13–19 vs girls aged 13–19; E. Households with males aged 20–29 vs females aged 20–29; F. Households with males aged 30–44 vs females aged 30–44; G. Households with males aged 45–64 vs females aged 45–64; H. Households with males aged 65+ vs females aged 65+.

where S^2 is the sample variance; x_i is the value of the one observation; $\bar{x}$ is the mean value of all observations and n is the number of observations.

2.7.4 Linear regression analysis (Schneider et al., 2010) was performed on some variables to determine their "Spearman's coefficient", that is, to ascertain whether they have positive, negative or no linear relationships with other variables as follows:

$$Y_i = f(X_i, \beta) + e_i \tag{4}$$

where Y_i is the dependent variable; f is the function; X_i is the independent variable; β is unknown parameters and e_i is the error terms.

3. Results

3.1. Survey data

This section presents a comprehensive analysis of the survey results, firstly by exploring the relationships between a myriad of households' variables (Fig. 3) and their PHC while underscoring the statistical significance of their differences. Secondly, a thorough comparative analysis is made whereby the results are split into the four household clusters (Fig. 1) for each variable. The analysis reveals the extent to which each cluster is influenced by the variables, both in terms of percentage of households and their PHC. Finally, we present a measure of how PHC and PCC are influenced by household variables and how these influences are swayed when one variable is conflated with another, with the view to testing H1 and H2.

Out of 750 targeted households, 220 responses were received with occupancy ranging from 1 to 6, comprising 136 males, 141 females and 27 children under 13. Results are presented under SD, SE, HWD, MC, and A&M broad categories (Fig. 2), each featuring a host of independent variables and their relationships with PHC and PCC (dependent variables). Fig. 3 summarises the SD and SE composition of the survey respondents.

3.1.1. Relationships between survey variables and the four clusters

Although the overall cluster proportions in the survey appear to be slightly skewed in favour of the LM cluster (at 34%, compared with 20% for EP, 24% EM and 22% MP), significant fluctuations have been observed in their proportions under all SD variables. This means some variables have a stronger predominance of certain clusters than others. The chi-square and fisher's exact tests of independence performed on the samples show statistical significance ($p \leq 0.05$) on the relationship between the clusters and Household tenure group, Occupancy, Age and Household income variables, meaning H_1 holds for these variables. Gender (unless when conflated with age) and dwelling type show p-values >0.05, indicating that the H_0, at least for those variables, cannot be reliably rejected based on the survey dataset. Results of significance tests on comparable variables from the other datasets will be used to accept or reject H0 conclusively. Fig. 4 illustrates the proportion of households in the clusters under each set of variables and their p-values.

Under the household tenure group, the four clusters are almost evenly distributed in the owner-occupier category, with LM having a slightly higher proportion. A similar pattern is observed under dwelling type in the house category. Private rented households, however, appear to have a significantly higher proportion of EP (56%) than the other clusters, while the social rented category is dominated by MP households (50%). Therefore, more than half of all privately renting households have most of their peak water consumption events between 19:00

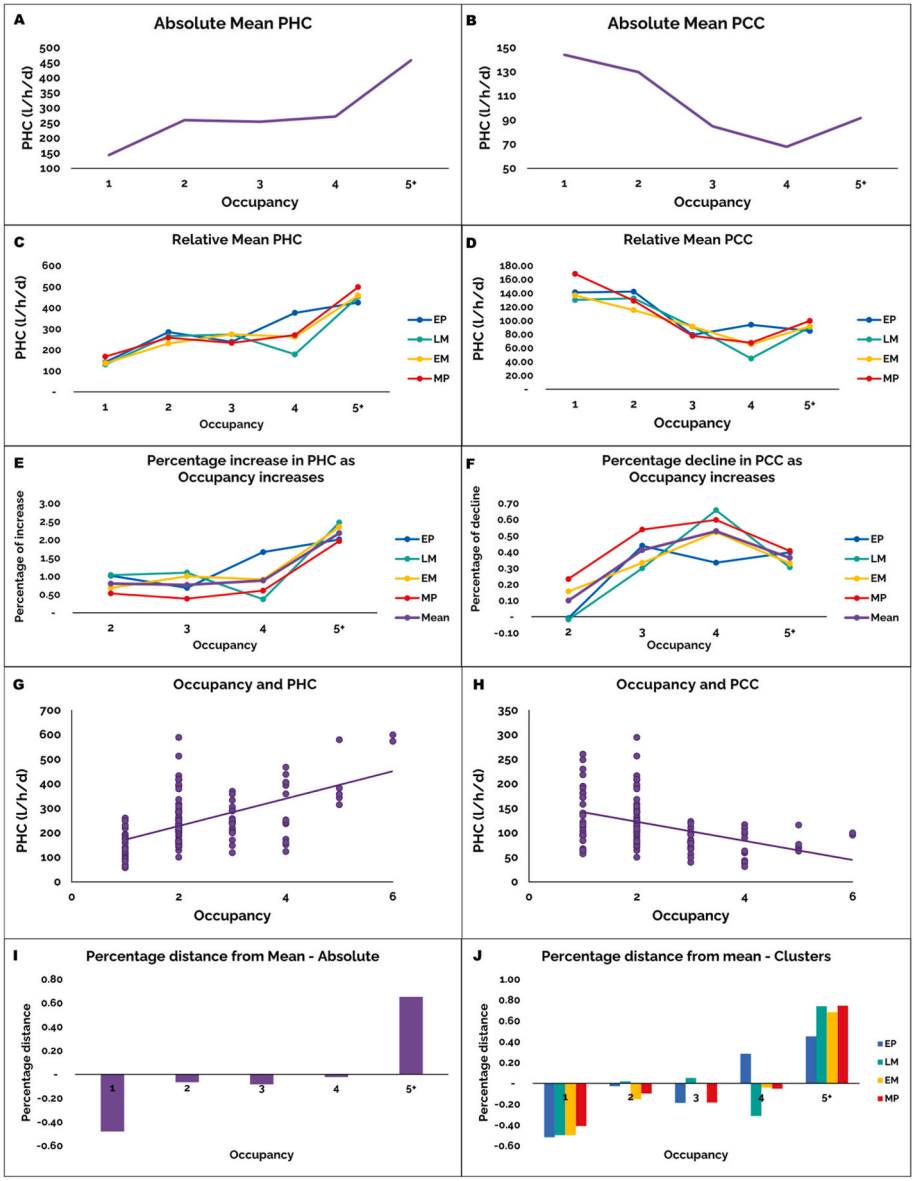


Fig. 8. Relationship between occupancy and PHC/PCC. A. Mean PHC as occupancy increases; B. Mean PCC as occupancy increases; C. Clusters' PHC as occupancy rises; D. Clusters' PCC as occupancy increases; E. Mean and clusters' percentage increase in PHC as occupancy increases; F. Mean and clusters' percentage increase in PCC as occupancy increases; G. PHC and occupancy correlation; H. PCC and occupancy correlation; I. Percentage distance of PHC from mean as occupancy increases; J. Percentage distance of PHC from clusters' mean as occupancy increases.

and 21:00, while half of those in social housing peak multiple times. Bungalow dwellers have a relatively equal proportion of EP, LM and EM households and a significantly lower proportion of MP. EM has the lowest proportion of flat dwellers (7%) compared with 42% LM, 22% EP and 28% MP.

With a *p*-value of 0.000239271, the household composition variable is an important benchmark for cluster representation. Single parents have a significantly higher ratio of LM and MP. In contrast, households with multiple unrelated families have a higher proportion of MPs, with unrelated adults (not families) being more than 60% EP, compared with other clusters. Gender is not a statistically reliable benchmark for cluster prediction as the results show both genders exhibiting identical presence across all four clusters and a *p*-value of 0.99. However, an interesting intragender variation in cluster manifestation emerges when the number of occupants of the same gender increases beyond one. For example, an increase of either gender to two sees a steep rise in EP and MP, whereas a rise to 3 or more in males manifests in EP, LM and MP increases, as contrasted with EM and MP rises in females, as illustrated in Fig. 4.

The survey shows that occupancy is a statistically significant indicator of household consumption patterns ($p = 0.039131323$). Households with two occupants are the dominant group constituting 48% of respondents, with five + occupants being the fewest, making up 6% of participating households (Fig. 4). One and two-occupant households have markedly higher LM and EM proportions than in 3–5+ households, which tend to have much higher proportions of EP and MP. In a nutshell, households with fewer occupants tend to have higher morning peak events than households with a higher number of occupants. Peak events become more frequent and temporally ubiquitous as the number of occupants reaches five and beyond.

Age is another statistically significant determinant of household water consumption patterns ($p = 0.0000000002775312$). Households with children under 13 up to adults aged 30–44 tend to dominate EP, followed by MP. Ages 45–64 have nearly equal shares of all four clusters, with MP being slightly higher. Over 65s have a clear dominance of the LM cluster. No noteworthy variations were found between the genders across all ages, although, in the 13–19 category, boys have slightly higher EP numbers than girls, who tend to have higher MP. While disability is not a statistically significant determinant ($p = 0.621385365$), ostensibly due to insufficient data, households with any number of disabled occupants tend to have higher LM patterns, with the ratio increasing exponentially as the disability count rises.

Out of the four SE sets of variables analysed, only household income

Table 3
PHC within the context of occupancy and other variables.

Other variables	Occupancy					Other variables	Occupancy				
Household tenure groups	1	2	3	4	5+	*Household dwelling type*	1	2	3	4	5+
Owner occupied	151.75	256.07	239.76	312.20	496.00	Bungalow	110.47	204.24	208.00	293.83	357.83
Private rented	96.03	367.04	262.94	251.21	357.83	Flat	114.90	232.92	199.92	152.33	–
Social rented	169.33	236.73	282.36	–	–	House	167.45	272.18	245.36	297.14	496.00
Mean ($\bar{X}$)	**139.04**	**286.61**	**261.69**	**281.71**	**426.92**	**Mean ($\bar{X}$)**	**130.94**	**236.45**	**217.76**	**247.77**	**426.92**
Std. Dev. (σ)	**31.25**	**57.42**	**17.41**	**30.50**	**69.08**	**Std. Dev. (σ)**	**25.88**	**27.85**	**19.79**	**67.50**	**69.08**

Other variables	**Occupancy**					**Other variables**	**Occupancy**				
Household setup	**1**	**2**	**3**	**4**	**5+**	***Age and gender***	**1**	**2**	**3**	**4**	**5+**
I am a single parent	–	238.64	–	361.00	–	*13–19*	–	257.00	233.24	310.40	430.00
I live alone	135.85	–	–	–	–	Male 13-19	–	256.75	289.33	269.56	399.00
I live with my partner	–	257.62	236.03	282.43	461.00	Female 13-19	–	–	177.15	351.25	461.00
I share with other families	–	229.27	272.25	335.32	362.92	Male 20-29	–	220.36	303.00	308.08	471.00
I share with unrelated adults	–	367.04	258.17	404.00	579.75	Female 20-29	–	277.00	231.11	326.00	–
						Male 30-44	117.17	275.33	305.00	407.00	426.97
						Female 30-44	183.04	334.00	243.68	264.00	513.00
						Male 45-64	119.08	249.08	266.00	243.58	499.00
						Female 45-64	157.68	242.29	239.50	315.33	499.00
						Male 65+	111.92	268.87	253.00	275.77	382.50
						Female 65+	145.01	264.66	225.58	123.92	382.50
Mean ($\bar{X}$)	**135.85**	**273.14**	**255.48**	**345.69**	**467.89**	**Mean ($\bar{X}$)**	**138.98**	**265.37**	**253.34**	**288.45**	**448.22**
Std. Dev. (σ)	**-**	**55.17**	**14.91**	**44.00**	**88.66**	**Std. Dev. (σ)**	**28.04**	**31.34**	**39.36**	**75.07**	**51.90**

Other variables	**Occupancy**					**Other variables**	**Occupancy**				
Employment	**1**	**2**	**3**	**4**	**5+**	***Household income***	**1**	**2**	**3**	**4**	**5+**
Employed	149.78	256.42	243.83	309.47	542.33	£27,000 or less	136.70	231.13	245.46	295.29	–
Self employed	174.67	203.84	248.58	359.08	579.75	£28,000 to £40,000	154.92	267.25	232.21	292.28	490.92
Unemployed	180.42	218.79	304.69	248.83	382.50	£41,000 to £57,000	–	290.27	250.25	319.33	465.54
Retired	155.45	256.09	258.78	295.83	382.50	£58,000+	135.25	326.52	255.33	364.98	314.67
Student	–	256.75	203.24	252.14	459.46						
Mean ($\bar{X}$)	**165.08**	**238.38**	**251.82**	**293.07**	**469.31**	**Mean ($\bar{\bar{X}}$)**	**142.29**	**278.79**	**245.81**	**317.97**	**423.71**
Std. Dev. (σ)	**14.76**	**22.60**	**32.49**	**40.66**	**80.87**	**Std. Dev. (σ)**	**10.96**	**34.69**	**8.60**	**29.10**	**77.80**

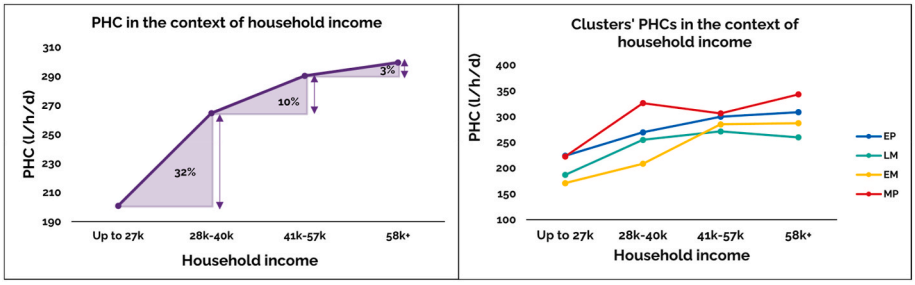


Fig. 9. PHC within the context of household income (mean and clusters).

is statistically significant in determining households' likelihood to belong to a particular cluster ($p = 0.04920749$), with Education, Employment, Standard Occupational Classification (SOC) showing $p > 0.05$, making them insignificant. As illustrated in Fig. 4, ~40% of households earning £27,000 or less are in the EP clusters, yet it only constitutes ~13% of households in the higher income brackets. MP's highest proportion (~38%) is in the £28,000 to £40,000 group, while EP constitutes over 50% of households in the mid-to-higher income group of £41,000 to £57,000. The EP and EM clusters represent nearly 70% of households in the highest income category (£58,000+) equally.

3.1.2. HWD and MC

While no significant correlations were found between clusters and HWD variables and the frequency of water use events (MC), in all likelihood, due to insufficient data, some unique patterns were observed within some of the variables. Regarding HWD, 31% of households have power showers compared with 69% with ordinary showers, while 40% owned single-flush toilets compared with 60% with double-flush. Over 65% of power showers are owned by LM and MP households, while ordinary shower ownership reflects the clusters' survey proportions.

Eight major MC events were captured in the survey: shower, bath, toilet flushing, dishwasher use, hand washing-up, washing machine use, kitchen taps use and outdoor water use (Fig. 5). Results show that 55% of all households use the shower once a day, 34% twice and 11% three times or more daily. Over 40% of households that shower more than twice daily belong to EP, followed by MP at ~30%. Toilet flushing shows an identical daily pattern to showering for all households and evenly distributed cluster proportion. Only a third of all households use dishwashers, all of whom once daily, with EP constituting over a third. Once-a-day washing up by hand is carried out by 45% of households, twice a day by 15% and 9% of households wash up more than twice, all equally distributed among the clusters except EP, which accounts for over 33% of washing up twice or more, daily. More than half of the households in the MP cluster wash more than once a day, with 89% using the washing machine once a day.

3.1.3. Times of water use

The survey results for times of water use were encapsulated into six

Table 4
MC frequency.

Months	Shower 1x	Shower 2x	Shower 3x	Flush 1x	Flush 2x	Flush 3x	Washing up 1x	Washing up 2x	Washing up 3x	Washing Machine 1x	Washing Machine 2x
Jan	182.95	232.41	281.89	142.50	225.48	235.95	206.55	255.06	300.65	223.75	334.92
Feb	183.41	241.30	304.42	185.50	388.81	281.97	220.00	277.07	312.18	233.61	320.25
Mar	175.46	274.62	337.92	202.00	297.34	266.76	302.59	239.30	278.60	254.63	321.17
Apr	171.34	244.21	295.50	150.33	227.03	225.64	225.85	226.21	304.99	221.14	306.41
May	196.99	248.76	292.98	120.50	203.56	257.32	277.67	262.42	286.13	239.34	294.08
Jun	176.24	304.84	370.56	130.33	559.44	245.29	291.42	288.71	283.91	260.91	323.04
Jul	201.00	333.33	282.63	125.00	226.60	234.66	257.89	326.29	294.07	257.51	364.68
Aug	192.19	288.13	289.32	142.50	187.94	268.01	231.69	253.69	296.85	269.02	291.02
Sep	197.73	255.84	288.07	140.00	209.26	258.19	219.69	286.32	265.86	231.22	318.12
Oct	163.23	224.54	281.03	109.67	206.10	225.29	184.99	263.52	276.60	208.23	300.08
Nov	195.59	233.89	270.44	129.83	191.27	221.59	214.65	279.85	304.48	220.51	327.01
Dec	167.77	240.39	274.42	116.83	199.63	225.54	207.13	228.03	301.33	214.73	293.99
***P*-Value**	0.013752209			1.85631E-36			2.85651E-07			0.042568771	
Mean ($\bar{X}$)	**183.66**	**260.19**	**297.43**	**141.25**	**260.21**	**245.52**	**236.68**	**265.54**	**292.14**	**236.22**	**316.23**
Std. Dev. (σ)	**12.92**	**33.33**	**28.92**	**27.43**	**110.07**	**20.39**	**37.07**	**28.45**	**13.89**	**19.99**	**21.07**
Standard Error ($\sigma_{\bar{x}}$)	**3.73**	**9.62**	**8.35**	**7.92**	**31.77**	**5.88**	**10.70**	**8.21**	**4.01**	**5.77**	**6.08**
Variance (σ^2)	**166.89**	**1110.96**	**836.47**	**752.15**	**12115.45**	**415.59**	**1374.42**	**809.47**	**192.83**	**399.52**	**443.74**
Median ($\sigma_{\bar{x}}$)	**183.18**	**246.49**	**288.69**	**135.17**	**217.37**	**240.62**	**222.93**	**262.97**	**295.46**	**232.42**	**319.19**
Min	**163.23**	**224.54**	**270.44**	**109.67**	**187.94**	**221.59**	**184.99**	**226.21**	**265.86**	**208.23**	**291.02**
Max	**201.00**	**333.33**	**370.56**	**202.00**	**559.44**	**281.97**	**302.59**	**326.29**	**312.18**	**269.02**	**364.68**
Q1	**174.43**	**238.76**	**281.67**	**123.88**	**202.58**	**225.61**	**212.77**	**250.09**	**282.58**	**220.98**	**298.58**
Q2	**183.18**	**246.49**	**288.69**	**135.17**	**217.37**	**240.62**	**222.93**	**262.97**	**295.46**	**232.42**	**319.19**
Q3	**195.94**	**278.00**	**297.73**	**144.46**	**244.61**	**260.34**	**262.83**	**281.47**	**302.12**	**255.35**	**324.03**
IQR	**21.51**	**39.24**	**16.06**	**20.58**	**42.03**	**34.72**	**50.06**	**31.38**	**19.54**	**34.37**	**25.45**

different time blocks: 05:00–10:00; 10:00–12:00; 12:00–16:00; 16:00–20:00; 20:00–00:00 and 00:00–05:00. Results show shower times to have a strong association with the clusters households belong to ($p < 0.003042583$). Shower times in the 05:00–10:00 block are associated with 56% of all households, while 23% of showers occur in the 16:00–20:00 block. EM and LM account for over 60% of all showers in the morning in comparable proportions. Details of the remaining MC times are illustrated in Fig. 5.

3.2. PHC and PCC

Previous research has established a strong connection between households' temporal peak demand patterns (the clusters) and their average daily consumption (Fig. 1). The results presented here, therefore, will aim to robustly test whether household water demand, in general and the patterns of consumption, in particular, are a function of the endogenous variables.

The hourly water consumption data for all 10,000 participating households for 2019 were analysed and summarised into PHC. The households recorded a mean annual consumption of ~31,800 m^3, averaging ~2,650 m^3 per month and a daily mean PHC of ~270 L per household per day (l/h/d). As illustrated in Fig. 1, the four clusters' shares of PHC on average are EP, 296 l/h/d; LM, 231 l/h/d; EM, 239 l/h/d and MP, 315 l/h/d. The absolute mean PHC for the 220 households surveyed was 256 l/h/d, ~5% below average, ostensibly due to the sample size. The clusters' shares of mean PHC in the survey, however, strongly reflect the proportions reported in the previous study. EP's relative mean PHC is 9% above the absolute mean, MP's is 21% above the absolute, while LM and EM both have a relative mean of 15% below the absolute. Table 1 details the monthly mean consumption values of the surveyed households according to their clusters.

All things being equal (cetaris paribus), that is, all other variables held constant, the PHC values in Table 1 typify consumption patterns attributable to the households in general and the clusters in particular. The absolute mean PCC for the survey participants is 144l/p/d, strongly reflecting the national average. The clusters' relative PCCs are 141, 130, 137 and 168 l/p/d in respect of EP, LM, EM and MP. This means that, while the other clusters are on par with or below the national average, MP households are 20% higher, all things being equal.

When observed within different variables, tremendous variations emerge in PHC and PCC. The results presented here would attempt to establish a three-way correlation: whether any link exists between patterns of consumption associated with the four clusters, household variables and the variations in PHC/PCC. The Chi-square test of independence was run on the PHC values and their associated variables and clusters to measure the divergence of the observed values from the values that would be expected under H_0 of no association. All tests on the SD and SE variables returned $p < 0.05$, which rejects H_0 and makes them strong determinants of PHC.

Table 2 presents the Clusters' PHCs within the context of four housing variables, along with their *p*-values. Owner-occupied households' mean PHC is ~18% higher than private-rented households and ~10% higher than social-rented ones. MP households possess the highest PHC in the owner-occupier (15% higher than the mean) and social-rented (13% higher than the mean) categories while EP has the highest in private-rented (25% higher than the mean). On average, houses consume ~26% more than bungalows and ~47% more than flats. In the household composition category, "I live alone" households expectedly have the lowest mean PHC, followed by single parents. "I share with unrelated adults" on the other hand, has the highest, whose dominant cluster happens to be MP with a mean PHC 30% higher than the average in that category. MP also has the highest PHC in the "I am a single parent", "I live alone" as well as "I live with my partner" categories, while EP has the highest share of consumption in the "I share with other families" category. Under occupancy, EP's PHC in the 2-person category is ~9% higher than average and ~28 higher in the 4-person category, while LM and EM are equally ~7% higher than average in the 3-person category.

3.2.1. PHC within the context of age, gender, and disability

Opposite variables within the age, gender and disability contexts are contrasted to determine whether any significant difference exists in their associated PHCs. The chi-square test of independence on the variables' associated PHCs to measure the variance within the observed values from the values that would be expected if there were no association returned $p < 0.00002$ for all variables. As illustrated in Figs. 6 and 7, while PHCs under most opposite variables are significantly different, the most marked divergence in PHC is found within the context of children,

Table 5
Acorn classification.

Main categories	Sub-category Code	Sub-category Name	Number of Network Households
1 Affluent Achievers	3	Young professionals	291
	4	Detached singles	477
	5	Flourishing families	758
	6	Accomplished suburban families	321
	7	Later-life professionals	391
	8	Exclusive empty nesters	203
	9	Middle-aged suburbanites	188
	10	Asset-rich retirees	512
	11	Affluent elderly	616
2 Rising Prosperity	12	Young flat buyers	25
	14	Socialising metropolitans	55
	16	Rising young families	392
	18	Mid-life singles	14
	21	Older owners	64
3 Comfortable Communities	22	Cosy young families	411
	23	Young families in terraces	1672
	24	Suburban large families	25
	25	Terrace-owning families	849
	26	Green-belt families	2038
	27	Young families in semis	628
	28	Contented families and couples	1801
	29	Rural pensioners	1057
	30	Contented elderly	43
	31	House-proud pensioners	1113
	32	Terrace-owning pensioners	168
4 Financially Stretched	35	Young renters in flats	166
	36	Squeezed singles and couples	432
	37	Squeezed young families	1135
	38	Renting young families	950
	39	Struggling social renting families	554
	41	Conventional middle-agers	497
	43	Elderly in terraced estates	155
	44	Post-industrial pensioners	340
	45	Elderly in semi-detached estates	254
	46	Pensioners in social rented flats	132
5 Urban Adversity	47	Younger privately rented adversity	139
	48	Younger social renting adversity	190
	50	Poorer social renting families	883
	51	Deprived younger families	267
	52	Struggling owner-occupier families	336
	53	Older people in social rented estates	194
	54	Struggling older owners	112
	55	Retired couples in social rented estates	86
	56	Deprived elderly renters	68
	57	Deprived older people renting flats	21
6 Not Private Households	60	Active communal population	1
	61	Inactive communal population	47

where households with children record a mean daily consumption 26% higher than households without children.

3.2.2. PHC and PCC within the context of occupancy

Occupancy is crucial in determining water consumption patterns, especially when conflated with other variables. The results show occupancy has a positive correlation with PHC and a negative correlation with PCC, as illustrated in Fig. 7G and H. A 10% reduction in PCC is observed when occupancy increases to 2, ~40% when occupancy increases to 3 and ~50% at occupancy = 4 before. The decline in PCC is reduced to ~35% when occupancy is ≥ 5. A significant inter-cluster variation in this pattern is found. For example, while EM and MP show a 16–23% drop in PCC with occupancy = 2, EP and LM remain the same (Fig. 8F).

Table 3 presents the divergence in PHC within the context of housing, employment and household income variables as occupancy changes. Social-rented records the highest PHC when occupancy = 1 (22% above average within the household tenure group context), while the private rented category's PHC when occupancy = 2 is 28% higher than average. Owner-occupied has the highest PHC when occupancy ≥4. In the context of the household dwelling type, PHCs for occupancy = 1 to 5+ in the house category are 28%, 15%, 13%, 20% and 16% higher than average, respectively.

Within the context of household composition, the "I share with unrelated adults" category has a PHC 24% higher than average at occupancy ≥5. Unemployed single occupants have the highest PHC (~10% above average); occupancy = 2 for all categories within the employment context have similar PhCs, while self-employed is ~24% higher than average for occupancy ≥5.

3.2.3. PHC within the context of SE, HWD and MC variables

As seen in Table 3, there are significant variations in PHC for different household occupancies within the context of employment and income. Results show income to be positively correlated to PHC, which rose by 32% between income brackets "up to £27k" and "£28k - £40k". The rise in PHC tapers to 10% as household income increases to £57k and down to 3% as income reaches beyond £58k (Fig. 9). Inter-cluster consumption trends within the context of household income were consistent with the clusters' established patterns. No correlation was found between PHC, educational qualification and the standard occupational classification (SOC) neither was there any note-worthy inter-cluster variation in consumption patterns attributable to those variables. Within the context of employment, however, while the categories "employed", "self-employed", "unemployed" and "retired" all have PHCs within average ranges, households with "students" have PHCs ~13% above average.

No significant variations were found in PHC within the context of HWD, and all consumption patterns are consistent with the established trends. The measured MC variables relate to the frequencies and times of microcomponent events. Results have revealed considerable variations in PHC and mixed significance in patterns within the context of time and frequency for three MC events: shower, toilet flush, washing up and washing machine. Table 4 presents complete descriptive statistics of the three MC events and their p-values. Households that reported having showers twice daily consume over 42% more water than those having

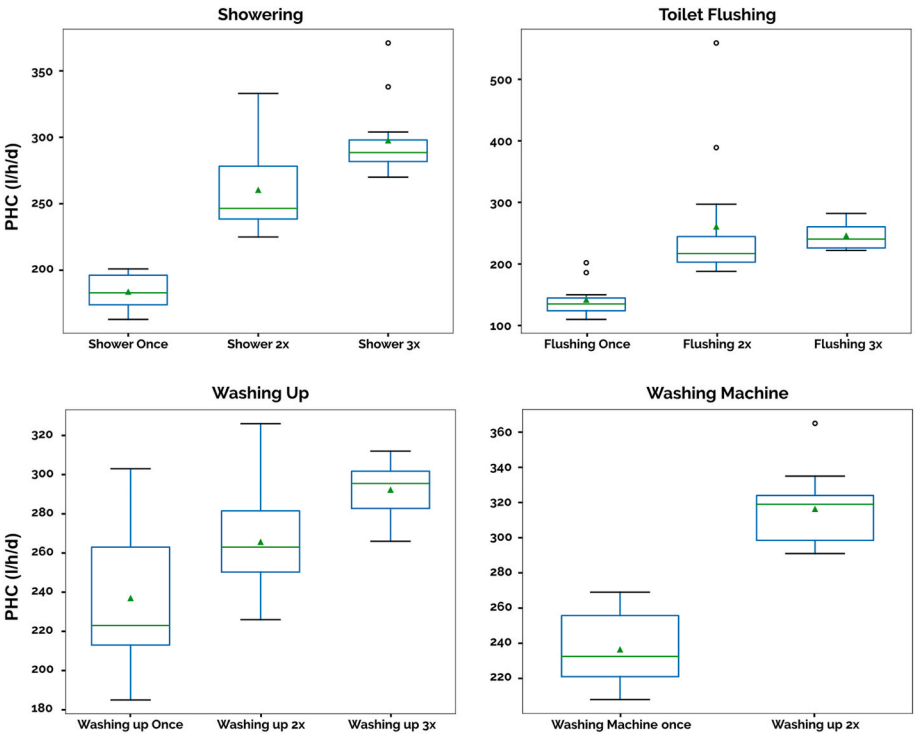


Fig. 10. PHC within the context of MC frequency.

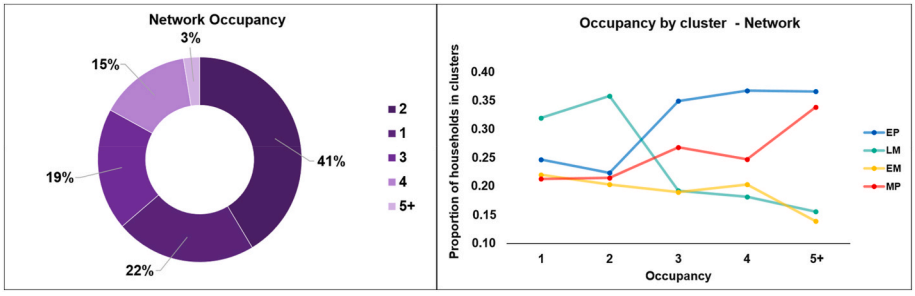


Fig. 11. Network and clusters occupancy proportions.

single daily showers, with households consuming 62% more water three times a day. Mean PHC for households that flush the toilet twice daily is 84% higher compared with 74% for three times. Notably, data for "twice daily" households have much higher variance and IQR than "three times daily", although Q1-Q3 for "three times daily" are much higher. Households that wash up twice a day have a PHC 12% higher, while those that wash up three times consume 23% higher. Finally, the mean PHC for twice-a-day washing machine users is 34% higher; there was no data on three-times-a-day households. Fig. 10 illustrates the divergence of PHC within the context of MC frequency. No significant correlations were found between times of MC and inter-cluster PHC divergence across all MC categories, and all mean PHCs are found to be consistent with established values.

3.3. Other datasets

This section presents the results of a scaled-up subsection of the analysis presented above by merging network occupancy data for over 9,000 households with their corresponding cluster and PHC data according to their Acorn categories. This is the second part of the data triangulation approach aimed at enhancing the validity of previous findings and interrogating different ways of understanding the SD and SE undertones of household water consumption from a much bigger sample size. The ONS dataset comprises UK Population and Household SD and SE data at Postcode and DMA levels. This dataset is used for correlation purposes to help establish how different variables (e.g. the population of a certain demographic) relate to consumption patterns (clusters) and mean PHC.

3.3.1. Network occupancy and Acorn data

The network occupancy data (Fig. 11) exhibited similar proportions of overall households and clusters to the survey data (Figs. 3J and 4F).

The Acorn classification data were matched to the PHC and occupancy data of over 9,000 households to gain further insight into regional distributions of the Acorn categories, consumption clusters, occupancy and PHC/PCC. Table 5 presents the Acorn classification categories, subcategories and the number of network households in each sub-category.

Fig. 12 has the illustration of the network households associated with these categories according to occupancy. The sub-category of "house-proud pensioners" (31) has the highest percentage of both single-occupancy (~30% above average) and two-occupancy households (~20% above average). Occupancy = 3 is dominated by "Young families in terraces" (16% above average), while "Green-belt families" and "Poorer social renting families" have the highest percentage of

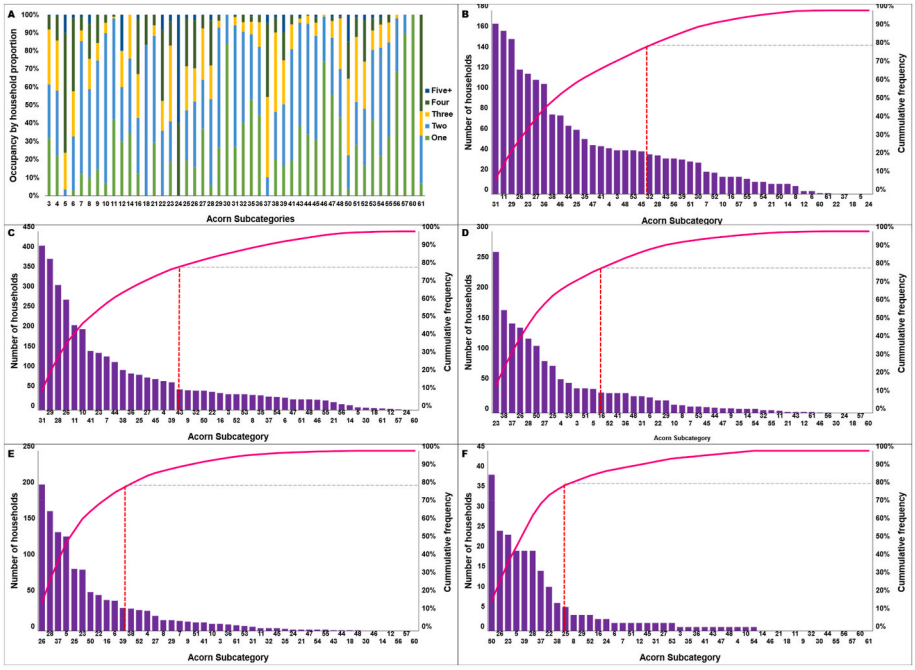


Fig. 12. Household occupancy within the context of the Acorn sub-categories. A. Occupancy rates of Acorn sub-categories; B. Acorn sub-categories at occupancy = 1, showing the vital few; C. Acorn sub-categories at occupancy = 2, showing the vital few; D. Acorn sub-categories at occupancy = 3, showing the vital few; E. Acorn sub-categories at occupancy = 4, showing the vital few; F. Acorn sub-categories at occupancy = 5+, showing the vital few.

households for Occupancy = 4 and 5, at 16% and 13% above average, respectively.

Fig. 13 illustrates the proportions of households in the four clusters within the context of the Acorn sub-categories. In many ways, the cluster proportionalities under the sub-categories and the survey variables are similar. For example, as with the survey, the LM cluster dominates nearly all of the elderly/pensioners demographic by more than 50%. In addition, under all six categories, the EP cluster accounts for more than 40% of the "young families" sub-categories, while over 47% of "large" families are in MP, with ~30% of "singles" in EM. More similarities are discussed in the next section.

PHC within the context of the Acorn sub-categories is significantly diverse, as illustrated in Fig. 14. With a mean PHC of 293 l/h/d, the "Comfortable Communities" category has both the highest consuming sub-category ("Suburban large families": 156% above average) and the lowest ("Contented elderly": 44% below average). Excluding these two extremes would reduce the category's mean PHC to 266 l/h/d, which would make the "Affluent achievers" category, which has a mean of 292 l/h/d, the highest. "Rising prosperity" has a mean of 277 l/h/d, similar to the national average, while "Financially stretched" and "Urban Adversity" have 234 and 240 l/h/d, respectively.

The PHCs observed under the clusters for each sub-category are mostly within the expected range, with the exception of "suburban large families", whose MP households' PHC is 1,069 l/h/d - 206% above the category's intra-cluster mean and 280% above the inter-cluster mean; EP, the second-highest in the sub-category is 520 l/h/d, i.e. 70% above the category's intra-cluster mean and 85% above the inter-cluster mean; LM for this sub-category is only 5% above average while EM is 7& below average. Conversely, PHC for the contented elderly sub-category is 33%, 39%, 15% and 66% below average for EP, LM, EM and MP, respectively.

3.3.2. *UK population and household attribute data*

This section presents the results of the correlation between PHC and the corresponding population attributes of households in the study area at Postcode level. A regression analysis was conducted between Postcode-level PHC and various household attributes to ascertain whether their relationship is statistically significant and whether they are correlated. Fig. 15 illustrates the correlation between Postcode-level PHC and the population variables.

Results show a positive correlation between the regional PHC and all PCCs as illustrated in Fig. 15 A – E. However, as illustrated in Fig. 15 F-J, PHC is negatively correlated to population except with MP households which are positively correlated. Table 6 presents the multiple regression analysis outputs for the relationships between the regional PHC values, PCC and the population.

3.4. *Triangulation*

Triangulating the low-sample-size survey data with Acorn Classification data (n = 9000) and network occupancy data (n = 9000) validated the results and made them generalisable. Over 90% similarity in statistically significant results was achieved between comparable variables within all three datasets. For example, there is a high percentage of LM households in the survey-generated sub-categories of the over 65 demographics, which correlates with many ACORN sub-categories, such as "Old Owners", "Affluent Elderly", "Rural Pensioners", and "House-Proud Pensioners". Additionally, the morning "peakers" (LM and EM) are dominated by "Owner-occupied", "Living Alone", "House Dwellers", "Females over 64" and "Male 20–29" survey subgroups, which correspond to ACORN's "Single Professionals", "House-Proud Pensioners" and "Elderly in Semidetached Estates".

4. Discussion

Water consumption is often perceived as a mundane human activity comprising a myriad of end-use events (e.g. showers, toilet flushing, washing up) without necessarily following any measurable patterns. It has been demonstrated in this and previous studies that household water consumption is highly influenced by a litany of endogenous and exogenous variables (especially tenure, dwelling type, occupancy, household composition, age, gender and household income). These variables do not only dictate the temporal patterns of consumption (as represented by the clusters) but also cause considerable divergence in PHC depending on how they interact with each other, as observed by Abu-Bakar et al.

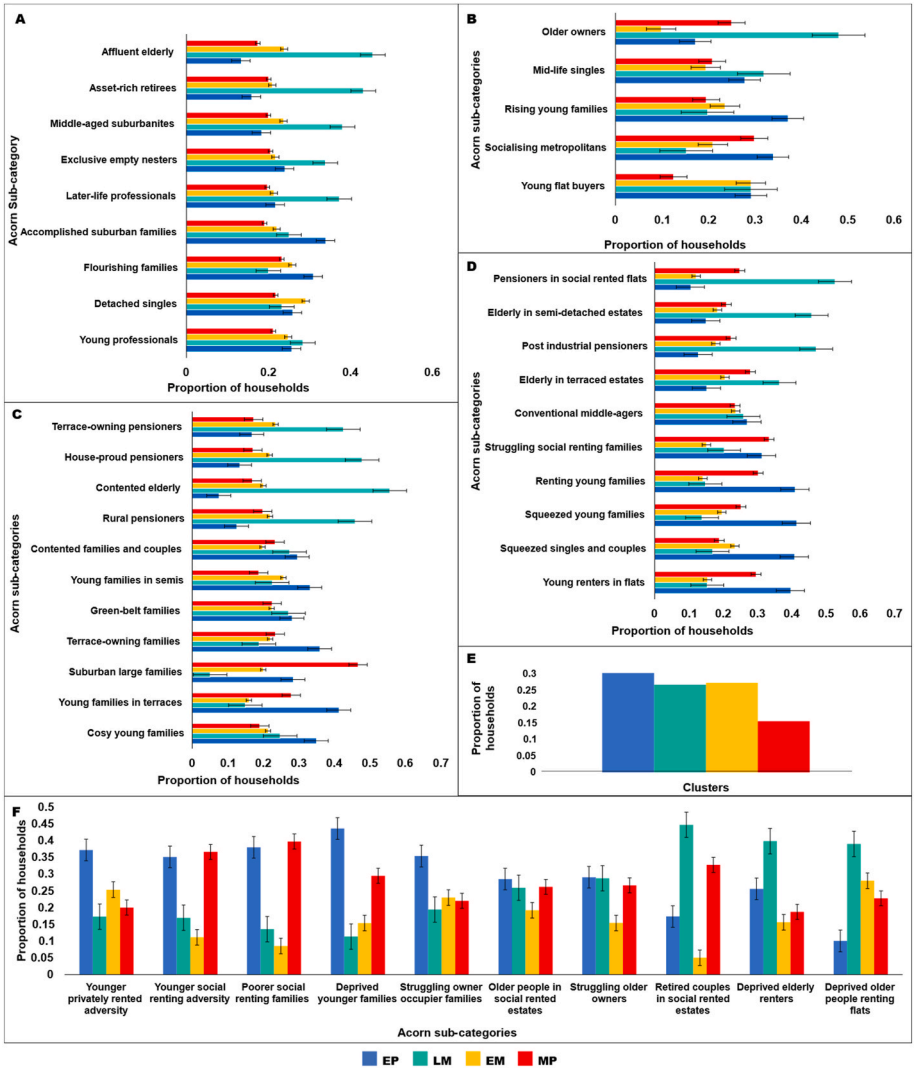


Fig. 13. Cluster proportions under Acorn categories and sub-categories. A. Affluent Achievers; B. Rising Prosperity; C. Comfortable Communities; D. Financially Stretched; E. Inactive communal Population; F. Urban adversity.

(2021a) and Fielding et al. (2012). Therefore, H_0 has been rejected and both research hypotheses (H_1 and H_2) upheld.

Peak demand is used to refer to the clusters' collective average demand at their respective peak times. On the other hand, average daily consumption refers to consumers' PHC or PCC.

4.1. *All things being equal*

We present a step-by-step rendering of the observed association between the clusters and the variables from all the data sources. In the "Private-rented" group, more than half of households belong to EP, accounting for~44% of the network water demand at a peak time, usually between 19:00 and 20:00. A similar proportion of households in the "Social-rented" belong in MP, which is responsible for an average of six daily sporadic instances of peak or near peak events constituting over 25% of network demand per instance. LM and EM (the morning peak clusters, respectively accounting for 38% and 34% of network demand at peak, at an average daily instance of two and one) each represents less than a quarter of households in the private and social rented group but have a 25% higher representation than EP and MP, in the "Owner-occupied" group. Some similar patterns are revealed by the Acorn dataset such that, EP constitutes the highest proportion of the "young privately rented" group while the "struggling social renting families" group tends to dominate MP (Fig. 13). Within the context of occupancy (Fig. 4F), the morning clusters have 23% more households than the other clusters in the single and two-occupancy categories, contrasted with having 47% fewer households in the higher occupancy categories (as observed within the network occupancy dataset – n = 9005). This reflects, to some extent, the pattern observed within the context of household composition, where the morning clusters make up 55% of the low-occupancy groups ("I am a single parent", "I live alone" and I live with my partner") compared with 74% of the medium to high occupancy groups ("I share with other families" and "I share with unrelated adults") going to EP and MP. As regards age and gender, nearly half of households with occupants aged "up to early 40s" are in EP, including over 56% of all households with children under 13 and 60% of all females between 20 and 29. MP has the second-highest representation of the "up to early 40s". Over 50% of all 65+ are in LM while EM and MP share the dominance of 45–64 (Refer to Fig. 4G). Results from the Acorn dataset does strongly corroborate these findings in that, as illustrated in Fig. 13, across all six categories, there are significantly higher proportions of the elderly and pensioner demographics in LM while the proportions of young families do reflect the values for EP and MP from the survey. Therefore, all things being equal, results from all datasets suggest that EP households are more likely to be families with younger occupants (especially children) and medium to high occupancy rates, live in

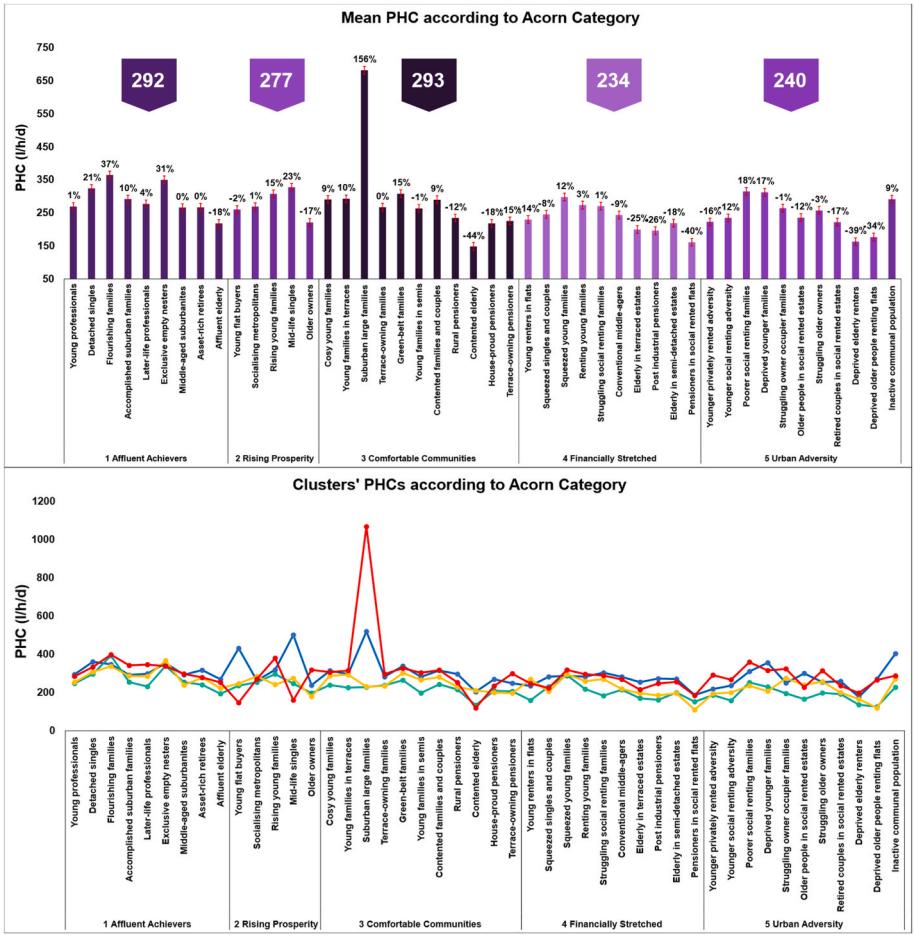


Fig. 14. PHC according to Acorn sub-categories.

privately rented houses, use more water in the evenings and have a higher than average PHC and PCC (279 l/h/d and 141l/p/d). MP households are likely to be socially renting, composed of multiple occupants (including unrelated adults and families) across all age groups but more in the younger demographics, with an increased propensity to engage in high-intensity water use frequently and sporadically; have the highest PHC and PCC (309 l/h/d and 168l/p/d). LM households are more likely to be composed of older occupants in low-occupancy settings (single or couples, no children), own houses, have two peak events on average, mostly late mornings and lower than average PHC and PCC (219 l/h/d and 130l/p/d). Lastly, EM households are likely to be a younger demographic, have low to medium occupancy (single or couples, with or without children), own houses, engage in a single daily intensive water use early in the morning and have a lower than average PHC and PCC (218 l/h/d and 137l/p/d).

4.2. *The interaction between clusters and variables*

PHC begins to vary significantly when contextualised using a blend of variables, resulting in uncharacteristic inter-cluster patterns. For instance, as shown in Fig. 6I, when gender, age and disability are considered, the clusters' PHCs fall outside of expected ranges. Fig. 16 shows how variables cause PHC to shift upwards or downwards from clusters' normal ranges. The most outlandish variance in cluster-related PHC was caused by the "Girls 13–19" variable resulting in EM increasing by 96% above average. Even though other variables have occasionally caused unusual divergence in PHC between clusters, only households with girls aged 13–19 have exhibited such high EM values, dwarfing the other clusters (LM being ~21% above average and MP ~13% below). Another unusual increase in EM is observed within the "Females" context (~33% above cluster average, compared with 1–6% in the other clusters). Conversely, males exhibit marginally higher than average values in all four clusters, although to a lesser extent with MP. The inference here is that when PHC is viewed solely within the context of age and gender, males tend to use more water than females overall. Males consume more heavily in the evenings while females tend to be heavy early morning consumers, with teenage girls being significantly more dominant. Although households with teenagers (both boys and girls) have much higher PHC overall, boys use nearly as much water in the evening (~37% higher than EP average) as in the morning (~34% above EM average). Unsurprisingly, over 62% of all morning showers are attributable to LM (25%) and EM(37%) as illustrated in Fig. 5A, which makes it logical to infer that the female and teenage demographics' heavy morning water use can be linked to shower use. This inference is corroborated by Makki et al.'s (2013) findings. It can also be theorised that EM females and teenage girls use more water in the shower because their PHCs are 14% and 47% higher than their male counterparts. The divergence in PHC across all clusters begins to wane significantly as age increases for both genders except for males 30–44, whose PHC is ~15% higher than the female counterparts, over 60% of which being attributable to an uncharacteristically high LM. Households with some disabled occupants have higher than average LM and EP (~26% and ~9%) and lower than average EM and MP (−17% and −13%).

To accurately attribute any changes in PCC/PHC to specific endogenous factors, it is important to delineate constituent variables from known exogenous factors such as perspiration and temperature, both of which have been linked to changes in consumption patterns and increased demand (Grafton et al., 2011; Kenney et al., 2008). July 2019

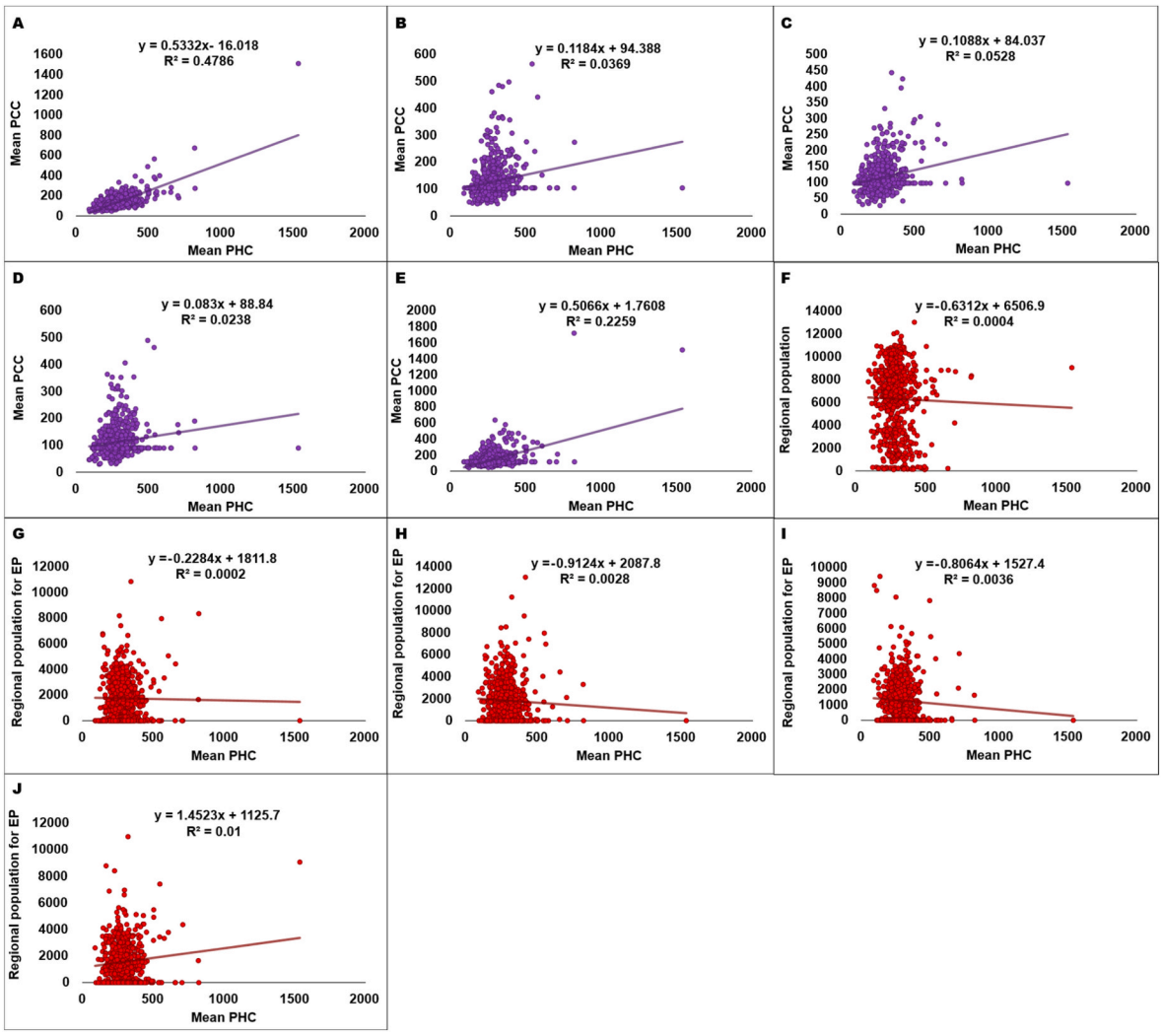


Fig. 15. Relationship between PHC/PCC and the regional population at postcode level, displaying the regression equation and the r^2 values. A.PHC vs PCC for the entire network; B. PHC vs PCC for the EP cluster; C. PHC vs PCC for the LM cluster; D. PHC vs PCC for the EM cluster; E. PHC vs PCC for the MP cluster; F. PHC vs entire network population; G. PHC vs the population of EP households; H. PHC vs the population of LM households; I. PHC vs the population of EM households; J. PHC vs the population of MP households.

average temperature was 69% higher than the annual average, making it the hottest month on record (METOFFICE, 2019). This manifested in a 10% above average increase in mean network PHC for July, translating into a 25% increase for EP, 12% for LM, 1% for EM and no increase for MP, whose highest PHC is recorded in December. The inference is that consumption for large family households with children has the strongest positive correlation with temperature than other family types. Fig. 17 illustrates the relationship between temperature and the four clusters.

Household and family sizes in the UK increased by 5.9% and 7.4%, respectively, according to the Office of National Statistics (ONS, 2021). Single parents make up 14.7% of all families. Additionally, while households comprising multiple families represent the smallest proportion of all households, they are the fastest-growing type of household and have increased by two-thirds to over a quarter of a million households in 2020. As previously discussed, single parents and households with multiple families have the highest PCC due to the former being more likely to have children and the latter having a high propensity to exhibit consumption patterns consistent with the MP cluster.

5. Conclusions

This paper aimed to establish the relationship between household water consumption behaviour, including PCC and microcomponents, and a variety of endogenous household variables. The purpose of the study is to provide utilities with a basis for classifying water consumers into behavioural clusters without relying on smart-meter data. A complete understanding of demand patterns and relevant underpinning factors is critical for developing policies that adequately address worsening water and helps better manage water resources.

The results of our study corroborated the previous studies and also provided new insights into the relationship between these variables and other consumption patterns. The influence of the discussed household variables on consumption is presented within the context of households' unique daily water consumption patterns: Early morning peakers, Late morning peakers, Late evening peakers and Multiple peakers. In contrast with previous studies, our results provide insight into, for example.

- the time of day young professionals are likely to use water most frequently;
- the micro-component event that is likely to occur;
- how much water they are likely to consume at peak;
- how many instances of that peak event are likely to occur; and
- how much effect this may have on the network's aggregate demand.

Table 6
Multiple regression analysis outputs for the relationships between the regional PHC values, PCC and the population.

Regional PHC vs Regional PCC												
PCC	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*	Multiple R	R Square	Adjusted R Square	Standard Error	Observations
Mean PCC	0.898	0.034	26.064	0.000	0.830	0.965	0.830	0.965	0.692	0.479	0.478	70.617	742
EP PCC	0.309	0.059	5.275	0.000	0.194	0.424	0.194	0.424	0.190	0.036	0.035	96.011	742
LM PCC	0.485	0.075	6.420	0.000	0.336	0.633	0.336	0.633	0.230	0.053	0.051	95.184	742
EM PCC	0.287	0.068	4.250	0.000	0.154	0.419	0.154	0.419	0.154	0.024	0.023	96.627	742
MP PCC	0.446	0.030	14.694	0.000	0.386	0.505	0.386	0.505	0.475	0.226	0.225	86.047	742
Regional PHC vs Regional Population													
Population	***Coefficients***	***Standard Error***	***t Stat***	***P-value***	***Lower 95%***	***Upper 95%***	***Lower 95.0%***	***Upper 95.0%***	**Multiple R**	**R Square**	**Adjusted R Square**	**Standard Error**	**Observations**
Population	−0.001	0.001	−0.570	0.569	−0.003	0.002	−0.003	0.002	0.021	0.000	−0.001	97.777	742
EP Population	−0.001	0.002	−0.403	0.687	−0.006	0.004	−0.006	0.004	0.015	0.000	−0.001	97.788	742
LM Population	−0.003	0.002	−1.497	0.135	−0.007	0.001	−0.007	0.001	0.055	0.003	0.002	97.651	742
EM Population	−0.005	0.003	−1.645	0.100	−0.010	0.001	−0.010	0.001	0.060	0.004	0.002	97.621	742
MP Population	0.007	0.003	2.728	0.007	0.002	0.012	0.002	0.012	0.100	0.010	0.009	97.311	742

Utility companies now have unprecedented insight into their network's water consumption behaviours based on household types and detailed consumption patterns.

Several stakeholders can use this research, including utilities and government policymakers (e.g. DEFRA and OFWAT), to inform important environmental and policy decisions. The study helps to understand the complex relationships between household variables and water consumption patterns. A detailed narrative is provided of the SD and SE undertones of residential water consumption in two connected parts: on the one hand, the influence of variables on the daily consumption patterns and the other, the PHC and PCC on a macro-scale (networks).

We have identified many ways that the findings described herein could form a part of the design of targeted conservation strategies for utilities. For example, targeting households with teenagers with shower time reduction messages or targeting the more seasonally sensitive clusters, such as EP, with seasonal conservation interventions. The findings herein would also enable micro-demand forecasting by identifying the various household factors underpinning the patterns and volumes of consumption as well as the drivers of seasonal variabilities. Utilities could predict, infer and detect consumption hotspots across their network by analysing the factorial components of household water consumption discussed here, even in the absence of smart meter data. Finally, smart meter penetration is one of the utilities' most critical targets. This study could set the candidate selection criteria for smart meter enrolment by focusing the enrolment efforts on households whose SD and SE attributes make them suitable candidates.

5.1. Future research direction

The ground is now set for further research into the water consumption habits and behaviours attributable to age, gender and disability that lead to the established patterns. For example, there is the need to investigate whether these patterns can be attributed to how people wash due to their gender, age, or disability and whether these patterns relate to social norms or values or are inherently linked to specific SD characteristics.

Future work along the path of this study will focus on building a metric-based framework derived from the results discussed herein (a) to measure the likelihood of households belonging to a particular cluster and (b) to predict households' likely PHC. Such a framework would enable the classification of households into consumption clusters based on their combined SD and SE attributes. This study will help utilities expand their DSM range of measures, which currently use estimation and extrapolation, by allowing ordinary-metered and unmetered households to be included. The framework would also provide a more reliable proxy for measuring PCC and PHC by policy and regulatory agencies such as OFWAT.

5.2. Limitations

Even though outliers have been removed from the consumption data, it is possible, to a very negligible extent, that the PHC in some categories has been marginally skewed by one or two temporary leakages or brief uncharacteristic fluctuations in consumption. The variables obtained from households in this study are not exhaustive. The study is limited by the non-availability of other household variables such as religion, cultural practices and ethnicity, which could have revealed further interesting insights.

Author contributions

All authors have approved the final manuscript. Halidu Abu-Bakar undertook the research and compiled the manuscript with inputs and guidance from Leon Williams, Stephen Hallett. All authors discussed the results and contributed to the final manuscript.

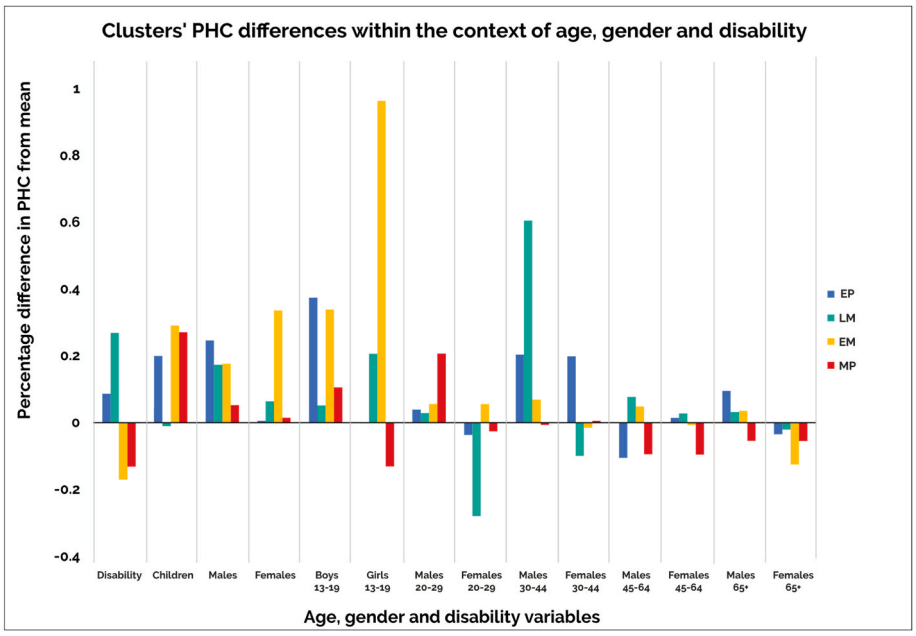


Fig. 16. Inter-cluster variations in PHC from mean within age, gender and disability contexts.

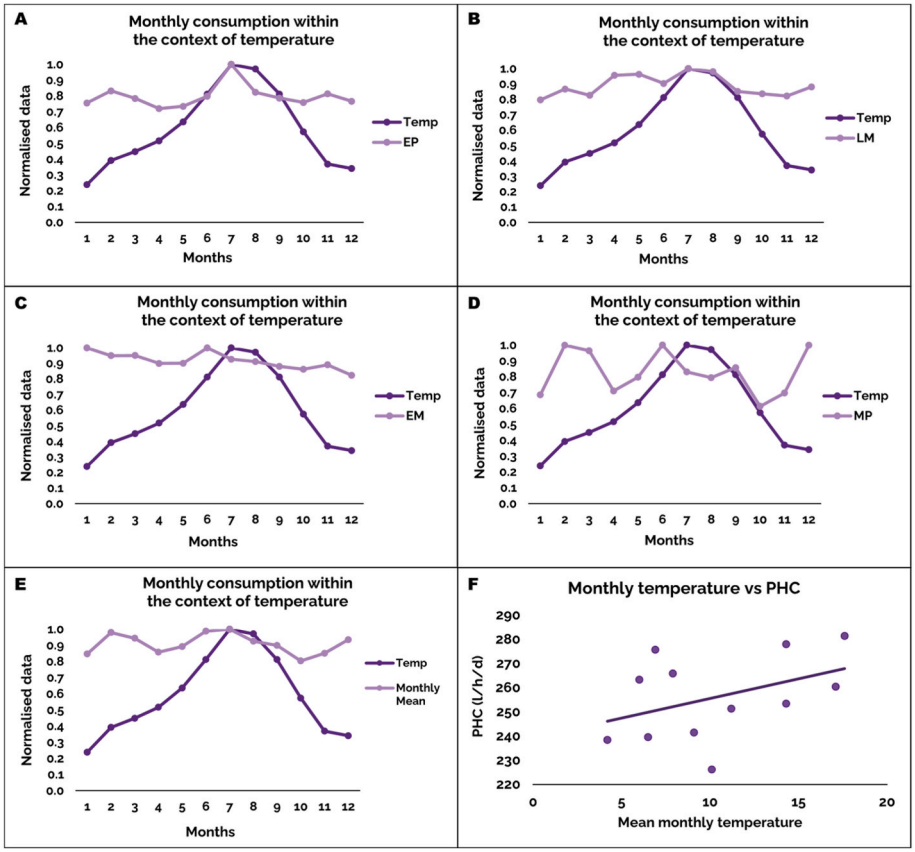


Fig. 17. Relationship between clusters' monthly PHC and temperature (lowest to highest expressed as a fraction of the max). Temperature data source: GOV.UK; UK Department for Business, Energy and Industrial Strategy; Met Office. A. EP consumption vs temperature; B. LM consumption vs temperature; C. EM consumption vs temperature; D. MP consumption vs temperature; E. Mean consumption vs temperature; F. Correlation between PHC and temperature.

Data statement

The network data were provided by Anglian water PLC and have not been made publicly available by the water company. Direct requests for these materials may be made to the provider.

Supplementary material

The data will be made available based on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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