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Residential consumer preferences to demand response: Analysis of different motivators to enroll in direct load control demand response

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ABSTRACT

Demand Response (DR) is a potential tool to help reduce the network and market stress with the ever-increasing renewable energy in the electricity system. This study aims to measure the different motivators of residential consumers towards Direct Load Control (DLC) DR to identify the influence of socioeconomic and demographic characteristics on the DLC DR motivators. To study this, we examined the preferences of Finnish residential consumers to DLC DR. The analysis from consumer responses resulted in the following findings: Firstly, the cluster analysis identified three distinctive consumer subgroups. Secondly, a multinomial-logistic regression provided the influence of gender, education, living conditions and income level on the consumer subgroups. Thirdly, a Qualitative Comparative Analysis (QCA) showed the effect of age group, presence of children and number of people in the household on the subgroups. Finally, an ANOVA test provides the influence of consumer characteristics on the DLC DR motivators. The results highlight the heterogeneity of different subgroups and the influence of consumer parameters on DLC DR motivators. The findings of this study have novel and practical implications for energy flexibility among residential consumers. The policy implications arising from this study are discussed which are essential to consider for widespread adoption of DR.

1. Introduction

The ever-increasing pollution levels and drastic effects of climate change has led to the formation of the Paris Agreement, which was then signed by 197 countries in the world on December 2015. This agreement holds the targets set by every signed nation to reduce their emissions and be more sustainable across all sectors (Intergovernmental Panel on Climate Change, 2018). Within the energy and electricity sector, the focus was to achieve a sustainable energy system through electrification of various sectors by switching from conventional energy resources to zero emission resources. Countries around the world have set their targets to reduce the dependencies on fossil fuels in the upcoming years and within the EU, countries should target 45% renewable energy in power generation by 2030 (European Commission, 2022).

Attaining such a sustainable energy system would create new problems posed by high loads in the demand side from electric vehicles and electric heating, as well as the intermittent nature of renewable energy production on the supply side (Strbac, 2008; Kroposki, 2017). Demand Response (DR) is an interesting option to consider that can help to mitigate against these problems (Yu et al., 2022).

DR represents flexible electricity demand, which can be increased or decreased at a specific time. This can be done, for instance, to utilize excess electricity production from wind farms or to reduce electricity demand during network congestion and peak-power pricing. Demand response can broadly be separated in two groups, based on the reason why consumer demands are changed. The first type is based on price signals, within which the time-varying electricity prices are used as a measure to change consumption patterns. These prices are dependent on the wholesale electricity price and the transmission constraints within the electricity network. Consumers change their usage based on the varying price to save money by utilizing more during low price hours and reducing usage in peak-price hours. The second type is called Direct Load Control (DLC) which is performed by a utility or aggregator to control certain appliances remotely for a limited period of time.

While commercial and industrial consumers have been significantly involved in DR in the past (Helen, 2022; Fortum, 2018), the residential

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sector has also a high theoretical potential to provide flexibility (Gils, 2014). With the widespread adoption of smart meters by residential consumers (Energy Authority, 2017) there have been many pilot studies within the Nordics to explore the residential demand flexibility (Söyrinki et al., 2018; Fjæ stad and Svensen, 2021; Ruwaida et al., 2022). Water heaters are an example of the loads for which flexibility potential can be sold to the ancillary services market while providing some electricity bill reductions for the consumer (Annala et al., 2018).

Despite DR being a benefit for the entire electricity system, the implementation and acceptance of residential DR has been significantly low (Stenner et al., 2017). One possible reason is the complex decision-making of consumer's willingness to enroll in DR. The identification of motivators for the residential consumers and quantification of said motivators would be essential to determine their participation in DR programs. A complete overview about the motivators for enrolling in different DR programs is provided by Parrish et al. (2020). The most common motivator for enrolling in DR programs is the financial benefit (Allcott, 2011; Dütschke and Paetz, 2013; Torstensson and Wallin, 2014; Raw and Ross, 2011; US DOE, 2016; Aloise-Young et al., 2021; Tayal and Evers, 2018; Broberg and Persson, 2016). The next important motivator after financial benefits is the environmental benefit (Georgarakis et al., 2021; Ruokamo et al., 2019; Bradley et al., 2016). Apart from these two main factors, some studies outlined other motivators to enroll in DR: comfortability (Gołębiowska et al., 2021), automation (Parrish et al., 2019; Fell et al., 2015), local sustainability (Georgarakis et al., 2021; Kalkbrenner et al., 2017; Hackbarth and Löbbe, 2020), interest in technology (Dütschke and Paetz, 2013; Strengers, 2010) and personal contacts enrolled in the same program (Distribution, 2016).

Comparing within the DR programs, DLC provides greater assurance over quantity, location and timing of flexibility than when compared with price based DR (Xu et al., 2018; Stenner et al., 2017; Newsham and Bowker, 2010; Nolan and O'Malley, 2015). Such an efficient and reliable demand flexibility is needed when participating in ancillary service markets, thus by making it the ideal choice for consumers to help reduce the electrical network stress. However, the acceptance of DLC programs have not been adequate, even though the programs have been available for years (Stenner et al., 2017; Nolan and O'Malley, 2015). Previous literature has examined participation around the world in DLC programs, which presents a complex user acceptance. The main concerns for the consumers were due to trust and security of the service provider (Fell, 2016; Poilitt et al., 2013; Balta-Ozkan et al., 2014; Throndsen and Ryghaug, 2015), overriding opportunities (Parkhill et al., 2013; Smale et al., 2017; Kobus et al., 2013; Fell et al., 2015), compensation problems (Paetz et al., 2012; Murtagh et al., 2014) and lack of control (Xu et al., 2018; Fell et al., 2015).

One of the main reasons for the complex user acceptance is due to the limited data on the importance of different motivators for consumers. A myriad of previous research has included the usage of choice experiment (CE) to identify consumer willingness to accept DR. In this type of experiment, the respondents are given a choice card with different options available for the respondent to choose. The options consist of sets of attributes with different possible values, and the customers are asked to make their choice for many choice cards. This process is done to analyze the importance of different variables and their influence in the DR enrollment. Ruokamo et al. (2019) has employed a CE to analyze the preferences of Finnish residential consumers to enroll in DR based on various contracts, electricity bill reduction and emission reductions. Broberg and Persson (2016) has employed CE to analyze the preference of Swedish consumers to provide DR control over loads-based electricity bill reduction. Gleue et al. used CE in Germany and Great Britain to study the willingness to accept flexible usage based on cost and emission reductions (Gleue et al., 2021). Yilmaz et al. used CE to analyze the preferences for DLC DR on heat pumps and EV within Switzerland (Yilmaz et al., 2021). One of the main drawbacks of CE is the limitation on the number of features. By increasing the features, the number of options increases, which in turn increases the overall option cards for respondents, which might be too large for one survey.

Though these studies help to analyze the impact of financial benefits and emission reductions, the studies themselves do not consider all other possible factors which can influence a persons' motivation to enroll in DR, as outlined by Parrish et al. (2020). In addition to analyzing the influence of different motivators for consumer DR enrollment, a direct comparison of different motivators has not been researched. Through quantification of the motivators for enrolling in DLC DR, proper schemes and incentives can be created which can attract more consumers to enroll in DLC DR.

Based on previous literature and the authors' best knowledge, there is a literature gap in quantification of different motivators for consumers to enroll in DLC DR programs. In addition, the decision to enroll in a DR program can be influenced by the individual's socioeconomic and demographic characteristics along with other personal motivators. Understanding the individual's personal motivators and analyzing the effect of socioeconomic and demographic characteristics characteristic on the decision-making process to enroll in DR is needed to boost the widespread adoption of residential DR.

To address the above issues, the objective of this study is:

To analyze the consumer motivators to enroll in DLC DR and the effect of consumer features on their motivation towards DLC DR.

In order to reach the research objective, the following research questions are formulated:

1. How can the residential consumer's motivators for enrolling in DLC DR be identified and quantified?
2. How can different consumers be grouped together based on their DLC DR motivators?
3. How do the sociodemographic and dwelling characteristics of residential consumers affect their DLC DR motivators?

To answer the above questions, a survey was formulated and was sent to answer by residential consumers from Finland. Finland is one of the leading countries for renewable energy production and has set ambitious targets to try to increase their renewable share drastically in the upcoming years making the residential DR important to analyze for the future. This study makes a step towards wider DR acceptance by quantifying different motivators in relation to people's socioeconomic and demographic characteristics. The findings from this research contribute to designing better DLC DR programs across different customer subgroups, and help in widespread adaptation of DLC DR.

The remaining sections of this paper are structured as follows: Section 2 discusses the various methodologies used in this paper, along with survey development and explanation of different dependent and independent variables in the overall analyses. Section 3 provides the results from the different analysis, and the results are further discussed in Section 4. Section 5 provides the policy implications of this paper along with the conclusion.

2. Methodology

2.1. Survey development

The survey was initially developed in English, and then a Finnish translation was added to it to provide the respondents the possibility to choose their preferred language. In order to obtain valuable responses from actual residential consumers, a collaboration was established with an electricity supplier operating within Finland: Pohjois-Karjalan Sähkö (PKS). PKS is one of the major electricity supplier within Finland operating for more than 75 years. The consumer database of PKS was used, to whom the survey was distributed. The consumer database uses the email addresses of the person responsible for paying the electricity bill within the household and is therefore considered as the main decision maker of the household. The survey was distributed to

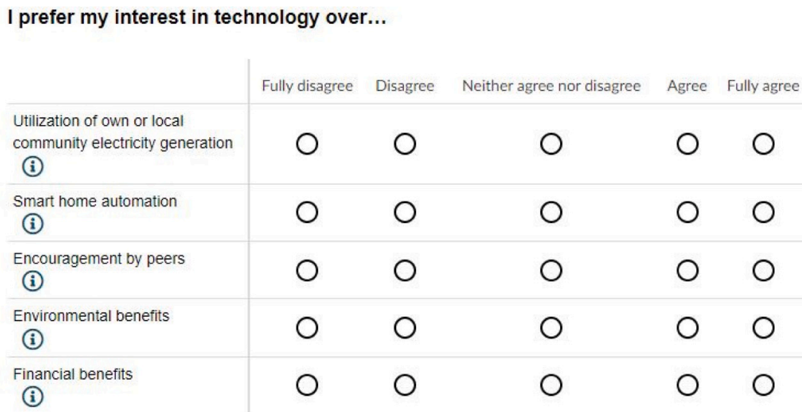


Fig. 1. Example question asked in the survey.

approximately 30,000 consumers, of which 4134 consumers started responding. The survey was kept open for a week and, 1468 consumers answered the whole survey. At the time of survey distribution, there were no DLC DR services provided by PKS to their consumers. The survey was distributed anonymously and no personal identifiers were collected, as per GDPR regulations and the Data Protection Act in Finland (Korpisaari, 2019). The general composition of the consumers using services from PKS is dominated by men (67%) and the average consumer age is 57–59 years.

2.1.1. Dependent variables

The dependent variables within this research consist of the quantification of motivators for consumers to enroll in DR. As per literature, six different motivators were considered:

- Financial gains **(Fin)**: The potential reductions in electricity bill.
- Environmental gains **(Eco)**: The potential reductions in CO_2 emissions and help transition to a green future.
- Local generation **(LG)**: The preference of local production and local sustainability.
- Encouragement by contacts/Peer pressure **(PP)**: The preference to enroll based on the number of personal contacts enrolled within the same program and based on their feedback.
- Smart home automation **(Auto)**: The preference to enroll based on smart home automation, which minimizes user's workload.
- Interest in technology **(Int)**: The preference to enroll based on personal interest to try new programs, which is interesting due to personal reasons.

In order to obtain the value for different motivators for DLC DR for residential consumers, the survey was designed in such a way that the questions asked the respondents to choose between two different motivators in a 5 point Likert scale having options as: Fully disagree, Disagree, Equal preference, Agree and Fully agree. An example of the question asked in the survey is shown in Fig. 1 and the survey questions is attached as a supplementary material.

From this question, if a person chooses *fully agree* for their preference of interest in technology over smart home automation, then for that consumer, the value of Int vs. Auto would be 5. Similarly, the answers from other questions were obtained and quantified.

Table 1
Independent variables for 1468 Finnish consumers.

Variable	Percentage
Gender	
Male	72%
Female	26%
Other	0.5%
DNS	1.5%
Age	
19–29	1%
30–39	5%
40–49	12.7%
50–59	21.3%
60+	57.1%
DNS[a]	2.9%
Education	
Basic	7.9%
Upper secondary	37.6%
Bachelors	27.6%
Masters or higher	22.6%
Other	4.3%
Dwelling	
Apartment	14.8%
Terraced	11.8%
Semi-detached	2.9%
Detached	68.4%
Other	2.1%
Presence of children	
Yes	14.16%
No	83.65%
DNS[a]	2.19%
Number of people in household	
1	22.2%
2	59.2%
3	8.6%
4 or more	9.2%
DNS[a]	0.8%
Gross monthly income	
less than 1000 €	4.5%
1000–2500 €	29.4%
2501–3500 €	23.9%
3501–4500 €	14.9%
4501–6000 €	9%
greater than 6000 €	5.7%
DNS[a]	12.6%

[a]DNS: Did Not State.

2.1.2. Independent variables

The independent variables within this research are the consumer data based on their socioeconomic and demographic characteristics, which were considered to influence the DLC DR enrollment. Based on the existing literature on analyzing socioeconomic and demographic features on consumer preferences from Yilmaz et al. (2020), Ruokamo et al. (2019), Broberg and Persson (2016) and Schöne et al. (2022), the study utilizes the following independent variables: gender, age, education level, dwelling (living place), presence of children, number of people in the household and gross monthly income and can be viewed in Table 1. The table shows descriptive information of survey respondents in percentages.

From Table 1, it can be observed that the composition of the sample reflects well the composition of the customers according to the PKS

Table 2
Overview of analysis performed.

Analysis	Purpose	Program
Cluster analysis	Identification and grouping of different consumer groups together	Python: scikitlearn package
Multinomial logistic regression	Analyzing the patterns of socioeconomic and demographic characteristics reflected on the cluster membership	Stata
Qualitative Comparative Analysis (QCA)	Investigate DLC DR motivators across multiple socioeconomic and demographic groups	MATLAB
ANOVA	Investigate DLC DR motivators across socioeconomic and demographic groups	Stata

customer database in terms of gender distribution and age skewed towards higher values and can therefore be utilized to provide valuable insights regarding DLC DR motivators.

2.2. Overview of analyses

This paper is split into four different analyses to study the motivators for DLC DR and the sociodemographic influences on the motivators. Initially a cluster analysis is performed in order to identify groups of consumers having similar motivators to enroll in DR. In this study, k-means clustering is applied on the quantified data from Finnish respondents to cluster different subgroups of consumers. In order to determine the effect of socioeconomic and demographic characteristics on the DLC DR acceptance, a multinomial logistic regression is performed which highlights the composition of the clustered consumers that are statistically significant, which are obtained from the previous step. In addition to this, to capture all other relationships which cannot be represented by statistical tests, a Qualitative Comparative Analysis (QCA) is performed. Finally, a series of one-way ANOVA test is performed to analyze the socioeconomic and demographic characteristics for different motivators to enroll in DLC DR. The overall overview of analyses performed in this paper can be observed in Table 2.

2.2.1. Cluster analysis

This analysis uses sets of dependent variables and clusters the consumers in different subgroups based on their similarity of responses. k-means clustering is one of the most common methodologies used in unsupervised machine learning approaches. It has been extensively used even within the energy field to extract groups (Alvarez et al., 2019; Mahmoudi-Kohan et al., 2009; Yilmaz et al., 2020; Schöne et al., 2022). Due to its extensive usage, ability to handle large datasets, low computational requirements and effectiveness, k-means clustering has been used to cluster the consumers based on their responses in this study. Within k-means clustering, in order to identify the correct number of clusters, elbow plot of inertia[1] vs. number of clusters are used and in order to verify the accuracy, the silhouette score is used. The silhouette score is defined as the ratio of the difference between the average shortest distance to another cluster and the average intra-cluster distance to the maximum value among them. This is also shown in Eq. (1).

$$silhouette\ score = \frac{b-a}{max(a,b)} \tag{1}$$

where: a = average intra-cluster distance; b = average shortest distance to another cluster

[1] Inertia measures the goodness of clustering of k-means. It is measured by the sum of square distances between each data point and its centroid. A good model should have a low number of clusters and a low inertia.

2.2.2. Multinomial logistic regression

Multinomial logistic regression is a type of classification method that applies logistic regression to multi class problems. This type of regression is used to predict the probabilities of different possible outcomes of a categorical dependent variable on a given set of independent variables. Yilmaz et al. (2020) clustered consumers based on their tariff and DR appliance preferences and then used multinomial logistic regression to identify cluster composition on consumer sociodemographic features based on a consumer survey from Switzerland. Similarly, Schöne et al. (2022) clustered consumers based on their tariff and DR appliance preferences and then used multinomial logistic regression to identify cluster composition based on consumer sociodemographic features based on a consumer survey from Mayotte. It can be seen from the previous literature that multinomial logistic regression is an effective method in terms of identifying relationships based on probabilities within the energy field and serves as an ideal methodology to help extract valuable results based on the clustered groups. In this study, for a given consumer i, the probability of i being assigned to a cluster k is provided by multinomial logistic regression as shown in Eq. (2):

$$P(y_i = k|x_i) = \begin{cases} \frac{1}{1+\sum_{j=2}^{3} exp(x_i\beta_j)} & \text{for } k = 1 \text{ reference category} \\ \frac{exp(x_i\beta_k)}{1+\sum_{j=2}^{3} exp(x_i\beta_j)} & \text{for } k = 2,3 \end{cases} \tag{2}$$

The Eq. (2) represents the probability of a consumer i being assigned to a cluster k through the variables x_i denoting the independent variables for consumer i and β_k denoting the coefficients of cluster k (Greene, 2003). In Eq. (2), i refers to the consumers (it varies from 1 to all the consumers) and j refers to the different cluster numbers which are: 1, 2, and 3.

2.2.3. Qualitative comparative analysis

This is another methodology which does not require statistical significance to study the effect of different variables within a subgroup. The basic idea of QCA is to investigate the amount of support for a given claim (relationship), formulated frequently in the form of IF-THEN rules, in the given dataset. For two statements A and B that can represent features, specific configurations of values or parameters of the entities being modeled etc. one assumes that "if A then B" is represented as $A \Rightarrow B$ and then the dataset is scanned for evidence in favor of this relationship (A and B is present in the given observation) and the evidence against it (A is present in the observation, but B is not). The relative amount of the observations supporting the existence of the relationship is then identified as the strength of support (consistency of the rule) and the relative share of observations that do not comply with (violate) the assumed relationship can be identified as the strength of evidence against the assumed relationship (see e.g. Schneider and Wagemann (2012) and Ragin (2014)). The statements A and B can be either crisp, or fuzzy (Stoklasa et al., 2017; Ragin, 2008). In its essence, the method is based on set subset hood and the evidence in favor of or against the assumed relationships is calculated based on cardinalities of the sets representing A, B, $A \cap B$ etc. In the crisp setting, the cardinalities represent numbers of elements, in the fuzzy setting they reflect the sums of membership degrees of the elements to the sets.

QCA and its fuzzy alternative fsQCA have found various applications in the fields where questionnaire data are a frequent source of information where less tangible or less measurable aspects of the elements of the modeled systems are being considered, also in the connection with discrete-scale survey data. Kumbure et al. (2020) recently applied QCA and fsQCA in strategic research context, it has been used in the context of investigation of linkages between ESG factors and mutual fund performance (Welling and Stoklasa, 2021), in analytics for the tertiary education sector (Stoklasa et al., 2020) and also in the analysis of cognitive structures of respondents (Mailagaha Kumbure et al., 2022).

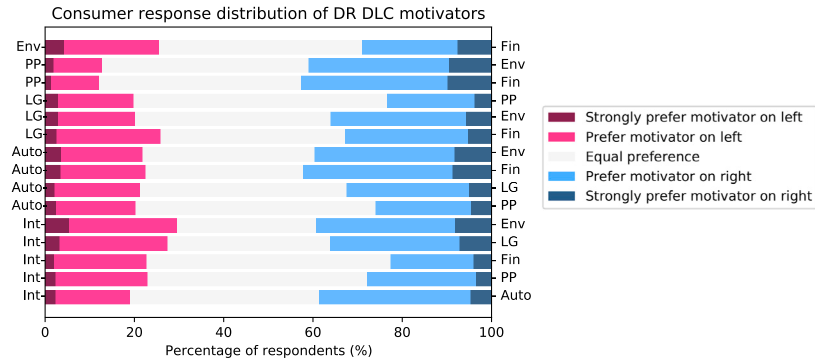


Fig. 2. DLC DR motivator distribution from consumer responses.

The method is thus well suited for the analysis of the survey data and various patterns present therein.

In QCA, there are two main metrics which are used to study the support of the given relationship ($A \Rightarrow B$) by the data: *consistency* and *coverage*. The consistency reflects how well the given claim is consistent with the observations in the given data. High consistency is obtained when there are many observations conforming to the rule (the $A \Rightarrow B$ relationship) and few that would violate it. Coverage, on the other hand, reflects the proportion of the observations with A and B present at the same time among all the observations with the outcome/feature B present. Consistency of $A \Rightarrow B$ can be considered to reflect how much A is a sufficient condition of B. Coverage of $A \Rightarrow B$, on the other hand, is a measure of how much A is a necessary condition for B. The equations for both can be viewed in Eqs. (3) and (4) provided by Stoklasa et al. (2018). These equations are more general than the original formulas by Ragin (2008) and allow for A and B to be fuzzy. For the case where A and B are considered boolean, formulas (3) and (4) coincide with the original consistency and coverage formulas in Ragin (2008).

$$Consistency(A \Rightarrow B) = \frac{1}{2}\left(1 + \frac{\sum_{i=1}^{n}(min(A(x_i)), B(x_i)) - min(A(x_i), B'(x_i)))}{\sum_{i=1}^{n} A(x_i)}\right) \tag{3}$$

$$Coverage(A \Rightarrow B) = \frac{1}{2}\left(1 + \frac{\sum_{i=1}^{n}(min(A(x_i)), B(x_i)) - min(B(x_i), A'(x_i)))}{\sum_{i=1}^{n} B(x_i)}\right) \tag{4}$$

In these formulas $A(x_i)$ represents the level to which x_i has the feature represented by the (fuzzy) set A, in other words $A(x_i)$ is the membership degree of x_i in A, or the truth value of the statement A for x_i. The interpretation of $B(x_i)$ is analogous. For boolean A and B, that is for the case when the statements A and B can be either true or false for any x_i, we have $A(x_i), B(x_i) \in \{0, 1\}$; otherwise we can assume that $A(x_i), B(x_i) \in [0, 1]$. For feasibility, we assume that $A(x_i) \neq 0$ at least for one x_i in the case of consistency and that $B(x_i) \neq 0$ at least for one x_i in the case of coverage. This means that there is at least one observation with the feature A and at least one observation with the outcome B.

2.2.4. ANOVA

ANOVA test is a type of statistical test which is used to find the effect of independent variables on the dependent variables based on statistical significance where the independent variables should be categorical. ANOVA test has been extensively used in statistics to identify if the responses are mere chances or is there any feature which could explain the specific response. ANOVA tests have been used by Yilmaz et al. (2020), Schöne et al. (2022), Chen et al. (2017) and Wang et al. (2020) to identify consumer sociodemographic effects on DR preferences. As ANOVA test is an established and proven methodology in statistics, it has been used in this study to analyze the effect of sociodemographic features on consumer DLC DR motivator preferences. ANOVA tests are usually measured by F and p values. The F value is used to check if the variance between the means of two groups is significantly different or not. It is calculated as the ratio of variance of the group means to the mean of the within group variances. The p value denotes the probability of getting a result as extreme as the one which was actually observed. For any test of ANOVA, if the p value is less than 5%, then it is statistically significant. Once the statistical significance is identified, a Tukey's HSD post-hoc test is carried out to identify the group which provided the significant result in the ANOVA test (Abdi and Williams, 2010). The significance level for Tukey's HSD post-hoc test is typically set at $\alpha = 5\%$ and the results identify the two subgroups which have a statistically significant result obtained between them.

3. Results

3.1. Cluster results of DLC DR

The cluster analysis uses 15 features which are based on answers of consumers to compare different motivators to enroll in DLC DR. The features are based on the DLC DR motivators from Section 2.1.1 and the features used for the cluster analysis were: (1) Int vs. Auto (2) Int vs. PP (3) Int vs. Fin (4) Int vs. LG (5) Int vs. Env (6) Auto vs. PP (7) Auto vs. LG (8) Auto vs. Fin (9) Auto vs. Env (10) LG vs. Fin (11) LG vs. Env (12) LG vs. PP (13) PP vs. Fin (14) PP vs. Env (15) Env vs. Fin. All the responses were collected via a 5 point Likert scale and as a result, there was no need of scaling. The respondents who did not know about their answer choice and have decided not to answer a specific question were treated as though their answer choice was equal preference. The distribution of consumers answer to DLC DR motivators can be observed in Fig. 2.

K-means clustering was used in this research, using Euclidean distance as the metric to compare similarity. The number of clusters was identified using the elbow-plot method, as observed from Fig. 3. From the figure, it can be observed that there is a gradual decrease in inertia after the number of clusters being set to 3 and hence it is considered as an elbow and the number of clusters was set to be 3. The cluster analysis on DLC DR motivators resulted in three different groups: Cluster 1 (adopters: 17.1%), Cluster 2 (followers: 31.4%) and Cluster 3 (neutral: 51.5%) with an average silhouette score of 0.28. The DLC DR motivators are clearly distinguishable, as can be viewed in the violin plots in Fig. 4. The distribution of answers for different clusters and the cluster centroids are represented in Fig. 5.

Consumers in cluster 1 prefer interest in technology and home automation over motivators to enroll in DLC DR and can therefore be classified as adopters similar to consumer classification proposed in Rogers et al. (2014). They have local generation as a higher motivator than financial and environmental factors. Consumers in cluster 1 slightly prefer environmental over financial motivators. Cluster 2 has a low interest in technology in new programs and prefer other motivators

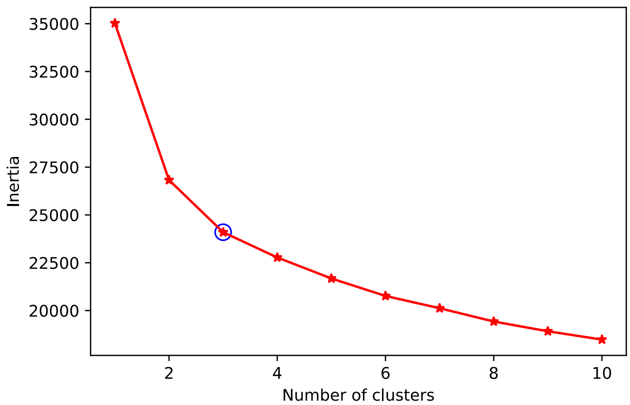


Fig. 3. Elbow plot for k-means clustering.

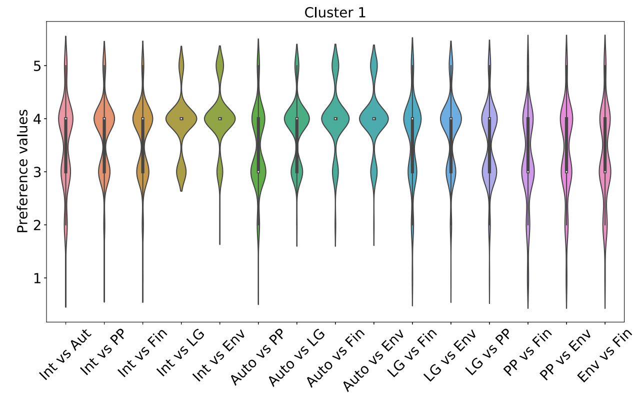
than home automation. They also have low preference towards local generation. Consumers within cluster 2 also have encouragement by contacts as a high motivator when compared with consumers from cluster 1, and can therefore be classified as followers. These consumers have an almost equal preference between financial and environmental factors, but slightly prefer environmental over financial factors. Consumers within cluster 3 has almost close to neutral preference to all the different motivators. They are the people who may or may not be interested to change their usage for DR or are the people who are neutral towards other DLC DR motivators and can therefore be classified as neutral.

3.2. Cluster prediction based on socioeconomic and demographic characters

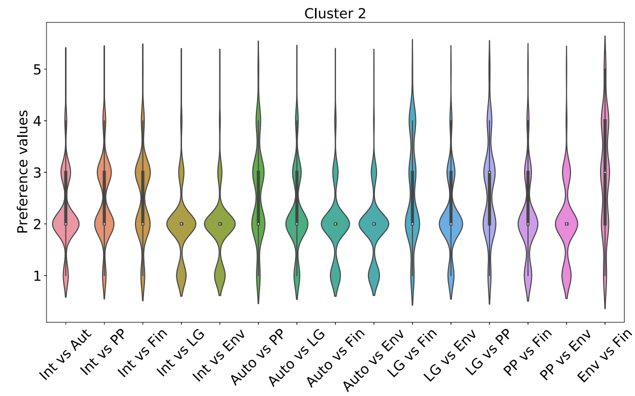
In order to examine the effects of socioeconomic and demographic characters on the clustering, a multinomial logistic regression is performed. The regression provides the probability of each consumer being placed in a specific cluster. The multinomial logistic regression is a preferred method to analyze the clusters, but it does pose difficulties to analyze the coefficients directly. In order to overcome this, marginal effects are used to analyze the clusters.

Marginal effects in regression explains how a dependent variable changes in relation to a change in one of the independent variables. In this paper, marginal effect is used to study how the clustering of a consumer changes with a change in the consumer's socioeconomic and demographic characteristics changes. The marginal effects of multinomial logistic regression are shown in Table 3.

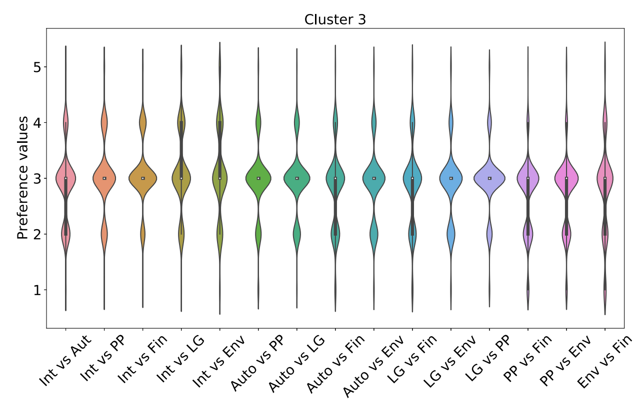
- *Cluster 1 (adopters 17.1%):* This cluster corresponds to households that are more likely to be dominated by males. In addition to this, higher forms of education (Upper secondary, bachelors' and masters' degrees, or more) are more likely to be underrepresented in this cluster.
- *Cluster 2 (followers 31.4%):* This cluster corresponds to households which are more likely to include women in the households. Higher forms of education are more likely to be represented in this cluster. The households which fall under this cluster are more likely to be semi-detached houses. Also, households earning less than 1000 € per month would more likely fall under this category.
- *Cluster 3 (neutral 51.5%):* This cluster corresponds to households which are more likely to be earning either 1000–4500 € per month or more than 6000 € per month.



(a) Cluster 1: adopters (17.1 %)



(b) Cluster 2: followers (31.4 %)



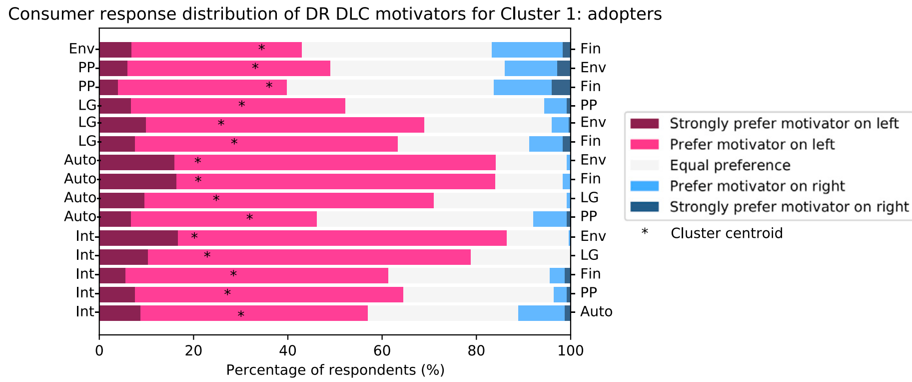
(c) Cluster 3: neutral (51.5 %)

Fig. 4. Cluster analysis of DLC DR motivators.

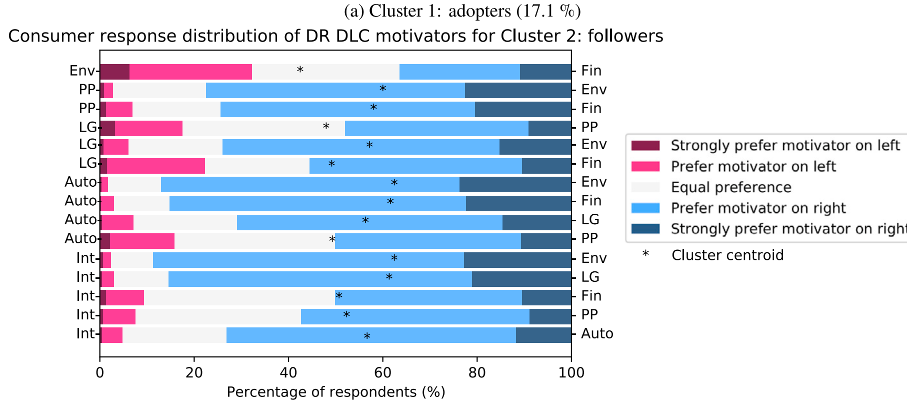
3.3. Qualitative analysis on socioeconomic and demographic characteristics on DLC DR motivators

As statistical tests require significant amounts of data, and the statistical significance was not being achieved for all the independent variables on the DLC DR motivators, a Qualitative Comparative Analysis (QCA) was undertaken to analyze the effect of independent variables that had not shown any statistical significance on the motivators.

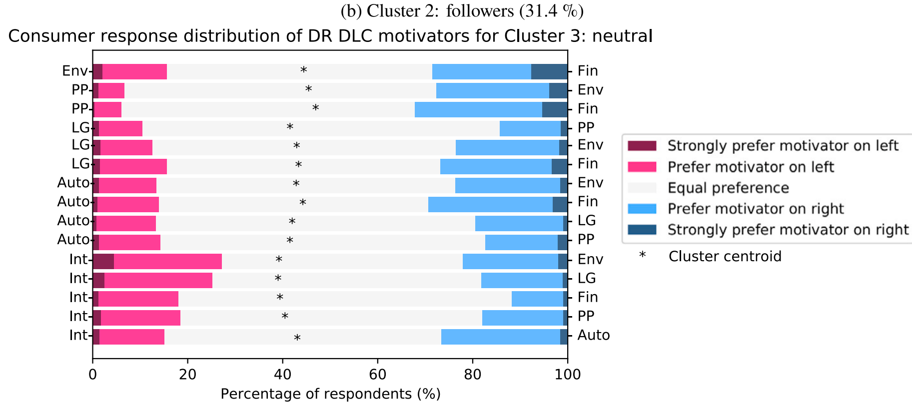
While using the Eqs. (3) and (4) in the dataset, the results can be observed in Table 4. This table contains all the parameters which are used in the multinomial logistic regression and the results which are shown depicts the frequency of occurrence of the specific parameters that are analyzed. To be more specific, the relationships of the type "IF the consumer's feature is F_i, then he/she belongs to cluster C_j", that is



(a) Cluster 1: adopters (17.1 %)



(b) Cluster 2: followers (31.4 %)



(c) Cluster 3: neutral (51.5 %)

Fig. 5. Distribution of consumer responses for different clusters and Cluster centroids of DLC DR.

$F_i \Rightarrow C_j$ and their support in the available data have been investigated. The features here are the values of the parameters considered in the logistic regression, the clusters are the three identified clusters, that is adopters, followers and neutrals. An example of an investigated relationship is "IF the consumer is male, THEN the consumer is an adopter (belongs to Cluster 1)"; consistency 0.187, coverage 0.777 according to Table 4. The consistency and coverage values vary from 0 to 1, with 1 denoting the maximum frequency of occurrence and 0 denoting no frequency of occurrence. The sum of the consistency values of a specific parameter across all clusters would be equal to one (or close to one as DNS answer choices are removed) and the sum of the coverage values of one cluster across one parameter would be equal to 1 (or close to one as DNS answer choices are removed). The socioeconomic and demographic characteristics of the consumers are studied separately within each cluster, and the results are as follows:

- *Gender:*
  - For Clusters 1 and 3, it is slightly more consistent with our data to claim that being a male implies the membership in the given cluster. On the other hand, in Cluster 2 the claim that being a woman implies membership in the cluster is more consistent with the data than being a male implying the membership therein. This is in line with the results from multinomial logistic regression in Section 3.2.
  - The male/female ratio is the highest for Cluster 1. This is again in line with Section 3.2. Males are over-represented in all three clusters, though.
- *Age:* does not offer clear cluster membership identification possibilities. Some observations that can be made:
  - all clusters are composed mainly of the respondents in the 60+ age category. This is partially caused by the fact that the 60+ age category is the largest one in our sample. Surprisingly, the share of 60+ respondents in Cluster 1 is

Table 3
Multinomial logistic regression of cluster membership on socioeconomic and demographic characteristics (marginal effects).

Variables	Cluster 1 (adopters 17.1%)	Cluster 2 (followers 31.4%)	Cluster 3 (neutral 51.5%)
Gender (1 = Female)	−0.0498(.0241)**	0.0605(0.0361)*	−0.0107(0.03336)
Age (30–39)	−0.0866(0.109)	−0.0705(0.148)	0.157(0.150)
Age (40–49)	−0.0523(0.106)	−0.0585(0.142)	0.111(0.143)
Age (50–59)	0.00529(0.106)	−0.0989(0.139)	0.0936(0.141)
Age (60+)	0.0436(0.105)	−0.147(0.132)	0.103(0.139)
Edu (Upper Secondary)	−0.145(0.0515)***	0.101(0.0438)**	0.0438(0.0557)
Edu (Bachelors)	−0.205(0.0535)***	0.189(0.0481)***	0.0162(0.0594)
Edu (Masters or higher)	−0.250(0.0543)***	0.268(0.0532)***	−0.0189(0.0634)
Edu (Other)	−0.231(0.0703)***	0.123(0.0828)	0.108(0.0936)
Liv (Terraced)	−0.0105(0.0463)	0.0275(0.0494)	−0.0170(0.0562)
Liv (Semi-detached)	−0.0604(0.0699)	0.147(0.0865)*	−0.0865(0.0908)
Liv (Detached)	−0.0478(0.0346)	0.0542(0.0379)	−0.00637(0.0429)
Liv (Other)	−0.0977(0.0735)	0.0917(0.117)	0.00603(0.121)
Children (1 = No)	−0.0166(0.0429)	0.0687(0.0466)	−0.0521(0.0523)
Number of people	−0.00260(0.018)	0.00470(0.0205)	−0.00210(0.0227)
Income (1000–2500 €)	−0.0513(0.0524)	−0.163(0.0668)**	0.214(0.0639)***
Income (2501–3500 €)	−0.0375(0.0543)	−0.157(0.0682)**	0.195(0.0655)***
Income (3501–4500 €)	−0.0394(0.0587)	−0.136(0.0722)*	0.175(0.0704)**
Income (4501–6000 €)	0.0116(0.0657)	−0.111(0.0777)	0.0990(0.0763)
Income (>6000 €)	−0.0935(0.0685)	−0.172(0.0838)**	0.266(0.0865)***

The marginal effects are computed at the sample mean. The standard error is provided within the parentheses. The DNS answer choices, and the gender: other, were removed in the analysis due to low percentage and to draw concrete results.
*Significance level at α = 10%.
**Significance level at α = 5%.
***Significance level at α = 1%.

the highest and visibly larger than in the other two clusters. Not only this, but also the claim that if you are 60+ then you belong to Cluster 1 is the most consistent with the data out of all age-based implications of membership in Cluster 1.
  – for Cluster 2 the age-based implication of membership in this cluster that is the most consistent with the data is (*age 19–29 ⇒ Cluster 2*). On the other hand, the consistency of this age group implying the membership in Cluster 3 is the lowest out of all age-based implications of membership in Cluster 3.

- *Education:* the results seem to confirm the results of the logistic regression well. Cluster 1 can be seen as more of a lower-education cluster, while Cluster 2 is the cluster with the highest share of higher university degrees:
  – Upper secondary education is the most represented type of education reported in Cluster 1.
  – for Cluster 3 all the levels of education implying the membership in this cluster have similar consistencies, still the education level that represents the largest share of Cluster 3 is Upper Secondary.
  – Cluster 2 has the highest share of people with Masters or higher education across all three clusters, which confirms the conclusions drawn from the logistic regression (see Section 3.2). It is the only cluster where Upper Secondary education does not represent as clearly the largest share across education levels. In this cluster, its share is similar to Bachelor and Masters or higher education.

- *Living:*
  – In all three clusters, the most represented type of housing is a detached house (it amounts for a majority of cases in all three clusters).
  – For Cluster 2 the claim "If you live in a semi-detached house, then you belong in the Cluster 2" is the most consistent with the data. For Cluster 3, living in an apartment implying the membership in this cluster seems to be consistent with the data.

- *Presence of children:* There does not seem to be any clear difference among the three clusters.
- *Number of people in the household:*
  – Two people in the household seem to be the most represented case across all three clusters.

- *Monthly income:*
  – Even though there are not many high-earners in the sample, the claim *income larger than 6000 EUR implies the membership to the given cluster* seems to be the least supported by the data for Cluster 1.
  – income intervals 1000–2500 EUR and 2501–3500 EUR seem to be the least consistent predictors of membership in Cluster 2 across all income-based predictors. At the same time, income less than 1000EUR seems to be a predictor of membership into this cluster that is the most consistent with the data among all income based predictors of Cluster 2 membership. This is again in line with Section 3.2.
  – low income (less than 1000 EUR) is the weakest predictor of membership in Cluster 3.

3.4. Sociodemographic characteristics on DLC DR motivators

In order to examine the DR motivators individually on the sociodemographic characteristics of the consumer, a series of one-way ANOVA tests is performed. The ANOVA test results can be observed in Table 5. The results from this table contains the various socioeconomic and demographic characteristics of consumers and their effect on the different DLC DR motivators. The table shows F and p values from the ANOVA test. If p value for a certain variable is less than 0.05 i.e., α = 5%, then there exists a statistically significant difference within the variable for that specific motivator. These values are marked with bold text in the table. For these variables and motivators, an additional test, Tukey's HSD post-hoc test, was performed to identify such statistically significant groups. The significance were checked for α = 5% and are indicated by the bold text in Table 5.

ANOVA test results show that there is a significant difference between age groups, gender, education level and presence of children

Table 4
QCA results between socioeconomic and demographic characteristics and clusters.

Parameters		Cluster 1 (adopters)		Cluster 2 (followers)		Cluster 3 (neutral)	
		Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Gender	Male	0.187	0.777	0.297	0.670	0.516	0.712
	Female	0.135	0.203	0.365	0.299	0.500	0.250
Age	19–29	0.143	0.008	0.500	0.015	0.357	0.007
	30–39	0.068	0.020	0.356	0.056	0.575	0.056
	40–49	0.113	0.084	0.349	0.141	0.538	0.132
	50–59	0.158	0.195	0.350	0.236	0.492	0.202
	60+	0.202	0.673	0.285	0.516	0.513	0.566
Education	Basic	0.371	0.171	0.155	0.039	0.474	0.073
	Upper Secondary	0.200	0.438	0.264	0.315	0.536	0.390
	Bachelors	0.141	0.227	0.345	0.302	0.514	0.274
	Masters or higher	0.100	0.131	0.427	0.306	0.473	0.206
	Other	0.116	0.032	0.261	0.039	0.623	0.057
Living	Apartment	0.190	0.163	0.278	0.130	0.532	0.152
	Terraced	0.179	0.124	0.324	0.121	0.497	0.114
	Semi-detached	0.119	0.020	0.452	0.041	0.429	0.024
	Detached	0.171	0.681	0.315	0.683	0.514	0.679
	Other	0.079	0.012	0.289	0.024	0.632	0.032
Children	Yes	0.125	0.104	0.337	0.152	0.538	0.148
	No	0.180	0.880	0.305	0.811	0.515	0.837
People in house	1	0.187	0.243	0.288	0.204	0.525	0.226
	2	0.177	0.614	0.313	0.590	0.510	0.587
	3	0.151	0.076	0.381	0.104	0.468	0.078
	4 or more	0.119	0.064	0.311	0.091	0.570	0.102
Income	<1000 €	0.227	0.060	0.424	0.061	0.348	0.030
	1000–2500 €	0.198	0.339	0.273	0.254	0.529	0.300
	2501–3500 €	0.175	0.243	0.310	0.234	0.514	0.237
	3501–4500 €	0.147	0.127	0.364	0.171	0.488	0.140
	4501–6000 €	0.191	0.100	0.405	0.115	0.405	0.070
	>6000 €	0.096	0.032	0.337	0.061	0.566	0.062

Table 5
ANOVA test of DLC DR motivators on socioeconomic and demographic characteristics.

(a)

Variables	Int vs. LG		Int vs. Auto		Int vs. PP		Int vs. Env		Int vs. Fin	
	F	p	F	p	F	p	F	p	F	p
Age	2.29	0.057	1.9	0.1074	0,77	0.543	1.99	0.0937	1.69	0.1493
Gender	**20.23**	**0.000**	**6.48**	**0.011**	**5.5**	**0.019**	**8.57**	**0.0035**	**6.48**	**0.011**
Education	**4.42**	**0.0015**	**3.81**	**0.044**	**2.59**	**0.035**	**4.96**	**0.0006**	**4.81**	**0.0007**
Liv	0.47	0.7563	0.46	0.7647	1.06	0.3757	0.59	0.6697	1.62	0.1657
Children	**4.21**	**0.0404**	0.9	0.3427	0.38	0.5388	0.01	0.9161	0.52	0.4692
PPL	0.59	0.6718	0.39	0.8158	1.03	0.3918	0.91	0.4546	0.41	0.8006
Income	0.8	0.5511	0.41	0.8399	0.38	0.8609	0.57	0.7268	0.3	0.9132

(b)

Variables	Auto vs. PP		Auto vs. LG		Auto vs. Fin		Auto vs. Env		LG vs. Fin	
	F	p	F	p	F	p	F	p	F	p
Age	1.58	0.177	**3.81**	**0.0044**	**5.01**	**0.0005**	2.02	0.0896	1.55	0.185
Gender	1.3	0.2545	2.76	0.0972	**4.29**	**0.0386**	**3.91**	**0.0483**	2.24	0.135
Education	0.91	0.4558	**4.44**	**0.0014**	**8.97**	**0.000**	**9.56**	**0.000**	1.86	0.114
Liv	0.67	0.6146	1.59	0.1753	0.9	0.4609	0.65	0.626	1.47	0.208
Children	0.47	0.4936	0.02	0.9018	0.63	0.4264	0.3	0.584	0.06	0.8
PPL	0.69	0.598	0.77	0.547	0.68	0.608	0.16	0.96	1.25	0.287
Income	0.8	0.5474	0.52	0.7602	0.38	0.8658	0.09	0.9943	0.48	0.791

(c)

Variables	LG vs. Env		LG vs. PP		PP vs. Fin		PP vs. Env		Env vs. Fin	
	F	p	F	p	F	p	F	p	F	p
Age	1.54	0.188	1.55	0.185	2.08	0.081	1.86	0.1158	1.32	0.26
Gender	2.94	0.086	2.24	0.135	0.29	0.592	0.38	0.536	**10.92**	**0.001**
Education	**6.61**	**0.000**	1.86	0.114	**6.25**	**0.0001**	**11.26**	**0.000**	**3.64**	**0.049**
Liv	0.76	0.551	1.47	0.2091	1.27	0.2805	0.83	0.507	1.18	0.3172
Children	0.49	0.483	0.06	0.8007	0.03	0.864	0.93	0.333	1.14	0.2866
PPL	0.8	0.525	1.25	0.2871	1.44	0.217	1.54	0.188	1.73	0.1405
Income	1.75	0.12	0.48	0.7914	1.05	0.384	0.66	0.654	0.41	0.8439

for DLC DR motivators. Hence, for these variables, Tukey's HSD post-hoc tests are performed. The results from Tukey's post-hoc test for age groups are shown in Table 6.

From Table 6, the age groups with mean and standard deviation are shown for the DLC DR motivators: Auto vs. LG (7) and Auto vs. Fin (8). The significant results observed for this variable are:

Table 6
Effect of age group on DLC DR motivators: Tukey's post-hoc test.

Age group	Auto vs. LG		Auto vs. Fin	
	Mean	Std Dev	Mean	Std Dev
19–29	2.46	1.20	2.54	1.27
30–39	2.71	0.80	2.51	0.97
40–49	2.70	0.88	2.57	1.04
50–59	2.83	0.86	2.71	1.01
60+	2.92	0.88	2.85	0.97
Significant results	**60+ vs. 40–49**		**60+ vs. 40–49, 30–39**	

Table 7
Effect of gender on DLC DR motivators.

(a) Tukey's post-hoc test - 1

Gender	Int vs. LG		Int vs. Auto		Int vs. PP		Int vs. Env	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Male	2.85	0.88	2.99	0.83	3.01	0.79	2.94	0.95
Female	2.57	0.83	2.83	0.84	2.86	0.85	2.72	1.03

(b) Tukey's post-hoc test - 2

Gender	Int vs. Fin		Auto vs. Fin		Auto vs. Env		Env vs. Fin	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Male	2.94	1.04	2.80	0.99	2.82	0.96	2.89	0.95
Female	2.74	1.10	2.62	0.99	2.65	1.02	3.09	0.93

- Age group 60+ has a higher preference towards smart home automation over local generation than age group 40–49.
- Age group 60+ has a higher preference towards smart home automation over financial benefits than age groups 40–49 and 30–39.

Table 7 shows the post-hoc test for the gender across different DLC DR motivators. The significant result for this variable are:

- Men have higher preference towards interest in technology over local generation, smart home automation, contacts (peer pressure), environmental gains and financial benefits.
- Men have higher preference towards smart home automation over financial gains and environmental benefits when compared to women.
- Women have a higher preference towards environmental benefits over financial gains when compared to men.

Table 8 shows the results for the effect of different education on different DLC DR motives. This variable has the most significant results in multiple DLC DR motivators than when compared to other variables. The significant results from this table are as follows:

- The education group basic have a lower preference towards interest to participate than local generation, smart home automation, influence from contacts, environmental benefits and financial benefits when compared to education group masters or higher.
- The education group basic have a higher preference towards local generation and environmental benefits than interest to participate when compared to education group bachelors.
- The education group upper secondary have a lower preference towards interest to participate than smart home automation, environmental and financial benefits.
- The education group basic have a lower preference towards smart home automation over local generation, financial and environmental benefits when compared to education group bachelors and masters or higher.
- The education group upper secondary have a lower preference towards smart home automation over financial and environmental benefits when compared to educational group bachelors and masters or higher.
- The educational group basic and upper secondary have a lower preference towards influence of contacts over financial and environmental benefits when compared to education group masters or higher.
- The educational group masters or higher have a lower preference to local generation than environmental benefits when compared to educational groups basic and upper secondary.
- The educational groups masters or higher have a higher preference towards environmental benefits than financial benefits when compared to educational groups bachelors and other.

The presence of children in the household had only one statistically significant result in motivator Int vs. LG (1) as observed from Table 9. People having children in their residence prefer interest in technology over local generation when compared to people not having children in their residence.

4. Discussion

The four findings and several key suggestions which would be of interest to retailers, utility companies, aggregators, distribution system operators and policymakers are highlighted below:

First, the heterogeneity of the DLC DR motivators among consumers is highlighted. The cluster analysis identified three distinct consumer groups: adopters (more interested in technology and prefer smart home automation), followers (prefer local generation and influence of contacts) and neutral (do not have a specific preference). The results from the cluster analysis provides a holistic approach to analyze the different motivators for DLC DR and adds value to the importance of all motivators for DR enrollment as stated by Parrish et al. (2020). In addition to this, the cluster analysis showed that for adopters, a DR plan with home automation and new technologies would be greatly influencing their willingness to enroll in DR while the followers would need more time and feedback before enrolling in it. The adopters would mainly need DLC DR programs to focus on environmental reductions possible through their participation in DLC DR, whereas followers would need both environmental and financial reductions that can be achieved through their participation in DLC DR. The neutral group of consumers does not have one specific motivator to make them enroll in DLC DR, and would rather need to be targeted individually to analyze their preference and provide plans that are suitable for them.

Second, the socioeconomic and demographic characteristics that are prevalent in the clusters are identified through statistical test: multinomial logistic regression. Gender, education, living conditions and income were some statistically significant variables within the cluster. The higher educated group were more represented in cluster 2: followers. These higher educated people would have motivators such as local generation and influence of contacts as important motivators. This is in line with the fact that the higher educated people would be more likely to have higher knowledge about climate change and the importance of local sustainability. In terms of gender, the cluster two has a higher share of females than other clusters and are motivated to enroll in DLC DR. This is in line with the results from Yilmaz et al. (2020), that females are more likely to enroll their household appliances in DLC DR.

Third, this study proposes QCA as an additional methodology that can provide further insights to the clusters and socioeconomic and demographic characteristics of consumers. The results from QCA were in agreement with the results from the multinomial logistic regression and can be considered as a valid approach to provide further insights to the clusters. These additional insights can be used to further describe each cluster, which can help group consumers to a specific group.

Lastly, this study analyzes the effect of sociodemographics directly on the DLC DR motivators through a statistical test: ANOVA. A direct comparison between different subgroups (age, gender, income level, education level, presence of children and number of people) on the

Table 8
Effect of education groups on DLC DR motivators.

(a) Tukey's post-hoc test - 1

Education group	Int vs. LG		Int vs. Auto		Int vs. PP		Int vs. Env	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Basic (1)	3.13	0.91	3.12	0.80	3.16	0.74	3.17	0.92
Upper Secondary (2)	2.81	0.84	2.99	0.80	3.00	0.76	2.95	0.92
Bachelors (3)	2.68	0.86	2.90	0.86	2.94	0.86	2.85	0.96
Masters or higher (4)	2.68	0.90	2.82	0.83	2.90	0.86	2.72	1.07
Other (5)	2.90	0.95	3.21	1.07	2.89	0.76	2.79	0.99
Significant results	**1 vs. 2, 3, 4**		**1, 2, 5 vs. 4**		**1 vs. 4**		**1 vs. 3, 4, & 2 vs. 4**	

(b) Tukey's post-hoc test - 2

Education group	Int vs. Fin		Auto vs. LG		Auto vs. Fin		Auto vs. Env	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Basic (1)	3.14	0.95	3.19	0.86	3.19	0.97	3.28	0.91
Upper Secondary (2)	3.01	1.00	2.90	0.81	2.89	0.96	2.85	0.94
Bachelors (3)	2.82	1.10	2.78	0.89	2.63	1.02	2.73	0.96
Masters or higher (4)	2.63	1.09	2.72	0.93	2.50	0.93	2.53	1.02
Other (5)	2.87	1.14	3.00	1.04	2.79	1.12	2.71	1.01
Significant results	**1, 2 vs. 4**		**1 vs. 2, 3, 4**		**1, 2 vs. 3, 4**		**1 vs. 2, 3, 4 & 2 vs. 4**	

(c) Tukey's post-hoc test - 3

Education group	LG vs. Env		PP vs. Fin		PP vs. Env		Env vs. Fin	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Basic	3.12	0.86	2.96	0.85	2.97	0.85	2.96	0.97
Upper Secondary	2.89	0.87	2.71	0.80	2.74	0.81	2.91	0.88
Bachelors	2.76	0.91	2.55	0.86	2.64	0.90	2.86	0.94
Masters or higher	2.61	0.92	2.39	0.90	2.32	0.90	3.12	1.01
Other	2.95	0.90	2.63	0.91	2.66	0.88	2.61	1.10
Significant results	**1 vs. 3, 4 & 2 vs. 4**		**1 vs. 3, 4 & 2 vs. 4**		**1, 2, 3 vs. 4**		**4 vs. 3, 5**	

Table 9
Effect of presence of children on DLC DR motivators: Tukey's post-hoc test.

Presence of children	Int vs. LG	
	Mean	Std Dev
Yes	2.79	0.89
No	2.70	0.87

different motivators yields the striking motivators which are statistically significant. People from age group 60+ preferred to have home automation over other motivators. This is also the case for men, they prefer home automation over financial and environmental gains than women. Women, on the other hand, preferred environmental gains over financial when compared with men. The people having basic education prefer other motivators than smart home automation when compared with people with different education. The people with basic and upper secondary education prefer local generation over environmental benefits and seem to be susceptible to the influence from their contacts in their choices People having a higher education level prefer environmental gains to financial gains, which is in line with the notion that greater knowledge results in a higher chance to be aware about current issues and would prefer the environmental choice, even though it may not be the most economical.

4.1. Limitations

In addition to these, this study does pose some limitations which are essential to understand the obtained results. Through this analysis, it is possible to see the different motivators for DLC DR preferences of residential consumers, but the actual preference would vary considering the level of trust consumers have on the DR service provider and the transparency of information shared within consumers as outlined by Yilmaz et al. (2021). Therefore, it is essential for the DR service providers to provide the necessary information for consumers to have a high degree of trust. In terms of the survey responses collected: 57% of the survey respondents corresponds to the age group: 60+. This is higher than the Finnish average of around 25% (Official Statistics of Finland, 2022). A possible reasoning behind this would be that old people (retirees) would have more free time to answer this survey than people who are working. 72% of the respondents were males, which is higher than the Finnish average of 50.5% (Clausnitzer, 2022). A possible reasoning behind this would be that the survey was sent to the people who are paying the electricity bills in the households. Though this is not similar to the national average, men are often overrepresented in surveys related to energy (Abrahamse et al., 2007; Steinhorst et al., 2015). Though the age and gender distribution are not representative of the Finnish population, the gender distribution and the high prevalence of high age among the respondents are in line with the characteristics of the consumer database of PKS and results from this study can therefore be valuable for the interested entities. Furthermore, the results from this survey quantifies the different DLC DR motivators in general, but an in-depth study on DLC DR acceptance needs to be performed on individual appliances to quantify the overall DLC DR acceptance of a residential household. Therefore, an in-depth study on the DLC DR acceptance on devices would provide detailed insights on these clusters and different consumer subgroups is recommended for further analysis.

5. Conclusion and policy implication

This study helps to bridge the gap in literature through the identification and quantification of DLC DR motivators for residential consumers. Based on the quantified DLC DR motivators, the study classifies consumers into three types: adopters, followers and neutral. The study also proposes the specific motivators to be targeted for different consumer subgroups, which is essential to increase the residential DLC DR adoption. In addition to this, the study also analyzes the influence of individual's socioeconomic and demographic characteristics on the DLC DR motivators and the clustered consumers. The results obtained through this paper emphasizes the underlying dynamics of consumers enrolling in DLC DR through different motivators and consumer characteristics. The results can be used as a basis for Finnish consumers, and policymakers can utilize the results to gain more insights to consumer decision-making to enroll in DR.

In this study, k-means clustering machine learning technique as well as statistical tests: multinomial logistic regression; ANOVA tests; and QCA, were performed to analyze the different motivators for consumers towards DLC DR. The socioeconomic and demographic characteristics of consumers were focused on specifically in this study.

The cluster analysis yielded three distinctive clusters: adopters, followers and neutral. A multinomial logistic regression was then performed on the cluster results to link the consumer's socioeconomic and demographic characteristics to the clustering results. The results from the regression suggests that the gender, education level, living conditions and income level are strong determinants of the DLC DR motivators.

The study also proposed QCA to further investigate the clustering results and identify striking characteristics among clusters which may not be statistically significant. The results from the QCA were in line with the multinomial logistic regression and provided more insights on age group, presence of children and number of people in the household with respect to the clusters.

5.1. Policy implications

From the point of view of designing demand response campaigns, the study shows that consumers can effectively be categorized into three different clusters and highlights the distinctive sociodemographic features within each cluster, that can help with proper timing and sequencing of the campaigns. Ideally, the DR service providers should target the adopters group who have a higher interest to participate and have a high focus on home automation. According to our results, these are the consumers who are typically male, have lower education and high interest to participate. Following adopters, the service provider should target the followers who are focused on environmental gains and local generation. These clusters correspond to the consumers having high education, are mainly female, mostly living in semi-detached houses and would essentially need some positive feedback from the adopters to enroll themselves. Once demand response has penetrated the residential sector with adopters and followers enrolling, then the service providers could target individual consumers of the neutral cluster and tailor the DR program accordingly to maximize DR adoption.

From a policymakers point of view, the results from the study shows that cluster specific target groups are necessary to urge consumers to enroll in DR. From the results, it could be seen that there is not one motivator which would make all consumers enroll in DR, which is in line with the results from previous studies (see Yilmaz et al. (2021), Sloot et al. (2022) and Lehmann et al. (2021)). Though residential DR is a potential solution to reduce network stress, it would take a significant amount of time to employ with targeting consumer subgroups individually. With different sociodemographic factors present in each cluster, the DR plans should be tailored accordingly to engage as many consumers as possible and alter it as the focus switches from one cluster to another. Moreover, the policymakers should acknowledge the timeframe of executing residential DR is significantly long and should actively increase awareness and engage the consumers regarding the importance of DR and its role in the future to increase participation. Though the impact of sociodemographic features of consumers on the DR motivators is significant, the results interpreted from this study can be improved by studying the psychographics of consumers (Sloot et al., 2022). Currently, such an analysis is resource intensive, though the constant advancement in technology and digitalization can pave the way for it in future studies.

In conclusion, this study provides advice to the distribution system operators, electricity retailers, aggregators and policy-makers on different DLC DR motivators for consumers which can aid in future planning of the electricity system with the increasing renewables and flexibility that can be offered by consumers. The consumers have different views and motivators, which can be clearly seen in the different clusters. The study also suggests that there is no one fix which can increase the residential DR participation and different groups needs to be targeted individually. The results from this study provides some initial insights to DLC DR motivators, while further research is much needed to analyze the DLC DR participation of consumers.

CRediT authorship contribution statement

Araavind Sridhar: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Samuli Honkapuro:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing – review & editing. **Fredy Ruiz:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Jan Stoklasa:** Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Salla Annala:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Annika Wolff:** Conceptualization, Methodology, Supervision, Writing – review & editing, Proof reading. **Antti Rautiainen:** Writing – review & editing.

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.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.enpol.2023.113420.

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