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Analysis of demand-side response preferences regarding electricity tariffs and direct load control: Key findings from a Swiss survey

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A B S T R A C T

Demand-side response (DSR), via price signals (e.g. tariffs) or via direct load control (DLC), is recognised as vital to the network operations with high levels of renewables. This study aims to measure the interest in electricity tariffs and acceptance of DLC, conducting a survey of 622 households and to identify the socio-demographic and dwelling characteristics associated with the decisions. Firstly, cluster analysis identified four DSR preferences: conservative (19%), reserved (20%), agreeable (34%) and flexible (27%). A multinomial logistic regression test showed that dwelling type, tenure, employment, and education influence DSR preferences. Secondly, ANOVA test showed that the interest in tariffs was significantly different across socio-demographics such as age, gender, and education level. Thirdly, we found that the acceptance of DLC is higher for devices (e.g. heat pumps, electric boilers, PV systems, home batteries) than appliances (e.g. tumble dryers, washing machines, dishwashers, EVs). Chi-square tests showed that employment status, presence of children, gender, age are significant factors for the acceptance of appliance DLC whereas it was dwelling type and education level for devices. These findings highlight the heterogeneity of DSR preferences, thereby pointing to challenges such as perceived control, and socio-technical dynamics are key to achieve high participation in such programmes.

1. Introduction

1.1. Background

As part of the global energy transition, there is an increase in self-generation (175 GW capacity increase in roof-top photovoltaics (PV) in 2018) [1], storage (increase of 1.1 GW deployment of in-home batteries in 2018) [2], number of electric vehicles (increase of 63% from 2018) [3], and electrification of heating (3.7 million heat pumps sold worldwide in 2019) [4]. These changes are introducing many unknowns and new challenges to the operation and planning of electricity systems in terms of the hardware side and the control architecture [5,6]. The increasing variability in energy supply and bi-directional flow of energy introduce significant challenges to the management of the distribution network. Several case studies have shown that with a given penetration level, the presence of PV may arise challenges in distribution systems such as load congestion [7,8], and network losses [9,10]. Considering the intermittent nature of the renewable technologies, integration of demand flexibility is recognised as vital to the operation of the distribution networks to tackle the above-mentioned challenges [11–14]. Major ways to provide this flexibility include energy storage and demand-side response (DSR) [15]. Of these, demand side response is recognised as the less capital-intensive approach to help system balancing [16].

Element Energy (2012) describes demand-side response as 'change in electricity consumption patterns in response to a signal' [17]. Two main types of signals are price signals via time-differentiated electricity tariffs and controlling signals via direct load control (hereafter DLC) contracts. For the first type of signal, consumers are incentivised to change their consumption patterns through price signals delivered via time-varying electricity tariffs in

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Nomenclature

Acronyms

ANOVA	Analysis of variance
CHF	Swiss francs
d.f.	degrees of freedom
DLC	Direct load control
DSO	Distribution System Operator
DSR	Demand side response
EV	Electric vehicle
GW	Gigawatts
kW	kilo watts
M	mean
MFH	Multi-family house
OLS	Ordinary Least Square
PV	Photovoltaics
SD	Standard deviation
SFH	Single family house
ToU	Time of Use
HSD	Honestly significant difference
U·S.	United States
χ^2	Chi-square

Subscripts

i	for i-th household
j	for the j-th cluster
k	for the k-th cluster
t	for the t-th tariff

Parameters and variables

α	Significance level
a	average intra-cluster distance
b	average shortest distance to another cluster
f	feature
InT_T	Interest in the corresponding tariff
x_i	row vector of independent variables
β_k	vector of coefficient for cluster k
β	coefficients of the OLS regression

which the price of electricity varies depending on factors such as the wholesale price of electricity and electricity network constraints. The electricity tariff structure includes a volumetric component (price/kWh). Examples are time of use tariffs (i.e. price of a kWh varies between periods with the highest price being for the on-peak period); real time pricing (i.e. reflecting wholesale spot prices and grid usage ratios, hence change hourly and daily); and power tariffs, also referred as capacity tariffs in literature, (*i.e.* charging according to the peak demand in price/kW during a period) which reflects the network costs associated with the peak power demand [18–21]. For the second type of signal, unlike programmes that rely on price signals, DLC programmes involve third party provider (e.g. utility companies) requesting operational control via signals over customers' specific household appliances (such as electric hot water systems, heat pumps or air conditioners especially in the U.S.) for a limited time period [22–24].

Electricity tariffs with price signals do not require a firm commitment by the consumer to adjust consumption at specific times, but leave it to the consumer's discretion, how and when to react to the price signals given. An extensive body of work demonstrates that consumers adjust consumption at specific times to different tariffs [25–28]. Regarding the consumer demand for electricity tariffs, a detailed international review and discussion of the acceptance of time of use tariffs is provided by Nicolson et al. [29]. They show that the uptake could be as low as 1%, enrolment could reach up to 43% with the marketing effort. On the other hand, the uptake of dynamic tariffs ranged between 5% and 28% across nine U.S. trials [30]; Fell et al. [31] found that willingness to participate in dynamic pricing is the lowest among all tariffs in the UK. Power tariffs are also reported less popular than time of use tariffs [29]. Many researchers have argued that DLC programmes could offer a more reliable source of demand flexibility by providing greater certainty over the amount, timing, and location of demand flexibility than solely depending on the households with price signals [32–36]. However, whilst DLC programmes have been available for decades worldwide, early trials suggest that participation rates have not been satisfactory [37]. Stenner et al. [37] presented that the customer enrolments in DLC programmes in the U.S. ranged from 0.11% to just 14.54%.

Research that has examined participant responses to the prospect of various DLC applications offers a mixed and complex picture of user acceptance. Murtagh et al. [38], reported that 'most participants interviewed were unlikely to agree to DLC, even if financial compensation is offered [39]. While other researchers show that users would be more open to DLC with an overriding option which allow the users bypass the automatic setting [40,41]. Factors that affect the customer engagement in DLC programmes are identified as i) trust and transparency between the aggregator and the customer [42,43], communication with the customers such as framing the need for automation [38,44–46], overriding opportunities [23,39,47–50], adequate compensation [31,38,51], concerns around privacy [45,52–55] and perceived lack of control [23,37,41]. These researchers investigated the public acceptability in general terms; or only focused on one device (e.g. air conditioners) [23]. There is still limited evidence whether the acceptance changes across different types of electrical devices and appliances.

Several researchers also discussed combining these signals to increase the reliability of implicit demand side flexibility provided by the households [56]. For example, Parrish et al. [57], reports that trials with automation technologies alongside pricing had a 15% higher rate of response than schemes with pricing alone. Furthermore, Stromback et al. [58] shows that automation increases the level of peak clipping for all types of variable tariff except for real time pricing. Nicolson et al. [59] found that dynamic time of use (ToU) is 'most effective when combined with additional equipment that reduces peak demand by automatically turning off non-essential electrical devices'. However, evidence on the acceptance of DLC devices linked with interest and acceptance of electricity tariffs is limited.

1.2. Aims and objectives

To address the abovementioned gaps, the objectives of this study are:

- To identify distinct DSR preferences (i.e. interest in tariffs and acceptance of DLC of individual electrical devices) via cluster analysis
- To discover how socio-demographics and dwelling characteristics influence these DSR preferences
- To research how socio-demographics and dwelling characteristics relate to i) interest in tariffs and ii) households' acceptance

of DLC and vary across different types of electrical devices and appliances
- To explore the relationship between interest in tariffs and acceptance of DLC

This study takes an important step towards the estimation of interest in electricity tariffs and DLC programmes across different types of devices and appliances in relation to socio-demographics and dwelling characteristics. We apply the k-mean clustering machine learning technique to analyse DSR preferences in Swiss households. We use multinomial logit regression analysis to determine how socio-demographic characteristics influence these DSR preferences. We apply statistical analyses (ANOVA and χ^2 tests of independence) to test the differences in interest in electricity tariffs and DLC acceptance across devices and socio-demographics. The findings contribute to designing better tariffs and DLC programmes across different customer subgroups.

2. Method

2.1. Survey measurement

The survey was originally developed in French and then translated into German. The customer database of a public utility in Switzerland in the canton of Fribourg and Neuchâtel, Groupe E, which is performing the role of distribution system operator (DSO) was used to distribute the survey to its customers. The customer database consists of the e-mail addresses of bill payers therefore the respondents are accepted as the responsible person of the household. The response rate of the survey was 12.4%. 622 people out of 5000 fully completed the survey with no missing information. The survey was anonymous, and no personal identifiers were collected.

2.1.1. Dependent variables

The first dependent variable of the analysis was the interest in pricing tariffs. Each respondent was presented with six different tariffs and asked to indicate their level of interest in each tariff. The second dependent variable was the willingness to accept DLC for the four electrical devices including heat pumps, electric boilers, in-home batteries, roof-top photovoltaics (PV) systems and four electrical appliances namely tumble dryers, washing machines, dishwashers, and electric vehicles (EV).[1]

2.1.1.1. Interest in tariffs. The levels of interest in each tariff were estimated from participants' responses on a 4-point Likert-type scale: 1) Not interested at all, 2) Slightly interested, 3) Interested and 4) Very interested. The tariffs mentioned in the survey were explained with a sentence and an example (Table 1).

2.1.1.2. Acceptance of direct load control (DLC). To measure the willingness to accept DLC programmes, participants were asked whether they would allow the utility company to pilot their electrical devices and appliances: "In order to keep network costs low and manage situations of high network demand, it may be useful for Group E to be able to control certain devices remotely (limitation, curtailment or start-up). which devices would you accept that Group E could control remotely? Please select one response per line." The participants were instructed to choose between "yes," "maybe," and "no" for each device/appliance.

2.1.2. Independent variables

This section describes the variables that are used as the grouping variables/predictors in the χ^2 tests of independence, ANOVA, linear regression, and clustering analysis. Table 2 shows the socio-demographic characteristics, dwelling characteristics, and appliance/device ownership that were considered as influencers of the interest in electricity tariffs and acceptance of DLC. The table also shows the descriptive information with percentages for the variables. Regarding the appliances, PV is explained as the 'installation of electricity production (Photovoltaics system)'.[2] In-home battery is explained as 'electricity storage battery' to the survey respondents.

2.2. Overview of analyses

Table 3 presents an overview of the analyses performed in this study and the samples and data used in each analysis. A cluster analysis was conducted first in order to identify the groups of households that display similar DSR preferences (interest in tariffs and acceptance of DLC). A multinomial logit regression is then used to explain the composition of clusters obtained in the previous step. Later, ANOVA and χ^2 tests of independence were performed to investigate the socio-demographics and dwelling characteristics for individual DSR preferences separately and individually. ANOVA test is then performed to link the acceptance of DLC of electrical devices and appliances to interest in electricity tariffs. Finally, OLS is conducted to link the overall DLC acceptance with the interest in electricity tariffs.

3. Results

3.1. Overview of DSR preferences

3.1.1. Interest in tariffs

Fig. 1 shows a) the percentages of participants who chose different interest levels and b) the means and standard deviations calculated based on the 4- Likert scale. Highest average interest was in the bonus tariff ($M = 2.77$, $SD = 0.88$), followed by the progressive tariff ($M = 2.59$, $SD = 0.87$). The average interest for other tariffs were, in decreasing order, dynamic tariff ($M = 2.12$, $SD = 0.97$), malus tariff ($M = 2.06$, $SD = 0.90$) and fixed tariff ($M = 2.02$, $SD = 0.91$). Lowest average interest was in the power tariff ($M = 1.79$, $SD = 0.86$).

3.1.2. Acceptance of direct load control

Fig. 2 shows the percentages of participants who chose "yes," "maybe," or "no" to the DLC over the electrical devices/appliances regardless their device/appliance ownership. Survey results show that people's willingness to accept DLC depended on the particular appliance/device type. Specifically, the acceptance rates were higher than the rejection rates on devices including electric boilers (58% yes, 23% maybe, 18% no), heat pumps (57% yes, 28% maybe, 15% no), batteries (47% yes, 28% maybe, 25% no), PV systems (45% yes, 30% maybe, 25% no). On the other hand, the rejection rates were higher than the acceptance rates on appliances including washing machine (25% yes, 22% maybe, 53% no) dishwasher (23% yes, 27% maybe, 51% no), tumble dryer (30% yes, 24% maybe, 46% no) and electric vehicle (27% yes, 30% maybe, 43% no).

[1] In this study, device is defined as piece of equipment made for a particular purpose (e.g. heating, cooling), whereas appliance is defined a non-manual apparatus or device used to perform functions (e.g. washing, driving).

[3] Gender was only recorded for the person who filled the questionnaire. This person is also the responsible person of the household for paying the electricity bill.

[2] Roof-top PVs are the most common PV installations in Switzerland [67]. All building integrated PVs are installed with an inventer in accordance with the norm established by the government [68].

Table 1
Explanations of electricity tariffs mentioned in the survey.

Fixed tariff:
Each client chooses his/her category of the tariff and pays a fixed price. For example, 'Medium consumer fixed price' which corresponds to an average consumption of 4500 kWh pays 1000 CHF per year. In case of higher consumption, it jumps to the 'Large consumer fixed price' which is 1500 CHF per year.
Power tariff:
This bill depends on the highest power you demand within the year (i.e. highest consumption of 15 min). For example, in February, while your heat pump is running, and you use three hobs, an oven and a washing machine at the same time; its power is then 13 kW and your annual bill will be 1300 CHF. If you use two hobs, the power demand would be 11 kW and your bill will be 1100 CHF.
Progressive tariff:
The first kWh consumed are less expensive than those which exceed a certain threshold. For example, you pay 20 ct/kWh for the first 1000 kWh and 25 ct/kWh for kWh above this threshold. The annual bill for an average household (4500 kWh) then would be 1075 CHF.
Bonus tariff:
The price per kWh is fixed at 23 ct/kWh throughout the year. However, if you manage to consume when there is a lot of electricity supply available and little consumption (in the afternoon, in summer), Group E pays you a bonus of 5 ct/kWh. For example, an average household consuming 4500 kWh per year of which 500 kWh in summer between 2 p.m. and 4 p.m., will pay 1035 CHF.- annually and will receive a bonus of 25 CHF.
Malus tariff:
The price per kWh is fixed at 22 ct/kWh throughout the year. However, if you consume when there is little electricity supply available and a lot of consumption (e.g. in the evening, in winter), Groupe E charges you a penalty of 10 ct/kWh. For example, an average household consuming 4500 kWh per year, of which 500 kWh in winter between 5 p.m. and 8 p.m., will pay 990 CHF annually plus a penalty of 50 CHF.
Dynamic tariff:
The price of your consumption is dynamic and thus varies from hour to hour and from day to day. For example, the price is different between 8 h and 9 h, between 10 h and 11 h, etc. The price of an annual household bill is therefore difficult to predict.

3.2. Clusters of DSR preferences

The cluster analysis is based on the 14 features that we defined for DSR preferences. These are namely interest in (1)fixed tariff, (2) power tariff, (3)progressive tariff, (4)bonus tariff, (5)malus tariff, (6) dynamic tariff, and acceptance of DLC of (7)heat pumps, (8)electric boilers, (9)in-home battery, (10)PV system, (11)tumble dryer, (12) washing machine, (13)dishwasher and (14)EV. Since the responses were on different scales (i.e. interest in tariffs on the 4-point Likert scale and acceptance of DLC were recorded as acceptors (1 = yes), in-between (0.5 = maybe) and rejectors (0 = no)), we used minmax normalisation to normalize the value of each feature (Equation (1)). Otherwise, features with a higher variation would have higher impacts on the clustering results.

$$normalised\ value = \frac{f - f_{min}}{f_{max} - f_{min}} \quad (1)$$

K-means clustering was applied using standard Euclidean distance as the similarity metric, using the implementation in the scikit-learn Python package [60]. The silhouette score [61], defined in Equation (2), was used to determine the optimal value for “k”. The silhouette score has a theoretical range of [-1, 1], and a score close to +1 indicates a better performance of the clustering algorithm i.e. low intra-cluster distances (high intra-cluster similarity) and high inter-cluster distances (low inter-cluster similarity). The “k” that has the highest silhouette score will be considered as the optimum number of clusters for our dataset.

$$silhouette\ score = \frac{b - a}{max(a, b)} \quad (2)$$

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

The cluster analysis of the households' DSR preferences yielded four distinct groups: Cluster 1 (conservative, 19%), Cluster 2 (reserved, 20%), Cluster 3 (agreeable, 34%) and Cluster 4 (flexible, 27%). As shown in the violin plots in Fig. 3, the DSR preferences are clearly distinguishable (average silhouette score = 0.31). Table 4 presents the clustering results and the position of each cluster in the space spanned (i.e. mean values of the 14 DSR preferences features).

Cluster 1 (conservative) exhibited generally low interest in tariffs except for progressive and bonus tariffs. Cluster 1 also expressed low willingness to accept devices/appliances DLC programmes. Cluster 2 (reserved) exhibited relatively higher interest in tariffs compared to Cluster 1 (conservative), however they were more open to DLC of certain devices (two subgroups for heat pumps and boilers) and they were very open or potentially open to DC of appliances (again two subgroups). Cluster 3 (agreeable) showed similar interest in tariffs compared to Cluster 2. They were open to DLC of more electrical devices. Finally, Cluster 4 (flexible) exhibits slightly higher interest in different tariffs as well as highest acceptance of DLC of electrical devices and appliances.

3.3. Predicting clusters based on socio-demographic characters

To investigate the socio-demographic and dwelling characteristics associated with the cluster membership of DSR preferences, multinomial logistic regression models were conducted. The results further provided the probability of each household being assigned to a particular cluster. Multinomial logistic regression models calculate the probability that household $i$is assigned to cluster $k$as shown in Equation (3):

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

where x_i is a row vector of independent variables for household i, and β_k is the vector of coefficients for cluster k [62].

Since the coefficients of a multinomial logistic regression model are difficult to interpret per se, marginal effects were computed according to the common practices. The marginal effects can be interpreted as the change in the probability of an individual case (a household in our study) being assigned to a particular cluster with a one-unit increase in the independent variable [62]. For binary variables (e.g. tenure as renter and owner), marginal effects indicate the changes in probability as a result of the binary variable changing from 0 to 1. The marginal effects of each variable on the different clusters sum up to zero by definition. We report only the marginal effects obtained in the logit model in Table 5 ($\chi^2 = 86.36$,

Table 2
Socio-demographic characteristics, dwelling characteristics.

Variable	Frequency (percentage)
Socio-demographic variables	
Tenure type	
Owner	375 (60%)
Tenant	247 (40%)
Gender[3]	
Male	436 (70%)
Female	186 (30%)
Age of respondent	
18–35 years	144 (23%)
36–50 years	201 (32%)
51–65 years	170 (27%)
65+	107 (17%)
Education level[a]	
Degree I	32 (5%)
Degree II	281 (45%)
Degree III	309 (50%)
Presence of children	
No	375 (60%)
Yes	247 (40%)
Household size	
1 person	93 (15%)
2 persons	235 (38%)
3 to 4 persons	229 (37%)
5 and more	65 (10%)
Employment status	
Not employed (unemployed & housewife/husband)	23 (4%)
Student	9 (1%)
Employed	452 (73%)
Retired	128 (21%)
Other	10 (1%)
Dwelling characteristics	
Dwelling type	
Apartment	308 (49%)
House	314 (51%)
Appliance characteristics	
Appliance ownership	
Heat pump	212 (34%)
Electric boiler	215 (35%)
In home battery	9 (2%)
Photovoltaic (PV) system	211 (34%)
Washing machine	519 (83%)
Tumble dryer	466 (75%)
Dishwasher	462 (74%)
Electric vehicle (EV)	22 (4%)
Number of observations	**622**

[a] Degree I is comprised of Swiss compulsory education (e.g. primary and secondary level); Degree II is comprised of Swiss secondary education level (e.g. initial vocational training (apprenticeship), gymnasium and general culture schools); Degree III is comprised of Swiss tertiary education level (e.g. universities, college, and higher degree).

$p < .001$, McFadden Pseudo $R^2 = 0.053$).

Cluster 1 (conservative): Higher education categories (namely Degree II and Degree III) are under-represented in this cluster. Households in Cluster 1 are also more likely to live in a house than in an apartment.

Cluster 2 (reserved): Households in Cluster 2 are more likely to be renters living in houses. These households are also more likely to include women however less likely contain people who are home based (i.e. unemployed and housewife/husband).

Cluster 3 (agreeable): Households in Cluster 3 are more likely to own their property and live in an apartment.

Cluster 4 (flexible): Households that have home-based respondents are more likely to be included in Cluster 4 compared to other clusters. Additionally, Households in Cluster 4 are also more likely to live in an apartment than in a house.

3.4. Socio-demographic characteristics of interest in tariffs

To further examine the DSR preferences individually and separately, a series of one-way ANOVA tests was conducted to compare only the interest in different tariffs across different socio-demographic groups (Table 6). Whenever the *F* value is significant, indicating that there is at least one group differing from one of the others, Tukey's HSD post-hoc tests were further performed to identify those groups.

ANOVA test results show there was a significant difference between age and the interest in power tariff and progressive tariffs. The post-hoc tests show the eldest (more than 65 years old) stated the highest interest in power tariffs ($M = 2.07$, $SD = 0.96$) than youngest (18–35 years old) ($M = 1.78$, $SD = 0.86$). Conversely, the youngest (18–35 years old) stated the highest interest in progressive tariffs ($M = 2.78$, $SD = 0.84$) than eldest (more than 65 years old) ($M = 2.54$, $SD = 0.86$). Women stated significantly higher interest in four tariffs namely fixed, power, progressive and malus than men. Regarding the education, post hoc comparisons using the Tukey HSD test indicated that the mean interest of participants with Degree I in tariffs such as fixed ($M = 2.58$, $SD = 1.00$), power ($M = 2.28$, $SD = 0.85$), bonus ($M = 3.09$, $SD = 0.69$) and malus ($M = 2.25$, $SD = 0.88$) were significantly higher to participants with Degree III (fixed ($M = 1.96$, $SD = 0.88$), power ($M = 1.64$, $SD = 0.84$) and bonus ($M = 2.71$, $SD = 0.89$)). Conversely, participants with Degree III stated higher interest in malus tariffs ($M = 1.96$, $SD = 0.88$), than to participants with Degree I ($M = 1.96$, $SD = 0.88$).

Participants who live in an apartment were significantly more interested in power tariff ($M = 1.88$, $SD = 0.86$) and bonus tariff ($M = 1.71$, $SD = 0.84$) than to those participants who live in a house

Table 3
Overview of the analysis performed in this study.

Analysis performed	Data	Purpose	Programme used
Cluster analysis	14 features explaining the DSR preferences (interest in six tariffs and acceptance of 14 appliances and devices)	Identify and segment various DSR preferences	Python- scikitlearn package [60]
Multinomial regression	Cluster membership and socio-demographic and dwelling characteristics	Investigate the determinants of the DSR preference patterns reflected in cluster membership	Stata (command mlogit).
ANOVA	Interest in six tariffs, DLC acceptance and socio-demographic and dwelling characteristics	Investigate how interest in tariffs differs across socio-demographic groups & Investigate the acceptance of DLC differences for the interest in tariffs	IBM SPSS 25.0
χ^2 tests of independence	Acceptance of DLC along with socio-demographic and dwelling characteristics	Investigate whether DLC acceptance relates with socio-demographic features	IBM SPSS 25.0
Ordinary Least Square (OLS)	Interest in six tariffs and overall DLC acceptance	Investigate the relationship between overall DLC acceptance and interest in tariffs	Stata (command rreg).

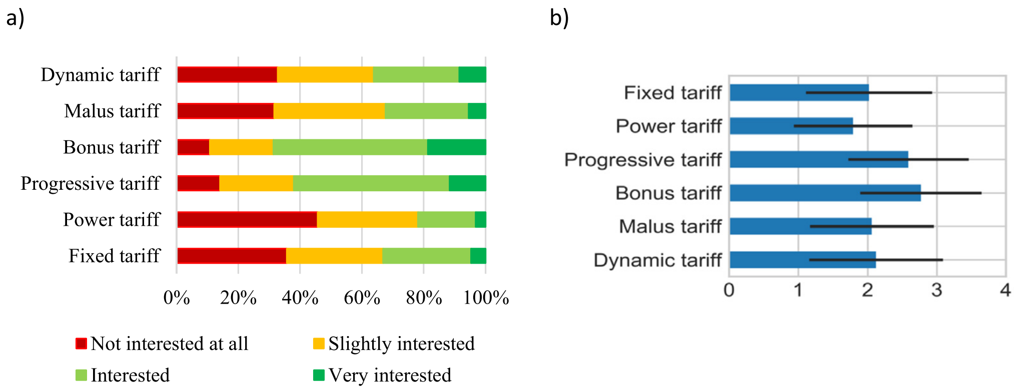

Fig. 1. Survey results for a) frequency distribution (%) for measured interest in different tariffs b) Mean and standard deviations using the 4-point Likert-type scale for different tariffs.

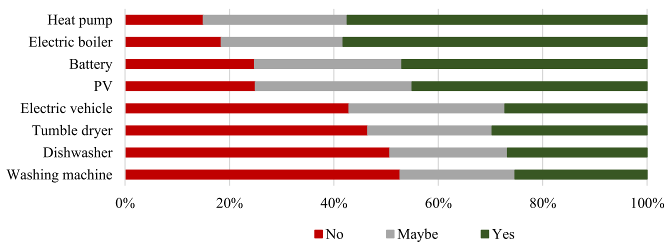

Fig. 2. Acceptance of automation of eight devices/appliances (N = 622).

(power tariff ($M = 2.86$, $SD = 0.86$) and bonus tariff ($M = 2.68$, $SD = 0.89$)). Regarding the tenure, participants who are renting were more interested in progressive tariffs ($M = 2.72$, $SD = 0.82$) to those who own their dwelling ($M = 2.51$, $SD = 0.90$).

There was not a significant difference between the presence of children, number of people and interest in tariffs. Finally, none of the socio-demographic characteristics differ significantly in dynamic tariffs.

3.5. Socio-demographic and dwelling characteristics of acceptance of DLC

This section addresses how the acceptance of the DLC of each device/appliance differed in their socio-demographic and dwelling characteristics to provide information that can help utility companies better match customers with the right type of incentives. A set of Π^2 tests of independence were conducted to find out whether there is any significant relationship between acceptance of device/appliance DLC and socio-demographic characteristics. Only significant values were shown in the table.

As shown in Table 7, for electrical devices, which are less related to daily activities and practices, the differences were mainly related to dwelling type, education, ownership of the corresponding device and gender of the person responsible in the household for electricity bill. For other socio-demographic characteristics such as employment, presence of children, household size (number of people), age and tenure, there was no significant difference in the acceptance of the DLC of the electrical devices.

Regarding the dwelling type, both apartment and houses have different superscripts for "no" (superscript a) and "yes" (superscript b), so we can conclude that the percentages are significantly different. This means that a downward trend was observed from no to yes in the houses for the DLC of electrical devices, whereas an opposite trend was observed for apartments in which more people accepted the DLC of these devices. Similarly, people with higher education (Degree III) were significantly more likely to accept the DLC of heat pumps and batteries than reject it. The acceptance of DLC of boilers was significantly higher for those who already owns it. For PV, on the other hand, PV owners were significantly less in favour of DLC of their PVs than non-owners. This can be explained by the fact that these households have been selling power to the grid therefore they can see the DLC of their PV as an obstacle to their profits.

On the other hand, for electrical appliances (relatively more related to activities and daily routine), the differences in acceptance were mainly related to socio-demographic factors such as employment status, presence of children, gender, number of people in the house, age and tenure (Table 8). For other socio-demographic characteristics such as dwelling type and education, differences in the acceptance of the DLC of the electrical devices were not significant (hence not shown in the table). Employed people and households with children are likely to reject the DLC of tumble dryers and washing machines. For tenure, there is downward trend from no to yes in the owner-occupied households for the DLC of washing machines and dishwashers, whereas an opposite trend was observed for rented homes in which more people accepted the DLC of these appliances. The acceptance of DLC of dishwashers was significantly lower for those who already owns them compared to non-owners. Lastly, the relation between acceptance of DLC of EVs was significant, χ^2 (N = 622) = 7.706, p = .021. Men are more likely to accept the DLC of EVs whereas women are more likely to reject it.

3.6. The relationship between interest in tariffs and acceptance of DLC

A series of one-way ANOVA tests was conducted to compare the interest in different tariffs across acceptance of DLC of different device and appliance types (Table 9). Whenever the *F* value is significant, indicating that there is at least one group differing from one of the others, Tukey's HSD post-hoc tests were further performed to identify those groups.

Results of ANOVA test suggests that there is a significant difference between the acceptance of DLC and the interest in the tariffs except for fixed and dynamic tariffs. Participants who indicated "yes" to acceptance of DLC were significantly more interested in tariffs than other respondents. Conversely, participants who indicated "no" to acceptance of DLC always significantly stated the least interest in any tariff.

Additionally, we conducted an ordinary least squares (OLS) regression analysis for the overall acceptance (the number of yes to

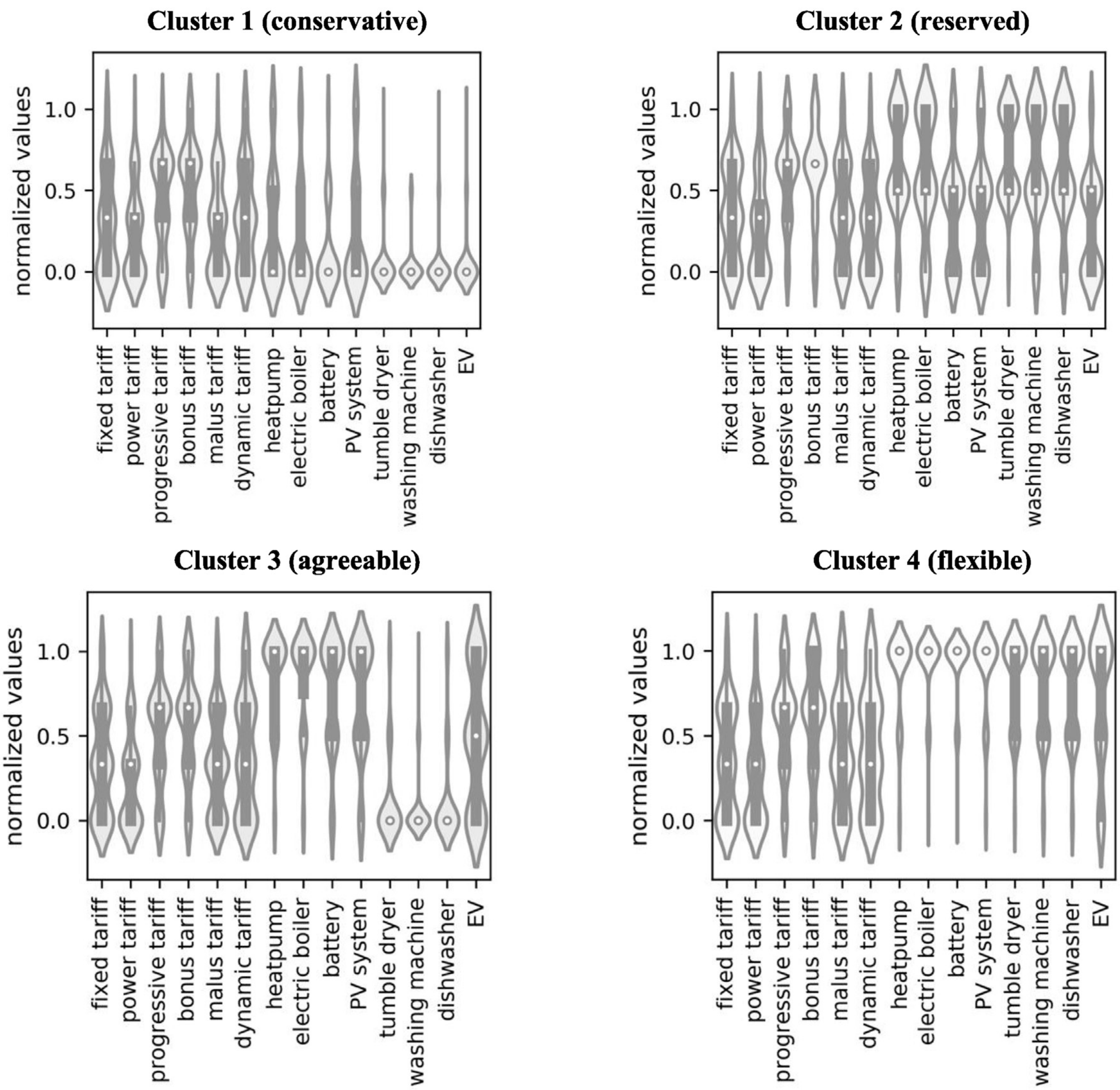

Fig. 3. Identified DSR preference clusters.

Table 4
Clustering results: Mean value of the each of the 14 features.

Percent of the sample	Cluster 1 (conservative)	Cluster 2 (reserved)	Cluster 3 (agreeable)	Cluster 4 (flexible)
	19%	20%	34%	27%
Interest in tariffs				
fixed tariff	0.24	0.29	0.24	0.29
power tariff	0.45	0.58	0.51	0.58
progressive tariff	0.53	0.61	0.58	0.62
bonus tariff	0.28	0.38	0.33	0.42
malus tariff	0.36	0.31	0.38	0.42
dynamic tariff	0.30	0.36	0.34	0.35
Acceptance of DLC of devices and appliances				
Heat pump	0.25	0.66	0.84	0.89
Electric boiler	0.20	0.61	0.85	0.93
Battery	0.14	0.39	0.75	0.93
PV system	0.23	0.39	0.72	0.90
Tumble dryer	0.05	0.72	0.11	0.84
Washing machine	0.03	0.64	0.05	0.79
Dishwasher	0.03	0.64	0.09	0.79
EV	0.05	0.29	0.48	0.71

Table 5
Multinomial logit regression of cluster membership on socio-demographic and dwelling characteristics (marginal effects) (N = 622).

	Cluster 1 (conservative)	Cluster 2 (reserved)	Cluster 3 (agreeable)	Cluster 4 (flexible)
Gender (1 = female)	0.015 (0.038)	0.073** (0.037)	−0.059 (0.477)	−0.029 (0.045)
Age of respondent: 18−35	0.140 (0.094)	−0.058 (0.094)	0.100 (0.132)	−0.182 (0.124)
Age of respondent: 35−60	0.073 (0.092)	0.004 (0.092)	0.118 (0.130)	−0.195 (0.122)
Age of respondent: 51−65	0.067 (0.080)	0.069 (0.078)	0.021 (0.119)	−0.157 (0.111)
Education: Degree II	−0.109* (0.064)	0.070 (0.080)	0.046 (0.101)	−0.007 (0.091)
Education: Degree III	−0.110* (0.065)	0.018 (0.082)	0.027 (0.102)	0.065 (0.092)
Employment: Employed	−0.104 (0.080)	−0.126 (0.078)	0.110 (0.116)	0.119 (0.111)
Employment: Home-based	−0.092 (0.115)	−0.349** (0.144)	0.091 (0.166)	0.350** (0.144)
Number of people in HH	−0.012 (0.021)	−0.015 (0.022)	0.041 (0.026)	−0.015 (0.025)
Presence of children in HH	0.057 (0.050)	0.038 (0.052)	−0.074 (0.061)	−0.021 (0.058)
Tenure (1 = owner)	0.003 (0.042)	−0.142*** (0.042)	0.152*** (0.053)	−0.013 (0.049)
Dwelling type (1 = house)	0.149*** (0.038)	0.119*** (0.040)	−0.186*** (0.047)	−0.082** (0.043)
# Obs. in cluster	116	128	211	167

Notes: Marginal effects computed at the sample means (discrete change from the base level for binary variables). Standard errors in parentheses.
*/**/*** significant at α = 10/5/1%.

Table 6
ANOVA results on interest in tariffs differing across socio-demographic groups.

	Fixed		Power		Progressive		Bonus		Malus		Dynamic	
	F	p	F	p	F	p	F	p	F	p	F	p
Age	.456	.713	**5.026**	**.002**	**3.171**	**.024**	1.225	.300	1.997	.113	1.765	.153
Gender	**4.975**	**.026**	**14.108**	**.000**	**10.779**	**.001**	**12.921**	**.000**	**7.936**	**.005**	.418	.518
Education	**3.326**	**.037**	**12.746**	**.000**	1.158	.315	**3.129**	**.044**	**6.262**	**.002**	2.873	.057
Number of people	.616	.605	.699	.553	.439	.725	2.427	.065	.434	.729	1.738	.158
Presence of children	.027	.869	3.045	.081	.875	.350	.138	.710	.853	.356	.082	.774
Dwelling type	.016	.899	**6.661**	**.010**	1.617	.204	**6.756**	**.010**	3.616	.058	2.668	.103
Tenure	.952	.330	.428	.513	**8.673**	**.003**	2.522	.113	2.695	.101	.019	.891
Employment	0.390	.677	**5.574**	**.004**	1.303	.272	0.971	.379	0.917	.400	0.377	.686

Table 7
Socio-demographic differences among acceptors, undecided, and non-acceptors of DLC of home electric devices.

	Heat pump			Electric boiler			Battery			PV		
Dwelling type												
	χ^2	*d.f.*	*p*	χ^2	*d.f.*	*p*	χ^2	*d.f.*	*p*	χ^2	*d.f.*	*p*
	17.602	2	0.000	13.266	2	0.001	13.303	2	0.001	13.582	2	0.001
	no	**maybe**	**yes**	**no**	**maybe**	**yes**	**no**	**maybe**	**yes**	**no**	**maybe**	**yes**
house	66%^{a}	56%^{a}	44%^{b}	60%^{a}	58%^{a}	44%^{b}	56%^{a}	59%^{a}	43%^{b}	60%^{a}	54%^{a}	43%^{b}
apartment	34%^{a}	44%^{a}	56%^{b}	40%^{a}	42%^{a}	56%^{b}	44%^{a}	41%^{a}	57%^{b}	40%^{a}	46%^{a}	57%^{b}
Education												
	χ^2	***d.f.***	***p***				χ^2	***d.f.***	***p***			
	13.713	4	0.008				11.818	4	0.019			
	no	**maybe**	**yes**				**no**	**maybe**	**yes**			
Degree I	11%^{a}	6%^{a,b}	3%^{b}				8%^{a}	5%^{a}	4%^{a}			
Degree II	42%^{a}	50%^{a}	44%^{a}				52%^{a}	46%^{a}	41%^{a}			
Degree III	45%^{a}	44%^{a}	53%^{a}				40%^{a}	49%^{a,b}	55%^{b}			
Owning the device												
				χ^2	***d.f.***	***p***				χ^2	***d.f.***	***p***
				9.716	2	0.008				13.582	2	0.001
				no	**Maybe**	**yes**				**no**	**maybe**	**yes**
Device-owner				32%^{a,b}	25%^{a}	39%^{b}				60%^{a}	54%^{a}	42%^{b}
Non-owner				68%^{a,b}	75%^{a}	61%^{b}				40%^{a}	46%^{a}	58%^{b}
Gender												
							χ^2	***d.f.***	***p***			
							7.268	2	0.026			
							no	**maybe**	**yes**			
female							34%^{a,b}	35%^{a}	25%^{b}			
male							66%^{a,b}	65%^{a}	75%^{b}			

Notes: Superscripts indicate significant differences between interest for each six tariffs. If two values do not share a letter, they are significantly different. For test values: χ^2 specifies the chi-square value obtained in the respective tests, d.f. the corresponding degrees of freedom, and p the probability value. Students and "other" were omitted from the employment analysis due to very low case numbers.

DLC of different device and appliance types as the continuous independent variable) and the interest in tariffs (continuous dependent variable based on Likert-type scale). The regression formula is shown in Equation (4):

$$\mathrm{Int\_T}_t = \beta_0 + \beta_1 \mathrm{.overall\_acceptance\_of\_DLC} \tag{4}$$

where Int_T = interest in tariff t (calculated separately for six tariffs).

Table 8
Socio-demographic differences among early acceptors, undecided, and straight non-acceptors of home electrical appliances.

	Tumble dryer			Washing machine			Dishwasher			Electric vehicle		
Employment												
	χ^2	d.f.	p	χ^2	d.f.	p						
	13.683	4	0.008	14.997	4	0.005						
	no	**maybe**	**yes**	**no**	**maybe**	**yes**						
Not employed	4%^{a}	2%^{a}	6%^{a}	4%^{a,b}	1%^{a}	6%^{b}						
Employed	80%^{a}	70%^{a,b}	70%^{b}	79%^{a}	72%^{a,b}	68%^{b}						
Retired	16%^{a}	28%^{b}	24%^{a,b}	17%^{a}	27^{b}	26%^{a,b}						
Presence of children												
	χ^2	***d.f.***	***p***	χ^2	***d.f.***	***p***						
	8.458	2	0.015	7.441	2	0.024						
	no	**maybe**	**yes**	**no**	**maybe**	**yes**						
yes	54%^{a}	64%^{a,b}	66%^{b}	55%^{a}	63%^{a,b}	68%^{b}						
non	46%^{a}	36%^{a,b}	34%^{b}	45%^{a}	37%^{a,b}	32%^{b}						
Gender												
										χ^2	**d.f.**	**p**
										7.706	2	0.021
										no	**maybe**	**yes**
female										35%^{a}	29%^{a,b}	22%^{b}
male										65%^{a}	70^{a,b}	77%^{b}
Number of people in the house												
	χ^2	***d.f.***	***p***									
	12.897	6	0.045									
	no	**maybe**	**yes**									
1	13%^{a}	17%^{a}	17%^{a}									
2	33%^{a}	41%^{a}	44%^{a}									
3 to 4	53%^{a}	20%^{b}	27%^{a,b}									
5 and more	12%^{a}	9%^{a}	9%^{a}									
Age												
	χ^2	***d.f.***	***p***									
	14.570	6	0.024									
	no	**maybe**	**yes**									
18–35	27%^{a}	18%^{a}	22%^{a}									
36–50	36%^{a}	29%^{a}	29%^{a}									
51–65	25%^{a}	29%^{a}	29%^{a}									
>65	12%^{a}	23%^{b}	20%^{a,b}									
Tenure												
				χ^2	***d.f.***	***p***	χ^2	***d.f.***	***p***			
				6.254	2	0.044	13.840	2	0.001			
				no	**maybe**	**yes**	**no**	**maybe**	**yes**			
Owner				63%^{a}	63%^{a,b}	52%^{b}	65%^{a}	65%^{b}	48%^{b}			
Tenant				37%^{a}	37%^{a,b}	48%^{b}	35%^{a}	35%^{a}	52%^{b}			
Owning the appliance												
							χ^2	***d.f.***	***p***			
							7.113	2	0.029			
							no	**maybe**	**yes**			
Device owner							78%^{a}	73%^{a,b}	68%^{b}			
Non-owner							22%^{a}	27%^{a,b}	32%^{b}			

Table 9
ANOVA results on DLC acceptance differing across interest levels in tariffs.

DLC of …	Fixed tariff		Power tariff		Progressive tariff		Bonus tariff		Malus tariff		Dynamic tariff	
	F	*p*	*F*	*P*	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*p*
Heat pump	1.013	.364	.013	.987	**3.821**	**.022**	1.822	.163	**3.719**	**.025**	1.380	.252
Electric boiler	**6.614**	**.001**	.684	.505	**4.738**	**.009**	**5.384**	**.005**	**7.417**	**.001**	1.092	.336
Battery	.585	.557	1.918	.148	**3.344**	**.036**	2.172	.115	2.168	.115	1.903	.150
PV	.603	.547	1.715	.181	**3.402**	**.034**	.355	.701	1.459	.233	.402	.669
Tumble dryer	**3.579**	**.028**	**8.862**	**.000**	**7.883**	**.000**	**3.096**	**.046**	**7.054**	**.001**	1.061	.347
Washing machine	2.604	.075	**8.443**	**.000**	**3.945**	**.020**	**3.040**	**.049**	**7.405**	**.001**	.757	.470
Dishwasher	**3.588**	**.028**	**8.621**	**.000**	**10.535**	**.000**	**8.589**	**.000**	**6.826**	**.001**	.462	.630
EV	.326	.722	.265	.767	2.607	.075	1.646	.194	1.128	.324	2.044	.130
Overall acceptance	2.36	.125	**5.910**	**.015**	**14.260**	**.002**	**9.03**	**.028**	**14.210**	**.002**	2.320	.128

Notes: Tests that yielded significant results ($p < 0.05$) are shown in bold.

β_0, β_1 = coefficients or parameter estimates, from here on labelled coefficients.

'rregfirst' performs an initial screening based on Cook's distance>1 to eliminate gross outliers before calculating starting values and then performs Huber iterations followed by bi-weight.

The regression model is statistically significant (F-values and *p* values are stated in Table 9) in power, progressive, bonus and malus tariffs. Participants who have accepted the DLC of higher number of appliances are more likely to state more interest in these tariffs in general (i.e. β_1. are positive). Lastly, there was not a significant difference between the acceptance of DLC for EVs and the interest in tariffs.

Given the fact that objectives of power tariffs and DLC align in the sense of minimising the peaks in the electricity demand to avoid the high strain on the grid, the results here are worth of particular attention. Results of ANOVA test show that there is not a significant difference between acceptance of DLC of four devices individually (e.g. heat pump, boiler, in-home battery and PV) as well as EV DLC and interest in power tariffs. On the other hand, those who accepted the DLC of washing machines, tumble dryers and dishwashers showed significantly more interest in power tariffs than those who rejected the DLC. Regarding the dynamic tariffs, though not significant, the interest by those who accept the EV and device DLC tended to be lower than those who reject the EV and device DLC.

4. Discussion

We highlight below five main findings and several key suggestions which could be of interest to utility companies, DSOs and policy makers.

First, our findings highlight the heterogeneity of DSR preferences, not only at an overall level but also with regard to specific patterns across various DSRs. The cluster analysis identified four distinct DSR preferences: conservative (moderate interest in different tariffs but low acceptance of device/appliance DLC), reserved (moderate interest in different tariffs and moderate acceptance of device/appliance DLC), agreeable (moderate interest in different tariffs and high acceptance of device DLC but low acceptance of appliance DLC) and flexible (higher interest in different tariffs and high acceptance of device DLC and appliance DLC). Our analysis further makes it possible to relate DSR preferences with individual characteristics (e.g. education level, employment, gender) and dwelling types. This provides a basis for pilot testing the potential of different electricity tariffs and DLC over various electrical devices and appliances in future field studies. Our consumer profiles should thus be of great value to utilities interested in introducing new electricity tariffs and DLC programmes.

Second, in terms of electricity tariffs, this study found that the majority of households indicated significant interest in at least one of the novel electricity tariffs. Meanwhile, power tariff (i.e. paying based on the power demand, in CHF/kW) was the least preferred tariff in general in line with literature [29]. Yet, demographics such as elderly (over 65 years), women and those who live in apartments showed higher interest compared to the other groups.

Third, this study identified significant differences between the acceptance of DLC for devices and appliances. Socio-demographic factors such as employment status, presence of children, gender, household size, age and tenure had no impact on the acceptance of device DLC (e.g. heat pumps, electric boilers, PV systems and in-home battery); however, they were significant determinants for the acceptance of appliance DLC (e.g. washing machine, tumble dryer, dishwasher and E.V.) which are more related to daily routines and practices. For example, families with children are less likely to accept DLC over washing machines, tumble dryer and dishwasher. Further, we infer that the type of activities associated with a particular appliance (especially how closely the activities connect with daily routines and practices) interrelated with household demographics and affect acceptance of DLC of such appliances. Therefore, the underlying socio-technical dynamics that affect the acceptance of DLC must be taken into account in order to decrease the level of inconvenience and should be addressed with several offers (e.g. overriding) as part of the DLC programmes.

Fourth, although the acceptance of device DLC was generally higher than appliance DLC, it is important to highlight that the acceptance of the DLC over these devices was significantly lower for house residents compared to apartment residents. We suspect this is related to "the need for control" as house occupants are the only owners of these systems as opposed to apartment occupants who, for example, share one heat pump in the whole building. Apartment occupants might have become used to the feeling of not having full control over appliances or devices. This finding is also in line with the work of Xu et al. [40] that the acceptance of DLC programmes of air-conditioners increased for house residents once the overriding option is given. In Switzerland, the ownership of heat pumps and PVs in houses (i.e. single-family households, SFH) are significantly higher than apartments (i.e. multifamily buildings, MFH). In 2018, 15% of SFH and 9% of MFH were equipped with heat pumps [63] while 9% of SFH and 6% of MFH were equipped with PV systems [64]. Hence, utility companies should think of offers such as overriding options to tackle the concerns regarding losing control in order to increase the participation of the single-family households in DLC programmes of electrical devices.

Lastly, results of ANOVA tests using demographics as the grouping variables suggested there was no significant difference between the acceptance of DLC over EVs and devices (e.g. heat pumps, electric boilers, PV, batteries), and interest in power tariffs, whereas the difference was significant for the acceptance of appliance DLC (tumble dryers, washing machines, dishwashers). Since devices are likely to cause higher levels of strain on the grid (e.g. high peak demand of heat pumps, and feed-in by PV systems), public authorities and DSOs should address this misalignment, provide guidance and promote the device DLC which will reduce peak demands, reduce the customers' bills, and at the same time better reflect DSO costs.

In this paper, we highlighted the non-technical factors such as interest in different electricity tariffs and acceptance of DLC programmes, however technical challenges including lack of metering, information and communication infrastructure, as well as the need for advanced computational methods [65,66] are equally important to holistically evaluate the impact of DSR schemes on the electricity system.

5. Conclusion

In this study, we applied machine learning techniques such as k-means clustering, multinomial logit regression, and other statistical tests (ANOVA &Π^2 tests of independence) to analyse the DSR preferences in residential households. Specifically, we focused on socio-demographic and dwelling characteristics to predict the differences in DSR preferences combined and individually.

The cluster analysis identified four distinct DSR preference groups: conservative, reserved, agreeable, and flexible. A multinomial logit regression was then applied to 622 households to link their socio-demographic characteristics (e.g. age, presence of children, and education level) and dwelling characteristics (e.g. dwelling type) with the group which they belong to. The results suggest that characteristics such as dwelling type, education level, tenure, employment and gender are strong determinants of the DSR preferences.

The surveyed customers are most interested in the bonus tariff and least interested in the power tariff. Further, the interest in tariffs was significantly differed across socio-demographic characteristics such as age, gender and education level. At the same time, we found that the acceptance of DLC is higher for electrical devices (e.g. heat pumps, electric boilers, PV systems and in-home batteries) than for electrical appliances (e.g. tumble dryers, washing machines, dishwashers and EVs), arguably due to the desire of maintaining daily routines. Somewhat in support of this finding, we found socio-demographic variables (e.g. employment status, presence of children, gender, age) serving as significant predictors of the acceptance of appliance DLC on the one hand and dwelling type and education level serving as significant predictors of the acceptance of device DLC on the other hand. In bridging DLC acceptance with the interest in tariffs, we found that those who accept DLC of devices/appliances did not show high interest in power tariffs. It is important to align DLC programmes with power tariffs which reflect the network costs better in order to reduce the bills by avoiding maximum peaks. Therefore, we suggest further research should be done in order to understand the relationship between DLC and power tariff acceptance.

In summary, this paper provides a basis for developing advice and guidance for DSOs, utility companies and policy makers that would enable households to participate in tariffs and DLC programmes for the future planning of Swiss distribution systems with increased renewable power generation. We observe significant differences in households' interest in tariffs and acceptance of DLC, and we suggest that there are no one-size-fits-all solutions in the design of electricity tariffs and DLC programmes. Our analyses provide some initial insights in the reasons for the aforementioned differences, while future research is warranted. It would certainly add another layer of depth to the decision model if socio-psychological variables (such as frugality value, environmental value, trust in utilities, social influences, and comfort needs) were also included. Further research with a multi-dimensional framework, which incorporates the financial with the social and the technical with the mental, is required to investigate and to promote the acceptance of DLC.

Author statement

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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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