ANALYSING DIFFERENCES IN HOUSEHOLD'S RENEWABLE TECHNOLOGY PROFILES: A COMPARISON OF SOCIO-PSYCHOLOGICAL CHARACTERISTICS

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Abstract
Electrifying the heating and transport sectors with renewable electricity has become one of the major decarbonization strategies in Germany. In the residential sector, the coupling of heat pumps and battery electric vehicles with photovoltaic systems plays an important role, as these couplings can create powerful synergies for sustainable energy systems. Therefore, it is important to know how consumers decide to invest in these technologies. This study examines the heterogeneity of renewable energy technology profiles among households in Germany and further analyzes the associations between these profiles and socio-demographic characteristics. For better understanding of this heterogeneity, we aimed to identify household subgroups using latent class analysis (LCA).
LCA revealed four clusters characterized by distinct technology profiles and building types. Socio-demographic factors and housing characteristics, such as age, type of the building and building ownership explained class membership significantly. Also, individual values and beliefs related to climate and energy problems predicted class membership of household participants.

Keywords
Renewable energy technologies; technology adoption; household profiles; latent class analysis

Overview
Globally, the residential sector currently accounts for more than 22% of total final energy consumption, according to data from the IEA (2022). It is therefore essential to accelerate the energy transition through a substantial expansion of renewable energy sources and the electrification of heating and transport. In this context, electrifying the heating and transport sectors with renewable electricity has become one of the major decarbonization strategies in Germany (Rinaldi et al., 2021). In the residential sector, the coupling of photovoltaic systems (PV) with heat pumps (HPs) and battery electric vehicles (BEVs) plays an important role. This development will lead to stronger interactions between traditionally decoupled sectors, which may additionally be enhanced by storage systems.
Germany, in particular, achieved a significant increase in small-scale PV systems with integrated battery storage as well as an increase in BEVs and HPs in the last few years (Bundesverband Wärmepumpe e.V [bwp], 2022; Figgener et al., 2021; Perau et al., 2021). These parallel developments on the generation and demand side have a large synergy potential, as the actual decarbonization impact of BEVs and HPs is highly dependent on the power source and, thus, dependent on PV expansion and storage capacity.
In 2022, 2.65 million installed PV systems with a nominal capacity of 66.5 GWp supplied about 12% of Germany's net electricity consumption, including more than 1.5 million small-scale rooftop systems (BSW Solar, 2023). In addition, incentives for self-consumption have increased in recent years due to cuts in feed-in tariffs, rising retail electricity prices, and the drop in lithium-ion battery prices (Kairies et al. 2019). Moreover, the recent energy crisis seems to be reinforcing households' desire for more independence from the grid. In 2022, 70% of small-scale PV plants in Germany were installed with a battery storage system. In total, about 630,000 home storage systems with a cumulative capacity of 5.2 GWh have been installed so far (BSW-Solar 2023).
Additionally, demand is being driven by the increasing adoption of battery electric vehicles (BEVs), which is also contributing to the decreasing cost of batteries. In Germany, 470,000 BEVs were newly registered in 2022, accounting for about 18% of new registrations. The accelerated development of the electric vehicle market can be compared to the development of the photovoltaic market, showing a similar market penetration (KBA 2022).
Space heating combined with hot water supply corresponds to nearly half of the energy consumption in buildings. In 2022, about 240,000 heat pumps were installed in Germany, which represents an increase of more than 50 % compared to the previous year (bwp 2023). In addition, Germany has set a target of installing 500,000 heat pumps per year from 2024 (BMWK 2022). This is primarily due to a future with a rapidly decarbonizing energy supply, where the use of electricity via heat pumps is one of the most environmentally friendly heating options (Fawcett, 2011). The benefits of heat pump technologies can best be realized when combined with PV in residential energy systems (Keiner et al., 2019).

Overall, a combination of PV, batteries, HPs, and BEVs in a residential energy system seems to hold great potential to meet the overall energy demand of households. Several studies analyze ways in which household energy technologies can be synergized in different ways and how different combinations of technologies can have positive impacts on the electrification of the household sector (for an overview, see Facci et al. 2018). On the other hand, renewable energy technologies are often still comparatively more expensive than systems using fossil fuels. Thus, it is still unclear whether renewable energy technologies will be increasingly deployed by exploiting synergies between technologies or whether technologies will be introduced gradually and independently, taking into account budgetary constraints. In this study, we therefore aim to model the energy technology profiles of German households based on the adoption of different renewable technologies. Apart from creating individual technology profiles, we try to examine their relationship with a number of potential predictors.
While most of the research studying the adoption of a renewable energy technologies uses socio-demographic as well as psychographic characteristics to explain the adoption of a single technology (see e.g. Alipour et al., 2020; Michelsen & Madlener, 2016; Schulte et al., 2022; Singh et al., 2020), there is very limited literature looking at multiple domains of energy use and their transitions within households (see e.g. Selvakkumaran & Ahlgren, 2019 for an literature review comparing determinants of adopting PV, heating systems, and alternative fuel vehicles).
However, specific pro-environmental attitudes are not necessarily translated into general adoption behavior (Ajzen, 1991; Curtis et al., 2018; Peattie, 2010), which calls into question the usefulness of specific individual attitudes as direct predictors of overall renewable technology profiles.
In addition, many scholars emphasize the importance of individual values for explaining pro-environmental behavior (Steg, 2016) and household energy decisions (e.g. Kastner & Stern, 2015). Since renewable energy technologies have the potential to reduce emissions associated with electricity generation, technologies that are perceived as "green" are more likely to be adopted to the extent that they are viewed as consistent with existing values and beliefs (Wolske et al., 2017).

Thus, the aim of this survey is, on the one hand, to fill the research gap by looking at different energy domains simultaneously and understand if there are typical subgroups of technology profiles among German households. And, on the other hand, we aim to explain these aggregated profiles by using sociodemographic characteristics and overall individual values and beliefs.

Methods

The procedure applied in this study consisted of two steps. In a first step, latent class analysis (LCA) with maximum likelihood estimation was used to determine subgroups of households. Subsequent analyses using multinomial logistic regression analysis assessed the associations between household subclasses and potential predictors, including socio-demographics, values, and beliefs.

Participants

Participants took part in a survey that was distributed via a commercial online panel between August and September 2022. The sample was representative of the German population regarding age, sex, income, and household size. Complete responses included those participants who passed an attention-check item and had no missing data on one or more variables. The final sample included 809 participants.

Measures

Socio-demographics: The participants reported their sex, age, education, and other demographic characteristics. Also, participants were asked about household-specific characteristics such as household income and size. In addition, characteristics of the household´s building and installed renewable energy technologies were asked.

Values: The second section included personal values as well and beliefs related to renewable energy.
Values were measured using an adapted version of Schwartz's (1992) Value Scale (see Stern et al., 1998). The scale has been extensively tested and validated in a variety of studies both in this and other forms (Dietz et al., 2005; Groot & Steg, 2008; Steg et al., 2014; Wolske et al., 2017). We included 13 values: Three to measure an egoistic value orientation (Cronbach's $\alpha = 0.67$; $M = 4.1$; $SD = 1.34$), four to measure biospheric and social altruism (Cronbach's $\alpha = 0.89$; $M = 5.8$; $SD = 1.15$), three measuring a traditional value orientation (Cronbach's $\alpha = 0.71$; $M = 5.7$; $SD = 1.09$), and three to measure openness to change values (Cronbach's $\alpha = 0.76$; $M = 4.9$; $SD = 1.31$). Respondents rated the importance of these values "as a guiding principle in their lives" on a 7-point scale ranging from 1 = *opposed to my values* to 7 = *extremely important*.
In addition to personal values, we measured the participants' **beliefs** on the extent to which they feel responsible for energy-related problems. Thus, we used four items in accordance with established literature to measure

ascription of responsibility in the energy context (Abrahamse & Steg, 2011; "I take joint responsibility for the depletion of energy resources", "I feel jointly responsible for the greenhouse effect" and "I take joint responsibility for environmental problems", "I feel jointly responsible for the increased use of fossil fuels").

Data analysis

First, we analyzed the descriptive statistics of socio-demographic and technology-specific characteristics among the participants. Second, latent class analysis (LCA) with maximum likelihood estimation was used to determine subclasses of households based on the household's building, type its renovation status, and the adoption of photovoltaics, a battery storage system, a heat pump, and an electric vehicle. Third, we used multinomial logistic regression analysis to examine the associations between household subclasses and potential predictors, including socio-demographics, building properties, values, and beliefs.

Latent class analysis is a model-based clustering approach that assigns observations probabilistically to distinct latent classes. Considering the proportions of observations in each class, LCA estimates the model parameters from the conditional probability of observations for each variable within a class (Bauer, 2022; Benassi et al., 2020; Magidson & Vermunt, 2002; Vermunt & Magidson, 2009). This probability-based clustering offers a conceptual advantage over the more traditional clustering methods using a deterministic assignment, since classification uncertainty is an explicit part of the statistical model (Bauer, 2022; Magidson & Vermunt, 2002). Also, LCA can be seen as a more statistically robust method for clustering given that it is model-based, allowing statistical inference to determine the most appropriate number of clusters for a population (Sinha et al., 2021).

A number of studies have shown that LCA often performs better than K-means or other deterministic clustering algorithms, especially when dichotomous variables are considered and the number of classes are unknown (see e.g. Brusco et al., 2017; Magidson & Vermunt, 2002; Schreiber & Pekarik, 2014). Several studies have already adopted the LCA approach to identifying latent behavioral or household patterns. In our analysis, we conducted an LCA to identify patterns or groups of energy technology adoption using the R package "poLCA" (Haughton et al., 2009; Linzer & Jeffrey Lewis, 2022; Linzer & Lewis, 2011).

Therefore, we used six categorical variables as indicators for the LCA, including the household's building, its renovation status, and the usage of photovoltaics, a battery storage system, a heat pump, and an electric vehicle. To determine the optimal number of latent classes, we estimated a series of models from one to seven latent classes.

The optimal number of latent classes was selected based on the best balance between the number of clusters considered and the corresponding model fit, taking into account Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and entropy.

After examining the underlying latent class structure, we used multinomial logistic regression to explore the significant predictors of class membership.

Table 1: Demographic and housing characteristics of the total sample

	% (n = 809)
Gender	
Female	50.1
Male	49.3
Age, years	
< 25	24.4
25 – 35	13.0
35 – 45	12.6
45 – 55	14.2
55 – 65	14.3
> 65	21.5
Size of the household	
Single	19.7
Two-person	34.2
Three-person	18.0
Four-person and more	28.1
Type of building	
Detached House	29.4
Semi-Detached House	7.4
Terraced House	7.5
Multi-appartment Building	52.2
Other	3.5
Building twnership	
Household property	45.5
Rented builidng	54.5
State of renovation	
Extensive retrofit	30.7
Replacement of the windows	21.3
No retrofit	48.1
Installed technologies	
Photovoltaic	9.9
Battery storage system	4.6
Heat pump	13.3
Electric vehicle	10.4

Results

The final sample consisted of 809 participants, 80 of whom already had a photovoltaic system installed, 37 had a battery storage system, 84 use an electric vehicle, and 108 participants had a heat pump installed in their home. Table 1 describes the profile of the sample, including the demographic characteristics of the participants and the corresponding relevant housing data.

Model fit and selection of latent class

Based on model fit indices and theoretical interpretability, a 4-class model was chosen, which indicated the most appropriate representation of the differences between households. Table 2 presents fit indices for the competing latent class models. Overall, AIC improved gradually for up to four clusters, and worsened for models with five clusters and more. The best model fit according to the BIC was with a 2-cluster model, slightly decreasing with additional clusters added. In accordance with Nylund et al. (2007) and Weller et al. (2020), who point out that statistical criteria should always be evaluated in conjunction with theoretical reasonability when deciding on the number of clusters in LCA, we decided to proceed with the 4-cluster model in favor of a better interpretability. We named the clusters for illustrative purposes as 'non-adopters of renewable energy technologies' (class 1: 84.5%), 'PV owners living in (semi-)detached houses' (class 2: 5.4%), 'Heat pump owners having completed comprehensive retrofit' (class 3: 7.05%), and 'multiple renewable energy technology adopters' (class 4: 3.0%). However, there was overlap between clusters. Overall, these results show that the adoption of sustainable energy technologies remains at low levels, in particular for the adoption of multiple technologies with the potential for synergies. Table 3 presents the distribution of socio-demographic characteristics of the participants by the four latent classes.

Table 2: Model fit indices for the latent class models

Model	AIC	BIC	Entropy
One-class	5461.8	5504.0	-
Two-class	5168.5	**5257.7**	0.88
Three-class	5146.8	5282.9	**0.91**
Four-class	**5136.6**	5319.8	0.89
Five-class	5142.3	5372.4	1.00
Six-class	5149.1	5426.2	1.00
Seven-class	5158.1	5482.1	0.75

Table 3: Distribution of demographic variables by latent class

	Class 1, % (N = 684)	**Class 2, %** (N = 44)	**Class 3, %** (N = 57)	**Class 4, %** (N = 24)
Gender				
Female	50.1	50.0	64.9	33.3
Male	49.9	50.0	35.1	66.7
Age, years				
< 25	23.8	18.2	36.8	20.8
25 – 35	11.5	6.8	24.6	37.5
35 – 45	12.0	13.6	15.8	20.8
45 – 55	14.2	20.5	12.3	8.3
55 – 65	15.2	20.5	5.3	0.0
> 65	23.2	20.5	5.3	12.5
Size of the household				
Single	21.1	9.1	12.3	16.7
Two-person	35.1	34.1	31.6	16.7
Three-person	17.3	18.2	24.6	25.0
Four-person and more	26.6	38.6	31.6	41.7
Type of building				
Detached House	25.6	84.1	29.8	62.5
Semi-Detached House	7.5	15.9	0.0	16.7
Terraced House	7.0	0.0	24.6	0.0
Multi-appartment Building	59.9	0.0	45.6	20.8
Building Ownership				
Household property	41.5	84.1	49.1	79.2
Rented builidng	58.5	15.9	50.9	20.8
State of renovation				
Extensive retrofit	23.0	38.6	91.2	91.7
Replacement of the windows	24.0	18.2	0.0	0.0
No retrofit	53.1	43.2	8.8	8.3

Predictors of class membership

With regard to the predictors of household technology profiles, we conducted multinomial logistic regression. Table 4 and table 5 present the results of the analyses examining predictors of latent class membership with the "non-adopters of renewable technologies" as the reference group.

Compared with non-adopters, we found that participants with building ownership are more likely to be in class 2 and class 4, but not class 3. Regarding the factors influencing membership in class 2 (PV owners), living in a small village (OR=4.32, p=0.008) or small town (OR=3.71, p=0.020) appeared to be a significant predictor. Also, people feeling responsible for energy-related problems were more likely to be in class 2, compared to the class of non-adopters (OR=1.58, p=0.003).

For class 3 (heat pump owners), we found that living in new buildings and being younger had a significant positive impact on class membership. In addition, participants that are attached to openness to change values, are more likely to be class 3 (OR=1.31, p=0.039).

On the other hand, participants with stronger egoistic values seem to be more likely in class 4 (multiple renewable energy technology adopters; OR=1.83, p=0.002) as well as participants who felt a stronger responsibility for problems related to energy use.

The size of the household, the household´s income, and altruistic as well as traditional values had no significant effect on class membership.

Table 4: Results of multinomial logistic regression for socio-demographic and housing variables (class 1 as reference group)

Predictors		**Class 2** PV owners living in (semi-)detached houses			**Class 3** Heat pump owners having completed comprehensive retrofit			**Class 4** multiple renewable energy technology adopters		
		OR	***p***	**95% CI**	**OR**	***p***	**95% CI**	**OR**	***p***	**95% CI**
Age	< 25	.032	.032	.048 - .873	7.730	.005	1.833 - 32.61	.415	.469	.039 - 4.471
	25 – 35	.204	.204	.078 - 1.723	7.079	.005	1.806 - 27.74	2.025	.458	.315 - 13.03
	35 – 45	.793	.793	.209 - 3.303	5.028	.032	1.145 - 22.09	.522	.566	.057 - 4.799
	45 – 55	.939	.939	.340 - 3.209	3.269	.110	.765 - 13.97	.458	.489	.050 - 4.175
	55 – 65	.804	.804	.380 - 3.482	1.386	.702	.259 - 7.409	0.000	.985	.000 -
	> 65	-	-	-	-	-	-	-	-	-
Year of construction	2002 – today	1.585	.631	.242 - 10.404	7.301	.014	1.508 - 35.36	2652549	.987	-
	1979 – 2001	4.147	.075	.867 - 19.840	2.361	.285	.489 - 11.41	2999341	.988	-
	1958 – 1978	1.833	.471	.353 - 9.526	1.483	.626	.304 - 7.246	356293	.990	-
	1919 – 1957	4.054	.098	.774 - 21.243	1.698	.554	.294 - 9.789	1104686	.989	-
	1919 & older	-	-	-	-	-	-	-	-	-
Building ownership	Property	5.229	.001	2.135 - 12.802	1.192	.599	.619 - 2.296	6.894	.006	1.756 - 27.07
	Rented	-	-	-	-					
Size of city (population)	Village	4.317	.008	1.468 - 12.692	.981	.964	.421 - 2.287	3.621	.101	.777 - 16.87
	Town	3.710	.020	1.227 - 11.223	.881	.758	.393 - 1.976	.785	.778	.145 - 4.247
	City	1.220	.766	.330 - 4.513	.718	.426	.318 - 1.622	3.631	.097	.791 - 16.67
	Large city	-	-	-	-	-	-	-		-
Education	Still in school	.000	.998	.000 - .	0.000	-	.000 - .000	.775	.866	.040 - 14.88
	No degree	.000	.998	.000 - .	1.079	.951	.093 - 12.53	11.98	.114	.553 - 259.5
	Lower sec.	1.135	.876	.229 - 5.620	1.790	.349	.529 - 6.051	.000	.992	.000 -
	Upper sec.	1.752	.360	.527 - 5.824	.489	.178	.172 - 1.386	.270	.196	.037 - 1.967
	Vocational	.791	.703	.238 - 2.635	.309	.046	.097 - .979	.637	.591	.123 - 3.300
	Tertiary	3.271	.036	1.077 - 9.928	.556	.165	.243 - 1.273	.555	.417	.133 - 2.305
	University	-	-	-	-	-	-	-	-	-

Table 5: Results of multinomial logistic regression for value and belief variables (class 1 as reference group)

Predictors	Class 2 PV owners living in (semi-)detached houses			Class 3 Heat pump owners having completed comprehensive retrofit			Class 4 multiple renewable energy technology adopters		
	OR	***p***	**95% CI**	**OR**	***p***	**95% CI**	**OR**	***p***	**95% CI**
Altruism	1.004	.981	.696 - 1.449	.972	.852	.721 - 1.410	.848	.533	.505 - 1.423
Self-Interest	1.221	.135	.940 - 1.585	1.132	.296	.898 - 1.427	1.828	.002	1.239 - 2.696
Traditionalsim	.999	.997	.699 - 1.429	.858	.304	.641 - 1.149	.930	.790	.543 - 1.591
Openness to Change	.937	.645	.710 - 1.236	1.310	.039	1.014 - 1.691	1.265	.292	.817 - 1.958
AR	1.581	.003	1.171 - 2.136	1.097	.451	.862 - 1.397	1.598	.025	1.061 - 2.409

Note: AR = Ascription of Responsibility

Conclusions

Our results support the existing literature (Keiner et al., 2019; Peñaloza et al., 2022), suggesting that households do not necessarily adopt renewable energy technologies separately from each other across building types, but multiple renewable energy technologies are installed together by interested households. Therefore, we identified four different subgroups of renewable energy technology patterns within a heterogeneous sample of German households: non-adopters (84.5%) photovoltaic owners living in (semi-)detached houses (5.4%), heat pump owners having completed comprehensive retrofit (7.05%), and ‘multiple renewable energy technology adopters (3.0%). The latent class approach demonstrated variability in technology synergies across groups of households with different technology profiles. The results also showed that certain sociodemographic and housing characteristics, as well as egoistic and openness to change values, together with attribution of responsibility for energy-related problems, can predict a household’s technology profile. However, sociodemographic indicators have a slightly higher explanatory power based on odds ratios. Analysis of sociodemographic characteristics also revealed that, contrary to widely used assumptions, household income as well as education and gender of the participants did not significantly influence class membership.

As latent class analysis is a type of person-centered approach, the subgroups should be seen as statistical summaries that identify households with similar response patterns. However, such analytic summaries are insufficient evidence to make the case that a specific typology has a concrete reality and should not be interpreted as realizations of a latent trait. Therefore, different results may be obtained from a different sample (Bauer, 2022). The main limitation of our explorative study is that the different classes of non-adopters are relatively small in comparison to the overall sample. Accordingly, it may be beneficial to conduct further studies that focus exclusively on comparing adopters of renewable energy technologies in more detail.

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