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What are the Key Factors that Influence Individual's Willingness to Adopt Demand Response Products and Services?

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Abstract

Climate change forces societies to transition from fossil fuels to renewable sources of energy. Solutions are required to more efficiently integrate electricity of variable renewables into the grid. Demand response (DR) involves products and services that offer demand side flexibility, and thus have potential to solve this problem. Much of DR's potential lies in private end users, but to date, a lack of knowledge reflects a major barrier for residential DR. In order to gain insights into factors that influence DR adoption, the present study made use of a correlational design, through which the relationship between the dependent variable, DR adoption intention, with the independent variables expected personal benefits, egoistic values, knowledge of DR, awareness of network congestion, awareness of DR congestion prevention function, environmental self-identity, perceived behavioral control, and mistrust and privacy concerns were examined. The sample consisted of 17 participants, nested within four separate energy communities in Europe. The variables expected personal benefits and awareness of DR congestion prevention function were positively related to DR adoption intention. While mistrust and privacy concerns were negatively related to DR adoption intention. Findings suggest that, in addition to financial benefits, also non-financial personal benefits should be highlighted, and that mistrust and privacy concerns are central for DR adoption. Furthermore, future research could investigate, if highlighting societal benefits like grid reliability offers an efficient way to increase customer trust and DR adoption. However, the small sample size and increased chances for false positives through multiple tests are limitations of this research.

Keywords: demand response, adoption, private end users, motivational factors

Disclaimer

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Anthropogenic climate change forces societies to rethink their social, economic, and political system (Dryzek & Norgaard, 2012, p 16). Worldwide, more than 80% of the used energy comes from fossil fuels, and those fossil fuels are responsible for about three-quarters of the total greenhouse gas emissions (Ritchie et al., 2020). Therefore, societies urgently need to transition from fossil fuels to renewable sources of energy (IPCC, 2021).

Various challenges for the energy system are expected in this energy transition. First, the electrification of sectors like transportation and heating (Parrish et al., 2019), which were traditionally based on fossil fuels, will lead to a rise in total electricity demand. Second, the electricity is increasingly generated by renewable energy sources like wind and solar, which generate electricity without emitting greenhouse gasses, but do so in a highly variable manner, dependent on external circumstances like weather conditions and season (strbac, 2008).

Supply and demand needs to be constantly balanced in close limits, to secure electricity supply (strbac, 2008). Outages are very costly, and to prevent those, electricity systems work around 20% under their potential generation capacity margin, so they can match demand at peak times (strbac, 2008). This represents the potential and opportunity for demand response (DR). DR involves technologies and services that can offer demand side flexibility through short-term load shifting (Gils, 2014). By managing not only the electricity supply but also the demand, network efficiency can be increased, by shifting load away from peak periods and thus reducing the need for generation capacity while increasing the utilization of power plants (strbac, 2008). Further, DR enables integration of electricity in particular high generation periods from wind energy or other variable renewables into the grid (Mount et al., 2012).

Demand response programs can be price based (varying electricity prices), incentive based (rewards for compliant behavior), or information based to foster energy consumption changes. The involved appliances can be operated manually (e.g., plugging the electric car only at night), by automation, (e.g., programming the laundry machine to run in a set time frame) or through direct load control (Parrish et al., 2019). Direct load control additionally involves allowing the energy provider to directly control the load of appliances, and shut them off at peak periods (strbac, 2008) and is typically done with heating or cooling systems. To make DR work, smart appliances receive and send information to and from the energy provider (O'Connell et al., 2014).

In Europe, the largest theoretical potential of DR flexibility lies in private end users (Gills, 2014). To get access to this potential a broad participation of private end users would be necessary, which represents a major barrier as many trials to date have participation rates of less than 10% (Parrish et al., 2019). To overcome this barrier, it would be crucial to overcome a lack of knowledge and understanding about the motivations of end users to participate in DR programs and how to segment those end users (Parrish et al., 2020). This study will enlighten some motivational factors to get a better understanding what motivational factors are particularly relevant in the adoption of demand response products and services. This is beneficial for customers and providers, as it helps to accurately predict which consumers can clearly benefit from demand response (Steel, 2014), and it is crucial for the main goal of engaging more people with demand response programs, to increase the efficiency and reliability of the electricity network and through this, effectively mitigate climate change.

Literature Review of Motivational Factors and Barriers that Influence DR Adoption

The current state of the literature is not highly advanced. The field of DR is new, and still in full development. A recent systematic review by Parrish et al., (2020), provides a comprehensive overview of enablers and barriers of residential end user engagement with DR, synthesized from 55 studies from the gray and academic literature. The review was used as a foundation for this research. Parrish et al. found that two main sources of motivations to participate in DR programs have been identified repeatedly, which are expected financial benefits, and expected environmental benefits of DR. Both of these motivations have been identified in research using surveys (Allcott, 2011; Torstensen & Wallin, 2014), as well as in studies employing qualitative methods like interviews and focus group discussion (Dütschke & Paetz, 2013; Bradley et al., 2016; Hall et al., 2016). Further identified categories of motivations were perceived benefits in the household like discounts for technology (Bradley et al., 2016), greater control over energy consumption and bills due to supplementary information (Hall et al., 2016), and fun or interest in responding to changing prices (Düschke & Paetz). Social motivations such as discussions with neighbors and contributing to increase the reliability of the electricity system were found to motivate people to adopt DR (Western Power Distribution, 2016), and this motivation may be intensified when the local community benefits from DR (Carmichael, 2014).

Parrish et al. (2020), further categorized general factors that impact residential user engagement other than motivations. *Familiarity and trust*: Consumers may mistrust involved companies, especially individuals who are unfamiliar with the concept of DR (AECOM, 2011), and trust in the involved parties and the technology were found to positively relate to DR adoption (Wiekens et al., 2014; Lopes et al., 2016). *Perceived risk and perceived control:* perceived risk may involve high electricity prices or unpredictability of prices (Allcott, 2011; Carmichael, 2014). Perceived risk may be reduced by automation of appliances or direct load control (so devices can respond automatically to dynamic prices; Fell et al., 2015). However, further automation is associated with a lower perceived control over appliances (Hall et al., 2016). Issues with control have been found to be a central point of concern for many customers, and are related to lower acceptance levels of DR (Buchanan et al., 2016; Lopes et al., 2016).

Complexity and effort was found to be another category. The higher the perceived complexity of DR, the higher the perceived effort for people, and higher perceived effort has been associated with lower DR adoption intention (Lopes et al., 2016). U*ser routines* reflect how well people can integrate DR into their daily life, and can be a hurdle for some customers (Nicholls & Strenger, 2014; Hall et al., 2016). The last category was *user characteristics*. Evidence regarding socio demographic characteristics of users is mixed, and only seems to weakly relate to DR adoption (AECOM, 2011; Carmichael et al., 2014).

It should be noted that although the review suggests that financial motivations are the most central ones, this is not necessarily the case. Sloot et al., (2022) argue that the findings from Parrish et al., (2020) point towards a need for more research examining environmental motivations to accurately assess their impact on adoption.

Theoretical Framework

In the following section I will introduce predictors from this research, and the reasoning why I believe predictors relate to DR adoption. Predictors can be broadly grouped into three categories: one cost-benefit oriented, one that is about knowledge and collective benefits, and another, that is control and trust oriented.

Expected Personal Benefits

DR programs to date rest on the assumption that a rational cost-benefit analysis underlies consumers' decisions to participate, respond and persist, as DR programs either use prices, or offer financial discounts to guide consumers electricity consumption (Albadi & El-Saadani, 2008). In line with the rational cost-benefit evaluation, the Theory of Planned behavior (TPB; Ajzen, 1985) is well applicable to the context of participation in DR programs (Sloot et al., 2022). In the TPB framework, attitudes, subjective norms, and perceived behavioral control are the main predictors of intention and behavior, and all other factors can influence intention only indirectly through these. For example, attitudes are built from expectations of consequences about a behavior, plus the perceived likelihood that these consequences occur (Ajzen & Fishbein, 1975). In the context of DR, expectations of personal benefits of adopting DR partly build the attitudes towards DR, and thus expectations of personal benefits regarding status, finances, and comfort/pleasure are predicted to positively relate towards the adoption intention of DR.

Egoistic Values

From the rational perspective, participation in DR programs is mainly motivated by financial gains (Albadi & El-Saadani, 2008), and anticipated financial gains are a typical motive for egoistic values (Van den Broek et al., 2017). According to Van den Broek et al., (2017), people with strong egoistic values are more persuaded by financial appeals than people with weaker egoistic values. For these reasons, egoistic values are expected to stimulate DR adoption when people anticipate financial benefits. A counter argument can be made: Individuals high in egoistic values tend to prefer reliable and perceived cheap energy sources like nuclear energy, as they focus primarily on individual consequences for themselves (Perlaviciute & Steg, 2014). The concept of DR is antagonistic to this: people adapt their own behavior and provide flexibility in electricity demand for collective benefits (and small personal rewards), by avoiding potential network congestion and making the grid overall more stable. Following this reasoning, egoistic values might negatively relate to DR adoption intention.

Knowledge of DR

Knowledge of DR products and services reflects a deeper understanding of DR. Knowledge is a necessary but not sufficient condition for deployment of DR on a voluntary basis. Precisely, the higher peoples' knowledge about subsidies, legislations, installations, and use of DR, the lower is the required effort for the adoption of DR. This is important, as exploratory research suggests that people compare expected effort to expected benefits when considering DR adoption, and therefore, the lower the perceived effort, the higher should be the intention to adopt DR (Lopes et al., 2016).

Awareness of Network Congestion and Congestion Prevention

According to the knowledge deficit model, awareness of a problem, and awareness about an alternative behavior, is at the root of behavior change in the face of environmental problems (Schultz, 2002, p 67). When people think about DR adoption, awareness of network congestion may relate to DR adoption as it represents a first step of understanding why DR can be beneficial to society, and this knowledge gives a purpose to DR adoption rather than financial or personal benefits.

Awareness of the potential prevention function of DR to network congestion reflects a deeper level of understanding, showing that people are aware of the connection between DR and societal benefits. Individuals may anticipate positive emotions when they see themselves as part of the solution to network congestion, rather than contributing to it, and anticipated positive emotions have been found to significantly affect comparable high involvement pro-environmental behaviors (Rezvani et al., 2017). Therefore, awareness of the DR congestion prevention function is reasoned to positively relate to DR adoption intention.

Environmental Self-Identity

Expected environmental benefits represent an alternative source of motivation for the adoption of DR. Here, I want to focus on environmental self-identity. Environmental self-identity as a construct reflects to what extent people perceive themselves as an environmentally friendly actor (Van der Werff., 2013a). The stronger peoples' environmental self-identity is, the more they tend to be motivated by expected environmental benefits, because environmental self-identity influences their preferences and intentions and is positively linked to all kinds of pro-environmental behaviors including energy behavior intentions (Van der Werff et al., 2013a). Indeed, previous research found a positive relation between environmental self-identity and DR quota scheme adoption intention (Sloot et al., 2022). This study will try to extend these findings, to test if environmental self-identity positively relates to general DR adoption intention.

Perceived Behavioral Control

Another TPB factor, perceived behavioral control, is theorized to be an influential predictor of DR adoption. Here it is conceptualized as control, risk and self-efficacy beliefs. Perceived behavioral control is thought to relate through multiple pathways to DR adoption intentions. In an educated Portuguese sample only 20.9% of participants were willing to accept direct load control, while 78% were willing to adapt their electricity use in a future scenario without any direct benefits (including 10% that already did), which demonstrates that people seem to be willing to adapt their electricity behavior, but they want to feel in control of their energy consumption (Lopes et al., 2016). Another dimension of control in the context of DR is peoples' inability to shift their electricity demand. Shifting electricity demand may be outside of their control due to external reasons like limited time or structural barriers in their housing situation (Hall et al., 2016). A third dimension of control in DR are dynamic varying prices. People may feel out of control when they perceive dynamically varying prices as unpredictable and risky, which can stop some customers from taking part in DR programs (Allcott, 2011).

Mistrust and Privacy Concerns

Being unfamiliar with DR has been linked to mistrust in the motivations of service providers (AECOM, 2011). DR services and technologies can be perceived as intrusive, as those are installed in peoples' homes (Fell et al., 2014) and smart appliances share information with their energy provider, which has been associated with privacy concerns

(McDaniel & McLaughlin, 2009). Fell et al., (2015) found that trust in the electricity supplier was the strongest predictor of DR tariff acceptance, while Wiekens et al., (2014) concluded that trust in the involved companies' intentions, services, and in the technological infrastructure is a necessary condition for DR adoption of end users. Trust might be particularly difficult to achieve when the involved companies are for-profit organizations as many customers seem to worry that they make an effort to adapt their electricity consumption, while their energy provider, or others members of their energy community profit from that (Wiekens et al., 2014). Generally, people seem to worry that energy providers don't act in their best interest (Fell et al., 2014). Extracted from the reasoning above, I propose the following hypotheses:

H1: Expected personal benefits relate positively to DR adoption intention.

H2: Egoistic values are positively associated with DR adoption intention.

H3: Egoistic values are negatively associated with DR adoption intention.

H4: Knowledge of DR relates positively to DR adoption intention.

H5: Awareness of congestion in the electricity network relates positively to DR adoption intention.

H6: Awareness of the DR congestion prevention function relates positively to DR adoption intention.

H7: Environmental self-identity is positively associated with DR adoption intention.

H8: Perceived behavioral control relates positively to DR adoption intention.

H9: Mistrust and privacy concerns relate negatively to DR adoption intention.

Current Study

The present research investigates motivational factors and barriers that influence the DR adoption intention of private end users, with the objective, to get an overview, which are the most important predictors of DR adoption intention. The hypotheses were examined through a questionnaire and tested in a correlational design. The results have implications for service providers who want to promote DR, and for potential future research.

Methods

This study is part of the BRIGHT project (https://www.brightproject.eu/), which aims to promote DR for private end users in Europe. To examine consumer engagement at the residential level, data was leveraged from four pilot projects on energy communities in Europe. Energy communities can be broadly described as entities that organize collective energy actions, through open and democratic participation procedures (Robert et al., 2019). Data in the present study came from the countries Belgium, Greece, Slovenia and Italy. The italian data was further divided into two separate use cases. Third parties distributed the questionnaire from Kort et al., (2022) to the members of the energy communities. In Belgium, the questionnaire was sent to all members of the energy community. In Greece and Italy, the questionnaire was distributed to a random subsample of members, and to customers outside of the energy community. The Slovenian subsample got excluded from this analysis, and is thus not of relevance here. Participation in the questionnaire was a voluntary and not incentivized. Data was collected in around two weeks of time per pilot, with a predetermined end date, and then anonymized before it was sent to TNO (https://www.tno.nl/en/).

A pre-registration according to the template from van't Veer and Giner-Sorolla (2016), including a hypothesis section, a method, and a detailed analysis plan can be found on the open science framework (https://osf.io/kn8cp). Further, to determine the required sample size, an a priori power analysis was conducted using GPower (Erdfelder & Buchner, 2007). The smallest population effect size of interest for one tested predictor was $f^2 = .03$ (Cohen, 1988, p 413; Sloot e al., 2022), with $\alpha = .05$, including all eight IVs, with 80% power resulted in a total required sample size of $N = 250$. I investigated the power curve for two additional reasonable effect sizes (f^2 = .05, and f^2 = .11), which resulted in N = 152, and N = 73 required participants.

In total, the sample included 131 participants, of which (N = 57) provided answers on the dependent variable. Non-respondents were excluded in order to prevent distortion of the demographic and descriptive characteristics of the sample. The Slovenian subsample was excluded due to the following reasons. Firstly, the mental capacity of the participants was called into question, the participants all having had been admitted to a facility for the elderly. Secondly, the data was not comparable to the other pilot study samples, nor to the target population. Thirdly, the technology of interest was a centralized heating system. This was not representative of the remaining DR technologies, as individuals had little to no influence over the choice of heating system installed. Therefore, all 40 participants from the Slovenian subsample were excluded, resulting in only 17 participants remaining for the main analysis. An alternative analysis with the full data set was run. Sample characteristics are shown in Table 1.

Design

The eight independent variables, namely expected personal benefits, egoistic values, knowledge of DR, awareness of network congestion, awareness of DR congestion prevention function, environmental self-identity, perceived behavioral control, and mistrust and privacy concerns, were all directly related to the dependent variable DR adoption intention. This research is correlational, no causal claims were made.

Materials and Procedure

A questionnaire was used to collect the data. The questionnaire had a general section which was provided across all pilot studies, including informed consent, what people value (e.g., technology, money, the environment), how aware they are of congestion in the

Table 1

Sociodemographic Characteristics of Participants

Sample	DR sample		Technology sample	
Baseline characteristic	*N* = 17	%	*N* = 85	%
Gender				
Female	3	18	24	28
Male	14	82	61	72
Age category				
< 30	6	35	14	16
31 - 60	10	59	61	72
> 61	1	6	9	11
Highest level of education				
Nursery school to 8th grade	1	6	4	5
High school	5	29	34	40
College	0	0	1	1
Trade/technical/vocational training	1	6	7	8
Bachelors' degree	5	29	16	19
Master's degree	5	29	21	25
Doctorate degree	0	0	1	1
Household income				
< 29	8	47	41	49
30 - 74	3	18	19	23
> 75	2	12	5	6
Prefer not to say	2	12	17	20
House type				
Apartment	7	41	43	51
Terraced house	1	6	11	13
Detached house	6	35	20	24
Semi-detached house	1	6	9	11
Other	0	0	0	0

Household income in 1000 dollars per year. Percentages were rounded.

electricity network, some demographic background information of the participants, and a thank you statement.

The questionnaire also contained several technology related parts, which were only provided if it was relevant for the particular energy community/pilot study and its members. These other sections were related to specific technologies, and DR products and services in regard to those technologies. They were split into five sections: Heat Pumps and DR products and services for heat pumps – Electric cars and DR products and services for electric cars –

DR products and services for public charging stations – Solar panels and DR products and services for solar panels – Home batteries and DR products and services for home batteries.

A short explanatory paragraph was provided at the beginning of each section. Participants were asked if they own a specific technology. If they replied with “yes”, they were forwarded to a set of questions regarding DR products and services for that technology. If respondents selected “no”, they got directed to an alternative path, where variables were assessed in relation to technology, without DR products and services. I will refer to such below as “technology variables”. This path was used to increase the robustness of results (see analysis plan). After each DR section related to specific technologies, participants were asked if they intend to adopt DR products and services for the technology that was assessed.

Structure-wise, the beginning of the questionnaire included general parts: informed consent, what people find important (e.g., values), and how aware they are of congestion in the electricity network. The middle section were the non-mandatory modules about specific technologies, and their DR products and services. This section differed between pilot studies, depending on the available technologies in the energy communities, modules were included or not. The last part asked about the demographic characteristics and presented a thank you statement.

Measures

The independent variables’ awareness of network congestion and awareness of DR congestion prevention function were measured as a categorical variable with a “yes/no” response option. Environmental motivations and financial motivations were measured each with one item on a 5-point Likert scale (0 = *strongly disagree* to 4 = *strongly agree*). The technology related independent variables including expected personal benefits, knowledge of DR, perceived behavioral control and mistrust and privacy concerns were measured with a 7-point Likert scale (0 = *strongly disagree* to 6 = *strongly agree*) with an additional “I don’t know" option. Participants choosing "I don't know" were not included in the analysis. An example item for a variable is: "I don't trust DR products or service providers for [technology]." Here [technology] is a filler either for heat pumps, electric cars, public charging stations, solar panels or home batteries. The dependent variable, DR adoption intention was also measured in relation to a specific technology. The dependent variable was measured with three items on a 7-point Likert scale (0 = *strongly disagree* to 6 = *strongly agree*). The first item asked if participants consider adoption of DR products and services for [technology], the second asked, if people are interested in DR products and services for [technology], and the last asked, if people will adopt DR products and services for [technology]. For the main analysis, there was made no differentiation between DR variables in regards to different technologies (e.g., "knowledge of DR for heat pumps" vs "knowledge of DR for solar panels"), therefore, I refer to them in general terms (e.g., "knowledge of DR"). All these measures can be found in Appendix A.

Table 2

Means and Standard Deviations of all Variables from the Main Analysis

Variable	Scale 0-6		scale 0-4		Nominal 0-1	
	M	*SD*	*M*	*SD*	*M*	*SD*
DR adoption intention	3.84	1.21	-	-	-	-
Expected personal benefits	3.54	1.23	-	-	-	-
Egoistic values	-	-	2.53	.94	-	-
Knowledge of DR	3.14	1.04	-	-	-	-
Awareness of network congestion	-	-	-	-	.82	.39
Awareness of DR c. prevention function	-	-	-	-	.47	.51
Environmental self-identity	-	-	3.41	.80	-	-
Perceived behavioral control	3.13	1.03	-	-	-	-
Mistrust and Privacy concerns	2.54	1.06	-	-	-	-

For all variables $N = 17$.

Analysis plan

First, variables were calculated as described in the pre-registration. Items from certain modules that belong together were calculated into sub-variables that were specific to one technology (e.g., electric car). Then these sub-variables (e.g., knowledge of DR for electric cars) were computed into general variables (e.g., knowledge of DR), from all the sub-variables across technologies. Non-responses were coded as system missing values, and “I don’t know” answers were coded as user missing values.

Originally, in the pre-registration it was planned to investigate H1 – H9 through a multiple regression analysis, with expected personal benefits, egoistic values, knowledge of DR, awareness of network congestion, awareness of DR congestion prevention function, environmental self-identity, perceived behavioral control, mistrust and privacy concerns as the independent variables, and DR adoption intention (from all technologies) as the dependent variable. However, with the remaining 17 participants, a multiple linear regression with eight independent variables would have resulted in an overfitted model (Hawkins, 2004). Further, it would mean that the participant/predictor ratio would have been about 2:1, which is much less than the widely mentioned rule of thumb of a participant predictor ratio of at least 10:1, and this rule of thumb underestimates adequate sample sizes in many scenarios (Maxwell, 2000). Thus, the main analysis was not performed as pre-registered. Instead, the individual relationships between the independent variables and DR adoption intention, which reflect the hypothesis, were illuminated through means, standard deviations, scatter plots, with a correlational analysis, and with eight individual simple linear regression analyses.

To increase the robustness of results, I further conducted a multiple regression analysis, with the technology variables from the path assessing not DR products and services, but technologies without DR (when participants indicated they did not own a technology). An example item from the dependent technology variable shows as follows: “My next means of transportation will be an electric car", in comparison to the DR related item: "DR products or services will be added to my electric car". All technology items can be found in appendix C. Since most people indicated not owning any of the technologies, there was far more data available for the technology variables (N =85) than for the DR variables (N = 17). Several people, owned one, or two of the technologies, but not all three, thus the DR and the technology sample overlapped. The demographic information of included participants is shown in Table 1.

Results

To evaluate the internal consistency of the scales, Cronbach's alpha was calculated. Because participants only responded to some of the modules (depending on their pilot, and the technology the owned), alpha could not be computed for the general variables. Reliability analysis in SPSS can only use listwise deletion and for this calculation there was N = 0 (IBM support, 2020). Thus, Cronbach's alpha was calculated for the sub-variables (e.g., knowledge of DR for electric cars). The scales were internaly consistent, showing that the underlying concepts are solid. Alpha levels for all scales can be found in appendix B. Knowledge of DR for electric cars had the lowest alpha from all scales (α = .723), with almost all scales being α > .8. Generally, alpha > .7 is considered to be acceptable (Spector, 1992).

Correlations of all variables can be found in Table 2. Expected personal benefits correlated highly positively with DR adoption intention, indicating that adoption intention was higher if people expected more benefits for themselves. Awareness of DR congestion prevention function correlated moderately positively with DR adoption intention, indicating that DR adoption intention was higher, when people were aware that DR can prevent network congestions. Mistrust and privacy concern correlated highly negatively with DR adoption intention, indicating that adoption intention was higher when people were low in mistrust and privacy concerns.

Table 3

Bivariate Correlations of all Variables from the Main Analysis

Variable	1.	2.	3.	4.	5.	6.	7.	8.
1. DR adoption intention	-							
2. Expected personal benefits	.68**	-						
3. Egoistic values	-.26	-.05	-					
4. Knowledge of DR	.23	.67**	-.03	-				
5. Awareness of network congestion	-.04	-.11	-.07	-.05	-			
6. Awareness of DR c. prevention function	.50*	.43*	-.55*	.47*	.44	-		
7. Environmental self-identity	.40	.18	.19	.10	-.15	.11	-	
8. Perceived behavioral control	.37	.73**	-.13	.61**	-.02	.40	.26	
9. Mistrust and Privacy concerns	-.69**	-.87**	.11	-.62**	.13	-.49*	-.26	-.68**

* $p < .05$. ** $p < .01$. $N = 17$ for all variables.

Main Analysis

Assumption testing

To test the nine hypotheses, eight simple linear regressions were conducted. For each regression, the assumption of normality, linearity, heteroscedasticity, and outliers were tested. To examine the normality of the residuals, a P-P plot was created. Several variables showed some deviations from the observed value to the normal z-distribution, indicating a non-normal distribution of the residuals, which can be expected with a small sample. For the variables with deviating residuals, a log10, square-root, and a quadratic transformation was performed, but none significantly improved the normality of the residuals. To examine, if the relationships between the independent variables and DR adoption intention is linear, a residual plot was created. Further, as comparison to the simple linear regression also quadratic relationships were tested for all variables. None yielded a higher explanatory power than its linear counterpart. The residual plot was also used for an eye test to judge heteroscedasticity. If there were indications of a heteroscedasticity, a Breusch Pagan test was performed employing the SPSS macro by Daryanto (2020). No relationships seemed to have heteroscedastic residuals. Outliers were searched for through case-wise diagnostics (-3 to 3 SD) and cook's distance (< 1). Participant 17 in the simple linear regression with awareness of network congestion as independent variable showed a cook's distance outside the desired range (*Cook's D* = 1.07). Furthermore, one data point was outside -3 to 3 *SD* in the regression with environmental self-identitity as independent variable, but as cook's distance was low (*Cook's D* = .14) it was not considered an outlier.

Hypotheses Testing

As predicted in H1, expected personal benefits positively related towards DR adoption (*p* = .003). Egoistic values on the other side were not significantly associated with DR adoption intention in either direction (*p* = .313), thus no evidence was found to support H2 and/or H3. Knowledge of DR had no influence on DR adoption intention (*p* = .382), meaning that people with more knowledge about DR, were not more inclined to adopt DR products and services than participants without knowledge about DR. Awareness of network congestion

Table 4

Outcomes of all Simple Linear Regressions from the Main Analyses

Predictors	*B*	95%*CI*	*β*	*t*	*p*
Expected personal benefits	0.66	[.0.26, 1.07]	0.675	3.55	.003
Egoistic values	-0.34	[-1.02, 0.35]	-0.260	-1.04	.313
Knowledge of DR	0.26	[-0.36, 0.90]	0.226	0.901	.382
Awareness of network congestion	-0.12	[-1.82, 1.58]	-0.037	-0.145	.886
Awareness of DR c. prevention function	1.19	[0.67, 2.31]	0.504	2.259	.039
Environmental self-identity	0.61	[-0.16, 1.38]	0.398	1.681	.113
Perceived behavioral control	0.44	[-0.17, 1.04]	0.370	1.541	.144
Mistrust and privacy concerns	-0.80	[-1.25, -0.34]	-0.692	-3.709	.002

N = 17 for all variables. DR adoption intention as dependent variable.

showed no influence on DR adoption intention (p = .886). The awareness of network congestion combined with the knowledge that DR can prevent such congestions was positively related to DR adoption intention of participants (p = .039). Thus, H4 and H5 were rejected, while evidence provided support for H6. For H7, there were indications of an association between environmental self-identity and DR adoption intention, but it was not significant (p = .113). Perceived behavioral control displayed no relation to DR adoption intention in this sample (p = .144) showing no evidence for H8, while mistrust and privacy concerns, consistent with H9 did predict DR adoption intention (p = .002). For more information, see Table 4.

Alternative Analysis with Full Sample

This part presents the outcomes of the analysis, with the full sample containing 57 participants. Beware of having confidence in these results, as the Slovenian data was excluded, because it was assessed in an elderly home from people with special needs. A multiple linear regression analysis with the independent variables expected personal benefits, egoistic values, knowledge of DR, awareness of network congestion, awareness of DR congestion prevention function, environmental self-identity, perceived behavioral control, and mistrust and privacy concerns was conducted. A P-P-plot showed deviation from normality, but as no other violations of assumptions were detected, and no log10, square-root, nor a quadratic transformation significantly improved the normality of the residuals, or resulted in a model, that could explain more variance, a multiple linear regression was performed. Missing values were deleted pairwise. The regression model had no significant predictive power (R^2 = .18, Adjusted R^2 = -.18, $F(8, 18)$ = .532, p = .837). Examining the individual relationships between the predictors and DR adoption intention, the regression coefficients revealed that personal benefits was the predictor closest to reach statistical significance, but no meaningful relationship to DR adoption intention could be found (*b* = .34, 95% *CI* = [-0.22, 0.90], *p* = .217).

Alternative Analysis on Technologies

To increase the confidence in the results from the main analysis, another analysis was done, with variables that were similar, but which were assessed in regards to technologies and not in regards to DR services. Note that this also affects the choice of the DV and thus the overall interpretation of this analysis, which is now only concerned with the intention to adopt a certain technology (e.g., electric cars) but not about DR. The advantage was that for this analysis a larger sample of participants ($N = 85$) from the same pool of respondents could be used (see Table 1 for details regarding the demographics). First, I conducted a bivariate correlational analysis with the independent variables: expected personal benefits, egoistic values, knowledge of technology, awareness of network congestion, awareness of DR congestion prevention function, environmental self-identity, perceived behavioral control, mistrust and privacy concerns, and the dependent variable technology adoption intention. Expected personal benefits $r(83) = .43$, $p < .001$, knowledge of technology $r(83) = .183$, $p = .047$, perceived behavioral control $r(83) = .41$, $p < .001$ were positively related to technology adoption intention, and mistrust and privacy concerns $r(83) = -.38$, $p < .001$ was negatively related to technology adoption intention. I followed up with a multiple linear regression, with the same set of variables. The assumption of normality of the residuals, linearity, heteroscedasticity, and outliers were tested as described above for the simple linear regression, with additionally testing the variance inflation factor ($VIF < 4$). No evidence for assumption violations were detected. The model was significant $R^2 = .25$, $F(8, 75) = 3.11$, $p = .004$. Expected personal benefits was the only individual predictor that was significant in the regression $b = 0.37$, 95%CI = [0.04, 0.69] $p = .028$.

Table 5

Outcomes of all Simple Linear Regression Analysis on Technology Sample

Predictors	*B*	95%*CI*	*β*	*t*	*p*
Expected personal benefits	0.37	[0.04, 0.69]	0.352	2.24	.028
Egoistic values	-0.18	[-0.43, 0.06]	-0.173	-1.47	.146
Knowledge of solar	-0.12	[-0.32, 0.08]	0.155	-1.16	.249
Awareness of network congestion	0.11	[-0.44, 0.67]	0.047	0.49	.684
Awareness of DR c. prevention function	0.20	[-0.32, 0.72]	0.092	0.78	.439
Environmental self-identity	0.04	[-0.23, 0.32]	0.04	0.34	.734
Perceived behavioral control	0.32	[-0.08, 0.73]	0.305	1.56	.123
Mistrust and privacy concerns	0.08	[-0.28, 0.45]	0.089	0.45	.652

N = 84 for egoistic values. For all other variables *N* = 85.

Discussion

This study investigated motivational factors and barriers that influence private end users willingness to adopt DR products and services. In the following section, I will describe and discuss findings of the current research, evaluate and compare these to the greater scheme of literature on DR, and come to a final conclusion.

Individual Predictors

Firstly, I will focus on all individual predictors, relate them to their hypothesis and previous literature.

Expected Personal Benefits

Anticipating personal advantages was positively related to DR adoption intention, confirming H1, which predicted that higher expected personal benefits are associated with higher DR adoption intention. Apart from financial and materialistic benefits, little research has looked into personal benefits as potential drivers of DR adoption. One study conceptualized personal benefits as monetary and energy security related matters, and found a relation with DR adoption intention (Sloot et al., 2022). The current study extends existing findings by showing that further personal benefits, including expected status as well as expected hedonic (e.g., comfort) benefits are related to DR adoption intentions.

Overall, present results corroborate the assumption that financial benefits are indeed appropriate in stimulating DR behaviors, and further suggest that other personal benefits like status and hedonic related benefits relate to DR adoption. Moreover, the finding supports the logic of the TPB framework in the context of DR adoption. Higher expected personal benefits build a more positive attitude, which relates to a higher DR adoption intention.

Egoistic Values

People's consideration to which extent they are generally driven by economic gains did not influence their intention to adopt DR, lending no support for H2 and H3. The statistics and the scatter plot show indications of a weak negative relationship between egoistic values and DR adoption intention. A negative relationship would support H3, which reasoned that the stronger people endorse egoistic values, the more they focus on individual outcomes, and tend to prefer stable, reliable, and (perceived) cheap energy sources (Perlaviciute & Steg, 2014). As the two lines of reasoning from H2 and H3 are contrary in their prediction, it is also possible that the two mechanisms balanced each other out.

To my knowledge, no other existing research examined egoistic values related to DR adoption. Interestingly, previous literature found a positive relation between price consciousness and DR adoption intention (Sloot et al., 2016). Thus, the evidence suggests that financially driven people tend towards being less likely to adopt DR, indicating that financial gains were too small to motivate them, while price conscious individuals were more likely to adopt DR, indicating that monetary gains were large enough to have a motivating function for them (Kim & Shcherbakova, 2011; Sloot et al., 2016).

Knowledge of DR

In hypothesis 4, I proposed that higher perceived knowledge about DR relates to higher DR adoption intention. Results did not show support for H4, as participant's knowledge and familiarity with DR and their knowledge about subsidies, legislations and policies of DR was not associated with people's intention to adopt DR. Previous research displayed different outcomes. An exploratory study suggests a positive relationship between knowledge and DR adoption. This could be due to the fact that knowledgeable people need less effort to adopt DR (Lopes et al., 2016). Qualitative research from Australia indicates that knowledge may more specifically relate positively or negatively to adoption intention, depending on whether it contributes to a positive or negative evaluation of DR (Hall et al., 2016). For example, knowledge about risks or public concerns may relate negatively to DR adoption (Allcott, 2011; Hall et al., 2016), while knowledge in terms of benefits or energy literacy has been found to positively relate to DR adoption (Bradley 2016; Reis et al., 2021). Further possible explanations for the different findings might be that the type of knowledge that was assessed (familiarity, and knowledge on subsidies, legislations, policies) differed from the type of knowledge in the mentioned studies, and that the small sample size did not yield enough power to detect the effect size.

Awareness of Network Congestion and Congestion Prevention

In hypothesis 5, I proposed that awareness of network congestion has an influence on DR adoption intention. However, no significant correlation was found. Interestingly, awareness of the congestion prevention function of DR in the electricity grid had a significant impact on DR adoption intention. This finding is in line with hypothesis 6, supporting the reasoning that people are willing to adapt their electricity consumption behavior for collective benefits, such as grid reliability (Bird et al., 2015). Therefore, knowledge of the congestion issue in the electricity grid does not seem to be sufficient information to motivate people to adopt DR. Instead, such knowledge needs to be further connected with the awareness that DR has the potential to solve or reduce congestion problems, for people to be motivated in adopting DR products and services. This finding supports the reasoning from Schultz (2002), that knowledge of a problem itself is not a motive for behavior change. Only when the knowledge is connected to social benefits (e.g., grid reliability) it becomes a motivating force.

Environmental Self-Identity

In the present research, there was evidence pointing towards a significant relation between environmental self-identity and DR adoption intention. The bivariate correlation nearly reached significance as well as the regression coefficient. However, the relationship is hard to evaluate, as participants scored very high on environmental self-identity, with all but one participant agreeing to at least “somewhat care for the environment”. The lack of clear support for the relationship between environmental self-identity and DR adoption meant that hypothesis 7 had to be rejected, although indications for an association exist.

To my knowledge, the only study that examined environmental self-identity in the specific context of DR adoption is Sloot et al. (2022). They indeed found a relationship between environmental self-identity and DR adoption intention. However, when personal norms were added to their model, the direct relationship disappeared, and environmental self-identity only had an indirect effect on adoption intention via personal norms. This means that an effect of environmental self-identity on DR adoption intention might exist, but that such effect is explained by more proximal predictors in the model, when included (Sloot et al., 2022).

Further research found environmental self-identity to be related to various pro-environmental behaviors, like the intention to adopt green products (Van der Werff et al., 2013b; Barbarossa & de Pelsmacker, 2016; Barbossa et al., 2017; Mutum et al., 2021), and various green energy behaviors (Whitmarsh & O'Neill, 2010; Van der Werff et al., 2013a; Grębosz-Krawczyk et al., 2021). However, the relation between environmental self-identity and DR adoption may be weaker than the one with green technology adoption and green energy behaviors. This could be because in regards to the latter constructs it may be easier to understand how and why those are more environmentally friendly than their traditional alternative (e.g., purchasing green electricity vs non-green electricity). In regards to DR services instead, it may be more difficult. That DR generates environmental benefits without reduction in total energy consumption seems to be particularly hard to comprehend (Hall et al., 2016). Thus, an explanation for the non-significant relation between environmental self-identity and DR adoption intention may be that people either didn't understand or didn't trust the environmental benefits of DR.

Perceived Behavioral Control

Perceived behavioral control did not predict people's DR adoption intention, not supporting H8, stating that higher perceived behavioral control is associated with higher DR adoption intention. This unexpected result is in contrast with previous research, which has consistently found relationships between control beliefs and DR adoption intention or DR acceptance (Allcott, 2011; Fell et al., 2014; Lopes et al., 2016). Participants in this study may have been not particularly concerned with losing control in the context of DR adoption, because DR was introduced on a rather conceptual level, without details about techniques of DR. Previous studies found particularly strong relations between perceived control and adoption/acceptance for direct load control, but weaker relationships for less automatic forms of DR (Fell et al., 2014; Lopes et al., 2016). Moreover, the sample size was small, and maybe the analysis did not have enough power to detect the effect.

Mistrust and Privacy Concerns

Participants who mistrusted service providers, the products or had general privacy concerns were less willing to adopt DR, while people who had trust and less worries about their privacy were more likely to intend DR adoption. This supports H9, according to which higher mistrust and privacy concerns relate to a lower adoption intention of DR. This result aligns with the literature, where a lack of trust in the service providers is described as a major barrier of DR acceptance and adoption (Wiekens et al., 2014; Fell, 2015). Furthermore, it extends those findings, as the high internal consistency of the variable mistrust and privacy concerns suggests that these concepts are indeed very closely related in regards to DR services. Moreover, mistrust and privacy concerns showed moderate to strong negative associations to multiple other predictors (expected personal benefits, perceived behavioral control, and awareness of DR congestion prevention function), which is indicative of its large overall influence on the model.

Implications of Results

In spite of consequential limitations, this research brought some interesting insights with theoretical and practical implications. Firstly, this research supports the notion that financial benefits are indeed appropriate to stimulate DR adoption, and it further indicates that other personal benefits relate to DR adoption on a more general level. Thus, the current assumption of DR programs according to which financial benefits are the driver of DR adoption appears to be too narrow (Albadi and El-Saadani, 2008). This is an especially interesting finding in regards to previous research, which showed that people are more likely to adopt DR technology for self-serving benefits compared to collective benefits (Gamma et al., 2021). Hence, in order to maximize DR adoption, it is of great importance to refer to all the personal benefits which can act as motivators. In the literature there is also evidence that hedonic (comfort) benefits relate to DR behavior. Direct load control has generally low acceptance rates (Fell et al., 2014; Lopes et al., 2016), but sometimes is associated with high satisfaction rates in customers (implying high acceptance), when direct load control is either accepted (Swing et al., 2015), or if it has features that increase users perception of control (EcoGrid EU, 2016). This indicates that comfort through a high degree of automation can result in high satisfaction of end users. Therefore, comfort benefits seem a promising starting point for future research, to explore how different personal benefits relate to DR adoption. For providers of DR programs, these findings mean that highlighting additional personal benefits, such as comfort or status, to the financial ones, may increase DR adoption in end users.

Secondly, an implication of this research stems from the finding that awareness of collective benefits like enhanced grid reliability from DR related to DR adoption intentions, while knowledge of DR, which was assessed in regards to familiarity and subsidies, legislations, and policies was not related to DR adoption intention. This suggests that for customer's willingness to adopt DR services, knowing about the advantages of DR, and how this contributes to collective societal benefits is more important than familiarity and knowledge about subsidies, legislations and policies.

Finally, this study brings interesting implications in regards to trust and awareness of collective benefits of DR. Awareness of collective benefits, such as improved grid reliability, gives DR services purpose and increases DR adoption intention. Mistrust and privacy concerns on the other hand reflect a major barrier when it comes to DR adoption. The negative relation between these two constructs, may indicate a buffering function for trust in the service providers. Multiple studies have shown that unclarity of the reasons why service providers pursue DR can fuel mistrust in customers (AECOM, 2011; Wiekens et al., 2014; Lopes et al., 2016). Knowing about collective benefits may reduce that concern. Thus, information about collective benefits of DR could be an effective target for informational campaigns, although it needs to be carefully considered whether this information is perceived as trustworthy by the public (Hall et al., 2016). Future research could investigate these connections, to test whether the described mechanism can be exploited to promote DR adoption.

Limitations of this Research

Although this study found interesting insights, these were accompanied by serious limitations. Firstly, the sample consisted of respondents out of four sub-samples which stem from different energy communities in four different countries. Depending on the energy community, participants received only certain modules of the questionnaire, from which they answered only specific sections, depending on what technologies they owned. The constructs were similarly operationalized, but measured in regards to different technologies. Effects might have balanced each other out, due to cultural or technological differences which influence the perception of DR in people. This is a fundamental weakness of the sample, which is pronounced due to its small sample size.

Secondly, the small sample size resulted in little power to detect effects, as well as deviations from normality which are expected for small samples. Furthermore, individual simple linear regressions had to be performed, instead of a multiple regression analysis, increasing the chance of false positive results (Bender & Langer, 1999). Testing the relationships individually also implied that it was not possible to account for any shared variance of predictors. This means that I could not investigate how much the total variance of the model was, and how much unique variance individual predictors explained in the full model. I tried to infer this from the data in relation to technologies (instead of DR). However, this should be interpreted cautiously as it is unclear which differences come from the inclusion of multiple variables at once, and which differences are due to constructs being measured in relation to technologies and not DR services.

Lastly, the variables financial motivations, environmental motivations, awareness of network congestion and awareness of DR congestion prevention function were measured only with one item. Generally, it is preferable to use multiple items to assess a construct, but research has shown that one item measures can be a valid form of assessing psychological constructs (Bergkvist & Rossiter, 2007).

Concluding Remarks

In light of the energy transition, solutions on how to integrate variable supply of renewable energy are urgently needed. A possible solution are DR products and services which offer demand side flexibility. This study adopted a correlational design to examine the relationships between expected personal benefits, egoistic values, knowledge of DR, awareness of network congestion, awareness of DR congestion prevention function, environmental self-identity, perceived behavioral control, and mistrust and privacy concerns with DR adoption intention as the dependent variable. Evidence of a positive relationship was found for expected personal benefits and awareness of DR congestion prevention function. While mistrust and privacy concerns was negatively related DR adoption intention. Findings indicated that non-financial personal benefits (next to financial) could be utilized to promote DR adoption, that mistrust and privacy concerns are central for DR adoption. Furthermore, future research could investigate, if highlighting societal benefits like grid reliability is indeed an efficient way to increase customer trust and DR adoption. The small sample had consequential limitations, as power to detect effects was low, and chances for type one errors were increased.

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Appendix A

Measures of Variables from the DR Sample:

All measures were developed by TNO, and come from the WP3 questionnaire by Kort et al., (2022). The variables that were measured via multiple items were calculated by computing the mean from all items that build that specific variable for each participant. [technology] can stand for: "heat pump", "home battery", "solar panels", "electric car" or "public charging stations".

5-point Likert scale

Environmental self-identity: "I consider myself someone that cares about the environment."
Egoistic values: "I consider myself someone that is generally driven by economic gains."

DR variables: 7-point Likert scale with an additional "I don't know" option.

Expected personal benefits

1. Hedonic: "I expect that DR products or services for a [technology] do not contribute to my pleasure or physical well-being (e.g., comfort)."
2. Status: "I don't think DR products or services for my [technology] will add to my status or popularity with others."
3. Financial: "DR products or services for a [technology] do not provide financial benefits for me."
4. Personal benefit: "DR products and services for a [technology] do not provide personal benefits."

Knowledge of DR

1. "I have no insight into the various subsidies, legislations and policies for DR products and services for my [technology]."
2. "I have no knowledge and I'm not familiar with DR products or services."

Perceived behavioral control

1. External circumstances: "Using DR products or services for my [technology] would require too many changes in my behavior."
2. Control: "The automation through DR products or services goes at the expense of my own control over my [technology]."
3. Self-efficacy approximation: "DR products and services for [technology] are too difficult to use."

mistrust and privacy concerns

1. User experience (impacts trust): "DR products or services for [technology] do not deliver a good user experience."
2. Trust: "I don't trust DR products or service providers for [technology]."
3. Privacy concern: "I'm concerned about my privacy when using DR products or services for my [technology]."

DR adoption intention

1. "I will consider DR products or services for my [technology]."
2. "I am interested in DR products and services for my [technology]."
3. "DR products or services will be added to my [technology]."

Categorical variable with two response options

Awareness of network congestion (one item, yes/no):
"The number of sustainable measures (such as heat pumps, solar panels and electric cars is growing. As we all take sustainability measures such as just mentioned we can cause peaks (network overload) and dips in the electricity network. The network might not be able to cope with these peaks and dips. Have you heard of this before?"

Awareness of DR congestion prevention function (one item, yes/no):
"Did you know that DR products and services might help to prevent these peaks and dips and network overload?"

Appendix B

Internal Consistency of all Variables

Table 5

Cronbach's alpha & n for Electric Car, Public Charging Station, and Solar Panel Related Variables

Variables	*Electric-car*		*Public charging*		*Solar panels*	
	α	*n*	*α*	*n*	*α*	*n*
DR adoption intention	.855	6	.827	9	.848	7
Expected personal benefits	.969	7	.813	9	.984	6
Egoistic values	-	-	-	-	-	-
Knowledge of DR	.723	5	.846	9	1.000	7
Perceived behavioral control	.869	6	.795	8	.928	7
Mistrust and privacy concerns	.914	6	.854	9	.977	7
Environmental self-identity	-	-	-	-	-	-
Awareness of network congestion	-	-	-	-	-	-
Awareness of DR congestion prevention f.	-	-	-	-	-	-

Variables with (-) were measured with one item.

Appendix C

Measures of Variables from the Technology Sample:

Expected personal benefits

1. "I expect that an electric car does not contribute to my pleasure or physical well-being (e.g., driving comfort)."
2. "I don't think an electric car will add to my status or popularity with others."
3. "An electric car does not provide financial benefits for me."
4. "An electric car does not provide personal benefits for me."

Knowledge of technology

1. "I have no insight into the various subsidies, legislations (e.g., taxes) and policies for electric cars."
2. "I have no knowledge about and I'm not familiar with electric cars."

Perceived behavioral control

1. "Using an electric car would require too many changes in my behavior."
2. "When I would buy an electric car, I would become too dependent on just one or a few service-, or product providers for electric cars. service-, or product providers for electric cars. I seriously doubt."
3. "Electric cars are too difficult to use."

Mistrust and privacy concerns

1. "Electric cars do not deliver a good user experience."
2. "I don't trust electric cars or the providers."
3. "I'm concerned about my privacy when using an electric car."

Adoption intention technology

1. "For my next means of transportation, I will consider an electric car."
2. "For my next means of transportation, I am interested in an electric car."
3. "My next means of transportation will be an electric car."