

A typology of end users' willingness to share energy data

C. Pfeiffer

Forschung Burgenland, Eisenstadt, Austria

S. Hatzl, E. Fleiß

University of Graz, Graz, Austria

C. Maier, T. P. Kremsner

Forschung Burgenland, Eisenstadt, Austria

ABSTRACT: The transition from a fuel-based, unidirectional to a renewable, de-centralized energy system requires the widespread adoption of new technological innovations. The project GEL-OpenDataPlatform (ODP) aims at implementing an open data platform for the energy sector to provide an easy access and overview of relevant data and interdependencies of a current and future integrated energy system. Hence, both personal and consumption data from end users are required to achieve a high-quality implementation. Considering all data protection regulations, these data must be provided on a voluntary basis. This voluntariness is questionable, as several studies have shown that individuals are concerned - amongst others - about data security and privacy. Moreover, individuals lack trust in actors, such as energy supply companies, when it comes to the adoption of smart technologies. As perceived concerns often prevail, or benefits for individuals are not apparent, their acceptance of new concepts is low. Previous studies underline the need for strong data protection practices, but also point out that the protection of privacy for end users is negotiable and that more efforts are needed to understand the willingness to share data. In order to foster a target group specific participation in the ODP, this paper identifies segments of end users based on data from a survey conducted in a climate and energy model region in Northern Burgenland. Results of a fuzzy analysis clustering indicate end user segments that can be labeled as Indecisives, Rejecting, and Open Minded. Whilst the biggest segment, the Indecisives, has an indifferent attitude towards the provision of energy data, the Rejecting show a very low willingness to share their energy data on an ODP. The Open Minded represent a relatively large cluster of 28 % in total. Although this segment (like others) expresses quite strong privacy concerns, it exhibits the highest level of willingness to share household energy data. Respondents in this segment have a higher level of education and predominantly live alone in their household. Furthermore, the results indicate a high sensitivity of willingness to share energy data depending on privacy concerns.

1. INTRODUCTION

The transition from a fuel-based, unidirectional to a renewable, de-centralized energy system requires the widespread adoption of new technological innovations. Energy data generated by smart devices and distributed in a smart grid can be used to improve decision-making process on energy related topics, bring about energy efficiency and grid optimization, which in turn reduces the environmental impact (Visser 2015). Moreover, energy data bear economic value as an important resource for the co-creation of energy services in data-driven business models (Camarinha Matos 2016, Visser 2015). Collaborative networks based on sharing platforms are needed in which energy data as resources are readily exchanged and shared in order to gain mutual benefits from the creation of value-added services (Grönroos 2008, Richter & Slowinski 2019). Novel technologies, which can foster end users' pro-environmental behavior, may require information exchange and data transfer among different stakeholders and, hence, face a lack of acceptance from end users (Fogg 2002).

The paper at hand presents results of the project GEL - OpenDataPlatform (ODP), which aims at contributing to these recent developments by implementing a web-based platform to provide consum-

ers an easy access, an overview and a better understanding of relevant energy data as well as to support behavior change and positively influence attitudes of consumers towards energy efficiency (Hamari et al. 2014).

Therefore, it is essential to understand the platform to be developed as a means of sharing and exchanging data, whereby personal and consumption data from end users are required. Considering all data protection regulations, these data must be provided on a voluntary basis. This voluntariness is questionable, as several studies have shown that individuals are concerned - amongst others - about data security and privacy (Chen et al. 2017). Previous studies underline the need for strong data protection practices, but also point out that the protection of privacy for end users is negotiable and that more efforts are needed to understand the willingness to share data (Silva et al. 2012). Thus, a recent report on energy data in the UK mentions: *“Consumers’ appetite to share data is an underexplored element of the current privacy debate, it may be that consumers are willing to share more data so long as they have sufficient control and receive a fair share of the benefits”* (Energy Systems Catapult 2018, p. 47). Segmentation based on consumer perceptions of the impact of data sharing is a starting point for this (Milne et al. 2017). Consequently, the paper at hand explores which end user segments can be distinguished based on their willingness to share energy data.

2. THEORETICAL BACKGROUND

Digital technologies like cloud computing, platforms and smart devices/IoT (Cao et al. 2016, Rehman & Batool 2015) enable the possibility for data sharing in a broad community between individuals in a convenient way (Huang et al. 2015). Data shared by consumers is on the one hand a monetary asset with which a company can generate income (Zhao & Xue 2013). On the other hand, data sharing platforms serve as peer-to-peer networks enabling the exchange of data and are “[...] *business models which follow various value propositions*” and therefore increase the willingness to share data (Richter & Slowinski 2019).

Several studies investigating data sharing show different factors that are essential for consumers’ willingness to share. Milne et al. (2017) distinguished four end user segments with respect to their willingness to share data, based on their perception of different types of risk (i.e., physical, monetary, social, and psychological risk), sensitivity and willingness to share personal data with marketers. Perceived benefits, like receiving monetary incentives due to sharing data, increase the intention to share personal data and, additionally, decrease internet privacy concerns (IPC), which negatively affect the willingness to share data online (Anic et al. 2018). Tschersich et al. (2016) examined perceived benefits and willingness to share data with regard to the benefits for oneself, others and companies. Their descriptive results show that the willingness to share data for one’s own benefit is highest. With respect to gender, women are less willing to share data. The findings of Lee et al. (2019), who state that women who are 40 and younger have higher IPC than men of the same age, may be an explanation for this. Consumers, who are generally more willing to share personal information, have fewer IPC (Taddicken 2014). Amongst others, Lee et al. (2019) show that age and the level of education positively correlate with IPC. Older people have higher IPC; however, they are less likely to use the internet at all. Particularly younger people with high education have noticeable high IPC.

Beside privacy concerns and trust the factors related to the theory of planned behaviour TPB (Ajzen 1991) can play an important role in explaining willingness to share data. The theory assumes that behavior, which is dependent on the intention, is determined by attitudes, social norms and perceived behavioral control. Regarding attitude, Kranz et al. (2010) found that consumers have a higher intention to use smart meters voluntarily if their attitude towards them is positive. In addition, consumers with a positive attitude perceived their own subjective control about smart meters higher. If consumers evaluate personal information as relevant for their own socialization, they are more willing to share such information online (Hargittai & Marwick 2016). This explains why consumers are often willing to provide very personal data on social media platforms, even if they have privacy concerns. Additionally, Taddicken (2014) states that the higher the social relevance in consumers’ perception, the more likely they are to ignore their own privacy concerns. The lack of control over online-shared information influences the sharing behavior of consumers negatively.

Individuals see a company or a platform owner in the responsibility to provide user-friendly regulations that help to maintain shared data (Hargittai & Marwick 2016). Moreover, perceived control is a very important factor that influences their attitude towards the smart meter technology and indirectly the intention to use smart meters in their households (Kranz et al. 2010).

To date, research results on the willingness to share specific energy data are rare. Energy data that can be traced to the household or an individual is personal data and is consequently subject of the General Data Protection Regulation. Therefore, households must give an active consent to share data (e.g., smart meter data “opt-in”). This consent or willingness to share data depends on the trust and benefit of households (Visser 2015, Deloitte 2017). Only one study could be found that asked households directly about their willingness to share energy data. The report on consumer views on sharing half-hourly settlement data from the UK government regulator Ofgem (2018) showed that energy consumption data are perceived to be least sensitive in comparison to other personal data. In addition, the study shows that almost half of consumers are willing to share their energy consumption data when this is connected to personal benefits (i.e., financial savings, improved energy efficiency) (Ofgem 2018), which partly supports the above-mentioned findings of data sharing in general.

In summary, it is assumed that the willingness to share energy data is determined by one's own benefit, the benefit for others, attitudes, social norms, control perception and privacy concerns. These factors, along with socio-demographic aspects, form the starting point for identifying user segments that are finally willing to share their energy data on the ODP.

3. METHODS

To identify different user segments based on their willingness to share energy data, a postal survey was conducted in December 2019 and January 2020 in a climate and energy model region in Northern Burgenland. Eight municipalities comprise this energy model region with a total of 8 351 households (Statistics Austria 2019). Sampling was designed by drawing one person (above 16) from each household by the “Last-Birthday Method” (Salmon & Nichols 1983). The final sample consists of $n=548$ respondents, thus the response rate was 6.56 %. A sample error of 3.40 % is to be expected.

However, to ensure fully representative statements, weighting was done by means of the standard integrated EU-SILC design (Osier et al. 2006) stated in equation (1).

$$1/C \leq \frac{(q_{ijk}/\bar{q}_{\cdot j})(w_{ijk}/\bar{w}_{\cdot j})}{d_{ijk}/\bar{d}_{\cdot j}} \leq C \quad (1)$$

C is a constant trimming value (which is set to $C=4.50$) to recode extreme weights to more acceptable values, q is the non-response correction, w is the calibration in terms of age, gender, and level of education, and d corresponds to the design weights, each for observation $i=1, \dots, n_j$, from municipality $j=1, \dots, 8$ and household size $k=1, \dots, 4$ as design characteristic.

At the very beginning of the survey, a brief description of an online energy platform was provided. The specific term “ODP” was consciously omitted in order to avoid confusion. Respondents received information that such an online energy platform provides private households the possibility to share energy data anonymously on a voluntary basis. To clarify the term “energy data”, some examples were provided (e.g. electricity consumption of a washing machine or a stove). Possible advantages of an online energy platform were described, such as the possibility to receive tailored information to save energy, or to compare own electricity consumption with other households.

Tab. 1: Constructs to elicit willingness to share energy data

Constructs ¹	Items	Alpha
<i>Personal advantage</i>	In general, I would be willing to share energy data on an OEP ² if I can profit from it. I would be willing to share energy data on an OEP if it provides useful services for me. If I see a benefit for myself, I would in general be willing to share energy data on an OEP.	0.95
<i>Advantage for others</i>	In general, I would be willing to share energy data on an OEP if other people could profit from it. I would be willing to share energy data on an OEP if it provides other people with useful services. If I see a benefit for other people, I would in general be willing to share energy data on an OEP.	0.96
<i>Privacy concern</i>	I am concerned about submitting information on the Internet because of what others might do with it. I am concerned that web sites require too much personal information for registration. I am concerned that someone may use my ID and password illegally. In general, I am concerned about my privacy when I use the Internet.	0.89
<i>Attitude</i>	Sharing energy data on an OEP would be... Very unpleasant ... very pleasant Very bad ... very good Very worthless ... very valuable Very harmful ... very beneficial	0.95
<i>Subjective norm</i>	People who are important to me think I should contribute to an OEP by sharing energy data. People who are important to me would share their energy data. People who can influence me think I should share my energy data.	0.89
<i>Perceived behavioral control</i>	It makes a difference whether I share my energy data on an OEP. Sharing energy-data on an OEP is entirely in my control. I am confident in my ability to share energy data on an OEP.	0.76

1 N ranges between 429 and 548; Alpha = Cronbach Alpha values for mean scales

2 Note: The abbreviation OEP is used according to the questionnaire: online energy platform.

The survey included different constructs that are commonly used in previous studies addressing individuals' willingness to share energy data in general. All items were adapted to the context of sharing energy data on an online energy platform. For all statements, a five-point scale was used, whereby higher values indicate stronger agreement (see Tab. 1). Items used for all constructs were aggregated, and consequently mean scales were computed. *Personal advantage* ($\alpha=0.95$) captures respondents' level of willingness in case they assume a general advantage or useful services whilst *advantage for others* ($\alpha=0.96$) addresses their willingness to share data, if they anticipate said advantages or services for others. Both constructs were borrowed from Tschersich et al. (2016).

The questionnaire also included items to measure *information privacy concern* ($\alpha=0.89$), i.e. if respondents are in general concerned about data security, information sharing and privacy when using the internet. Therefore, four items were lent from Lee et al. (2019). Moreover, constructs from the TPB, lent from Cho et al. (2010), were adapted to the context of data sharing. These include respondents' general *attitude* ($\alpha=0.95$) towards data sharing, *subjective norm* ($\alpha=0.89$), which captures important referents' opinions towards data

sharing, and *perceived behavioral control* ($\alpha=0.76$), i.e. if people think they are able to share energy data if they want to. Furthermore, the way in which social media are used was investigated (i.e. mainly active, partly/partly, mainly passive, not at all).

The questionnaire concluded with several sociodemographic characteristics, i.e. gender, age, highest educational level and household size.

To identify end user segments, a fuzzy analysis clustering (Kaufman & Rousseeuw 2005) was used by minimizing the objective function stated in formula (2).

$$\sum_{v=1}^k \frac{\sum_{i,j=1}^n u_{iv}^r u_{jv}^r d(i,j)}{2 \sum_{j=1}^n u_{jv}^r} \quad (2)$$

The number of clusters is chosen with k , n is the number of observations, u_{iv} denotes the membership of observation i in cluster v (with u_{jv} and j , respectively), r is the membership exponent (which is set to $r=1.10$), $d(i,j)$ the dissimilarity between the observations i and j , calculated by the squared Euclidean distance.

4. RESULTS

4.1 SAMPLE DESCRIPTION AND CONSTRUCTS

Respondents are on average 56.04 years old ($sd=15.11$). 57.84 % ($n=310$) were male, and 42.16 % ($n=247$) female. With respect to the highest level of education, 57.89 % state to have no high school diploma, whilst 26.90 % have one, and 15.20 % hold a university degree. Respondents predominantly live in a two-person household (50.19 %). 14.34 % state to live alone. 16.04 % live in a three-person household, whilst households with more than four persons are also quite frequently present (19.43 %).

The highest mean value (3.84) is observed for privacy concerns, indicating that respondents are rather concerned about sharing information on the internet, or providing personal information, e.g. for registration purposes. Privacy issues in general, and potential misuse of password or ID are also part of this rather broad privacy concern. However, respondents are neutral towards willingness to share energy data, if they anticipate a personal advantage ($mean=3.04$) in terms of general profit/benefit or useful services. A similar result can be observed if respondents assume that their sharing will be useful for others ($mean=2.90$).

All three constructs lend from the TPB exhibit comparatively lower mean values, although the differences are not substantial. Whilst respondents perceive to have – at least to some extent – behavioral control ($mean=3.19$), they tend to show a rather negative average attitude towards sharing energy data on an online energy platform ($mean=2.79$); this result is similar for subjective norm, which means that respondents are more likely directed in a negative direction with respect to sharing energy data ($mean=2.51$).

A weak negative relationship is identified between respondents' privacy concerns and their personal advantages-driven willingness ($r=0.12$). There is no further correlation of privacy concern with any other construct. However, the constructs respondents' willingness to share energy data driven by personal advantages, their assumption that their sharing will be useful for others, their general attitude towards sharing energy data on an online energy platform, their subjective norm, and their perceived behavioral control indicate strong positive bivariate correlations ($r>0.05$; see Tab. 2).

Tab. 2: Descriptive statistics and correlations

	Constructs ¹	mean	sd ²	2	3	4	5	6
1	Personal advantage	3.04	1.29	0.85**	-0.12*	0.71**	0.69**	0.79**
2	Advantage for others	2.90	1.27		-0.08	0.70**	0.74**	0.80**
3	Privacy concern	3.84	1.09			-0.05	-0.01	-0.03
4	Attitude	2.79	1.39				0.59**	0.70**
5	Subjective norm	2.51	1.06					0.74**
6	Perceived behavioral control	3.19	1.14					

1 N ranges between 429 and 548.

2 standard deviation; + p < 0.10, * p < 0.05, ** p < 0.01.

All scales range from 1 to 5; higher values indicate stronger agreement.

4.2 END USER SEGMENTS

Based on the six constructs of willingness to share energy data (see section 3), a fuzzy analysis clustering was performed that supports a three-cluster solution. To represent this cluster solution, a principal components analysis was carried out in advance. In accordance to correlation analyses, the first principal component comprises the constructs personal advantage, advantage for others, attitude, subjective norm and perceived behavioral control with loadings of $0.41 < \gamma < 0.47$. The second principal component is characterized only by the construct privacy concern ($\gamma = 0.98$). In comparing the groups and their willingness level, there are quite big differences among the first principal component (see Fig. 1).

One segment is more toward the average scale values, comprising 42.77 % of the participants, whereas the remaining teenagers belong to two more extreme groups, one with a rather high willingness (28.30 %) and one with a very low willingness to share energy data (28.93 %). The group with the highest level of willingness was named the *Open Minded*, as they had most positive scores in all the constructs. The members of the *Indecisives* had the average level of willingness and the *Rejecting* formed the segment with the lowest willingness to share energy data.

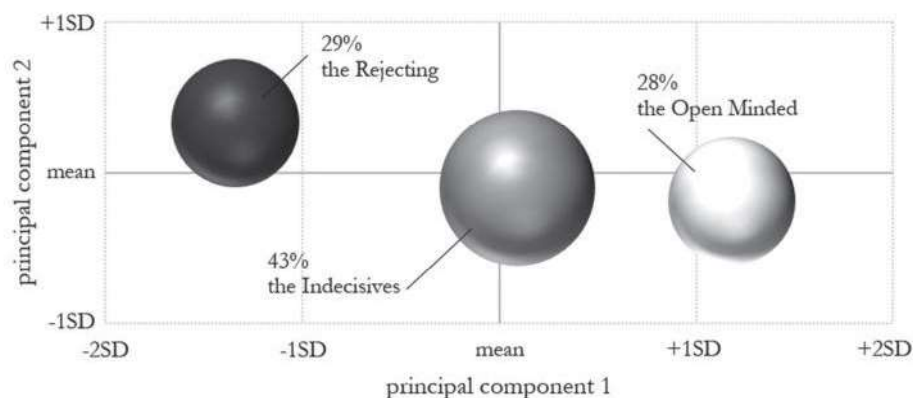


Fig. 1: Cluster proportions according to the constructs of willingness to share energy data

The biggest group, named the *Indecisives*, has an average age of 55.89 years (sd=13.09). Whilst age and level of education is distributed as expected, the Indecisives are characterized rather by households with 2 or more persons. Although their subjective norm is rather weak (mean=2.58), their willingness to share energy data is moderate if they anticipate both a personal advantage (mean=3.18), and the expectation that their sharing will be useful for others (mean=3.02). Their characteristics in terms of behavioral control (mean=3.36) and average attitude (mean=2.77) indicate no direction worth mentioning. However, the members of this group have rather high privacy concerns (mean=3.73).

The *Rejecting* represent a segment with an overproportionate number of females (47.79 %). With an average age of 60.69 years (sd=11.76), they are comparatively older and tend to have no high school diploma (80.00 %). The Rejecting are characterized by very low willingness to share energy data among all constructs. According to this, their privacy concerns are highest among all segments (mean=4.15). They more often do not use social media at all (39.84 %).

In the third segment, the *Open Minded*, the proportion of males (58.65 %) predominates. They have an average age of 58.42 years (sd=12.12). Respondents in this segment tend to have either a high school diploma (18.75 %) or university degree (7.81 %) and predominantly live alone in their household (37.12 %). Although this segment (like others) expresses quite strong privacy concerns (mean=3.64), it exhibits the highest level of willingness to share household energy data. The Open Minded show a very positive average attitude towards sharing energy data on an online energy platform (mean=4.34), perceive quite high behavioral control (mean=4.23) and are driven by personal advantages that they expect from sharing energy data (mean=4.22). In general, this segment is more likely to use social media actively (8.21 %).

Tab. 3: Profiling the user segments and dominating demographic characteristics

	the Indecisives	the Rejecting	the Open Minded
n (%)	204 (42.77 %)	138 (28.93 %)	135 (28.30 %)
Age	55.89 (13.09)	60.69 (11.76)	58.42 (12.12)
Personal advantage	3.18 (0.77)	1.62 (0.95)	4.22 (0.78)
Advantage for others	3.02 (0.78)	1.45 (0.67)	4.12 (0.86)
Privacy concern	3.73 (1.08)	4.15 (1.05)	3.64 (1.04)
Attitude	2.77 (0.91)	1.39 (0.73)	4.34 (0.78)
Subjective norm	2.58 (0.64)	1.43 (0.56)	3.43 (1.00)
Perceived behavioral control	3.36 (0.51)	1.86 (0.88)	4.23 (0.76)
Gender	balanced	female	male
Level of education	balanced	no diploma	at least diploma
Household size	at least 2	balanced	1
Use of social media	balanced	not at all	active

n=477; mean values, standard deviations in brackets.

5. DISCUSSION AND CONCLUSION

This paper examined the willingness to share energy data in a climate and energy model region in Northern Burgenland that comprises eight municipalities. Further, a fuzzy analysis clustering showed that the respondents can be segmented into three different groups that differ in their willingness to share energy data: the Indecisives, the Rejecting, and the Open Minded.

The *Indecisives* have a neutral or even indifferent attitude towards the provision of energy data. In addition, the subjective norm, which is an important factor influencing the willingness to share energy data according to Hargittai & Marwick (2016), is rather weak in this segment. The *Rejecting* show a very low willingness to share energy data. They perceive neither a personal advantage, nor an advantage for other people by making their own energy data available. In this segment the considerable concerns about privacy are also reflected in the extremely low use of social media. This finding is in line with Tschersich et al. (2016), who found a lower willingness of women to share data, and Lee et al. (2019), who identified a connection between women and higher IPC. In slight contrast to the results of Lee et al., the average age in this segment is considerably higher. The *Open Minded* express quite strong privacy concerns but exhibit the highest level of willingness to share energy data. Due to the active use of social media in this segment, the results of Taddicken (2014) and Hargittai & Marwick (2016) are supported. In terms of household size, this segment represents the counterpart to the Indecisives, especially since it is characterized by one-person households with a higher level of education. People in this segment expect both own advantages and advantages for others from sharing energy data.

In respect to the ODP, the primary target group of the Open Minded represents a relatively large segment of 28 % in total. Their characteristics indicate that people living alone (can) devote their leisure time more intensively to the topic of energy and optimizing their own household. Expressed in absolute values, this means an impressive number of $2\,363 \pm 81$ households that are very receptive to voluntarily provide their own energy data to an ODP.

As the results indicate a high sensitivity of willingness to share energy data depending on privacy concerns, possible interactions between privacy concerns and other barriers to data provision remain unclear. Adequate procedures for raising the users' awareness and targeted communication must be found to clarify possible misconceptions or fears among end users. Furthermore, appropriate incentives or added values for the provision of data must be designed. This will enable further valuable data to be utilized for the deployment of an integrated and sustainable energy system.

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Contact:

Christian Pfeiffer

Campus 1

7000 Eisenstadt

Email: christian.pfeiffer@forschung-burgenland.at