Modelling household energy consumption to understand sustainable energy behaviour

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5. Do socio-demographic variables and psychological factors explain sustainable photovoltaics use?

Reducing fossil energy consumption is important to reduce greenhouse gas emissions and to mitigate climate change (IPCC, 2018). Indeed, household energy behaviours are a major contributor to the emission of greenhouse gasses that are largely responsible for current trends in global climate change (Swim, Clayton, & Howard, 2011). Therefore, to mitigate climate change, it is important to promote a sustainable energy behaviour, and reduce fossil fuel consumption by various actors, including households.

One important way to reduce fossil fuel consumption and greenhouse gas emissions is to install residential photovoltaic systems (PV) (IPCC, 2018). The mitigation potential of residential PV would be particularly high if households would adjust their energy demand to the production of their self-generated solar energy (Geelen et al., 2013; Nicolson et al., 2017; van der Kam & van Sark, 2015) rather than demanding energy from the grid as this is currently still mostly being produced by fossil energy sources. Hence, to mitigate climate change it is important that households not only adopt PV, but also use them in a sustainable way (Steg, Perlaviciute, & Van der Werff, 2015), by reducing electricity demand from the grid and delivering electricity to the grid, as reflected in a lower net electricity use from the grid.

Despite the importance of using PV in a sustainable way, to our knowledge, no studies have examined what factors encourage sustainable PV use. Notably, most research has typically focused on understanding which factors are related to total electricity consumption (Bedir, Hasselaar, & Itard, 2013; Đurišić, Rogić, Smolović,

& Radonjić, 2019; Kavousian, Rajagopal, & Fischer, 2013; Kim, 2018; Laicane, Blumberga, Roša, & Blumberga, 2014; Ye, Koch, & Zhang, 2018). Further, some studies have aimed to understand which factors predict PV adoption, including socio-demographic variables (Robinson et al., 2016; Vicente-Molina et al., 2018). These studies have found that households with higher income, older people and household with higher education levels are more likely to adopt PV (Davidson, Drury, Lopez, Elmore, & Margolis, 2014; Islam, 2014; Kwan, 2012; Sigrin, Pless, & Drury, 2015). Next, a few studies have examined to what extent PV owners use their self-generated electricity in a sustainable way. A study found that, in general, Dutch PV owners do not have a lower electricity consumption after sunset than non-PV owners (Bhushan, Steg, Jans, & Albers, 2021), suggesting that PV owners generally do not use their PV in a sustainable way by limiting electricity use during night-time. Another study showed that many Dutch households reported that they do use their PV less sustainably than they anticipated before installing their PV (Peters, van der Werff, & Steg, 2019). However, these studies did not examine differences in sustainable PV use across households, and which factors affect the likelihood that PV owners would use their PV in a sustainable way.

We aim to address this gap in the literature by examining which factors affect net electricity use from the grid as an indicator of sustainable PV use. We define net electricity use as the difference between electricity consumed from the grid and delivered back to the grid by households who installed PV; we consider a household as more sustainable when they deliver more electricity to the grid than they demand from the grid, as this implies that they rely more on their self-generated renewable energy and even enable others to consume renewable energy. We aim to examine which socio-demographic and psychological factors affect net electricity consumption of PV owners. Below, we discuss which socio-demographic and psychological factors may be related to net electricity use.

5.1 Socio-demographic variables that may affect sustainable PV use

Sustainable PV use can be considered as a type of pro-environmental behaviour, suggesting that using PV in a sustainable way could be influenced by similar socio-demographic variables as other types of pro-environmental actions. Literature reviews on the relationships between socio-demographic variables and pro-environmental behaviour suggest that age, gender, household size, educational level, and income are related to different pro-environmental behaviour, including sustainable energy use (Azam, Khan, Zaman, & Ahmad, 2015; X. Chen, Peterson, Hull, et al., 2011; Ifegbesan & Rampedi, 2018; Majcen, Itard, & Visscher, 2015;

Marzouk & Mahrous, 2020; Mastrucci, Baume, Stazi, & Leopold, 2014; Namazkhan, Albers, & Steg, 2019; Olli, Grendstad, & Wollebaek, 2016; Sánchez, López-Mosquera, & Lera-López, 2015; Yan, Wang, Xiao, & Gao, 2015).

First, age seems to be associated with pro-environmental behaviour, yet the direction of this relationship varies per behaviour. Specifically, older people are more likely to engage in energy conserving behaviour and pro-environmental behaviour, such as green consumption, reuse and recycle of materials, and to use public transport to travel from and to work than younger people (Abeliotis, Koniari, & Sardianou, 2010; Hallin, 1995; Olli et al., 2016; Roberts, 1993; Tilikidou, 2007). At the same time, older people are more likely to use more gas to heat their homes than younger people, probably because older people have bigger houses and spend more time at home (Harold, Lyons, & Cullinan, 2015; Kelly, Shipworth, Shipworth, et al., 2013; Majcen, Itard, & Visscher, 2015; Namazkhan, Albers, & Steg, 2020). Therefore, the question remains of how age is related to sustainable PV use; we aim to explore whether age is positively or negatively related to sustainable PV use.

Further, studies showed that women generally act more pro-environmentally than men. This may be because women are more likely to care for others and feel more responsible for others (Eisler, Eisler, & Yoshida, 2003; Lee, Jan, & Yang, 2013; Sánchez, López-Mosquera, & Lera-López, 2015; Xiao & McCright, 2012; Zelezny, 2000). Yet, one study found that gas use is higher when the number of women increases in households, which may be due to the fact that women generally have a lower body temperature and are more likely to show thermal dissatisfaction than men (Namazkhan, Albers, & Steg, 2019). Hence, the question remains about how gender is related to sustainable PV use.

In general, larger households tend to use more energy (Desalu, Ojo, Ariyibi, Kolawole, & Ogunleye, 2012; Hara, Uwasu, Kishita, & Takeda, 2015; Majcen, Itard, & Visscher, 2015; Namazkhan, Albers, & Steg, 2020; van den Brom, Meijer, & Visscher, 2018). This may imply that larger households may be less likely to use their PV in a sustainable way, as they may generally demand energy more from the grid.

A higher educational level is generally associated with more pro-environmental behaviour such as the reduction of overall consumption, and the purchase of green electricity (F.-Y. Chen, Hsu, & Lin, 2011; Rowlands, Scott, & Parker, 2003; Sánchez, López-Mosquera, & Lera-López, 2015; Tilikidou, 2007). On the other hand, a higher educational level is generally related to a higher energy consumption, presumably because people with higher education level are more likely to live in larger houses, which is associated with higher energy use (Boukarta & Berezowska-Azzag, 2018; Harold, Lyons, & Cullinan, 2015; Saeed & Sharawi, 2015). Hence, the question remains of how education level is related to sustainable PV use.

A higher income is generally associated with more pro-environmental behaviour (Ifegbesan & Rampedi, 2018), such as buying organic food (Rimal et al., 2005; Wee et al., 2014). On the other hand, households with higher income are more likely to use more energy, presumably because higher income households tend to live in larger houses (Abrahamse & Steg, 2011; Desalu, Ojo, Ariyibi, Kolawole, & Ogunleye, 2012; Gatersleben, Steg, & Vlek, 2002; Hara, Uwasu, Kishita, & Takeda, 2015; Mashhoodi & Van Timmeren, 2018). Yet, some studies found that households with lower income consume more energy than those with a higher income, as higher income households are less often present in their home (van den Brom, Meijer, & Visscher, 2018). Therefore, the relation of income and sustainable PV use could be positive as well as negative.

5.2 Psychological factors that may affect sustainable PV use

Various psychological factors that promote pro-environmental behaviour may also promote sustainable PV use. First, values may affect sustainable PV use. Values reflect general desirable and transsituational goals that serve as guiding principle in individual's life (Schwartz, 1992). Four types of values are particularly related to pro-environmental behaviour, including sustainable energy use (Namazkhan, Albers, & Steg, 2019, 2020; Steg, 2016): altruistic values (i.e., reflecting concern for other human beings), biospheric values (i.e., focusing on valuing the environment), hedonic values (i.e., focusing on pleasure and comfort), and egoistic values (i.e., focusing on increasing one's personal resources). Values vary in importance and people are motivated to act in line with the values they endorse. Generally, people with stronger altruistic and particularly stronger biospheric values are more likely to engage in sustainable energy use because doing so would protect others and the environment (Steg, 2016; Steg, Perlaviciute, & van der Werff, 2015; Steg, Shwom, & Dietz, 2018). Therefore, it is likely that strong biospheric and altruistic values are also related to more sustainable PV use. In contrast, stronger hedonic and egoistic values generally reduce the likelihood that people engage in pro-environmental behaviour, such as sustainable energy use, possibly because such behaviours are oftentimes associated with less comfort and higher costs (Şener & Hazer, 2008; Steg & Groot, 2012; Stern & Dietz, 1994). Therefore, it is likely that stronger hedonic and egoistic values inhibit sustainable PV use.

Sustainable PV use may also be related to more specific goals, notably the goal to engage in sustainable energy behaviour. Specifically, a stronger sustainable energy use goal is likely to be associated with more sustainable PV use, as people are motivated to act in line with such goals. A sustainable energy use goal is likely to be more strongly related to sustainable PV use than biospheric values, as it is more a behaviour-specific factor (Sloot et al., 2018).

Another general motivational factor that is likely to encourage sustainable PV use is environmental self-identity that reflects the extent to which someone perceives himself or herself as a person that acts pro-environmentally (Van der Werff, Steg, & Keizer, 2013a, 2013b). Environmental self-identity is likely to encourage pro-environmental actions, as people are motivated to act in line with how they see themselves in order to (appear to) be consistent. Indeed, people with a stronger environmental self-identity are more likely to engage in a wide range of pro-environmental behaviours, including sustainable energy use (Dermody, Hanmer-Lloyd, Koenig-Lewis, & Zhao, 2015; Kuswati, Purwanto, Sutikno, & Aritejo, 2021; van der Werff, Steg, & Keizer, 2014; Van der Werff et al., 2013a). Therefore, we expect that a stronger environmental self-identity will also be associated with more sustainable PV use. Environmental self-identity is related to biospheric values: the stronger people's biospheric values the higher their environmental self-identity tends to be (van der Werff & Steg, 2016). Yet, environmental self-identity also depends on other factors, such as previous pro-environmental action. We will examine to what extent biospheric values and environmental self-identity are uniquely related to sustainable PV use, even though they are related.

People are more likely to act pro-environmentally when they feel a stronger sense of moral obligation to engage in pro-environmental behaviour, as reflected in a stronger personal norm to act pro-environmentally (Stern, 2000). People are likely to act in line with their personal norm as this elicits positive feelings such as proud, while not doing so elicits negative feelings such as feelings of guilt. Indeed, many studies have found that a stronger personal norm is related to more pro-environmental behaviour, including sustainable energy behaviour (Ajibade & Boateng, 2021; Ateş, 2020; Geiger, Steg, van der Werff, & Ünal, 2019; Huijts, Molin, & Steg, 2012; Sahin, 2013; van der Werff, Taufik, & Venhoeven, 2019; van der Werff & Steg, 2016). Therefore, we expect that a stronger personal norm to reduce energy consumption is related to more sustainable PV use.

People are also more likely to engage in sustainable behaviour when they think such behaviours would help reduce environmental problems, as reflected in a higher outcome efficacy (Stern, 2000). Indeed, people are more likely to engage in a range of pro-environmental behaviours, including energy saving behaviour when they think these actions would reduce environmental problems (Bockarjova & Steg, 2014; Hiratsuka, Perlaviciute, & Steg, 2018; Huijts, Molin, & Steg, 2012; Jakovcevic & Steg, 2013; Steg & de Groot, 2010; Ünal, Steg, & Gorsira, 2017; Ünal, Steg, & Granskaya, 2019; van der Werff & Steg, 2016; Van Der Werff & Steg, 2015). Hence, we expect that people are more likely to use their PV in a sustainable way when they more strongly believe that doing so would help reduce energy problems.

The different types of motivation discussed above are likely to be related. For example, the Value-Belief-Norm theory (VBN theory; Stern, Dietz, Abel, Guagnano, & Kalof, 1999) suggests that pro-environmental behaviour is more likely when people have stronger personal norms, which are activated when people have stronger biospheric values and a higher outcome efficacy. Yet, VBN theory proposes that each of these variables may still directly affect pro-environmental behaviour as well. Furthermore, the Value-Identity-Personal Norms (VIP) model proposes that stronger biospheric values are associated with a stronger environmental self-identity, which in turn results in stronger personal norms (REF; Ruepert, Keizer, Steg, et al., 2016; Van Der Werff & Steg, 2015). We aim to examine the extent to which each of these psychological variables is uniquely related to net electricity use, even though they may be related.

5.3 Understanding dynamics in actual net electricity use

Importantly, rather than relying on self-reports of electricity use that may be inaccurate, in this study, we rely on the actual electricity usage data obtained from smart meters. Specifically, we examine to what extent sociodemographic and psychological factors are uniquely related to actual net household electricity consumption, i.e., the difference between electricity consumed from the grid and delivered back to the grid of households who installed PV. Notably, net household electricity usage is not likely to conform to a linear pattern, as it varies across the day, and depends on factors such as climate (e.g., temperature and relative humidity) and seasonal changes (Bedi & Toshniwal, 2019; Klaassen et al., 2015; Ploennigs et al., 2013; Zhu et al., 2011). For example, in the Netherlands, where the current study is conducted, electricity use strongly differs across time of the day (e.g., daytime and night-time), month (e.g., summer versus winter), and year (due to yearly variation in temperature). Hence, aggregating electricity usage across time (e.g., day, week, month, or year) is not appropriate as it does not take into account these important patterns. Therefore, extending previous studies, we examine dynamics in net electricity demand, rather than average demand over a given period of time. By including time of use variables, in particular "hour of the day" and "month of the year", as well as the interaction effect between the daily and monthly usage patterns, we are able to capture the non-linear pattern (seasonal effect of electricity demand) of the data.

To this end, we employ a methodological approach, that not only allows us to capture the nonlinearity pattern of net electricity use, but also to examine the differences in dynamic electricity usage patterns across the days and month of a year: a Generalised Additive Model (GAM; Hastie & Tibshirani, 1986; Andersen, 2008; Wood, 2017). GAM allows more accurate modelling by considering the impact of various exogenous variables affecting energy use[15], and more accurate estimates of the effects of socio-demographic variables and psychological factors on net household electricity consumption. This is a major advantage over multiple regression analysis and therefore GAM is likely to provide a more comprehensive insight into factors related to net electricity use. In addition, unlike linear regression models, GAM can deal with the non-linear pattern of net household electricity usage across time.

We extend previous work that examined whether PV owners are likely to shift electricity use to times when their PV production is high, by comparing net electricity use over time of people who did and did not install PV use (Bhushan, Steg, Jans, & Albers, 2021). Notably, we will examine whether PV owners differ in the extent to which they use their PV in a sustainable way, and whether any differences can be explained by the socio-demographic and psychological factors that we described above. In doing so, we focus on net electricity usage as an indicator of sustainable PV use (rather than load shifting behaviour, like Bhushan et al., 2021). We employ GAM to address these questions, which are further explained in Section Data Analysis.

5.4 Method

Data collection

A questionnaire study was conducted among households, who installed a smart meter and PV. Households were members of Buurkracht (Buurkracht, 2018), a network of energy initiatives that aims to promote sustainable energy use in their

15 Specifically, GAM enables to identify the factors that govern the energy consumption through using the proportion of the deviance variance in order to capture the effect of time of day, time of year or temperature as well as anomaly detection and diagnosis of energy use via constructing the prediction band (PB) of the baseline consumption from the previous step (as any observation falling outside the PBs is considered as an anomaly) and computing the submeter that caused anomaly (Ploennigs, Chen, Schumann, & Brady, 2013).

community in the Netherlands[16]. For each household, one person (usually the 'head of the household') filled in the questionnaire that included questions on socio-demographic variables and psychological factors. Additionally, participants were asked to share their electricity data collected via their smart meters with the research team[17]. We collected data on household electricity use from the power grid measured every 15 minutes, based on smart meter readings, in the years 2015 and 2016 (from 1 January 2015 to 31 December 2016). Besides, the smart meters recorded the amount of electricity households generated by PV that was delivered back to the grid. Households pay their power provider for the difference between the electricity they use from and deliver back to the grid. Hence, households receive money when they provide more electricity to the grid than they use from the grid and have to pay the electricity provider when they use more electricity from the grid than they deliver back to the grid. We use this difference, net metering, to obtain the net electricity consumption of each household. We have access to data of 75 households that completed the full questionnaire, installed PV, and gave access to their net electricity use data every 15 minutes over a period of 2 years.

Questionnaire

Socio-demographic variables

Table 5.1 shows the descriptives of socio-demographic variables included in this study. In total 50 males and 25 females filled in the questionnaire[18]. Age ranged from 35 to 71 (M = 57.56, SD = 9.58). Respondents indicated the total net income of their household per month, their household size (number of persons in a household), and the highest educational level they have completed. Most households comprised of two-persons (48% of the sample). Almost 39% of the participants had an academic degree, which is the largest proportion, whereas less than 2% of households had lower vocational education. Around 37% of households had more than 4,000 euro net income per month, while only 4.6% had an income of 2,000 euro or less. Our sample is not fully representative of the Dutch population, which is not surprising as PV are still being installed by a selective group of households, mostly richer and

16 The energy data is from Buurkracht members (4,044 households). Out of the 4,044 households, 1,159 (29%) installed PV on their roofs. Out of the 1,159 total PV owners, 75 households also completed the questionnaire.

17 Explicit consent was given by the participants for the use of electricity data and combining this data with the questionnaire.

18 A possible reason of a higher proportion of male respondents can be that Buurkracht has more male members (Sloot et al., 2018). Another reason could bet that males are more likely to respond to web-based questionnaire than females (Smith, 2008). Furthermore, males are more likely to participate in questionnaire studies on energy than females.

higher educated people. In addition, these are all households who are involved in Buurkracht, thus in some way they are interested and engaged in a sustainable energy transition (Sloot, Jans, & Steg, 2018).

Table 5.1. Descriptive for socio-demographic variables

Variable	Response categories (percentage)
Respondent age	*M* = 57.56, *SD* = 9.58, *Min* = 35, *Max* = 71
Respondent gender	Female (33.31%), Male (66.69%)
Household size (person per household)	1 (8%), 2 (48%), 3(12%), 4 (26.7%), 5 or more (5.3%)
Educational level	Lower vocational education (1.19%), Secondary general education/ vocational education (22.71%), Higher general education/ vocational education (37.34%), Academic education (38.76%)
Income (net per month)	Less than 1,000 euro (1.5%), 1,000-2,000 euro (3.12%), 2,000-3,000 euro (25.94%), 3,000-4,000 euro (32.66%), 4,000-5,000 euro (25.78%), More than 5,000 euro (11%)

Psychological factors

Values. Respondents filled in a value questionnaire with 16 items to measure their altruistic, biospheric, hedonic, and egoistic values (see Steg et al., 2014). A short explanation was given of the relevant values. The scale included four altruistic values (Equality: equal opportunities for everyone; A peaceful world: free from war and conflict; Social justice: restoring injustice, taking care of the weak; Helpful: working for the good of others), four biospheric values (Respect for the earth: living in harmony with other species; Unity with nature: feeling connected to nature; Environmental protection: preservation of environmental equality and nature; Environmental pollution avoid: protect natural resources), three hedonic values (Fun: pleasure, fulfilment of desires; Enjoy life: from food, sex, relaxation; Enjoy yourself: doing pleasant things), and five egoistic values (Social power: control over other people, dominance; Wealth: material possessions, money; Authority: the right to lead or command; Influential: affect people and events; Ambitious: hardworking, aspiring). Respondents were requested to indicate to what extent these values were important to them as a guiding principle in their life, on a 9-point scale (–1 opposed to my values to 0 not important to 7 extremely important). Following Schwartz (Schwartz, 1992, 1996), respondents were advised to distinguish as much as possible between the importance of the values by selecting different numbers, and to rate no more than two values as extremely important, to ensure that participants distinguished between the importance of the different values. The items of altruistic values, biospheric values, hedonic values, and egoistic values formed reliable scales; Table 5.2 provides an overview of the reliability, means, and standard deviations of the value scales. The mean scores indicate that people generally rather strongly endorse biospheric, altruistic and hedonic values, while egoistic values were relatively less important to people.

Sustainable energy use goal. Sustainable energy use goal was measured with three items: I find it important to be conscious about my energy behaviour; I find it important to save energy; I find it important to use more sustainable energy. Respondents indicated to what extent they agree with the items on a 7-point scale ranging from 1 (completely disagree) to 7 (completely agree). The items formed again a reliable scale; the mean score indicates that respondents find it generally important to use energy in a sustainable way (see Table 5.2).

Environmental self-identity. A validated scale was used to measure environmental self-identity, comprising three items: Being environmentally friendly is an important part of who I am; I am the type of person who acts environmentally friendly; I see myself as an environmentally friendly person (Van der Werff, Steg, & Keizer, 2013a, 2013b). Respondents rated each item on a 7-point scale, ranging from 1 'completely disagree' to 7 'completely agree'. The items formed a reliable scale. The mean score indicates that respondents generally see themselves as a person who acts pro-environmentally (see Table 5.2).

Personal norm. Personal norm was measured with two items: I have the moral ideal to reduce my energy consumption; I feel morally obliged to reduce my energy consumption (adapted from Zeiske, Venhoeven, Steg, & van der Werff, 2020). Respondents rated each item on a 7-point scale, ranging from 1 'completely disagree' to 7 'completely agree'. The two items formed a reliable scale. Respondents generally experience a strong personal norm to reduce their energy use (see Table 5.2).

Outcome efficacy. Outcome efficacy was measured with one item: I can make an important contribution to reducing energy problems by reducing my energy consumption. Respondents indicated to what extent they agree with the item on a 7-point scale ranging from 1 (completely disagree) to 7 (completely agree). Respondents generally think they can to some extent contribute to reducing energy problems by reducing their energy.

Table 5.2. Descriptive statistics for the psychological factors

Variable	*Cronbach's alpha*	*M (SD)*	*Min*	*Max*
Altruistic values	.83	5.51 (0.79)	3.25	7.00
Biospheric values	.81	5.38 (0.87)	3.25	7.00
Hedonic values	.82	4.81 (1.11)	2.00	6.67
Egoistic values	.86	2.44 (1.17)	2.00	5.20
Sustainable energy use goal	.82	5.76 (0.72)	4.00	7.00
Environmental self-identity	.80	4.84 (1.02)	2.33	6.33
Personal norm	r =.74[19]	5.45 (1.04)	2.00	7.00
Outcome efficacy	-[20]	4.83 (1.45)	1.00	7.00

Net household electricity consumption

We collected data on actual electricity consumption used from the grid, as well as data on electricity delivered back to the power grid when participants' PV produce more electricity than used at that moment via smart meters. These data were measured every 15 minutes from January 1, 2015 to December 31, 2016. We computed net electricity consumption by taking the difference between the two readings, the electricity consumed from the grid and delivered back to the grid of households who installed PV every 15 minutes, which was included as a dependent variable in the analyses.

Statistical analysis: Generalised Additive Model (GAM)

We used the GAM method (Andersen, 2008; Wood, 2017) to study how the socio-demographic variables and psychological factors relate to net household electricity consumption across the day and month of the year. GAM is an extension of linear regression models. Specifically, with the help of smoothing functions, GAM allows to establish dynamic relationships between net household electricity consumption (the dependent variable) and time of use (in our case the hour of the day and month of the year), socio-demographics and psychological variables (the predictor variables), using a sum of smooth functions of time of use variables, which is very useful for interpretation and visualisation (James, Witten, Hastie, & Tibishirani, 2013; Pathak, Ba, Ploennigs, & Roy, 2018). These smooth terms are used to describe the relationship between the hour of the day and month of the year variables and net electricity consumption. The advantage of smoothing functions of GAM is that they can automatically model non-linear relationship of various forms such as the

19 Personal norm was measured with two items, and therefore, the reliability of two-item measures is assessed by computing a Pearson correlation coefficient.

20 Outcome efficacy was measured with one item, and therefore, there is no reliability coefficient.

ones likely to be encountered in daily and yearly net household electricity usage patterns. In the context of household electricity consumption, this feature allows us for understanding whether net electricity use differs across the hours of the day depending on the month of the year. This may be important, as our data has been collected in the Netherlands where electricity use differs across time of the day, month, and year. Therefore, an interaction effect between the daily and monthly usage pattern (i.e., the electricity usage patterns across a day depending on the month of the year), is added to the model to capture the effect of daily and seasonal electricity demand patterns. Unlike "black-box" techniques (such as boundary value analysis, equivalence partitioning and state transition testing), GAM provides better interpretability as the contribution of each time of use variable, socio-demographics and psychological factors to the prediction is clearly encoded, without compromising prediction accuracy. The other benefit of GAM is that it has more flexibility in handling the non-linear relationships between time-of-use variables and net electricity consumption, compared to the regression model, potentially resulting in more accurate estimations of net household electricity consumption as it typically follows a non-linear pattern over the course of a day and a year.

To perform GAM in this study, we use the "mgcv" package (Wood, 2011) in R programming (Computing, 2020; for more information on the GAM method, see Duchon, 1977; Wood, 2017). The main function used from this package is "bam" which is performed to fit a generalised additive model to the dataset. The model shows the decomposition of GAM into time of use variables as "hour of the day" and as "month of the year". Each time of use predictor variable is selected to be inside the smoothing terms with specified degrees of freedom. The degrees of freedom selection are defined by the "bam" function inside "mgcv" package[21]. The code used for our analyses, is based on the code of Bhushan et al. (2021).

5.5 Results

Table 5.3 displays the results of the GAM to explain net electricity household consumption through the hour of the day, month of the year, the interaction effect between the hour of the day and month of the year usage, socio-demographic

21 The output of GAM, estimated degrees of freedom (edf), stands for the number of effective degrees of freedom. This value represents an estimate of how many parameters are needed to represent the smooth. It shows the complexity of the smooth, and the amount of the non-linearity of the smooth. An edf of 1 is equivalent to a linear pattern. An edf greater than 1 shows a more complex pattern, (i.e., non-linear). Next, Ref.df and F correspond to test statistics used in an ANOVA test reflecting the overall significance of the smooth. The Ref.df value is indicative of the reference number of degrees of freedom used for hypothesis testing (based on the associated F-value).

variables, and psychological factors (please note that the bivariate correlations can be found in Appendix A). The model explained about 11.5% of the variance in net household electricity consumption. Time of use variables explained 9.3% of the variance in net electricity use. Socio-demographic variables and psychological factors predicted an additional 2.2% of the variance in net electricity consumption.

First, the fixed effects of hour of the day and month of the year and the interaction effect between the daily and monthly usage patterns were significantly related to net household electricity consumption. Specifically, the hour of the day smooth has an edf of 20.84 ($p < .0001$), equivalent to a complex relationship indicating that net household electricity consumption depends on the hour of the day. Next, the month of the year smooth has an edf of 8.98 ($p < .0001$), again describing a complex and non-linear relationship indicating that month of the year is significantly related to net household electricity consumption. The significant interaction effect between the daily and monthly usage patterns with edf equal to 211.20 ($p < .0001$) indicates that net household electricity consumption patterns across a day depend on the month of the year. It is not surprising that net household electricity demand is highest during the evening and winter months.

Second, the results indicate that all sociodemographic and psychological factors were uniquely associated with net household electricity consumption[22].

Regarding socio-demographic variables, household size, educational level, and income are positively related to net electricity consumption, indicating that larger households, higher educated people, and households with higher income had a significantly higher net electricity consumption and thus used their PV less sustainably. Age of respondents was negatively associated with net electricity consumption, implying that older people had a lower net electricity use, and thus used their PV more sustainably. Furthermore, females had a lower net household electricity use than males.

As expected, biospheric values and personal norm to reduce energy use had a significant negative relationship with net electricity consumption, implying that people with stronger biospheric values, and a stronger personal norm to use energy in a sustainable way had a lower net electricity use, and thus used their PV more sustainably. In contrast to what we expected, altruistic values, a sustainable

22 The results were very similar when we treated gender, household size, educational level, and income as categorical/ordinal variables in our analysis. Therefore, we report them as the type of numerical discrete variables. For gender, 1 reflects female and 2 male.

energy use goal, environmental self-identity, and outcome efficacy were positively associated with net household electricity consumption, indicating that stronger altruistic values, a stronger sustainable energy use goal, a stronger environmental self-identity and a higher outcome efficacy are uniquely related to higher levels of net household electricity consumption, and thus less sustainable PV use. Moreover, unexpectedly, stronger hedonic values and egoistic values were significantly associated with a lower net electricity use, and thus more sustainable PV use.

Table 5.3. Results of the GAM analysis explaining the net electricity use (kWh) of Dutch households, including time of use (the hour of the day and month of the year), the interaction between the daily and monthly usage pattern, socio-demographic variables, and psychological factors as predictor variables

Independent variables				
Smooth (time-of-use) variables	**Estimated DF**	**Ref.df**	**F**	**p**
Hour of day	20.840	21.000	31324.184	< .0001
Month of the year	8.987	9.000	18173.012	< .0001
Month ´ hour of day	211.200	218.902	728.832	< .0001
Linear variables	**Estimate**	**SE**	**t**	**p**
Age	-0.0058	0.0012	-40.973	< .0001
Gender	0.0250	0.0196	127.438	< .0001
Household size	0.0073	0.0013	7.287	< .0001
Education level	0.0036	0.0066	55.125	< .0001
Income	0.0043	0.0065	66.823	< .0001
Altruistic values	0.0326	0.0017	244.005	< .0001
Biospheric values	-0.0284	0.0019	-208.386	< .0001
Hedonic values	-0.0145	0.0012	-141.786	< .0001
Egoistic values	-0.0027	0.0080	-33.657	< .0001
Sustainable energy use goal	0.0040	0.0016	24.063	< .0001
Environmental self-identity	0.0105	0.0013	79.504	< .0001
Personal norm	-0.0131	0.0012	-105.531	< .0001
Outcome efficacy	0.0169	0.0070	227.333	< .0001

We next examined whether the unexpected relationships may be due to including multiple variables that are related in the same analyses. When inspecting the bivariate relationships between socio-demographic variables and psychological factors and total net electricity use (see Appendix A), we see that most of the variables for which we found unexpected relationships were not significantly correlated with net electricity use. Specifically, hedonic values, sustainable energy use goals, and environmental self-identity seem to be mostly not significantly or very weakly related to total net electricity consumption. Yet, we again found that stronger altruistic values and a higher outcome efficacy are related to a higher net electricity use. However, egoistic values are positively related to total net electricity consumption when the other variables are not controlled for. Hence, the unexpected finding may partly be due to including multiple variables in the analysis that are correlated. Another explanation may be that in the GAM, we considered the dynamics in net electricity consumption, while the bivariate correlation focuses on total net electricity use of households, not taking into account that electricity use varies across time.

5.6 Discussion

This paper examined to what extent electricity consumption of PV owners in the Netherlands can be explained by socio-demographic variables and psychological factors, when controlling for time of use to account for seasonal effects and varied daily energy use patterns, using a novel method, a Generalised Additive Model (GAM). Previous research suggests that, on average, PV owners may not use their PV in a sustainable way, as they do not use less electricity from the grid in the evening and night compared to non-PV owners (Bhushan, Steg, Jans, & Albers, 2021). Moreover, PV owners seem to use their PV less sustainable than they intended before installing PV (Peters, van der Werff, Steg, 2019). Yet, previous studies did not examine whether PV owners differ in the extent to which they use PV in a sustainable way. Extending previous research, we examined whether PV owners differ in the extent to which they use their PV in a sustainable way, and whether any differences can be explained by socio-demographic and psychological factors while controlling for variations in use across the day and year. Moreover, extending previous work, we looked at dynamics in actual net electricity use measured every 15 minutes, rather than average scores over a given period of time.

As expected, the hour of the day, month of the year, and the interaction effect between the daily and monthly usage pattern were significantly related to net household electricity consumption, indicating that net household electricity consumption depends on the hour of the day, the month of the year as well as net household electricity consumption patterns across a day depend on the month of the year. This suggests that it is indeed important that we control for the effect of seasonal and daily electricity demand pattern as net household electricity usage typically follow a non-linear pattern over the course of a day and a year (Klaassen, Frunt, & Slootweg, 2015).

Interestingly, all socio-demographic factors and psychological variables significantly contributed to explaining net household electricity consumption, indicating that both socio-demographics and psychological variables are important to understand net electricity use.

Specifically, older respondents were more likely to use their PV in a sustainable way than younger households. This may be because older people are more strongly motivated to conserve energy and they are more likely to have higher level of environmental awareness and concern for the environment (Franzen & Meyer, 2010; Mtutu & Thondhlana, 2016). Yet, this finding is in contrast to previous studies that found that older households are likely to use more energy than younger households as older people spend more time at home (Harold, Lyons, & Cullinan, 2015; Kelly, Shipworth, Shipworth, et al., 2013; Majcen, Itard, & Visscher, 2015).

Furthermore, males are less likely to use PV in a sustainable way than females. This finding is in line with previous studies that indicate that females act more pro-environmentally than males (Sánchez, López-Mosquera, & Lera-López, 2015; Xiao & McCright, 2014).

Furthermore, larger households were less likely to use their PV in a sustainable way than smaller households. This may be because larger households have bigger houses and more appliances. This finding is in line with previous research indicated that larger households use more energy and are less likely to engage in sustainable energy use (Desalu, Ojo, Ariyibi, Kolawole, & Ogunleye, 2012; Hara, Uwasu, Kishita, & Takeda, 2015; Marzouk & Mahrous, 2020).

Higher educated households, and households with higher income have a higher net electricity use. This may be explained by the fact that higher educated people, and people with higher income own more appliances, and have bigger houses, and generally use more energy in their home (Abrahamse & Steg, 2011; Boukarta & Berezowska-Azzag, 2018; Gatersleben, Steg, & Vlek, 2002; Harold, Lyons, & Cullinan, 2015; Saeed & Sharawi, 2015). Yet, our findings contrast with some previous studies that show that a higher educational level and a higher income are associated with more pro-environmental behaviour, and a higher adoption of green electricity (F.-Y. Chen, Hsu, & Lin, 2011; Ifegbesan & Rampedi, 2018; Sánchez, López-Mosquera, & Lera-López, 2015; Tilikidou, 2007). It may be that people do not know why it is important to use their PV sustainably, and how to use their PV sustainably. The finding that households with higher income have a higher net electricity use is an interesting finding, as it could be assumed that higher income would install more PV, and thus have more options to deliver electricity back to the grid. Our results suggest that this is not the case, as net electricity use is higher among higher income groups compared to lower income groups.

In addition, all psychological factors were related to net electricity use, although not always in the expected direction. Specifically, in line with our expectation, people with stronger biospheric values were more likely to engage in sustainable PV use, probably as they are more aware and concerned about environmental problems, and engage in sustainable PV use as this will protect the environment (Steg, 2016; Steg, Perlaviciute, & van der Werff, 2015). Similarly, people with a stronger personal norm to reduce energy use were more likely to use PV in a sustainable way. This finding is in line with previous research showing that people are likely to act in line with their personal norms (Geiger, Steg, van der Werff, & Ünal, 2019), as doing so makes them feel good (Steg, 2016).

Yet, in contrast to what we expected, stronger altruistic values, stronger sustainable energy use goals, stronger environmental self-identity, and a higher outcome efficacy were related to a higher net electricity consumption. We explored whether these unexpected findings may be due to the fact that we included multiple variables in the GAM that were correlated. Yet, when inspecting the bivariate correlations, we again found that stronger altruistic values and a higher outcome efficacy were related to a higher total net electricity use. Strong altruistic values may inhibit sustainable PV use as people who strongly care for others do not want to restrict others who live in their houses to reduce net electricity use, resulting in a higher net electricity use. The question remains of why a higher outcome efficacy inhibits sustainable PV use, particularly since related indicators of pro-environmental motivation (notably stronger biospheric values and personal norms) to promote sustainable PV use. Yet, hedonic values, sustainable energy use goals, and environmental self-identity seem to be mostly not significantly or very weakly related to total net electricity consumption, while egoistic values were positively (in opposite to what we found in the GAM) related to total net electricity consumption. Hence, the unexpected findings can partly be due to including multiple predictor variables in the GAM that are related; future research is needed to explore this further. Specifically, future research can consider causal relationships between predictor variables, as proposed by a number of theories, such as the VBN theory (Stern et al., 1999) and the VIP model (REF; Ruepert et al., 2016). Such studies would need to employ different statistical models, as GAM does not allow to test of causal chains as proposed by the VBN theory and other theories. Yet, it is also possible that psychological variables affect sustainable PV use in a different way compared to other types of pro-environmental behaviour; future research is needed to explore this further.

Also, in contrast to what we expected, households with stronger hedonic and egoistic values were more likely to use their PV in a sustainable way. These findings are in contrast to previous studies that suggested that people with stronger hedonic values and egoistic values are less likely to act pro-environmentally (Şener & Hazer, 2008; Steg & Groot, 2012). One explanation for the positive relationship between egoistic values and net electricity consumption could be that people can gain money when they use their PV in a sustainable way, as they would receive money when they provide more electricity to the grid than they demand from the grid. Future research is needed to study why stronger hedonic values are also associated with more sustainable PV use.

Our findings have important practical implications, as it reveals which factors could best be targeted to promote sustainable household energy use. Policies could particularly consider socio-demographics related to sustainable PV use by targeting populations that are less likely to use their PV in a sustainable way yet, such as larger households, higher educated households, households with a higher income, older people, and men. Future research is needed to examine which interventions would be most effective to empower and motivate different socio-demographic groups to use their PV in a sustainable way. Moreover, our results suggest that policies could target the psychological factors that are related to net electricity use. Specifically, households can be encouraged to use their PV in a sustainable way by targeting biospheric values and strengthening personal norm to reduce energy use as these appeared to be the main factors that are uniquely and most strongly related to lower net household electricity consumption. For example, personal norm to reduce energy use can be strengthened by increasing individuals' awareness of the environmental consequences of not using PV in a sustainable way. Also, interventions could try to motivate people to prioritize biospheric values more, and by helping people to act in line with their biospheric values by facilitating and enabling sustainable PV use (Steg, 2016). For example, households could be provided with feedback on their net electricity use, so they understand when they would need to reduce their energy demand as to prevent using energy from the grid.

In summary, we found that a range of psychological factors uniquely explain sustainable PV use, next to socio-demographics, but not always in the expected direction. Our findings suggest that sustainable PV use is differently related to some of the demographics and psychological factors than other pro-environmental behaviours. One of the issues is that sustainable PV use not only depends on whether households match the supply and demand of electricity, but also on how many PV they have installed, as people are more likely to have a low net electricity use when they installed more PV than needed to accommodate their energy demand. Therefore, the initial choice of installing many PV allows households to be more sustainable even when people put little effort into reducing electricity demand from the grid, and this may affect net electricity use more than the psychological variables.

A limitation of the current study is the relatively small sample of 75 households, and a sample that is most likely already more engaged with sustainable energy behaviours (i.e., all Buurkracht members). Hence, the samples of our studies were not fully representative of the general population. Yet, the strong point of this study is that our model is built on actual high-frequency energy use data obtained from smart meters, whereas previous studies typically have relied on self-reports to measure sustainable use of PV, which may not reflect their actual net electricity use, and thus sustainable PV use. The high frequency data gathered during a period of 2 years implies that we had sufficient power to accurately estimate the parameters of our model. Still, future research is needed to test the robustness of our findings, using a larger and more varied sample. Moreover, using larger samples would allow us to fully benefit from the dynamic properties of the GAM method. Although, we used GAM to study how socio-demographics and psychological factors are related to net electricity use across the day and month of the year rather than multiple regression models as multiple regression models would not be able to handle the many data points included in our analyses. However, we only considered the smooth functions for the time of use variables, as we could not use the smooth functions (dynamic properties) for socio-demographic variables and psychological factors in our analyses due to relatively small sample. To fully understand the dynamics in net electricity use comprehensive, larger samples would be needed to consider the dynamics for the socio-demographic and psychological factors that help to reveal the graphical relations among these different types of variables over time. Using a larger sample, GAM would also allow us to assess how the specific non-linear net electricity patterns varied depending on demographic and psychological characteristics of people (e.g., female/male, personal norm) while simultaneously taking other socio-demographics and psychological factors in our data into account.

Our model explained about 11.5% of the variance in net household electricity consumption, of which 9.3% was predicted by the time of use variables, while only 2.2% of the variance in net electricity use was explained by socio-demographic and psychological factors. Hence, 88.5% of the variance in net household electricity consumption remains unexplained. Only a modest percentage of the variance was explained by socio-demographics and psychological variables, suggesting that other factors play an important role in explaining net electricity use such as building characteristics and occupant behaviours. However, on a large scale, targeting 2.2% of the variance still is a worthwhile endeavour, and still implies a substantial amount of electricity use. In addition, although our studies included a wider range of factors that may explain net electricity consumption and sustainable PV use than most earlier studies on household energy behaviour, still other factors may be relevant to understand sustainable energy behaviour. Specifically, we did not consider the capacity of each household to generate solar energy that would depend on how many PV are installed, the size of the roof, the orientation of the roof, the presence or absence of shade, and the amount of sun hours, or some households might have a smaller ability to be net deliverer of electricity than others. Therefore, future research could examine to what extent building characteristics (e.g., size of the roofs, number of PV panels) would be uniquely related to net electricity consumption and sustainable PV use. Moreover, future studies could examine which other factors help to explain net electricity consumption and sustainable PV use, such as social norms and occupant behaviours (e.g., the amount of time household members is present in the house).

5.7 Conclusion

We employed a novel method, a generalised additive model, to study whether and which socio-demographics and psychological predictors can uniquely explain sustainable PV use, which we defined as net electricity consumption, reflecting the difference between electricity consumed from the grid and delivered back to the grid of households who installed PV, by relying on actual energy use data obtained from smart meters. We found that besides time of the day and month of the year, a range of socio-demographic variables and psychological factors explain sustainable household PV use, but not always in expected direction.

Appendix A: Bivariate correlations

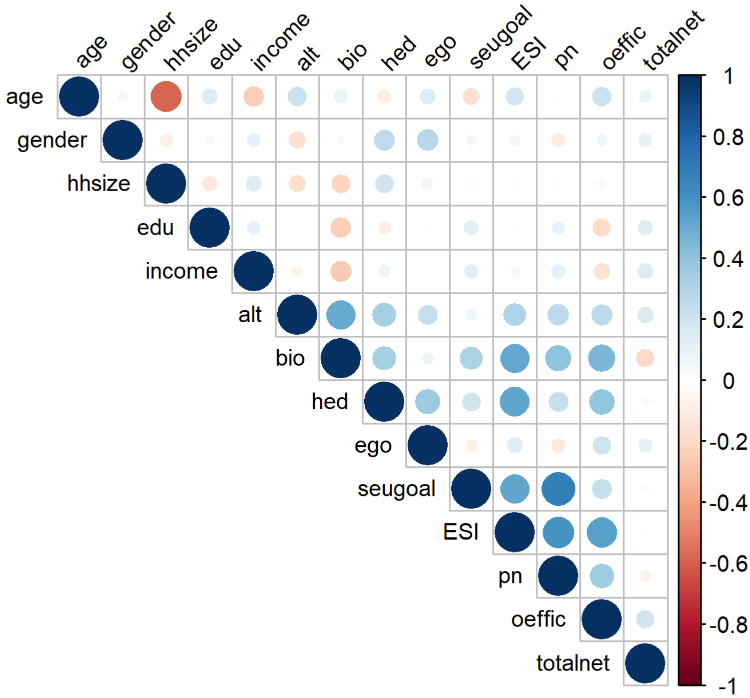

Figure 5.1. Bivariate correlations between total net electricity use, socio-demographic variables and psychological factors. All correlations with coloured dots are significant at the 0.05 level. Correlation coefficients are coloured according to the direction of the relationships. Positive correlations are shown in blue and negative correlations in red. Colour intensity and the size of the circle are proportional to the strength of the correlation coefficients.