Drivers of energy saving behaviour: The relative influence of intentional, normative, situational and habitual processes

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A B S T R A C T

Campaigns aiming to induce energy saving behaviour among householders use a wide range of approaches that address many different drivers thought to underpin this behaviour. However, little research has compared the influence of the different processes that influence energy behaviour, meaning campaigns are not informed about where best to focus resources. Therefore, this study applies the Comprehensive Action Determination Model (CADM) to investigate the relative influence of intentional, normative, situational and habitual processes on energy saving behaviour. An online survey on a sample of Western European households (N = 247) measured the CADM variables and data were analysed using structural equation modelling. Results showed that 1) the model was able to account for a large amount of variance in energy saving behaviour and 2) situational and habitual processes were best able to account for energy saving behaviour while normative and intentional processes had little predictive power. These findings suggest that policy makers should move away from mo- tivating householders to save energy and should instead focus their efforts on changing energy habits and creating environments that facilitate energy saving behaviour. These findings add to the wider development in social and environmental psychology that emphasizes the importance of extra-personal variables in shaping behaviour.

1. Introduction

Domestic energy consumption, including gas, electricity, liquid and solid fuels, accounts for 28% of the UK's total energy use (BEIS, 2018). This energy consumption is associated with significant societal issues such as climate change (IPCC, 2007) and the global energy crisis (Buchan, 2010), and therefore has been the focus of extensive energy policy aiming to reduce householders energy consumption. Despite this policy, and increased energy efficiency in household appliances, no reductions in household energy consumption have been observed in the past few decades (BEIS, 2018), leaving room to optimise these policy efforts. Current behaviour change campaigns targeting energy consumption use a wide range of approaches, which (implicitly) tend to target energy norms, habits, intentions or contextual factors, which are assumed to influence householder's energy behaviour. However, research does not currently provide a consensus on which of these factors have the greatest impact on energy behaviour, leaving energy policy makers uninformed about where best to focus resources. For example, should policy makers aim to motivate householders to save energy (i.e. changing their intentions) or should they create structural environments that facilitate automatic energy saving behaviour (i.e. targeting habits or contextual factors)? Energy policy aiming to reduce householders' energy consumption is likely to be more successful when addressing the key drivers underpinning energy behaviour and/or take away the most important barriers to it. Hence, the current study aims to inform future energy policy targeting domestic energy use by investigating the role of intentional, normative, situational and habitual influences on energy behaviour.

1.1. Stimulating energy conservation

Many behaviour change campaigns use an explicit approach, which aims to elicit (stronger) intentions to save energy. For example, campaigns often emphasise both the environmental and economic benefits

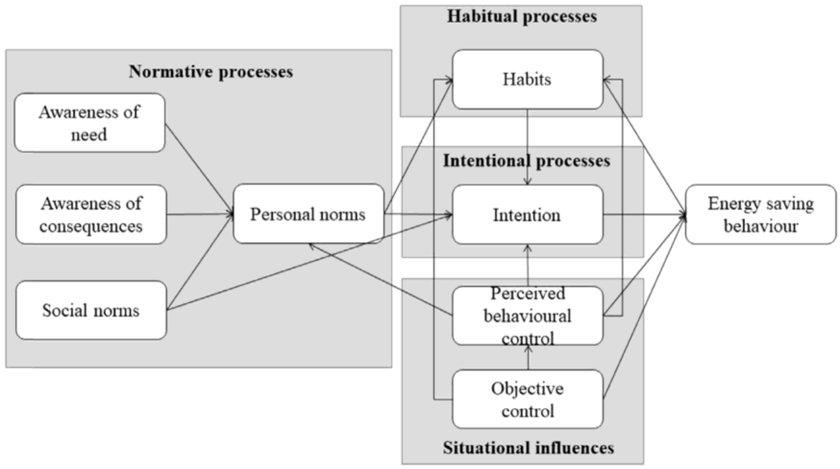

Fig. 1. Comprehensive Action Determination Model adapted from Klöckner and Blöbaum (2010).

of energy saving behaviour although this may not be the most persuasive method (van den Broek et al., 2017). Alternatively, motivational campaigns can involve a type of pledge, where participants pledge to save more energy in the future. For example, the *Student Switch Off* energy saving campaign encourages students to pledge to save energy in their university halls of residence (NUS, 2017). However, previous research on the effectiveness of interventions that involve pledges or goal-setting reports mixed findings (McCalley and Midden, 2002).

Other campaigns have focused on social norms to persuade householders to reduce their energy use. After studies had proven the utility of social norms in feedback on energy conservation (Schultz et al., 2007), this has been implemented by energy company OPOWER to promote energy conservation among its customers (Allcott, 2011). Although this programme was successful, energy use reductions were estimated at only 2.3–2.4%. Perhaps social norms were not utilised effectively or alternatively, social norms are not a key driver of energy use. Behaviour changes that small might also simply represent a Hawthorne Effect, which accounted for 2.7% reductions in energy use in a study that investigated this effect in energy use interventions (Schwartz et al., 2013).

Alternative energy saving campaigns have recognised the habitual nature of energy conservation and focused on changing these habits. For example, the State of Jersey in the United States (2017) provides its citizens with free stickers that remind users to switch off appliances not currently in use. When such stickers are placed in close proximity of where the behaviour occurs they can discontinue energy-squandering habits (Austin et al., 1993). However, this prompting method has been criticised for having weak and only short-term effects (Bell et al., 2001). Finally, policy aiming to reduce householders' energy use has also often focused on introducing structural (i.e. physical) changes to create environments that facilitate efficient energy behaviour or omit the necessity of the behaviour altogether. For example, homes can be designed or innovated to stimulate energy efficiency through home automation, which involves a control system that automates the use of lights, heating, ventilation, air-conditioning, appliances and security. However, research has demonstrated that automation can undermine environmental actions and may impair perceived responsibility to take action (Murtagh et al., 2015) as it leaves householders experiencing a lack of control in their homes (Barkhuus and Dey, 2003). The absence of environmental behaviour and perceived responsibility is likely to prevent positive spill-over effects, in which the engagement in one pro- behaviour increases the likelihood of engaging in other, unrelated pro-environmental behaviours (Thøgersen and Ölander, 2003).

These examples of energy saving campaigns show the wide range of approaches in the field and demonstrates a lack of consensus on the most effective approach. Although previous research has explored the effectiveness of intervention studies aimed to induce domestic energy conservation (e.g. Abrahamse et al., 2005), little research has explored *why* certain approaches work while others are less effective. It is likely that a key factor determining the success of energy saving campaigns is whether the key drivers of the behaviour are being addressed (although these may vary across settings, populations, time etc.). Understanding which factors are the most important determinants of energy use will help policy makers design more successful energy saving campaigns. Therefore, this paper will investigate the relative influence of drivers of energy behaviour.

1.2. Understanding the antecedents of energy use

To assess the relative influence of the different drivers of energy use, a broad framework is needed that includes the relevant variables that influence this behaviour. Dominant theories seeking to explain the antecedents of behaviour include the theory of planned behaviour (Ajzen, 1985), norm activation model (Schwartz, 1977) and value-belief-norm theory (Stern, 2000) but each of these models focus on a different subset of factors that might influence behaviour. A more recent model, the Comprehensive Action Determination Model (CADM), attempts to integrate the theory of planned behaviour (TPB), the norm activation model (NAM) and Ipsative theory to produce a multi-factor model (Klöckner and Blöbaum, 2010) (see Fig. 1).

From the theory of planned behaviour, the CADM borrows the assumption that behaviour follows from behavioural intentions to engage in a particular behaviour (Ajzen, 1985). Although little research has investigated the link between intention and behaviour in the domain of energy use, research investigating this link in other behaviours has consistently found that intention and behaviour only moderately correlate with actual behaviour (Armitage and Conner, 2001; Bamberg, 2002; Rhodes and De Bruijn, 2013; Sheeran and Orbell, 1998), the so-called intention-behaviour gap. Ouellette and Wood (1998) demonstrated that intention only predicts behaviour in situations characterised as difficult and unstable, leading individuals to make conscious decisions to engage in a particular behaviour, which is unlikely to be the case for many daily energy behaviours.

The norm activation model informed the normative components in the CADM. These consist of 1) personal norms (perceived moral obligations to engage in particular pro-environmental behaviour), 2) social norms (the type of behaviour relevant others generally approve of), 3) awareness of need (the level of awareness of the adverse consequences of not acting pro-environmentally) and 4) awareness of consequences (the extent to which individuals believe their own behaviour has negative environmental consequences) (Schwartz, 1977).

In applications of the NAM to energy behaviour, the normative variables (personal norms, awareness of need and awareness of consequences) could not significantly predict energy use (direct and indirect energy use before an intervention that provided householders with tailored information on energy conservation), or energy savings (self-reported change in energy use after the intervention or intentions to save energy) (Abrahamse & Steg, 2009, 2011).

The ipsative theory states that decision-making is influenced by 1) objective constraints, meaning the true circumstances that facilitate or obstruct the implementation of the behaviour, 2) ipsative constraints, which reflect the salient behavioural options available to the individual, and 3) subjective constraints, which are the perceived opportunities and barriers to perform an action (closely resembling the concept of perceived behavioural control) (Tanner, 1999). These factors have been integrated into the CADM as objective constrains and perceived behavioural control, which are grouped under situational influences as they reflect (perceptions of the) situation in which the behaviour takes place. Various situational constraints to energy conservation have been identified such as high (financial and behavioural) costs of energy curtailment and inadequate availability of alternatives (e.g. energy efficient equipment) (Maréchal, 2010; Semenza et al., 2008; Steg, 2008). Such situational processes are likely to overrule intentions to save energy as they may limit a householder's ability to implement such intentions.

In addition to the intentional, normative and situational processes, the CADM also integrates habitual processes into the model. Habits are automatic behavioural responses to contextual cues that facilitate obtaining certain goals or end states (Verplanken and Aarts, 1999). In other words, habits are 1) performed in stable contexts, 2) do not require high levels of cognitive engagement, 3) are successful in achieving certain objectives, and 4) occur frequently. Many energy behaviour are likely to be of habitual nature because these conditions for habits are satisfied for daily energy use: energy consumption is functional, often occurs in stable contexts (homes and work places), can be performed automatically, and occurs frequently (Jackson, 2005; Maréchal, 2010). Macey and Brown (1983) found that frequent energy behaviours were best predicted by past experience whereas infrequent energy behaviours were better predicted from intentions. Considering that strong habits (i.e. a great degree of automaticity of the behaviour in response to contextual cues) can prohibit new intentions from being implemented (Maréchal, 2010; Verplanken and Faes, 1999), habits are likely to have a relatively strong influence on energy behaviour.

Hence, the CADM assumes that environmental behaviour is a result of a trade-off between intentional, normative, situational and habitual processes. Applying the model to energy saving behaviour, we propose that normative processes influence intentions to save energy and energy habits. Energy saving behaviour in turn is expected to be influenced by these intentional processes, as well as by habitual processes, and objective and subjective control to save energy. This model has been applied to travel-mode choice (Klöckner and Blöbaum, 2010), recycling behaviour (Klöckner and Oppedal, 2011; Ofstad et al., 2017), adoption of new heating systems (Sopha and Klöckner, 2011), as well as a range of environmental behaviours (Klöckner, 2013). Importantly, recent qualitative work has used the model as a framework to understanding young adults' own perceptions of the drivers of their energy use (van den Broek and Walker, 2019a). This research showed that these householders 1) did not tend to perceive norms on environmental conservation to drive their energy use, but rather thought monetary incentives motivated them to save energy, and 2) were strongly aware of how their energy habits influenced their behaviour. This study will build on this work by, for the first time, quantifying the relative influence of intentional, normative, situational and habitual processes on energy behaviour.

Since the CADM has been successful in explaining various environmental behaviours (Klöckner and Blöbaum, 2010; Klöckner, 2013; Klöckner and Oppedal, 2011; Sopha and Klöckner, 2011), we expect that this model will also be able to explain individual differences in energy saving behaviour well. This will be reflected in a large amount of variance explained for energy saving behaviour ($r^2 > 0.25\%$, Cohen, 1992) (Hypothesis 1). Furthermore, based on the energy consumption literature reviewed above, we hypothesise that habitual processes (Jackson, 2005; Macey and Brown, 1983; Maréchal, 2010; Verplanken and Faes, 1999) and situational influences (Semenza et al., 2008; Steg, 2008) will be the strongest predictors of energy saving behaviour (as reflected in the highest standardised parameter estimates) (Hypothesis 2).

2. Method

An online survey was conducted that included measurements for all the CADM items in relation to energy saving behaviour. These data were analysed using structural equation modelling to compare the influence of the various variables on the behaviour.

2.1. Participants

The sample consisted of 247 participants, which were mostly young people and students ($M_{\text{age}} = 27.33$, $SD_{\text{age}} = 10.69$, 69.6% female) from Western European countries (67% British, 7% Dutch, 4% German and other nationalities). Since living arrangements are likely to influence energy saving practices, we aimed to include a sample of participants with varying living arrangements (31% living with friends, 28.3% living with a partner, 20.2% living with fellow-students in university accommodation, 19.4% living alone, 4.5% living with parents). Furthermore, 64.4% of the sample paid for their energy bills, whilst 34.8% had their energy bills included in their rent. Participants were recruited through advertisements on online fora (e.g. Reddit) and offline noticeboards (e.g. on university campus) that offered a chance of winning a £100 gift voucher from a shop of their choice in exchange for their participation or, alternatively, undergraduate psychology students could earn course credits with their participation, resulting in a convenience sample. The dataset originally consisted of eight additional participants, but responses for many variables were missing for these participants. The large amount of data missing for these participants made the reliability of their data questionable, and hence, a conservative approach was taken by excluding all data for these participants from analysis.

2.2. Measures

The online questionnaire included scales to assess the relevant constructs of the CADM in relation to energy saving behaviour, see Table 1. We chose an online format rather than paper questionnaires to reach more respondents and allow for a diverse sample. Since the questionnaire was publicly advertised, no response rates can be reported. Scales on other constructs were also included in the questionnaire but these were not used in the analysis of the current paper and will therefore not be further discussed. The questionnaire was piloted with a small sample ($N = 11$), after which some items were slightly reworded to ease interpretation. The CADM variables were measured using Klöckner and Blöbaum (2010)'s items, which have demonstrated good reliability and factor loadings. These questions were adapted to apply to energy behaviour where necessary (e.g. "*Driving a car contributes to climate changes*" became "*Energy use contributes to climate change*") and were rated on a 7-point Likert scale (1 = *Strongly disagree*, 7 = *Strongly agree*). Habits were measured using the self-report habit index (Verplanken and Orbell, 2003) using the same Likert scale where higher values indicated stronger energy habits (i.e. strong degree of automaticity of energy behaviour). To measure objective control of energy use we asked participants whether they could control their thermostat, lights, radiator and washing machine settings (in line with the behavioural items), as a considerable proportion of the sample lived on campus where most residents do not have much control over these settings. Respondents were given three possible answer possibilities (*yes/no/I don't know*), the latter response was coded as missing data, the '*yes*' responses were recoded as 1 and '*no*' as 0 to create a binary variable.

Energy saving behaviour was measured using a self-report measure on daily household energy use that covered a range of household domains (cooking, washing, entertainment etc.). Participants indicated how often they had engaged in 10 different energy behaviours over the past week on a 7-point Likert scale (1 = *Never*, 7 = *Every time*). The daily energy behaviours included better management energy behaviour ("*Putting a lid on a saucepan when boiling water*") and curtailment of comfort behaviour ("*Wearing a jumper instead of turning up the radiator when I'm cold*"). Efficiency investments (e.g. installing insulation) were not included as these types of energy behaviour are unlikely to be daily energy behaviours, and were therefore expected to differ greatly in their antecedents. We inevitably had to measure *past* behaviour as *future* behaviour would reflect intentions to save energy rather than actual energy saving behaviour. Furthermore, reporting on past behaviour instead of current or future behaviour is more likely to reflect actual behaviour and may mitigate biases associated with self-report measures (Gatersleben, 2013). Hence, we will be predicting past energy saving behaviour from current intentions to save energy. Although this may be deemed problematic from a philosophic stance, previous research has successfully predicted past behaviour from current intentions (Harland et al., 1999; Heath, 2002). This issue will be discussed in more detail in Section 4.3.

Some of these variables did not reach the conventional cut-off value of $\alpha = 0.80$ (see Table 1), and therefore the reliability will be further investigated with confirmatory factor analysis as part of the structural equation modelling analysis (see the measurement model test indices in Section 3). This approach has been found to give more reliable and valid results than Cronbach's alpha (Said et al., 2011).

Table 1
Overview of the measurements including their reliability and descriptive statistics.

Variable	Example item	No. Of items per scale	Cronbach's alpha	Mean or %	Standard deviation
Awareness of need	I believe that using energy causes many environmental problems	3	0.77	5.47	1.05
Awareness of consequences	My personal energy use affects the quality of life for future generations	3	0.81	5.14	1.21
Personal norms	Due to values important to me, I feel obliged to use as little energy as possible	3	0.82	4.49	1.32
Social norms	People who are important to me support me when I curtail my energy use.	3	0.67	4.07	1.20
Intention	My intention to use less energy in the next seven days compared to the last seven days for my daily activities (showering, controlling the radiator, doing the laundry etc.) is strong.	2	0.82	3.60	1.57
Perceived behavioural control	Circumstances force me to use a lot of energy	3	0.88	4.24	1.01
Habits	Considering my energy use in my daily activities is something that I do totally automatically.	6	0.91	4.74	1.32
Objective control	Can you control the thermostat in your accommodation?	4	NA	83%	0.27
Energy saving behaviour	Only boiling the amount of water I need in the kettle	10	0.67	5.50	0.89

2.3. *Analysis*

For this analysis, Structural Equation Modelling (SEM) was performed using AMOS software. SEM simultaneously evaluates: 1) how observable variables relate to latent variables through confirmatory factor analysis, 2) the links between latent variables by producing regression parameter estimates, 3) the amount of variance that can be explained in each dependent variable in the model, and 4) the fit of the entire model by producing model-fit indices (Ullman, 2013). SEM therefore produces a much more detailed account of the model compared to alternative approaches such as multiple regression or mediation analysis.

Maximum likelihood estimation (MLE) was employed to estimate the discrepancy between the observed covariance matrix and the model-implied covariance matrix as this is the most effective method available for SEM, especially in smaller samples (Kline, 2005; Lei and Wu, 2007; Norman and Streiner, 2003). In the model specification, no measurement error covariations were allowed. To evaluate the model fit, various indices are reported to ensure diverse aspects of model fit are assessed. The Standardised Root Mean Square Residual (SRMSR) will be reported as an absolute fit measure, where values smaller than 0.10 demonstrate a good fit (Kline, 2005). For a relative fit index, the Comparative Fit Index (CFI) will be reported, where values larger than 0.90 indicate a good fit (Kline, 2005). The Root Mean Square Error of Approximation (RMSEA) will be reported to cover the non-central chi-square distribution indices, where values smaller than 0.06 indicate a good model fit (Hu and Bentler, 1999). The chi-square statistic will be reported, but it needs to be noted that this statistic is very sensitive to small deviations from the model, meaning that the model may be rejected unnecessarily (Bearden et al., 1981).

A key assumption of MLE is that there are no missing values in the dataset (Kline, 2005; Schumacker and Lomax, 2010; Ullman, 2013).

Only a small proportion of the total dataset was missing (1.4%), and was found to be missing completely at random using Little's MCAR Test (χ^2 (3245, $N = 247$) = 3348.53, $p > .05$). Therefore, the data could be imputed using maximum likelihood estimation (Schafer and Graham, 2002). For the objective control items, the estimated values were rounded up or down to the closest binary value.

In order to meet assumptions of multivariate normally distributed variables (Ullman, 2013), skewness was removed from items by transforming variables with skew with a natural logarithm (reverse scoring items with negative skew). Alternatively, other estimation methods could have been used such as Weight Least Square Estimation (WLSE) that does not require multivariate normally distributed endogenous variables. However, this estimation method has been found to be inferior to MLE as the latter method is scale-free and scale invariant (Kline, 2005; Norman and Streiner, 2003). Furthermore, the use of WLSE for the analysis of ordinal data (as measured in this study) tends to result in high levels of bias for the parameter estimates, especially with smaller samples sizes (as is also the case in this study) (Hoogland and Boomsma, 1998). Therefore, a transformation of the skewed variables was preferred (see Appendix A for the transformations).

3. Results

The model was specified by including the factors and links from the CADM (Klöckner and Blöbaum, 2010). Specifically, in this model, behaviour was predicted by habits, intentions, objective and perceived behavioural control. Intentions were specified to be preceded by habits, personal norms and social norms, while habits were predicted by personal norms, objective control and perceived behavioural control. In the model, personal norms were predicted by awareness of consequences, awareness of need, social norms and perceived behavioural control, which in turn was preceded by objective control, see Fig. 2. This diagram includes the model fit and standardised regression weights to allow for direct comparison across parameters, additionally unstandardized parameters are reported in Table 2. This table consists of the measurement model, which includes 1) the observable variables (i.e. the items that measured each construct) and their relation to the latent variable (i.e. the confirmatory factor analysis) and 2) the structural model, which tests the hypothesised relations between the latent variables. The parameter estimates for the covariances and correlations are reported in this table under the structural model.

The results show that the model performs well for energy saving behaviour: habitual processes, intentions and situational influences could account for 61% of variance in energy saving behaviour, confirming the first hypothesis. A post-hoc power-analysis for this fixed factors multiple regression analysis showed that despite the modest sample size, statistical power to reject the null hypothesis that the model explained no variance was 1.0, indicating a sufficiently large sample size if an effect was present (Gatsonis and Sampson, 1989). However, the chi-square results indicate a significant difference between the predicted and observed data. This could indicate a poor model fit, although type 1 errors are likely when the sample size is small ($n < 500$) and the model complex, meaning that the models are rejected unnecessarily (Bearden et al., 1981). Hence, many scholars argue that model fit indices may be more reliable to assess model fit (Lei and Wu, 2007). All the model fit indices demonstrated a good model fit (Hu and Bentler, 1999; Kline, 2005).

Confirmatory factor analysis was conducted to test whether measures of a construct were consistent with the latent variable. The results show that all observed variables (the individual items measured) significantly loaded on the latent variables (the constructs that the observed variables measure) except for the fourth item measuring objective control (controlling lights in accommodation) which loadings bordered on statistical significance (see measurement model in Table 2).

The results of the structural regressions showed that energy saving behaviour was significantly predicted by habits, objective control and perceived behavioural control. Specifically, habits ($B = 0.51$, $p < .001$) was the strongest predictor of energy saving behaviour, followed by perceived behavioural control ($B = 0.25$, $p < .01$) and objective control ($B = 0.36$, $p < .05$), while intentions did not predict energy saving behaviour ($B = 0.06$, $p = .37$), confirming the second hypothesis.

The model was also successful in accounting for 60% of variance in personal norms, which was mainly due to social norms, which was the only significant predictor in this model ($B = 0.50$, $p < .001$). For habits, 43% of variance could be explained by personal norms ($B = 0.52$, $p < .001$) and perceived behavioural control ($B = 0.34$, $p < .001$), while objective control could not significantly predict habits ($B = 0.00$, $p = .98$). Furthermore, the model could account for 34% explained variance in intentions, which was significantly predicted by personal norms ($B = 0.62$, $p < .001$), not social norms ($B = 0.05$, $p = .65$). Finally, objective control was not found to significantly predict perceived behavioural control ($B = 0.03$, $p = .80$) and hence, no variance could be explained in perceived behavioural control.

4. Conclusion and policy implications

This study applied the CADM to assess the relative influence of drivers of energy saving behaviour. Results showed that 1) the model

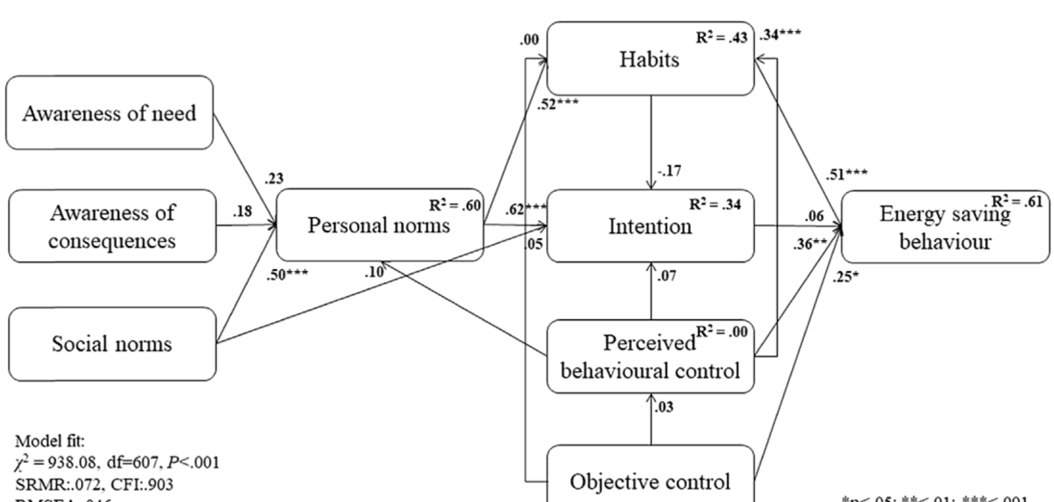

Fig. 2. SEM results for the CADM with standardised regression coefficients and R-squares shown.

Table 2
Detailed results from SEM analysis.

Measurement model					Structural model					
Model Link	*B*	S.E.	*p*	Beta	Model Link	*B*	S.E.	*p*	Beta	R^2
AN→ AN1	1.00	–	–	.70	AN→PN	0.74	.49	.13	.23	
AN→ AN2	0.91	.10	< .001	.72	AC→PN	0.51	.43	.23	.18	
AN→ AN3	1.21	.11	< .001	.80	SN→PN	0.69	.14	< .001	.50	
AC→AC1	1.00	–	–	.76	PBC→PN	0.70	.47	.14	.10	
AC→AC2	0.88	.08	< .001	.72	PN					.60
AC→AC3	1.07	.09	< .001	.80						
SN→SN1	1.00	–	–	.53	OC→PBC	0.05	.29	.80	.03	
SN→SN2	0.98	.16	< .001	.61	PBC					.00
SN →SN3	1.43	.21	< .001	.77						
PBC→PBC1	1.00	–	–	.48	PN→H	0.17	.02	< .001	.52	
PBC→PBC2	1.14	.28	< .001	.37	PBC→H	0.79	.20	< .001	.34	
PBC→PBC3	1.60	.35	< .001	.78	OC→H	0.01	.32	.98	.00	
PN→PN1	1.00	–	–	.79	H					.43
PN→PN2	0.92	.08	< .001	.72						
PN→PN3	1.03	.08	< .001	.78	SN→INT	0.09	.20	.65	.05	
OC→OC1	1.00	–	–	.43	PN→INT	0.79	.17	< .001	.62	
OC→OC2	2.30	.68	< .001	.46	PBC→INT	0.60	.75	.42	.07	
OC→OC3	1.47	.43	< .001	.51	H→INT	−0.68	.36	.06	.17	
OC→OC4	0.54	.28	.05	.19	SN					.34
H→H1	1.00	–	-	.73						
H→H2	0.88	.09	< .001	.61	PBC→BEH	0.44	.17	< .01	.25	
H→H3	1.10	.09	< .001	.79	OC→BEH	1.11	.38	< .05	.36	
H→H4	1.30	.09	< .001	.92	INT→BEH	0.01	.01	.37	.06	
H→H5	1.23	.10	< .001	.82	H→BEH	0.39	.07	< .001	.51	
H→H6	1.27	.09	< .001	.90	BEH					.61
INT→INT1	1.00	–	–	.92						
INT→INT2	0.97	.09	< .001	.86	AN↔AC	.13	.02	< .001	.83	
BEH→BEH1	1.00	–	–	.58	AN↔SN	.15	.04	< .001	.46	
BEH→BEH2	1.17	.19	< .001	.52	AN↔OC	.01	.00	< .05	.23	
BEH→BEH3	0.92	.20	< .001	.36	AC↔SN	.15	.04	< .001	.43	
BEH→BEH4	1.06	.18	< .001	.51	AC↔OC	.01	.00	.11	.17	
BEH→BEH5	1.08	.18	< .001	.51	SN↔OC	.01	.01	.38	.09	
BEH→BEH6	0.87	.19	< .001	.35						
BEH→BEH7	0.65	.15	< .001	.34						
BEH→BEH8	0.85	.19	< .001	.35						
BEH→BEH9	0.66	.18	< .001	.28						
BEH→BEH10	1.19	.21	< .001	.45						

AN = Awareness of Need, AC = Awareness of Consequences, SN= Social Norms, PBC= Perceived Behavioural Control, PN= Personal Norms, OC= Objective Control, H= Habits, INT= Intention, BEH= Behaviour.

was able to account for a large amount of variance in energy saving behaviour and 2) situational and habitual processes were best able to account for energy saving behaviour while normative and intentional processes had little predictive power.

Comparing these findings to application of the model to other domains (see Table 3), the model performs relatively well in terms of explained variance, much better than for recycling, adaptation of new heating systems or in a meta-analysis, which is likely due to the strong habitual nature of energy behaviour. Indeed, this model explained much more variance than a previous application of the theory of planned behaviour to energy saving behaviour which explained 26% of variance, and when combined with the norm activation model, still only 31 % of variance in energy savings could be accounted for (Abrahamse and Steg, 2009). However, the model fit indices show a slightly poorer model fit in comparison to previous applications of the model, which might be a result of the insignificant paths in the model within the normative processes, and between intentions and behaviour. Alternatively, these different findings may be due to the slight differences in model specification across studies.

4.1. *The nature of energy saving behaviour*

The findings of this study provide a novel insight into the nature and antecedents of energy behaviour. This model's ability to explain energy saving behaviour can be attributed to the inclusion of habits and perceived and objective control, as these variables were found to significantly predict behaviour – while this was not the case for intentions. These findings therefore suggest that contextual factors are extremely

Table 3
Model fit indices of this study in comparison to application of the CADM in other domains.

Model fit index	Values indicating good model fit (Cohen, 1992; Hu and Bentler, 1999; Kline, 2005)	Energy saving behaviour (current study)	Travel mode choice (Klöckner and Blöbaum, 2010)	Recycling(Klöckner and Oppedal, 2011; Ofstad et al., 2017)	Adoption of new heating systems (Sopha and Klöckner, 2011)	Various environmental behaviours(Klöckner, 2013)
R^{2} [a]	> 25%	61%	65%	44%, 43%	56%	36%
p-value for χ^2	> .05	< .001	.001	< .001, < .001	< .001	< .001
CFI	> .90	.903	.987	.961, .951	.949	.965
RMSEA	< .10	.046	.032	.027, .055	.052	.071
SRMR	< .10	.072	.032	.036, .054		.023

[a] Explained variance in target behaviour.

important in understanding energy behaviour. Previous environmental behaviour models assumed that behaviour is intentional and that these intentions are formed through a conscious process in which people weigh the consequences of the behaviour and the normative context of the behaviour (Ajzen, 1985). The findings do confirm that this normative process influences intentions, but the results suggest that these energy saving intentions do not tend to translate into energy saving behaviour, in line with previous studies (Abrahamse & Steg, 2009, 2011). Therefore, the findings of this study suggest that the opposite may be true for energy behaviour: this behaviour could be largely unrelated to intentions, and strongly driven by habits and the perceived and objective ability to control energy consumption – echoing findings from previous energy research (Maréchal, 2010; Semenza et al., 2008; Steg, 2008).

Most energy behaviour takes place in stable contexts (homes) where strong energy habits can be formed and this study suggests that these habits may override people's intentions. Indeed, habits have consistently been found to be relevant to energy use (Macey and Brown, 1983; Maréchal, 2010) as energy behaviour is context dependent, automatic and frequent (Verplanken and Aarts, 1999). Furthermore, the strong influence of perceived and objective control on behaviour in this model are likely to be unique to energy behaviour in particular due to the strong context-dependency of the behaviour. However, it needs to be noted that these findings are likely to apply to individuals in stable contexts, i.e. people who tend to consistently live in the same household. Disrupted contexts may result in the behaviour being more dependent on intentional processes again (Bamberg, 2006; Verplanken et al., 2008; Verplanken and Wood, 2006; Walker et al., 2015).

4.2. From motivating to facilitating energy conservation behaviour

These findings suggest that the focus of energy conservation policy should shift from motivating householders to save energy to altering the environment to facilitate this behaviour – particularly in such a way that energy saving habits are fostered. For a large part, current energy conservation policy consists of soft policy measures, which aim to elicit behaviour change by means of information and persuasion. For example, the UK Government informs its citizens of the financial savings that can result from energy conservation practices in the *Green GB & NI* campaign (HM Government, 2018) . However, financial motivators for energy behaviour are only successful if people make rational choices *and* behaviour follows from intentions. The findings of this study indicate that this is unlikely for daily energy behaviour, which helps explain why the introduction of incentives has not always resulted in significant reductions of domestic energy use (Asensio and Delmas, 2015).

Furthermore, research shows that incorporating social norms in energy feedback only results in short-term energy savings (Schultz et al., 2007). Participants themselves also claim that social norms on environmental conservation do not persuade them to change their energy behaviours (van den Broek and Walker, 2019a). The limited effects of social norms on energy behaviour found in the literature are in line with the findings in this study. That is, not social norms, but habits and contextual factors were found to have a strong influence on energy behaviour, which suggests that these factors should be the focus of policy that aims to induce everyday domestic energy conservation. Addressing the factors that have a strong influence on energy behaviour is likely to result in a more effective energy conservation policy because habits and contextual factors may over-ride any influences of social norms or intentions. However, it needs to be noted that these policy recommendations may be limited to the characteristics of the sample that for a large part consisted of students (see Section 4.3).

As such, one could argue that the findings of this study imply that there is little role for psychology in stimulating domestic energy conservation, and that instead energy conservation policy should be based on engineering solutions. In other words, the results might suggest policy makers endeavour to create environments, such as new homes, that facilitate efficient energy behaviour. For example, through home automation, which does not rely on people's motivations to save energy and thereby overcome the reliance on factors that were found to have an indirect influence on daily energy use at most. However, as discussed above, there are various limitations to this approach, not least the impairment of the perceived responsibility and a lack of spill-over effects. A better approach for energy conservation policy might be to take the habitual aspects of energy behaviour into consideration in the design of interventions (Kurz et al., 2015). Specifically, interventions aimed to induce energy conservation may be more effective when taking the *habit discontinuity hypothesis* into account. This hypothesis assumes that behaviour change interventions are more likely to be successful when they coincide with life course changes as this provides a window of opportunity to change habits (Bamberg, 2006; Verplanken et al., 2008; Verplanken and Wood, 2006; Walker et al., 2015). This hypothesis has gained strong empirical support in a study that found that interventions that aimed to stimulate sustainable behaviour (including energy conservation) were most successful among households who had recently moved house (Verplanken and Roy, 2016). Since energy habits were found to be the strongest predictor of energy behaviour in the current study, the findings by Verplanken and Roy suggest an excellent opportunity to improve interventions for energy behaviour and change energy habits. Considering householders' awareness of the strong influence of energy habits on their daily energy consumption (van den Broek and Walker, 2019a), changing energy habits or establishing new energy saving habits may be more straightforward than one might think. We are not aware of any current energy saving campaigns that target householders that are in the stages of moving house specifically, and therefore urge policy makers to consider this target group for future energy policy. Alternatively, policy makers could endeavour to target householders' perceived behavioural control by improving their energy literacy (or understanding of their household energy consumption). For example, research has shown that giving householders simple rules to determine the energy use of their household appliances (e.g. the more heat an appliance produces, the more energy it uses) can improve energy literacy (van den Broek and Walker, 2019b), which may help householders to feel more in control of their energy consumption.

4.3. Limitations and future research directions

This study relied on self-reported past energy saving behaviour, to mitigate biases associated with self-report measures (Gatersleben, 2013), and because retrospective behaviour has been successfully predicted from current intentions in previous studies (Harland et al., 1999; Heath, 2002). However, various authors have warned that predicting past behaviour from future intentions is problematic (Abrahamse et al., 2009; Steg and Nordlund, 2013). To assess the predictive power of intention, alternative models that did not include objective control and habits (the strongest predictors) were run, and now intention *did* significantly predict behaviour in these models. This suggests that the limitations of the measure of intention did not impose a major threat to its validity. Nevertheless, by measuring actual energy consumption rather than relying on self-report data, future research could improve the validity of this measure.

Moreover, the type of energy behaviour that was measured (daily energy use including better management energy behaviour and curtailment of comfort behaviour, but excluding efficiency investments) is likely to have affected the findings in this study. That is, efficiency investments that involve large financial investments or effort (e.g. installing insulation) are more likely to be a result of elaborate thought processes, and therefore intentions. Therefore, habits may have been less predictive of energy behaviour if such behaviour would have been included in this study. It would be valuable if future research could further investigate the impact of intentional, normative, situational and habitual processes on efficiency investments.

Finally, the sample in this study represented mostly young people and students, many living in university accommodation, and more than a third did not pay separately for their energy bills. It may be possible that this latter group is more driven by energy habits than energy saving intentions because they are not responsible for their energy bills. Moreover, their behaviour may be more likely to be determined by objective/subjective control, as university accommodation tends to give residents less freedom to control one's energy use. On the other hand, young people, who tend to have less experience in energy practices compared to an older population, may be less driven by habits as a stable context is an important condition for the development of habits (Danner et al., 2008). Therefore, it remains unclear if the findings in this study only reflect the characteristics of this convenience sample or the population at large. Future research should therefore investigate whether a sample with a wider age range, and more householders in private accommodation, will confirm the findings of this study.

To conclude, through an application of the CADM to energy saving behaviour, this study showed that normative and intentional processes have a limited influence on the energy saving behaviour of this sample. Instead, the findings show that the main drivers of this behaviour are habitual and situational processes. This has important implications for policy makers who are advised to shift from motivating householders to save energy, to changing energy habits and creating environments that facilitate energy saving behaviour.

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Appendix A. Pre and post-transformation scores for indicator variables

Table 2
Skewness of the observed variables before and after transformation

Variable	Original Skew	Skew Post-Transform	Transformation used
AC1	-.57	.51	Reversed Ln(x)
AC2	−1.11	.23	Reversed Ln(x)
AC3	−1.00	.17	Reversed Ln(x)
AN1	−1.29	-.15	Reversed Ln(x)
AN2	-.61	.50	Reversed Ln(x)
AN3	-.88	.14	Reversed Ln(x)
H1	-.42	.51	Reversed Ln(x)
H2	-.05	.89	Reversed Ln(x)
H3	-.70	.35	Reversed Ln(x)
H4	-.70	.30	Reversed Ln(x)
H5	-.70	.27	Reversed Ln(x)
H6	-.55	.41	Reversed Ln(x)
Int1	.15	–	
Int2	.15	–	
SN1	.18	–	
SN2	-.31	–	
SN3	-.20	–	
PBC1	−1.0	.63	Reversed Ln(x)
PBC2	−1.47	-.24	Reversed Ln(x)
PBC3	-.430	.28	Reversed Ln(x)
PN1	-.19	–	
PN2	-.32	–	
PN3	-.19	–	
OC1	−4.22	–	
OC2	-.84	–	
OC3	−3.20	–	
OC4	−3.20	–	
Beh1	−2.33	−1.07	Reversed Ln(x)
Beh2	−1.54	-.85	Reversed Ln(x)
Beh3	−1.00	-.52	Reversed Ln(x)
Beh4	−2.00	−1.28	Reversed Ln(x)
Beh5	-.75	.01	Reversed Ln(x)
Beh6	−1.01	-.49	Reversed Ln(x)
Beh7	−1.36	-.30	Reversed Ln(x)
Beh8	-.72	-.14	Reversed Ln(x)
Beh9	-.82	-.06	Reversed Ln(x)
Beh10	-.48	.02	Reversed Ln(x)
Squared total skew prior to transformation			−35.68
Squared total skew post-transformation			−4.68

AN = Awareness of Need, AC = Awareness of Consequences, SN= Social Norms, PBC= Perceived Behavioural Control, PN= Personal Norms, OC= Objective Control, H= Habits, INT= Intention, BEH= Behaviour.

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