CRANFIELD UNIVERSITY

OMOLOLA ADESAYO AYANGBAYI

UNDERSTANDING FACTORS THAT INFLUENCE ENERGY SAVING CAMPAIGNS USING THEORY AND AGENT BASED MODELLING.

SCHOOL OF WATER, ENERGY AND ENVIRONMENT

PhD

Academic Year: 2017 - 2018

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This thesis is submitted in partial fulfilment of the requirements for the degree of PhD

ABSTRACT

Utilising data from a sample of UK HEI students, this study investigates factors that influence informational interventions for energy saving. It makes an original contribution by developing an original method for testing theory and explaining how known persuasion and behavioural variables can interact to influence behavioural outcomes. It achieves this by integrating two empirically established theories—the Theory of Planned Behaviour and the Elaboration Likelihood Model—and using these, develops an agent-based model based for explaining behavioural response to an energy saving intervention. In a first phase, questionnaire surveys based on the stated theories are used to elicit essential information relating to energy use among students. Findings demonstrate that both theories can be used successfully as a framework for understanding how information-based interventions influence energy use. The second phase involving agent-based modelling demonstrated that although the adoption of energy saving behaviour is time-dependent, it is neither proportional to population size nor to time. Further findings show that s*ubjective norms* such as the opinions of important others, significantly influence students' intentions to save energy; and maximum levels of peripheral cues, personal relevance and cognitive ability are individual factors which determine the highest levels of aggregate energy saving. Interrelationships observed among variables indicate that the degree to which cognitive, social, environmental, and situational factors etc. interact in the face of persuasive information, may be more instrumental to achieving desirable energy behaviours than the communication of useful information or even, the information itself. Ideas and findings from the study will be useful for informing the design of behavioural interventions. Further research to investigate the affective tendencies of subjective norms and any effects on attitude and the intention-behaviour gap will be useful for gaining more insight which may help extend the *Theory of Planned Behaviour.*

Keywords:

Agent-based model, Attitude, Behaviour, Behavioural interventions, Elaboration Likelihood Model, Energy conservation, Informational interventions, Peripheral cues, Persuasion, Theory of Planned Behaviour, Simulation, Subjective norms.

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LIST OF ABBREVIATIONS

ATP	Ability to Process
BTS	Bartlett's Test of Sphericity
CURES	Cranfield University Research Ethics System
EEA	European Environment Agency
EFA	Exploratory Factor Analysis
ELM	Elaboration Likelihood Model
ESB	Environmentally Significant Behaviour
FA	Factor Analysis
GHG	Greenhouse Gases
KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
NAM	Norm Activation Model
PBC	Perceived Behavioural Control
RMSE	Root Mean Squared Error
SN	Subjective Norms
SPSS	Statistical Package for Social Sciences
SSO	Student Switch Off
TPB	Theory of Planned Behaviour

1 INTRODUCTION

1.1 Background and Rationale

Despite the continued use of information campaigns to create awareness and encourage energy saving behaviours, significant levels of success are often not achieved even where attitude change and increase in knowledge are recorded (Costanzo et al., 1986). Unfortunately, an incomplete understanding of barriers to desired behavioural change frustrates the potentials of these interventions (Stokes et al., 2012). The thought that information availability and educating are enough to cause targeted changes in attitudes and consequently behaviour is simplistic and flawed; especially where targeted changes are in the collective behaviour of a group or system. Consumer behaviour is complex, even at the level of the individual; therefore, simplistic recommendations for change should be carefully considered (Jackson, 2005). The provision of information, though necessary is only one of a wide range of factors that can influence pro-environmental behaviour (Stokes et al., 2012).

1.1.1 What problem does this study seek to solve?

This study seeks to explain the problem of informational interventions designed to reduce energy use not achieving success.

1.1.2 The Problem Statement

An informational intervention is the use of information or education to promote a target behaviour. Informational interventions depend on persuasion and knowledge to succeed. It is assumed that persuading people about the need to save energy and providing information on how to do so will motivate the desired behaviour change. Delmas et al. (2013) suggests that there is no concrete empirical evidence as to whether information-based interventions are effective or ineffective. However, other studies show that informational campaigns are mostly unsuccessful (Ramos et al., 2015; Staats et al., 1996) with the awareness of the need to save energy, changed attitudes and having the intention to act, often not resulting in energy saving behaviour (Godin et al., 2005). This is known as the attitude/intention-behaviour gap (e.g. Carrington et al. 2010; Bhattacherjee & Sanford 2009; Mohiyeddini et al. 2008; Froehlich 2009; Abrahamse et al. 2005) Identifying variables that play a potentially significant role in this disconnect and studying the significant relationships among them are important for energy saving interventions—for evaluation, understanding success/failure and creating lasting tailored solutions. In this study, these will be achieved by using two established behavioural theories— the Elaboration Likelihood Model and the Theory of Planned Behaviour. From a methodology perspective, this is beneficial because such theories have a standard set of constructs which have been tested in different contexts and used by researchers to provide insight in various fields of study (Dale et al., 2001). More so, as asserted by Lewin (1951), "there is nothing as practical as good theory." Unfortunately, the use of "theory, pre-testing or the measurement of impacts" are deemed scant in existing evaluation methods for energy-related behavioural interventions (Matthies and Trondheim, 2009; Wilson, 2014).

Furthermore, Abrahamse et al. (2005) points out a need to go beyond showing the degree to which interventions have been successful to offering insights into why. As a contribution towards filling these research gaps, agent-based modelling will also be used to support the theoretical approach. This modelling approach is used because it can subject theories to the pressure of different scenarios and create phenomena that can emerge from the microlevel relationships being investigated within the system. This level of information will be useful for making deductions based on the dynamics of both individual and collective behaviour within a system and provide explanations for salient issues such as the attitude/intention-behaviour gap in energy saving. **Figure 1.1** illustrates the approach used to achieve the study's aim and objectives.

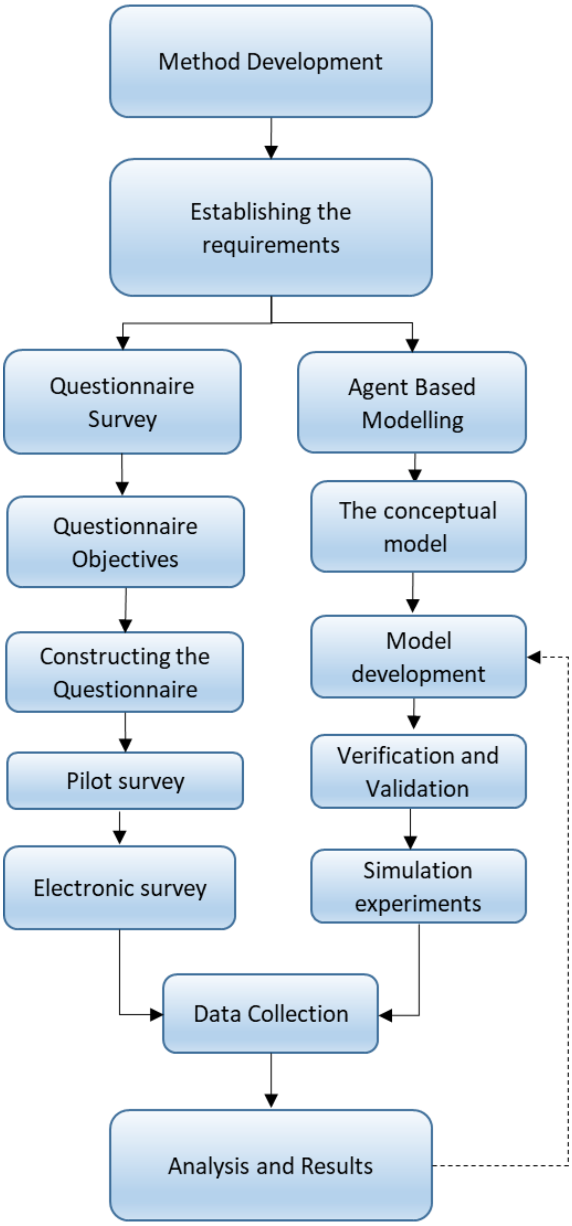


Figure 1.1 The study's approach to investigating the topic

1.1.3 **Justification for a theory-based approach**

Behavioural theories help us understand decision making by providing explanations for behaviour and identifying the significant drivers for such behaviours. Where interventions have been designed to target specific behaviours, theories can also provide a framework within which their impact can be empirically investigated. These characteristics are especially applicable for understanding decision making and behaviours in relation to environmental conservation (Jackson, 2005).

In using a theory-based approach, this study exceeds typical evaluation (e.g. effective vs. ineffective) to understanding reasons and contexts behind decisions and actions for energy saving or the lack of it.

1.1.4 **Justification for using the Elaboration Likelihood Model and the Theory of Planned Behaviour over other theories of behaviour.**

When deciding or making a choice to act in a certain way, several factors play a role. Some more strongly than others. Important factors to consider when seeking to understand how people make decisions include: information and knowledge about the decision, individual level factors such as attitudes, contextual factors that could act either as a driving force or a limitation, the effect of cues, and the influence of others i.e. normative factors (Olson and Jacoby, 1972; Stern, 2000).

In understanding success factors for informational energy saving interventions, it could be argued broadly that there are two streams of investigation—the message of the intervention and the target behaviour.

Considering that environmental communication is essentially about persuasion, the message component of this research is investigated using a known persuasion theory, the Elaboration Likelihood Model (Petty and Cacioppo, 1986a). It is a message-oriented theory of attitude change and deemed well suited for the study because it gives insight into the effect of information on attitude by addressing not only core variables such as motivation in the recipient but also external factors such as the quality of the argument and rating of the communication source (Petty and Cacioppo, 1986b; Wilson, 2014). These attributes could be extremely useful in explaining interventions in which knowledge acquisition did not result in the desired change in attitudes and behaviour. Other theories of persuasion which were considered are the cognitive dissonance theory (Festinger, 1957) and inoculation theory (McGuire, 1962).

Cognitive dissonance theory was developed by Leon Festinger in 1957 (Aronson, 1969; Stone and Cooper, 2000). It “is a negative, unpleasant state that occurs whenever a person holds two cognitions that are psychologically inconsistent” (Aronson, 1968). When faced with choices, people often struggle with conflicting thoughts and when a decision is made, there might be a feeling of dissonance at thoughts of either disadvantage(s) associated with the choice made or missing out on the benefit(s) of the rejected option. Examples of methods used to alleviate this inner discord are playing down choices made and suppressing thoughts of any problems associated with the decision and sticking to it (Perloff, 2003). An example from marketing is dieters being offered sugar-free versions of foods and drinks (Dainton & Zelley, 2004)

In an environmental context, cognitive dissonance may be used by introducing ideas that contradict environmentally unfavourable thought patterns. Although people may reduce cognitive dissonance in several ways, attitude and behaviour change are not guaranteed choices (Klöckner, 2015).

In terms of the theory's relevance to this research, cognitive dissonance can be used to explain contradictions in environmental attitudes and behaviours (e.g.Thøgersen 2004). However, because its focus is more on attitudes and behaviour and less on individual elements that influence their formation, it is likely to be a less useful tool for understanding the "why" behind attitude and behaviour formation.

Inoculation theory (McGuire, 1962) is based on the idea of protecting existing beliefs and attitudes from undesirable persuasion by providing weak arguments from the undesirable position. The logic is that by refuting these weak arguments, recipients are prepared for stronger arguments and can resist contrary persuasion. Although, this theory can be tested and has proven to have good predictive power in marketing and health-related fields, only limited support is found for it in the sphere of environmental studies (Klöckner, 2013). In terms of providing explanations for understanding energy saving intervention success, the theory's focus on attitudes and beliefs is likely to be more valuable for testing attitude certainty. Also, it does not allow for the assessment of new information provided by an intervention unlike the Elaboration Likelihood Model.

The target behaviour—energy saving, is considered largely rational as it is being investigated in response to an intervention, and this requires conscious effort. However, it is understood that non-rational factors also play a role in the making of such choices. Choosing to reduce energy demand is a decision often based on an evaluation of outcomes such as personal economic gains e.g. lower energy bills, or the “feel-good” factor of helping the environment (altruism). The TPB ticks the boxes as a theory well suited for investigating rational behaviours. This has been criticised as a limitation of the theory which has been extended by adding on other constructs, in some studies (e.g. Chan and Bishop, 2013; Filatova et al., 2013; Klöckner, 2013; Manstead and Parker, 1995). For example, adding habits to account for habitual behaviours (Conner and Armitage, 1998). However, it is well supported empirically and has been used successfully to identify and investigate determinants of pro-environmental behaviours (Conner and Armitage, 1998; Greaves et al., 2013a).

In many aspects of life, it is common to find individuals behaving contrary to their stated attitudes. The area of energy use is not left out and could be attributed to the energy attitude-behaviour relationship not being a straightforward one. There are often other mediating factors to consider. The Theory of Planned Behaviour explains this by showing an inter-relationship between antecedent beliefs, attitudes, social norms, perceived behavioural control, intention and behaviour (Ajzen, 1991).

Another theory that can provide useful explanations for the study is the norm activation Model (Onwezen et al., 2013; Schwartz, 1977). This theory explains altruistic behaviour highlighting personal norms as a direct predictor of behaviour. In this regard, it is favoured for describing the moral contexts of environmentally significant behaviours over the TPB. However, the norm activation theory lacks the straightforwardness of the TPB and has been criticised for not being formalised (Han, 2014). These factors have brought about considerable differences in the methods by which it has been applied and tested, leading to less conclusive results than the TPB (Klöckner, 2013). Attention has been drawn to the norm activation theory not being very capable of explaining environmental behaviours. Studies show that when personal norm was added to the TPB to explain environmental behaviours, contrary to the posit of the norm activation theory, the influence of personal norms on behaviour was mediated by intention (Klöckner 2013b; Bamberg & Möser 2007; Bamberg & Schmidt 2003). In terms of explaining the effects of informational interventions on behaviour, the NAM does not clearly consider the role of new information on personal norms neither does it have any clear links with other message-oriented persuasion theories unlike the TPB which shares the attitude construct with the ELM.

Other theories that have been used in environmental studies to explain behaviour include the theory of interpersonal behaviour (Triandis, 1977), goal framing theory (Lindenberg and Steg, 2007), value-belief-norm theory (Stern, 2000). However, the Theory of Planned Behaviour was deemed most suited for the study not only because of the empirical support it has received, but also because of its potential to extend the ELM via its attitudinal element while also considering normative and control factors.

1.1.5 Justification for using modelling

To understand how interrelationships among the theoretical variables may influence energy saving behaviour in response to persuasive information, it is vital to explore how various combinations of the theoretical variables being studied can produce useful outcomes. Mathematical/statistical methods such as correlation and multiple regression analyses are often used for this purpose (e.g. Corradi et al., 2013; Lynne et al., 1995; Miniard and Cohen, 1981; Park, 2000; Peng et al., 2015; Thondhlana and Kua, 2016) and are initially applied in the first phase of the study. Although the value of such methods is not being reduced, certain considerations leading to the additional use of modelling (simulation) were made. These include the fact that mathematical/statistical analysis mainly depicts a point in time compared to modelling which can be dynamic. Also, varying multiple parameters can easily become complicated and muddled up during mathematical/statistical analysis (Jager and Mosler, 2007; Law, 2015).

Being able to create a representation of a real system, modelling is a valuable tool that can be used to gain some understanding of possible ways the system can behave in different scenarios. Although there are several types of models e.g. physical, mathematical, simulation models etc., models are generally made up of assumptions depicted as mathematical or logical relationships. Where these relationships are simple enough, mathematical methods such as algebra, calculus or probability theory may be sufficient for rigorously extracting answers to questions of interest. However, such analytic solutions are not always adequate for understanding the complex nature of real-world systems. For real-world complex systems, computer simulation can be used to numerically evaluate a model and generate data which can be used to estimate and make inferences about the required attributes of the model (Law, 2015). However, a model is only as good as its design (Azar and Menassa, 2014; Jager and Mosler, 2007).

Simulation modelling is used in this study to support the initial findings from mathematical methods used i.e. correlation (to determine straightforward relationships) and regression (to determine causality). Due to the advantage of being able to represent real and complex systems without associated risks, simulation experiments can be conducted flexibly and repeatedly to investigate and understand structures and behaviours of the target system, under different conditions (Borshchev Andrei, 2013). Therefore, the expectation is that this will generate information on some characteristics of interest e.g. heterogeneity in target populations and behavioural outcomes which are critical for understanding the impact of interventions designed for energy saving and efficiency (Jager and Mosler, 2007; Wilson and Dowlatabadi, 2007) but cannot be explained using mathematical methods (Law, 2015). This way, the use of simulation modelling adds value that cannot be achieved using mathematical methods alone.

Three popular methods in simulation modelling are discrete event modelling, system dynamics and agent-based modelling (Marshall et al., 2015). *Discrete event* modelling is best used to model a system as a process with a sequence of operations (or events) as typically represented in a flowchart (Borshchev, 2013; Eldabi et al., 2002). This type of simulation modelling on its own may not be well-suited for studies such as this one, where relationships can be indirect and non-linear. However, it could be combined with other simulation methods in a multi-method model.

Central to *system dynamics* are the feedback loops within a system. These feedback loops account for circular causal dependencies within the system. This method takes a top-down approach to modelling a system in that it looks at a system from an aggregate level (Law 2015; Sterman 2000). These characteristics imply that it may be useful for investigating dependencies that produce energy saving behaviour or the lack of it within a system. However, unlike agent based models which are more accommodating of random or probabilistic components, system dynamic models tend to be more deterministic in nature (Law, 2015).

Agent based modelling (ABM), a more contemporary modelling approach than *systems dynamics* and *discrete event*, is a bottom-up modelling approach and can provide deeper insight into systems that cannot be adequately depicted by traditional modelling methods (Law, 2015; Wilensky and Rand, 2015). The modelling method of choice in this study is ABM because it is useful for modelling heterogeneous systems, where interactions between members are important and social learning is expected or believed to occur (Gilbert, 2008). While a single universal language for ABM does not exist, features such as state charts and object oriented programming often characterise ABMs and are used when defining agent behaviours and interactions within a model (Borshchev, 2013). ABMs have successfully been used in energy behaviour studies. Published ABM-energy research include Azar and Menassa (2014)—a model of the impact of interventions on occupants' behaviour in commercial buildings in the United States and Jensen et al. (2015)—the impact of feedback devices on household heating use and diffusion of such devices. UK based examples include Snape et al.'s (2011) model on examining the effect of individual behaviour and social learning on energy use patterns and Natarajan et al.'s (2011) work on modelling UK domestic energy and carbon emissions.

Sometimes, the three approaches discussed are used within a model to best capture different aspects of a system. This is known as a multi-method model.

Also, internal dynamics of agents in an agent based model may be depicted using the discrete event or system dynamics approach (Borshchev, 2013).

1.1.6 Why Agent Based Modelling?

The aim of using ABM in this study is to integrate agents and environments in settings representative of the real world. This will enable an experimental study of the social processes that can influence energy behaviours and an investigation of 1) how and 2) the extent to which macro energy saving behaviours emerge over time and across different scenarios. The outcome will provide decision support for policy and intervention designers.

Achieving these involves testing the theories of interest by analysing their independent variables which are also the same as the micro-drivers; so, rather than just accepting these variables as model inputs that lead to certain behaviours, focus is also directed at these variables. This is vital for improving or developing theories of energy use that will contribute towards providing adequate explanations for complex energy systems.

To successfully exploit the opportunities that exist in consumer behaviour for managing the energy resource and achieving climate change related goals, it is important to understand the reasons behind consumer choices, how they respond to information about the advantages and disadvantages of those choices and how energy related interventions influence behaviour individually and collectively (Rai and Douglas Henry, 2016).

A good understanding of these will contribute towards the design and creation of policies and programmes that will reduce climate change without negatively affecting human wellbeing. However, the complexity of consumer energy behaviours poses a limitation to conventional methods such as system dynamic models, which have been used considerably to investigate energy systems.

ABM is useful for demonstrating the complexities of consumer behaviour in ways that can improve the understanding of energy demand and its management (Natarajan et al., 2011). It is also practical for testing theories (Smaldino et al., 2015) and experimental modelling of energy demand systems (Jager and Mosler, 2007).

Economic modelling approaches—such as systems dynamics and dynamic discrete choice—used for understanding consumer energy choices and demand tend to assume that consumers are rational actors (Rai and Douglas Henry, 2016). However, behavioural research shows that this is not quite the case (Wilson and Dowlatabadi, 2007). The assumption of rationality in modelling consumer choice can pose problems. For example, dynamic discrete models often equate collective agent expectations to actual market outcomes (Sargent, 2008). However, in real life, various factors could influence expectations e.g. consumers may lack prior knowledge or experience on which to base their expectations and this could invalidate predictions for actual market outcomes (Rai and Douglas Henry, 2016). In cases like this, social networks and interactions are valuable for transferring information and in the process, can shape beliefs, opinions and in due course behaviour. Regarding energy behaviours, social networks can play a significant role as a provider of energy related information such as new technologies and interventions for conserving energy. Furthermore, they can influence the adoption of energy saving behaviours by influencing normative beliefs about energy saving, its advantages and any perceived disadvantages.

Empirical studies (e.g. Carrico and Riemer, 2011; Costanzo et al., 1986; McMichael and Shipworth, 2013; Nolan et al., 2008) have highlighted either the potential or actual importance of networks and peer influence on energy saving and other environmental behaviours. This recognition suggests that energy-use and related models should begin to dig deeper into the social aspects of energy use by investigating and/or integrating real social networks or realistic representations, and the processes happening within them (Dennis et al., 1990). However, it has been suggested that the typical systems dynamics representation of innovation diffusion cannot fully capture the social processes through which energy behaviours may be influenced within a network (Kiesling et al., 2012; Zsifkovits, 2013).

The ABM approach on the other hand has the advantage of being flexible enough to accommodate the micro details of complex systems like low-level social interactions, different environments and different types of agent behaviours (Bruch and Atwell, 2015; Jager and Mosler, 2007; Twomey and Cadman, 2002).

In ABMs, agents could be individuals or a group of individuals and represent discrete decision makers. As such, agent decisions and how they vary among agents and over space and time are a core focus of the approach. Rather than agent behaviour being specified or controlled from a common source, simple decision rules are programmed into the model and as agents interact with themselves and their environment over time, they make decisions endogenously (Gilbert, 2007). This is vital to achieving emergence—for which ABM is known—and understanding the extent to which different behaviours can occur.

A relevant example from the developed ABM are the simple decision rules specified to govern attitude formation (see Table 4.5). Here, one of the rules are that when an agent comes across information about energy saving, the following agent properties: *motivation, ability to process* and *cognitive processing* must all be present in an agent to achieve long-term attitude change in favour of energy saving.

ABMs have been used across different fields to investigate a variety of related behaviours. In the environmental and energy domain, there has been an increase in ABM studies on consumer behaviour especially in relation to the uptake of sustainable energy options and new efficient technologies (An, 2012; Kiesling et al., 2012; Macal and North, 2010). In contrast, the focus of this study is energy-saving behaviour in response to informational interventions where economic costs and benefits are not necessarily considered a key motivation. However, not many references to using ABM to investigate energy saving in response to informational interventions are available in the literature. Considering the role of information as foundational to other energy interventions—e.g. energy efficient technologies—in addition to the benefits ABM can offer by integrating elements of both theory and practice for understanding energy behaviours, this study uses the ABM approach to further investigate how informational interventions influence energy saving. It does this by incorporating primary data obtained from a survey conducted in the first phase of the study into the agent-based model. Variables from the Elaboration Likelihood Model and Theory of Planned Behaviour are represented as model parameters. The values given to the parameters were obtained from survey data using hypotheses testing which also served as input validation. This is further discussed in sections 4.3.7 and 5.2.1. Using survey data in the model enables a virtual demonstration of ways in which identified variables interact to influence behaviour within the survey sample and context studied. It also allows an appreciation of how the variable characteristics present in the sample can influence behaviour in a larger population.

1.1.7 Rationale for studying the Student Switch Off campaign

Financial benefits have been shown to incentivise energy saving. However, this tactic may be crowding out intrinsic motivation which is likely to be more beneficial for energy saving in the long run (Frey and Oberholzer-Gee, 1997; Sweeney et al., 2013).

Students motivation to save energy is likely to stem from other sources because with students there tends to be a lack of financial incentive to do so since energy bills are not borne directly; in many cases, having been pre-paid in accommodation charges. In light of this, the UK HEI student switch off campaign was chosen as the campaign of focus.

The Student Switch Off campaign is not-for-profit and encourages students to take actions to combat climate change. It organises competitions for energy-saving and recycling within halls of residence at universities in the UK, Bulgaria, Cyprus, Greece, Ireland, Lithuania, and Romania. More details on the campaign are provided in 3.3.1 and can also be found on their website — http://studentswitchoff.org/.

1.2 Motivation: Research gaps identified

Research gaps (

Table **7.1**) identified from the literature provided the motivation for the study. Some of these have also been alluded to by other researchers. Although all the identified gaps are not addressed exhaustively, the study makes contributions to lessen the identified gaps. These contributions are highlighted (in italics) within the thesis and are also summarised in

Table **7.1**.

Available information on how individual-level factors contribute to the impact of behavioural interventions for energy saving at a group level is limited (Dixon et al., 2015; Lo et al., 2012; Scherbaum et al., 2008; Staats et al., 2000). This shortage is addressed in this research by using agent-based modelling (ABM) to obtain behavioural outcomes from interactions between individual level factors theorised to influence behaviour in the Elaboration Likelihood Model (ELM) and the Theory of Planned Behaviour (TPB). These factors comprise constructs from both theories. These were measured through a questionnaire survey which formed the basis for the findings from the first phase of the research.

Janssen & Ostrom (2006) and Fagiolo et al. (2007), draw attention to the need for innovative empirical testing methods that allow for more generalisable agent-based models. The model developed in this study was tested using both theory and real data. Agent decision rules are based on established theories (ELM & TPB) and model output were evaluated using survey data. Therefore, the extent to which the model re-produces a known outcome from specific input provides a means of empirically testing the model and applying it in different contexts.

Currently, there is limited use of theory and measurement of impacts for evaluating energy use behavioural change projects (Wilson, 2014). Furthermore, agent-based modelling literature on energy saving interventions is scant. The first phase of this research work demonstrates how the TPB can be extended by the ELM as a framework to understand factors that impact on the success of informational interventions for energy saving. Agent based modelling as used in this project provides an up-to-date means of measuring the impact of contributory factors on an energy saving intervention while providing insights useful for extending the theories of focus. As Rai & Douglas Henry (2016) put it “The real opportunity is at the intersection of theory and applications—models that help refine theories of behaviour, while also offering practical insights for low-carbon energy system design.”

Nearly two decades ago, Wilhite et al. (2000) observed that compared to the eighties, there had been a substantial decline in researching the social science perspective of energy demand, with the focus shifting to technological aspects of energy consumption. Recently, a summary on the UKERC website (2016) pointed out that the attention paid to social aspects of energy use has been sporadic over the years, thereby not establishing societal changes alongside technological solutions. This research therefore contributes an additional information resource for demonstrating factors that could influence energy saving from a social perspective.

There is a vital policy need for relevant information required for the planning and design of successful interventions (Wilson and Chatterton, 2011). The first set of findings from the study links communication, attitudes and behaviour. This demonstrates that the ELM-TPB framework can expose interactions which offer explanations for different processes of behavioural choices. This is useful for targeted planning and design of successful interventions. In the second phase, the application of theory through agent-based modelling produces behavioural outcomes which provides further information on influences to consider during the planning and design of informational interventions aimed at energy saving.

1.3 Research Aims, Questions and Objectives

1.3.1 Research Aim

The aim of this study is to understand how persuasive and behavioural factors influence the success of informational interventions for energy saving using established theories and agent-based modelling, thereby providing explanations for achieving favourable attitudes and behaviours towards energy saving.

1.3.2 Research Questions

1. In what way can the Theory of Planned Behaviour (TPB) and the Elaboration Likelihood Model (ELM) be jointly used to understand energy
    a. What relationships can be observed between the core constructs of the Theory of Planned Behaviour and the Elaboration Likelihood Model for reducing energy demand?
    b. Which constructs are potentially most significant in influencing intervention success?
    c. Under what conditions do different elements of the TPB and ELM produce energy saving behaviours?
2. Within the context of agent-based modelling, what outcomes or trends can be observed from using the TPB and ELM to explain energy saving behaviour and intervention success in the long term?
3. What are the different types of responses to informational interventions for energy saving and how do these affect intervention success?
4. How do informational interventions influence energy-saving behaviour?

1.3.3 Research Objectives

1. To understand factors that affect intentions and energy saving behaviour among HEI students.

2. Determine the relationships between core constructs of the TPB and the ELM from data to demonstrate how both theories can jointly serve as a useful tool in understanding energy use behaviours as a response to interventions.

3. Understand how variability and inter-relationships between TPB and ELM constructs can influence behavioural responses to energy saving information.

4. Develop an ABM to model and simulate factors that influence collective energy-saving behaviour in response to informational interventions in a social system.

1.4 Structure of the thesis.

The remaining aspects of the thesis are presented in two distinct phases. The first phase—chapters two and three—describes the direct use of theory to understand and explain the success of energy saving interventions with the aid of mathematical methods. The second phase comprises chapters four to six, covering the development, evaluation and simulation aspects of the agent-based model built using data obtained from the first phase of the study. A synthesis of findings from both phases are presented in the seventh chapter along with a discussion of the thesis' contribution to knowledge. The thesis also concludes in the same chapter with a summary of the research, practical implications and recommendations for future research. See Figure 1.2 for a pictorial outline of the thesis.

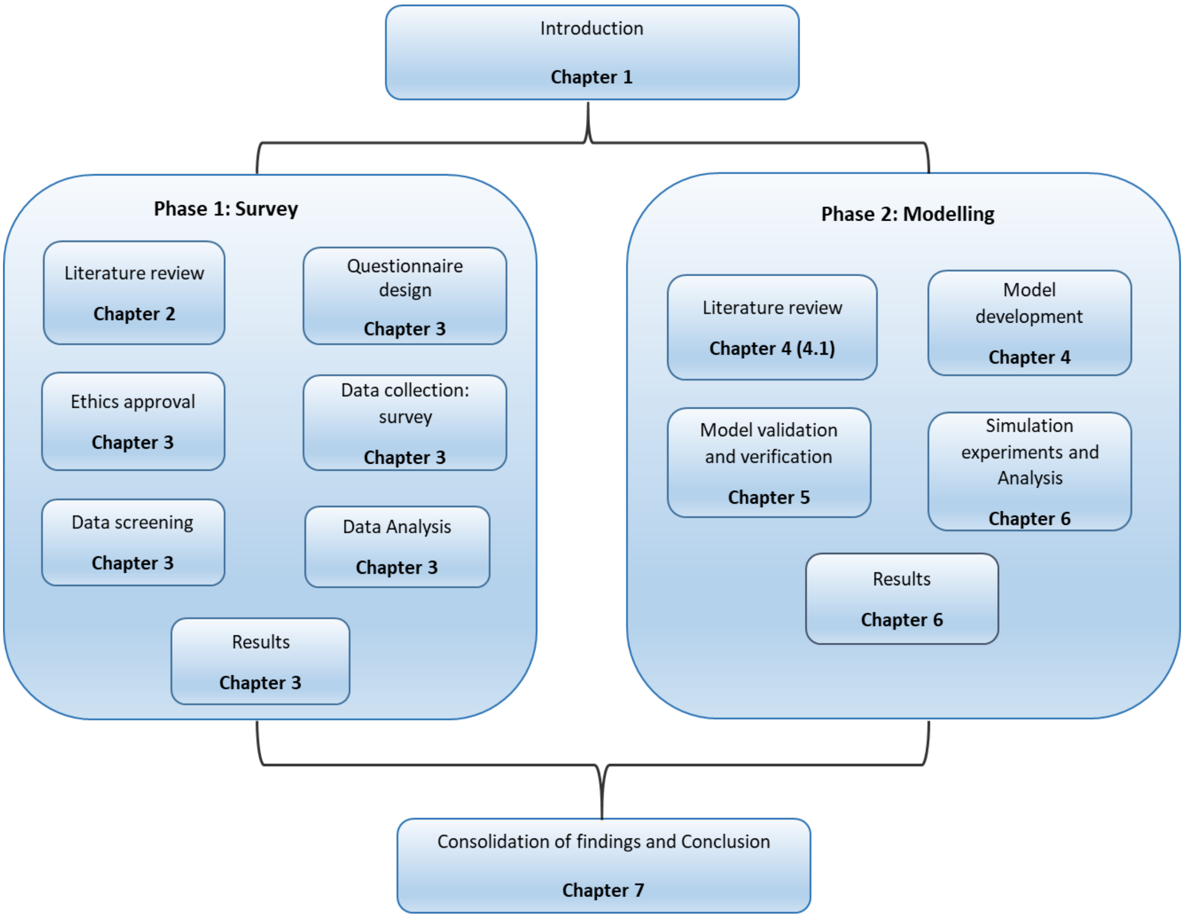


Figure 1.2 The Thesis' structure

2 LITERATURE REVIEW

2.1 Introduction

With over 30 million people in employment (Office of national statistics, 2014) and more than 2,266,000 students in UK Higher Education Institutions (Higher Education Statistics Agency, 2016), the non-domestic demand for energy is significant. Indeed, the priority for reductions in consumption and environmental impact is evident in many organisational strategies and examined in several studies (e.g. Herrmann et al. 2011; Cagno et al. 2015; Etzion 2007). Altan (2010); Lo et al. (2012) and Ward et al. (2008) have looked at a range of issues which could surround environmental performance within HEIs and trends show that reducing energy use in this sector must become a necessity. However, factors at the individual-level and how these contribute to changing energy saving behaviour in non-domestic settings have received little attention (Dixon et al., 2015; Lo et al., 2012; Scherbaum et al., 2008; Staats et al., 2000).

Wilson (2014) highlights the need to use theory-based approaches for evaluating energy behaviour schemes, having observed weaknesses in this area especially those relating to the measurement of impacts. As a contribution to filling this gap, this phase of the research is a theory-based study conducted to understand the effects of individual-level factors on behavioural interventions for energy saving. In addition to reviewing relevant literature, it uses statistical analyses to examine an energy saving intervention— “student switch off”—in the light of the Elaboration Likelihood Model and the Theory of Planned Behaviour. It focuses on dynamics which influence persuasive communication, examining the impact of an information-based energy saving initiative on the attitude and behaviour of individual students.

Energy is generally regarded as being abstract and invisible. Although its effects can be observed, it is not tangible (Froehlich, 2009). This characteristic makes it susceptible to wastage, especially because people are unable to immediately see or quantify the effects of their routine actions.

In today's world, innovative methods of promoting reduction in energy demand have been developed (e.g. smart feedback technologies). These may seem to relegate conventional behavioural interventions like information campaigns; However, in a recent survey of 50 organisations, 80% regarded communication as being "influential" in promoting positive energy use behaviours, with 30% of these alluding to it being "greatly influential" (Clarity Sustainability, 2015).

This literature review sheds light on topics that inform the understanding of how intervention success may be achieved, particularly in an environmental context.

The term "energy saving behaviour" is used interchangeably with others such as "environmental behaviour", "conservation behaviour", or pro-environmental as deemed appropriate considering that the target behaviour—energy saving—is embedded in broader themes of environmental and conservation behaviours.

2.2 Environmentally Significant Behaviour (ESB)

The terminology "environmentally significant behaviour" seems to be generally accepted as any behaviour that is pro-environmental in nature as opposed to behaviours that significantly harm the environment (e.g. Gatersleben et al., 2002;

Stern, 2000) Environmentally significant behaviour can be direct or indirect when considered in terms of impact. Certain behaviours (such as recycling household waste) can have direct impact on the environment (landfill) whereas others influence the context in which environmentally relevant choices are made and therefore have indirect but significant impact e.g. petitioning on green or conservational matters can influence policies which in turn can bring about individual and collective positive behavioural change simultaneously.

With environmental protection now a current priority issue around the globe, it is common to find that behaviours viewed as environmentally significant are those that are carried out with the intention of benefitting the environment, particularly from the doer's point of view. This could be regarded as consistent with Ajzen's (1991) Theory of Planned Behaviour (broadly speaking); however, according to Stern (2000), this intent-oriented perception of environmentally significant behaviour focuses on environmental intent as an independent precursor or reason for behaviour; however, such behaviour may not necessarily translate to environmental impact (Bhattacherjee and Sanford, 2009). Take for instance not using aerosol sprays because of the belief that this will help protect the ozone layer. Today, such behaviour has no impact because as of September 2009 a unanimous agreement was reached unanimously to protect the earth's ozone layer by phasing out chlorofluorocarbons and other ozone depleting substances from production (United Nations, 2016)

Whereas impact-orientation is useful in identifying and targeting ESBs, defining these behaviours from an intent orientation helps in understanding people's beliefs, objectives and driving forces with respect to the target environmental behaviours, thus helping in the creation of effective behavioural interventions. Although distinct in focus, both definitions of environmentally significant behaviours can each contribute to making considerable difference to the environment (National Research Council, 2005; Stern and Gardner, 1981).

Direct energy-saving behaviours as investigated in this work, are largely impact orientated; although, it could be argued that they are also intent-orientated when the action itself is targeted towards influencing others to engage in energy saving as is the case in interventions with strong peer influence undertones like the SSO campaign.

2.3 Current trends in environmental/energy saving intervention research and practice.

Environmental issues are known to have been regarded as an added cost in the past, particularly in organisational settings where these were largely considered a mere distraction which reduced business profits (Adams, 1990; Simpson et al., 2004). However, environmental good practice is now known to foster competitive advantage in the business world with considerable financial savings associated with preventing resource wastage (Carmona-Moreno et al., 2012; D'Souza and Taghian, 2017; Simpson et al., 2004). Although, it may be argued that if the driver for energy conservation and related behavioural practices is solely monetary, benefits achieved could be short term, considering that employees may not feel motivated if they do not directly benefit from advantages gained. For example, competitive advantage implies job security for employees but does not promise bonuses or salary increments.

In general, consumers are becoming more aware of green issues and committing to environmental causes (Green et al., 2000; Shrivastava, 1995). As such, a reliable approach may be to build on intrinsic motivational factors (Chai and Baudelaire, 2014; De Young, 1996; Kals et al., 1999; Turaga et al., 2010); Examples are the satisfaction that comes from feeling useful or of participating in a worth-while venture and a love of nature. This way people can relate to the cause (De Young, 1996; Widman et al., 1984), leading to greater likelihood of favourable and long-term behaviour change. To achieve this, however, underlying dynamics of the desired behaviour need to be understood. Evidence from research shows several underlying factors in different combinations that determine various types of pro-environmental behaviour. In a study carried out by (Stern et al., 1999), a factor analysis was performed on data from a national environmental survey. Items evaluating self-reported behaviours and intentions were analysed, exposing three factors namely consumer behaviours, environmental citizenship, and policy support. These factors each had a separate pattern of predictor norms, beliefs and values. Their findings correlated with those from a previous research in which a factor analysis was also carried out on data from the environmental component of a General Social Survey (Dietz et al., 1998). Similarly, several factors (behavioural types) with a unique set of predictors were identified.

Although environmentally significant behaviours (ESB) such as energy saving are increasingly becoming the focus of many interventions—for sustainability and economic reasons—many of these have been implemented with different levels of success (Abrahamse et al., 2005). While interventions may create awareness about energy saving, there is no guarantee that the desired behavioural changes will occur especially in the long term. For instance, where rewards have been used to induce energy savings, it has been shown that these can be counter-productive (Frederiks et al., 2015). This indicates that there are other factors at play in determining energy use and savings.

In the energy efficiency domain, several types of interventions are used as policy tools. Initiatives centred on engineering investments, enforcement as well as voluntary behaviour have been used at both organisational and domestic levels. However, voluntary behaviour change interventions, particularly at individual consumer level are likely to be more acceptable and produce faster results especially considering that engineering-based interventions may be inhibited by the consumer's way of life (Delmas and Kaiser, 2013; Wilson, 2014)

In a longitudinal study carried out by Staats et al (2000) on energy saving informational interventions in 384 offices, some improvements were observed in energy saving two years after implementation. However, the targeted energy saving behaviour was only partially present two years later despite augmenting the intervention periodically to sustain behavioural changes. In another study carried out by Abrahamse et al. (2007), there was evidence that tailored interventions were effective in achieving energy savings in households. Here, the information regarding energy saving measures was adapted for each household and they were encouraged to save 5% of their normal energy consumption. They also received information on how much could be saved as well as feedback on actual savings. When compared to a control group, these households saved more energy and were more knowledgeable about energy saving measures. A major observation was that Energy savings seemed to be mainly associated with individual influences like perceived behavioural control. This suggests that seeking to understand individual factors that affect energy use decisions and behaviours is a useful starting point for designing successful energy saving interventions.

2.4 Popular interventions for reducing energy demand

Generally, energy saving behaviours can be classed as either curtailment behaviour or investment behaviour (Han et al., 2013). Curtailment involves making behavioural changes to save energy e.g. switching off lights when not in use. Investment behaviour on the other hand involves investing in technology to achieve energy savings e.g. buying more energy efficient equipment. In creating interventions to tackle both categories of energy saving behaviour, various strategies are known to have been adopted. Some examples are economic methods, regulations and policies, and structural and technological methods. These are discussed below.

Economic methods: Pricing and financial rewards as strategies for reducing energy consumption appears to be well utilised in attempting to influence consumer energy usage (Faruqui and Sergici, 2010; Sweeney et al., 2013). Studies carried out as far back as the eighties show consumer receptiveness to economic strategies at both individual and collective levels (Winkler and Winett, 1982). Although such strategies cannot be regarded as ineffective, certain studies suggest that they may not be as effective as presumed. In cases of monetary rewards, it has been noted that these can supersede other motives and in the long run backfire e.g. where the cost-benefit analyses support the undesirable behaviour (Frederiks et al., 2015; Handgraaf et al., 2013). Also, there is evidence that people adjust to increased prices, initially making efforts to reduce energy consumption and then in the long-term default to their previous habits (Allcott, 2011; Geller et al., 1982). Also, Market forces alongside associated consumer response tend to react more often to short term returns than to longer term collective results (Heilbroner and Thurow, 1982). Worth mentioning also, is that pricing does not necessarily guarantee that consumers are correctly informed about simple, effective methods of reducing energy use at minimal cost, neither does it mean it is a strong enough motivator for consumers to seek out such methods (Steg, 2008). In a study on crowding out effects of pricing, Frey & Oberholzer-Gee (1997) suggest that pricing can crowd out civic duty and in areas where intrinsic motivation can be shown as important, pricing should not be used. However, in situations where intrinsic motivation is lacking, pricing holds promise.

Regulations and Policies: Energy use regulations and standards, while aimed at safeguarding resources and increasing innovation and productivity levels, may be erroneously seen as capital intensive. Obligated by law to conform, recipients may have a less than keen attitude; thus, slowing the progress and effectiveness of this approach. Building regulations were shown to be effective at reducing energy demand in newer buildings, according to a study carried out in Denmark between 1984 and 1995 (Leth-Petersen and Togeby, 2001). However, this was not the case for older buildings. For such regulations to be fully effective, it is important that consumers have a good understanding of associated issues such as building heat loss, reasons to invest in energy efficient technologies and the significance of consumer role in maximising these factors.

Structural and Technological methods: This approach entails measures like designing energy efficiency into an item, insulating buildings, using energy saving devices, retrofitting existing technology to use less energy etc. The downsides associated with this method include high monetary costs of replacing or upgrading existing facilities, the time associated with seeing a product through concept to delivery/implementation as well as the time required to fully replace existing technologies at different levels and so on. In cases of retrofitting, there is a possibility that underlying causes of problems with the original system may be overlooked (Costanzo et al., 1986; Goodland, 1995) e.g. replacing the heating system of a building with a more efficient one without considering its insulation level. Also, availability of energy efficient technologies does not mean consumers are going to adopt them even if affordable. Most energy efficient technologies require some human for operation and ultimately, the consumer makes the decision to identify, purchase, set up and use the technologies in question (Adua, 2010; Siero et al., 1996; Winett and Ester, 1983). In a study of retrofitted commercial buildings in the U.S, a significant percentage of tenant's energy use (estimated at 70%) was through equipment settings and patterns of use (Talbot and Love, 2014). This shows that focusing predominantly on technology is a limited strategy for energy conservation as it ignores the potential for significant further energy savings through changes in behaviour. Steg and Vlek (2009) observe that regardless of widespread efficiency efforts, energy demand still tends to surmount any resulting benefits. Notwithstanding, where people-oriented interventions have been implemented, there is also little evidence to show that such interventions achieve maximum potential and will continue to do so in the long run (Delmas et al., 2013; RAND Europe, 2012)

In discussing the limitations of the methods above, the intention is not to trivialise their value but to highlight the need for additional approaches that firmly incorporate behavioural inputs in understanding and reducing energy demand (Lorenzoni et al., 2007; Winett and Ester, 1983).

Energy conservation may be achieved by using devices that consume less (energy efficiency) or using devices less (energy saving behaviour). Although the behavioural approach is particularly useful in situations where options for the technology counterpart are limited e.g. old buildings with poor insulation (Azar and Menassa, 2014), a combination of both methods will achieve better and more sustained results (Scherbaum et al., 2008). In most cases, behaviour change only happens as a result of interventions which target people's e.g. by promoting energy saving, educating about the causes of climate change etc. (Bull et al., 2015).

2.5 Behavioural interventions for energy saving

Behavioural studies relating to energy use and savings have largely been directed by psychology research in the past decade (Lopes et al., 2012). This is understandable as a vital feature of sustainability is "widespread behaviour change"(McKenzie-Mohr, 2000).

Several concepts have been researched and proposed in environmental psychology; the attitude construct being one which has repeatedly been used as a predictor of conservation behaviour (Kaiser et al., 1999). However, methodological factors such as not measuring attitude and behaviour with the same level of specificity and not considering how situational influences impact on a given behaviour can affect the effectiveness of the attitude concept in the environmental context (M. Fishbein and Ajzen, 1975). Nonetheless, Kaiser et al. (1999) affirm that these limitations can be overcome by using the probabilistic measurement approach proposed by Ajzen in the Theory of Planned Behaviour, when assessing ecological behaviour. Over the years, attitude change research has evolved. In seeking to explain attitude change as an outcome of persuasion, different ideas, assumptions and theories (sometimes conflicting) have been formed successively by researchers in the field. Ranging from variables having only one influence on an outcome to there being only one explanation for why such an outcome is produced.

Early research on persuasion appeared to be centred on principles of learning theory where attitude change was linked to the extent to which the substance of a message could be learned or understood. In such instances, distractions would interfere with understanding, lessening the chances of persuasion (Hovland et al., 1953; Petty, 1997). Moving forward from this, researchers like Festinger and Maccoby (1964) researched persuasion from a resistance perspective and hypothesized that attitude change depended on whether recipients disagreed with the arguments contained in the message presented. Their reasoning was that since people would normally provide counter arguments if they disagreed with a message, any distraction while the message was being communicated could sway in favour of persuasion unlike in the learning theory where distractions are more likely to prevent learning and therefore decrease chances of persuasion. Following on from these two separate ideologies, (Petty et al., 1976) theorised that distractions could work either for or against persuasion depending on what recipients were thinking and not only in the presence counter-arguments, suggesting that even if recipients had been thinking positive thoughts about a message, distraction would still disturb these thoughts, resulting in less persuasion compared to if there were no distractions at all. Results from experiments conducted to test this thought disruption premise suggested that when arguments where strong, distractions worked against persuasion and when arguments were weak, distractions worked in favour of persuasion (Cacioppo and Petty, 1989; Petty et al., 1981). Other studies also buttress that many variables originally believed to have a single effect on persuasion could produce dual effects subject to the strength of the argument contained in the message (e.g. Johnson and Eagly, 1989; Petty and Cacioppo, 1986; Updegraff et al., 2007)

Subsequent research based on learning theory showed that repeating messages (previously believed to increase the likelihood of persuasion due to increased opportunities to pay attention to and understand a message) but varying the message quality supported the position that a variable could have dual effects on persuasion or attitude change. Cacioppo and Petty (1989) demonstrated that repeated exposure to a weak message resulted in less persuasion while repeating a strong message resulted in more persuasion.

These earlier distraction and learning streams of research on persuasion may be regarded as birthing dual process theories of persuasion like the Elaboration Likelihood Model being applied in this study (Cacioppo et al., 1985; Petty and Cacioppo, 1983). The figure below gives an example of how ideas have evolved in the area persuasion.

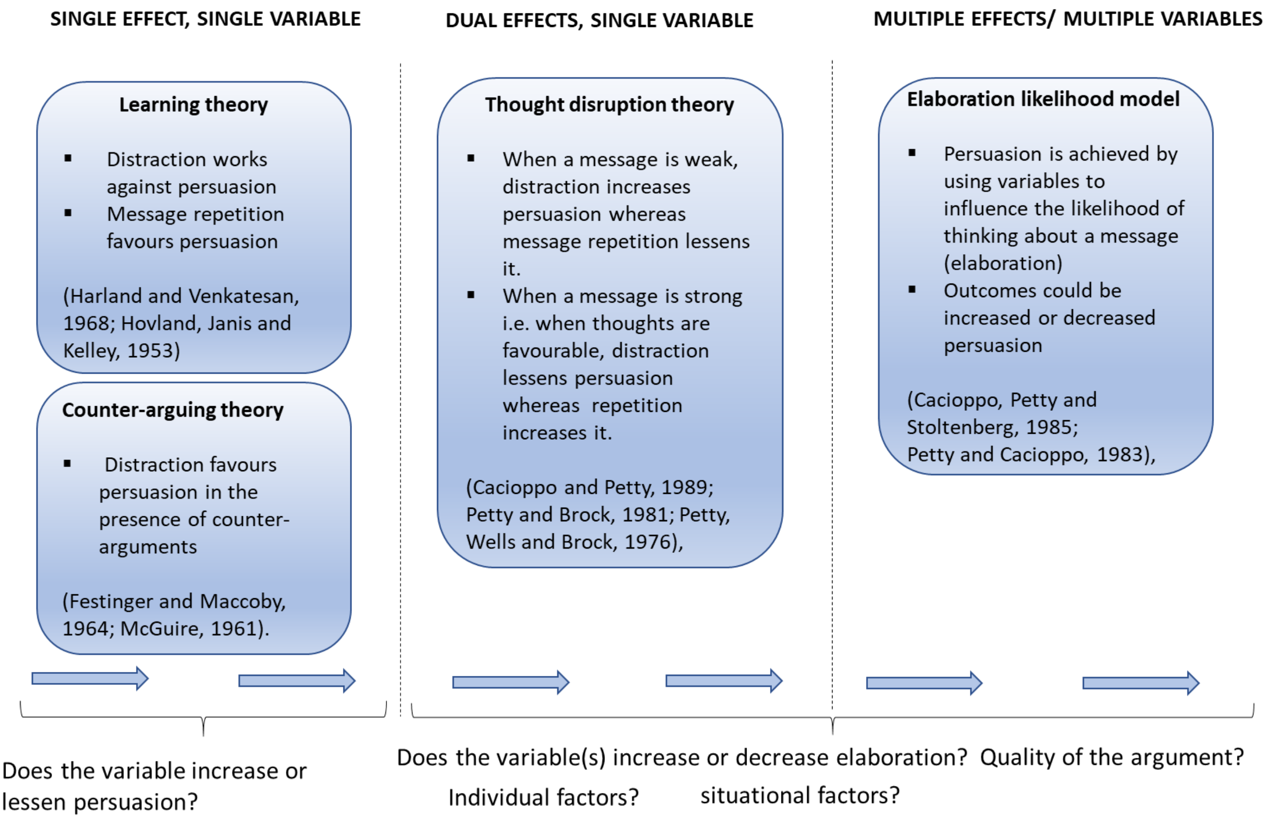


Figure 2.1 An illustration of progression in persuasion theory

There is empirical evidence that amongst groups of people, behavioural interventions can be a cost-effective way to reduce energy consumption and associated negative consequences, comparing positively to other traditional methods when successful (Allcott and Mullainathan, 2010). Generally, behavioural interventions can be categorised as informational or structural. Informational approaches aim to improve the knowledge base of recipients with a view to changing beliefs, norms, attitudes and ultimately behaviour e.g. awareness campaigns. Structural approaches on the other hand, focus on creating a setting conducive for making desired behavioural decisions (Dixon et al., 2015) e.g. providing recycling facilities to encourage recycling. As the focus of this study is informational interventions, structural strategies will not be further discussed.

The use of information to encourage energy saving behaviours can be a key strategy particularly when combined with the methods earlier discussed in 2.4 (Clarity Sustainability, 2015). It is also considered appropriate when trying to induce behaviour change voluntarily at the individual-level (Abrahamse et al., 2005). Typically, informational interventions aim to increase consumer knowledge of energy conservation options, to inspire a reduction in use and can be classified into two groups based on their underlying dynamics and characteristics (Azar and Menassa, 2014). The first are those delivered at a set point in time e.g. adverts and training to achieve energy savings. The underlying dynamics of the second group are more on-going in nature and aim to continuously influence recipients' decision making. Providing consumers with their real-time energy usage via smart meter monitors and using peer influence to consistently promote energy saving behaviours, are good examples in this group.

Popular informational strategies used in the environmental domain include education/ enlightening, feedback, prompting, goal setting and commitment (Steg et al., 2012). Given the direct relevance to the intervention studied (i.e. the “student switch off”), the discussion below is limited to education and feedback. (Klöckner, 2015) gives a succinct overview of other informational strategies.

Educating: This type of strategy is founded on the theory that there is a deficiency in knowledge about a problem and/or possible solutions and targets correcting this. In a study by Staats et al. (1996), a global warming awareness campaign increased people’s knowledge about global warming without any resultant behaviour changes. Several other studies have also shown educating to be limited in motivating behaviour change (e.g. Lorenzoni et al., 2007; Whitmarsh et al., 2011), indicating that it may be more effective when used alongside other initiatives. It may be inferred from combined results of several studies that the effectiveness of this approach as an intervention strategy also depends on the method or style of delivery. For example, tailoring information to a specific audience has been shown to be a more productive approach to providing information (Abrahamse et al., 2007; Dixon et al., 2015; Winett and Ester, 1983). Another tactic based on the *social learning theory* (Bandura, 1977), is to get other people (separate from the target population) to perform the behaviour being promoted, suggesting that new behaviour can be learned by directly observing others perform the same behaviour.

Feedback: This strategy involves providing people with information about results of their environmentally related actions e.g. energy savings. By offering some insight into the cause and effect relationship between certain behaviours and their consequences, links can be made between desirable outcomes and the behavioural changes required to achieve them. Feedback interventions can be quite varied in outcomes and although it can be effective in motivating behaviour change (Geller et al., 1982; Kluger and DeNisi, 1996), features such as style and frequency of delivery have been shown to be strong determinants of effectiveness (Fischer, 2008). In a review of intervention studies by Abrahamse et al.(2005), continuous or daily frequency of feedback achieved higher energy savings than control groups or irregular (monthly) feedback.

The feedback intervention theory proposed by Kluger and DeNisi (1996) recognises the role of moderators in feedback effectiveness. These include task (i.e. energy-saving related) familiarity, presence of knowledge enhancing cues (e.g. those that help in understanding or learning the result of inconsistencies in performing the stated task) and absence of cues that focus on the feedback receiver. Together, these moderators are likely to yield substantial effects. However, these by themselves do not guarantee the success of feedback interventions due to factors such as the possibility of performance reversal when the feedback is stopped.

2.6 Communication and persuasion in a pro-environmental context

Communication, though a vital aspect of human behaviour can be perceived in different ways by different people. This indicates that there are various sides to communication. More wide-ranging than speech, finding a singular definition of communication has shown to be out of the question. The inclusion or exclusion of different elements (such as observation, intentionality, judgement etc.) characterise the many definitions that exist. These differences underlie the various communication theories that exist. Although potentially confusing, having multiple definitions offer researchers a double opportunity to focus on distinct perspectives while enabling them to compare or merge their findings with those from other perspectives (Littlejohn and Foss, 2010).

Communication can influence values, beliefs, attitudes and consequently behaviour. Applying human communication in an environmental context, Klöckner (2015) outlines three categories of communication:

- **Direct communication:** between people in the same situation and place. Here communication is interactive and flexible with advantages of feedback and opportunities to adapt information and delivery to suit the recipient(s). However, this form of communication cannot be repeated in exactness, as each opportunity is one-off, happening at a given moment in time. Being first-hand, recipient understanding is likely to be more established with a heightened chance for persuasion and attitude change. Direct persuasion, less prone to being overlooked is likely to produce a peripheral attitude change based on initial trust built from the word-of-mouth feature of person-to-person contact (Costanzo et al., 1986). However, this communication style is susceptible to being regarded as social pressure and some people may find it bothersome, leading to a rebound effect (Bandura, 2001; Festinger et al., 1951). The benefits of direct communication make it seem an attractive option for environmental communication; however, its cost in terms of human and time resources, alongside inadequacy to reach a large target audience, detract from its overall usefulness. Environmental campaigns involving donations or petitions often use direct communication methods.

- **Mediated person to person communication:** Modern technology provides several means of communicating between two or more people. From telephone-based to computer-based channels, mediated communication offers all parties the opportunity to be actively involved in the communication process. However, unlike in face to face communication, certain aspects are often missing e.g. body language or facial expression missing in telephone conversations, emails and text messages. It can be argued though, that text functionalities such as emotional icons (emoticons) may be used to enhance the emotional tone of written communication (texts, e-mails) by conveying features of face to face communication such as confusion, embarrassment, happiness etc. (Klöckner, 2015); However, emoticons are subject to misinterpretation or being taken out of context by the receiver. It may also be used inappropriately especially where the sender lacks precise understanding of potential effects on the recipient. Whereas body language and intonation tend to be purely spontaneous, the use of emoticons is a conscious act—this implies that the receiver is more likely to reflect on the motive behind the symbol when interpreting the message than if it were body language in a face to face communication (Wang et al., 2014).

  In using mediated person-to-person communication for environmental purposes, pro-environmental campaigns can be tailored to recipients to a considerable extent, offering the opportunity to reach out individually to people through personalised emails or telephone calls. The costs of such campaigns are generally lower than face-to-face campaigns (Illingworth et al., 2002).

- **Mass media communication:** This method of communication reaches a large audience simultaneously from a central source and is the most cost-effective method for environmental communication. Channels of mass communication include television, internet, books, newspapers, magazines, art, radio etc. Though cost-effective and able to reach a large audience, this communication style lacks the advantage of interaction present in the two methods discussed above (arguably, except for social media). The consequence here is that there is a lesser likelihood of achieving the desired behaviour change and an increased chance of causing an undesirable response among recipients resulting in a rebound effect (European Environent Agency, 2016; Klöckner, 2015).

Persuasion often underlies communications to bring about desired behaviour change and according to Klöckner (2015) “environmental communication is essentially persuasion.”

Persuasion has been defined by communication experts in many ways. Dainton and Zelley (2004, p.104) adopt the definition of persuasion as “human communication that is designed to influence others by modifying their beliefs, values, or attitudes”. It is generally accepted that persuasion has certain attributes namely: it is a process (i.e. it is not accidental), its purpose is to sway a recipient in favour of a specified subject by means of communication, and the recipient must have a freedom of choice. Although persuasion cannot always be disengaged from negativity, the freedom to choose distinguishes it from uncivilized mechanisms such as coercion, placing the responsibility for decisions taken on the recipient. Unfortunately, not all approaches to persuasion are ethical and senders of persuasive messages must make decisions on appropriate means of reaching out to their audience. Understanding inherent processes, effects and associated ethical considerations will help in using persuasion mechanisms more productively (Perloff, 2003).

The European Environent Agency (2016) has identified some emerging approaches that might be useful for persuading people to be pro-environmental in their choices. These include nudging e.g. visual signs suggesting the desired behaviour, social innovations e.g. car sharing schemes, eco-labelling, social marketing e.g. offering competitive offers in favour of pro-environmental choices and using social media as platforms for encouraging interaction on environmental issues among people and communities.

Several theories of persuasion have been proposed by scholars in the field. Examples of these are cognitive dissonance theory, the Elaboration Likelihood Model, social judgement theory and the narrative paradigm among others (Dainton and Zelley, 2004). The ELM is used in this study and justification for this choice is discussed below.

2.7 The Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model (ELM) is a dual process theory of attitude change (Petty et al., 1991; Petty and Cacioppo, 1986). It was proposed in response to a need for consistent and generalizable principles of effective communication in an era where existing theoretical explanations and research findings appeared to be mostly inconsistent and contradictory (Petty and Wegener, 1999). The aim was “to integrate the many seemingly conflicting research findings and theoretical orientations under one conceptual umbrella” (Petty and Cacioppo, 1986, p.125). Being message-oriented, the ELM is suitable for understanding information-based interventions, providing an integrative framework through which processes fundamental to the effectiveness of persuasive communications can be organised, categorised and understood. The ELM provides insight on the effects of communication on attitudes by not only addressing core variables such as motivation (often used interchangeably with “involvement”) in the information recipient but also external factors such as the perceived quality of the argument and rating of the communication source (Wilson, 2014). Integrating these factors has good potential for explaining complicated results such as interventions in which knowledge acquisition does not result in the desired change in attitudes and behaviour. In such scenarios, ELM variables can be measured in the context of the intervention being assessed i.e. by gathering relevant information from recipients and analysing this to understand relationships which may explain lack of success.

In an exploratory study, Kerr et al. (2010) sought to examine the ELM’s applicability in the 21st century by replicating an original study conducted by Petty and Cacioppo (1983). Although their findings largely differed, those linked to peripheral cues were consistent. It is worth noting that although attempts were made to replicate the study as closely as possible, important features like the original advertising environment and relevance of the advertised product could not be replicated for obvious reasons. It is believed that these factors (and maybe others) could have influenced outcomes of the study.

Despite criticisms like the model's failure to account for the possibility of the central and peripheral routes affecting attitudes in a similar manner (Stiff, 1986; Stiff and Boster, 1987), it has proved valuable for consumer research (Lien, 2001)—featuring in numerous studies over the years (e.g. Chen and Lee, 2008; Park et al., 2007; Susan et al., 1998; Wilson and Stuart, 2013). Its authors have also provided support by responding to critiques and adapting the model where deemed necessary (Petty et al., 1987a, 1987b; Petty and Wegener, 1999). However, Kitchen et al. (2014) notes that compared to its application, there is noticeably less empirical testing of the model in the literature.

Figure 2.2 is an illustration of the Elaboration Likelihood Model. It shows that a person's level of motivation is fundamental to the success of any communication aimed at inducing long-term change(s) in attitude. It argues that if a person feels motivated about a message, they are inclined to think more deeply about it i.e. cognitive processing. Conversely, the ELM also considers that recipients may not feel motivated or be able to adequately review a given message for various possible reasons. Take for instance, a situation where a potential buyer comes in contact with an advert for an equipment with high-end technical specifications. Being able to understand the pros and cons of such features become necessary for considering the ad's argument effectively. Where the buyer lacks the technical ability to do this, peripheral cues like the brand name, social norms, etc. may help guide the decision to buy (Krcmar et al., 2016).

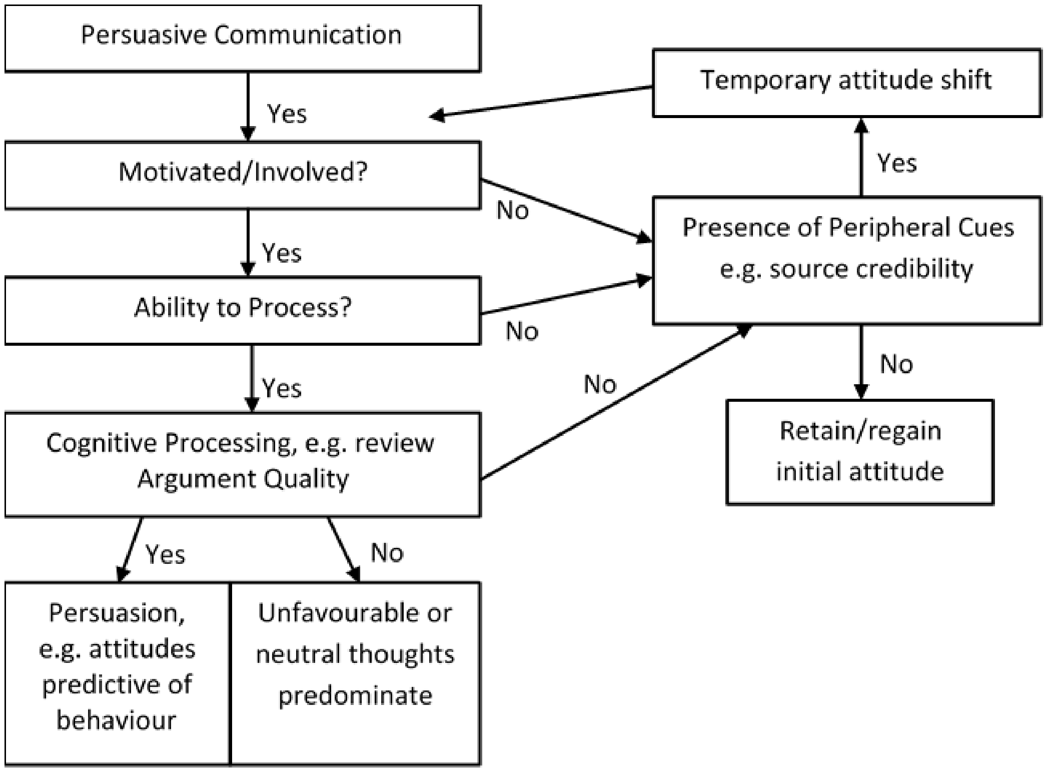


Figure 2.2 The Elaboration Likelihood Model (Petty et al., 2002)

When assessing motivation in an intervention, participants are asked to rate how they feel, in terms of relevance and how involved they regard themselves in relation to the concepts contained in the intervention. This is known as issue involvement. The quality of arguments in a persuasive message is typically evaluated using criteria such as clarity, ease of understanding, authenticity and the extent to which it is stamped on participants' memory (Park et al., 2007; Updegraff et al., 2007). Source credibility (or peripheral cues) on the other hand is the extent to which the message source is perceived to be credible, consistent, knowledgeable and dependable (Hu and Shyam Sundar, 2010; Jones et al., 2004; Pegels et al., 2015)

Being a linear model, the ELM allows for a more convenient application in the design and evaluation of environmental behavioural programmes by policy makers (Wilson, 2014). Organisations looking to inspire environmentally significant behaviours such as energy saving often look for cheap but high yielding options. In such situations, theories like this one, which explain persuasion and give indicators of behaviour are applicable and useful (Abelson et al., 2003).

2.8 The Theory of Planned Behaviour.

The Theory of Planned Behaviour (TPB) is a social psychological theory developed to predict and explain human behaviour in specific contexts (Ajzen, 1991). It can be beneficial in devising strategies for developing desirable or constructive behaviour (Ajzen, 2002a; Francis et al., 2004). Simply, the TPB concept is used to postulate that intention is the main antecedent of behaviour and an individual's intention to behave in a certain way is jointly fuelled by three variables namely; *attitude*, *subjective norm*s, and *perceived behavioural control*. These variables regarded as the core constructs of TPB, each have underlying beliefs as key determinants (see Figure 2.3). The TPB has been used successfully to examine motivations for pro-environmental behaviours especially in domestic settings (Conner and Armitage, 1998; Greaves et al., 2013a). However, it assumes that behaviour is a rational choice which occurs from weighing the pros and cons of available options (Ajzen, 1991).

In many daily scenarios, it is common to find individuals behaving contrary to their stated attitudes. This may be because the attitude-behaviour relationship is not straightforward as there are other mediating factors to consider. The Theory of Planned Behaviour explains this by showing an inter-relationship between antecedent beliefs, attitudes, social norms, perceived behavioural control, intention and behaviour (Dermody and Hanmer-Lloyd, 2011). Its core constructs are briefly described below.

Attitude: Simply put, this is how a person feels about a targeted behaviour in terms of possible outcomes and how they view the effects of such outcomes. In other words, this construct shows a person's overall evaluation of a specified behaviour, based on the expectancy that the behaviour will result in certain outcomes and the value attached to such outcomes (e.g. worthwhile or worthless, good or bad) (Francis et al., 2004). "Extensive research indicates that attitudes are a reliable indicator of behavioural intention; hence they are a very tangible and readily measurable variable in helping to explain why employees do and do not adopt energy saving behaviour in the workplace." (Dermody and Hanmer-Lloyd, 2011). However, changing people's attitude is not singularly an effective way of changing behaviour and should not be incorrectly targeted as a proxy for behaviour change. The TPB and several other behavioural theories show that additional factors (e.g. circumstances and priorities) may pose as strong drivers or barriers of behaviour change and consider the extent to which attitudes predict behavioural change in the light of these.

Subjective norm: The extent to which a person feels the need to conform their behaviour to the behaviour or expectations of other people or groups they consider important i.e. social influence. People may be motivated to conform to social pressure for different reasons for example if they feel that others are better informed on a subject or simply because they do not want to stand out from the crowd (Allcott and Mullainathan, 2010).

Perceived behavioural control (PBC): Referring to the feeling of control a person has about his/her behaviour in a given context, this construct also measures the degree to which a person feels able to behave in a certain way (Ajzen, 1991). The *TPB* model implies that in addition to having a direct influence on *intention,* PBC can directly predict behaviour in cases where it parallels actual control (Sheeran et al., 2003) or where actual control diminishes (Armitage and Conner, 2001). This is plausible as behaviour is partly influenced by situational and personal factors (ibid.)

Intention: According to the *Theory of Planned Behaviour,* intention to engage in any behaviour depends on three variables— *Attitude*, *subjective norms,* and *perceived behavioural control*. These have been found to predict intentions across various types of behaviours with considerable precision (Ajzen, 1991); however in a meta-analysis by Armitage and Conner (2001), subjective norms were found to be weak predictors of intention, possibly due to issues surrounding interpretation of subjective norms and perhaps, measurement quality.

Generally, the extent to which these three variables are present determines the strength of intention as well as the certainty of behaviour (Ajzen, 2002a). However, there are no givens when it comes to predicting behaviour (Armitage and Conner, 2001); findings from several studies suggest that attitude, subjective norm and perceived behavioural control do not share equal power in determining the strength of intention (Godin and Kok, 1996; Sheppard et al., 1988).

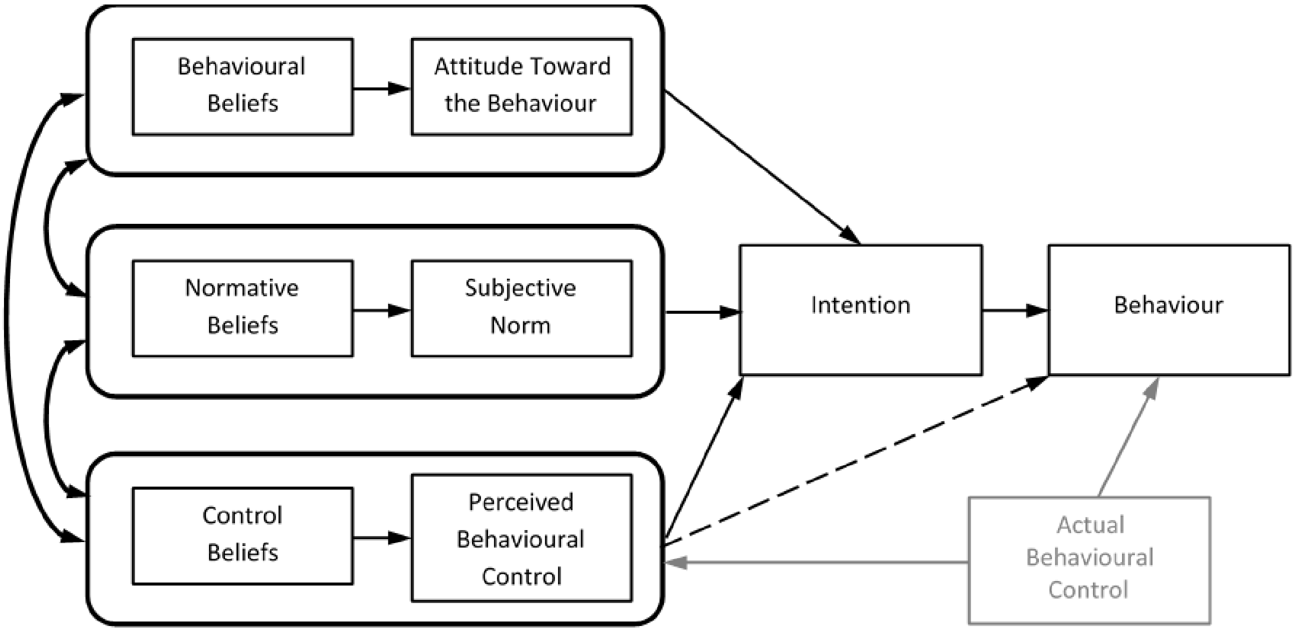


Figure 2.3 The Theory of Planned Behaviour (Ajzen,2002)

Attitude, *subjective norms* and *perceived behavioural control* are each reinforced by antecedent beliefs—behavioural beliefs (for attitude), normative beliefs (for subjective norms) and control beliefs (for PBC). These represent specific factors and may be responsible for inconsistencies or variations in behaviours (Ajzen, 1985; Ajzen, 1991). Being able to identify specific factors that could affect energy saving behaviours on campus is of interest as it enables the identification of behavioural barriers and driving forces (Greaves et al., 2013), which could be useful in designing targeted intervention programmes. Although not depicted visually in the TPB model, each antecedent belief is accompanied by another set of beliefs which evaluate the consequences of the belief. Take for instance the behavioural belief, “I believe recycling is good for the environment”. Although the individual holds this belief, he/she may also feel (evaluate) that, “sorting household waste for recycling is time wasting”. This evaluation plays a significant role in determining if the antecedent belief turns to behaviour (Ajzen, 1991; Martin

Fishbein and Ajzen, 1975). However, research studies of environmental behaviour that take into account antecedent beliefs are few; typically, the focus is on the three core constructs, in seeking explanations for variance in behavioural intentions (de Leeuw et al., 2015; Greaves et al., 2013)

The TPB has been utilised extensively by researchers in a wide variety of fields including; medicine (e.g. Araujo-Soares et al. 2013), commerce (e.g. Shah Alam & Mohamed Sayuti 2011), health education (e.g. Abraham et al. 2011) and transportation (e.g. Abrahamse et al. 2009). It has also been employed in researching environmental conservation-related behaviours to some degree and as stated by Greaves et al. (2013), "The *Theory of Planned Behaviour* is well supported empirically as a theoretical foundation to investigate environmental behaviours and furthermore provides a suitable basis for the investigation of such behaviours at work". However, some meta-analyses (e.g. Bamberg and Möser, 2007; Klöckner, 2013; Rivis et al., 2009) across various behavioural domains, including the environmental domain, have results that contest the TPB's scope. These support Gifford's (2014) position that the TPB could benefit from having additional personal and social factors that could boost its predictive and explanatory validity. An example from one of the meta-analyses cited above is moral norms as a direct predictor of intention (Rivis et al., 2009). In response to evidence-based concerns such as the above, Fishbein & Ajzen (2010) made a case for what could be regarded as formal updates to the TPB in recent years. For example, they argue that moral norms should be included as a core variable in the TPB model when investigating behaviours that have a clear moral element. Also, descriptive norms have formally been added on as a component of subjective norms which was previously only explained in terms of injunctive norms (de Leeuw et al., 2015). This is a valuable addition, in light of several extensive studies which have been published on the significant effects of descriptive norms on behaviour (e.g. Allcott, 2011; Cialdini et al., 2006; Manning, 2009; Nolan et al., 2008; Rivis and Sheeran, 2003).

The overall aim of any energy saving intervention transcends short term success to sustained positive change that can be measured by tangible energy savings. However, it may be said that despite the insights that the TPB provides, measures of its key constructs are largely by means of self-reports, and these may not always capture actual states, particularly in the long-term (Gifford, 2014). However, the reliability of the TPB and its constructs may be strengthened by using multi-item scales i.e. by using more than one question to extract manifest indicators of a particular construct and calculating the internal consistency (Ajzen, 2002). Also, any data obtained from observations may be used in conjunction with self-reports to further lend reliability to these measures (Stuart et al., 2013).

3 RESEARCH METHODOLOGY, ANALYSES AND RESULTS

This chapter outlines and discusses the design, data collection, analysis and results of the first phase of the study. The framework, intervention and questionnaire survey are also discussed. In section 1.2, research gaps were identified. One of which relates to the limited use of theory and measurement of impacts for evaluating energy use behavioural change projects. To this end, the Theory of Planned Behaviour and the Elaboration Likelihood Model are being used as a joint framework to understand motivations for energy saving among HEI students and factors that influence informational strategies for reducing energy demand. The rationale for this design is further explored below.

3.1 The basis for the theoretical design

Methods used to study energy use behaviours vary in many ways; from observational, e.g. case studies, to self- reports, e.g. surveys, to experiments, e.g. laboratory and modelling/simulation, and so on. These methods may or may not be firmly grounded on theory and could be designed to explain and/or predict behaviour. In the seventies and eighties, exploratory methods without firm theoretical influences were commonly used in environmental studies (Bamberg and Schmidt, 2003). Perhaps, because these were the early days for research on environmental behaviours. Similar lines of research conducted in the nineties and subsequent years tended to be more theory driven than before (e.g. Abrahamse et al., 2005; Gatersleben et al., 2002; Staats et al., 2004; Stern et al., 1999). This leaning towards theory could be an offshoot of numerous foundational studies conducted in the preceding decades as these have resulted in the availability of more empirically proven theories. It could also have been due to a realisation that many established theories could be applied to the study of environmental behaviour.

While all these methods are beneficial in providing useful information for different purposes and stakeholders, none is without limitations. For example, a key consideration in designing a theory-driven method is that theories are confined to the ideas they carry; therefore, no single theory gives a holistic explanation for any type of behaviour. In this case, the challenge becomes choosing the theory most appropriate for the goals of the study. However, the use of theory lends structure to the understanding of how choices and behaviours are formed. As pointed out by Wilson and Dowlatabadi (2007), applying theory helps to understand how energy use choices and behaviours are made. A recognised energy efficiency gap—where attitudes and intentions do not always lead to behaviour—is proof that no single theory or even combination of theories embodies all influencing factors or offers exclusive explanations for energy-use behaviours, as each theory or model tends to be limited by its peculiar assumptions (Lopes et al., 2012). However, theories and models are beneficial because of the ability to link behaviours with underlying motivations within the sphere of respective rationales. Thus, they can offer different means by which interventions can be tailored. Furthermore, the extent to which the objectives of interventions are achieved can be evaluated using theoretical methodologies (see Wilson 2014; Scherbaum et al. 2008; Dixon et al. 2015).

3.2 The ELM-TPB Framework

Having recognised a deficiency in the use of theory, pre-testing or measurement of impacts for assessing behaviour change energy conservation projects across the EU, Wilson (2014) proposes a framework to evaluate information or communication based energy saving interventions. The framework consists of constructs that could offer useful theoretical support for assessing relevant behaviour change projects. A fusion of the Elaboration Likelihood Model and the Theory of Planned Behaviour, it is considered to have the potential to evaluate interventions at various stages of its life cycle. Past studies have shown that both theories are independently able to predict behaviour at significant levels (see Sections 2.7 and 2.8). Figure 3.1 shows how the theories have been linked for use in this study.

The relevance of mixing approaches to understand behaviour change was highlighted in a review of behaviour change evaluations by the House of Lords' science and technology committee (House of Lords, 2011). Likewise, Wilson and Chatterton (2011) buttress this and suggest considering four factors when choosing models to explain emissions related behaviour change—1) actor, e.g. individuals or communities? 2) scope, e.g. isolated or interrelated behaviour? 3) durability, e.g. one-off or routine behaviour? and 4) domain, e.g. technological or psychological? In line with these and further grounded on earlier work done by Wilson (2014), this research draws on the *Theory of Planned Behaviour* and the *Elaboration Likelihood Model* as a combined framework to offer insights into the type and context of behavioural change targeted by the intervention.

In using the combined framework to evaluate the information-based intervention, measured ELM variables were used to investigate factors that might increase or lessen the chances of careful deliberation, allowing an explanation of how variables linked with people's reasoning are changed. Measured TPB variables on the other hand helped to assess any subsequent changes in beliefs, attitudes, intentions and behaviour by explaining when or under what conditions behaviours are altered. Conner & Armitage (1998, p. 1450) in a review regarding extending the Theory of Planned Behaviour convey that "a dual-process model of attitude-behaviour relationships" (e.g. The ELM-TPB framework) may provide wide-ranging, useful explanations of how behaviour is influenced by attitudes. They submit that motivation and opportunity allowing, attitude may affect behaviour through intentions as put forward by the TPB. In the absence of the stated antecedents, however, they suggest that attitudes may affect behaviour more spontaneously (perhaps via the peripheral route of the ELM?).

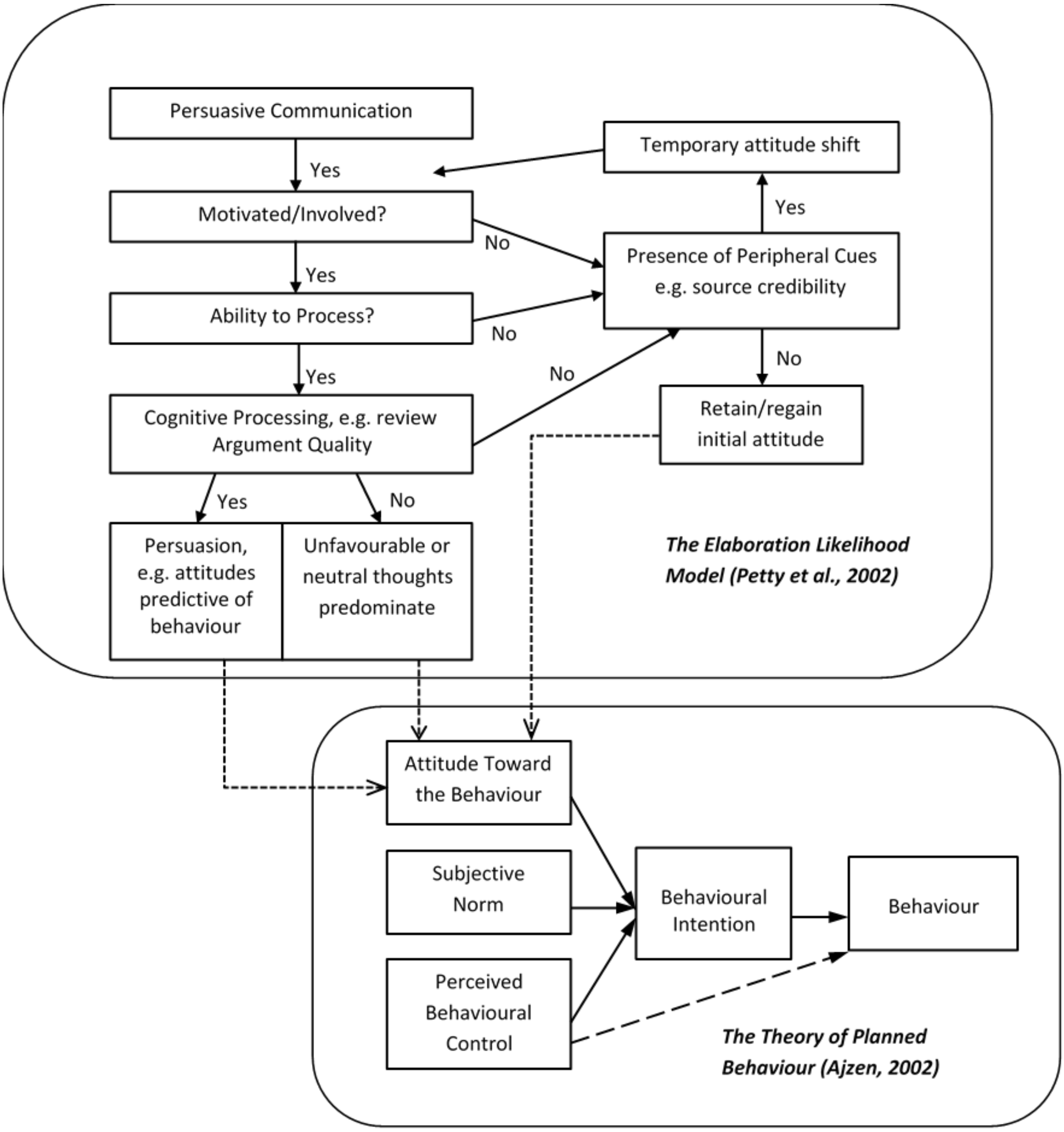


Figure 3.1 Connecting the ELM and TPB

In research conducted by Wilson (2014), the TPB-ELM framework's suitability was tested across a range of communication activities which included some simple curtailment behaviours such as routinely switching off unused pieces of equipment, one-off energy saving investment, e.g. loft insulation and offering personalised environment-related behavioural advice. Two surveys were carried out at different times after the communication activity. Results showed that communication variables influenced behaviour via TPB independent variables; attitude, subjective norms, and perceived behavioural control. Although her work showed that using the ELM-TPB framework in the design, monitoring and evaluation of energy conservation interventions is a promising approach, she called for further research as, “repeated use of the framework would confirm more detail about the relationship between the two theories and highlight differences in communication acceptance according to situation and context” (p. 307). This study may be regarded a response to that call.

3.3 The Empirical Study

Given that questionnaire surveys have been used successfully in several studies to elicit measures for the theoretical constructs being researched (e.g Icek Ajzen, 1991; Chen and Lee, 2008; Francis et al., 2004; Ozawa-Meida and Fleming, 2016), the appropriate first steps in tackling the research questions and objectives involved conducting a survey. These steps are outlined below and illustrated in Figure 3.2.

1. Identification of relevant information-based energy saving intervention for the study i.e. The “student switch off” (SSO) campaign which runs in Cranfield University and several UK universities. Questionnaire items were tailored to directly assess the impact of the campaign using constructs of the *Elaboration Likelihood Model* and the *Theory of Planned Behaviour*.

2. Two sets of questionnaires were developed based on questionnaire construction literature specifically relevant to the theories being studied (Ajzen, 2002; Francis et al., 2004). This stage entailed several processes.
    a. Identification of reliable measures of variables from literature.
    b. Creation of first drafts of two sets of questionnaires. The first questionnaire measured awareness of the SSO campaign and ELM variables (*motivation, ability to process, argument quality and peripheral cues*). The second measured the TPB dependent (*intention* and *behaviour*) and independent variables (*attitude, subjective norms* and *perceived behavioural control*)
    c. Ethics approval. Authorisation was received from Cranfield University's ethics committee, CURES before questionnaires were distributed. See appendix A.1 for a screen shot of the approval email.
    d. A pilot study was conducted to trial the first draft of questionnaires. 15 respondents trialled the first questionnaire and 9 respondents the second. The length of the first questionnaire was 14 questions and the second, 16 questions. The output of this stage provided data for a reliability analysis using Cronbach's alpha as a measure of internal consistency for questionnaire items (see Table 3.2). This stage also exposed issues relating to clarity of questions, questionnaire length, completion time etc. Suggestions for improving the questionnaire from respondents' perspective were also received and incorporated in the final draft. A factor analysis of first draft of questionnaire items

was also carried out. A significant use of factor analysis at this stage, in addition to the test of internal consistency was to condense or eliminate questionnaire items (See Factor Analysis (FA)).

e. Final drafts of questionnaires were prepared and distributed electronically using *Qualtrics*, the recommended survey tool by Cranfield University. The links to both surveys are as follows: https://cranfielduniversity.eu.qualtrics.com/SE/?SID=SV_55sTle4Q8VSbqND and https://cranfielduniversity.eu.qualtrics.com/SE/?SID=SV_0Nwau3Ss1TPRgtD

3. Distribution of the first questionnaire which was 12 questions long with estimated 10 minutes completion time. Initial response was poor (10 participants) so the response window was increased, and attempts made to reach a wider audience. Total response window was approx. 1 month with 32 respondents.
4. Distribution of a second questionnaire which had 15 questions and approximately 10 minutes completion time. This was originally planned for four weeks after the first questionnaire. However, due to time constraints, it was sent out with the second distribution of the first questionnaire. Response window was 3 weeks and 14 responses obtained.

   (The original aim of a four-week interval between distributing the first and second questionnaires was to prevent bias that could originate from respondents' awareness of the link between the two questionnaires which could hinder objective responses to the behavioural items in the second questionnaire).

5. Analysis of data and evaluation of results.

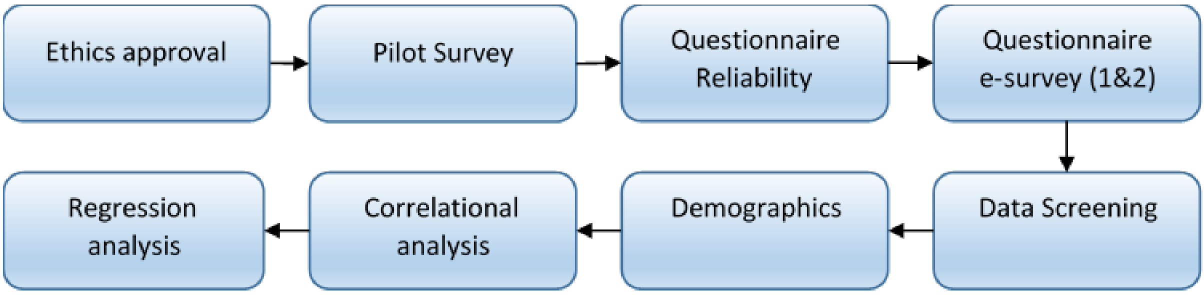


Figure 3.2 A summary of the data collection and analyses in the 1st phase of the research.

3.3.1 The Intervention — The Student Switch Off campaign.

Broadly speaking, students do not bear direct costs for additional energy use; most live in rented accommodation where energy costs tend to be estimated or inclusive with the rent. This is likely to rule out the motivation that could come from direct financial benefits of energy saving (Lo et al., 2012) and helps to appreciate the "Student Switch Off" (SSO) campaign, an initiative designed to encourage energy conservation behaviours in students living in halls of residence. Raising energy saving awareness by engaging students in an inter-hall energy saving contest and other competitions, it relies largely on peer influence for spreading the message while giving them a chance to win prizes. Students are also encouraged to upload photographs of themselves doing an energy saving activity on social media (Facebook). Key messages provided are:

- Switch off lights and appliances

- Do not overfill the kettle
- Take short showers
- Put a lid on it (when cooking)
- Put a layer on, not the heating (when feeling cold)

Focused on making energy conservation pleasurable and attractive, the SSO has recorded notable achievements. In 2012, the campaign won the prestigious Ashden Award and in the 2014-15 academic year, the initiative prevented more than 1,300 tonnes of CO_2 emissions by reducing an average of 6% electricity use across participating halls of residence.

3.3.2 Questionnaire development

3.3.2.1 Objectives

Objectives were formulated to provide a means for gauging that the questionnaires achieved the original intent. These are as follows.

1. To elicit and record energy saving views on a bipolar rating scale as a measure of the attitude, subjective norm, perceived behavioural control, source, message and receiver variables of the above theories and to determine combined effects on reducing energy demand among students in UK HEI.
2. Understand the type of message elaboration suited to informational energy saving interventions by collecting information on associated attitudes, attitude certainty and thoughts

See appendix A.1 for an explanation of the SMART elements of these objectives.

3.3.2.2 Defining questionnaire constructs

(Ajzen, 2002) recommends defining the behaviour under investigation according to four elements: target, action, context and time (TACT). Defining the behaviour in this manner prevents ambiguity and makes it easier to adhere to the *Principle of compatibility* which requires that other Theory of Planned Behaviour (TPB) constructs be described in exact terms as the behaviour e.g.

Target: Energy

Action: Saving

Context: on campus

Time: at every opportunity

According to the TACT elements specified above, the **behaviour definition** is saving energy on campus, at every opportunity. The *attitude* being investigated is therefore attitude towards saving energy on campus, at every opportunity. The *subjective norm* is the perceived social pressure to do so; the *perceived behavioural control* is the control an individual has over behaving as defined and the *intention* to be assessed will be that of performing the defined behaviour. The population of interest is students in UK Higher Education Institutions

Theory of Planned Behaviour predictor variables (*attitude*, *subjective norms* and *perceived behavioural control*) can be measured directly or indirectly. Ajzen,

(2002) and Francis et al. (2004) suggest using both methods in a TPB questionnaire. For indirect measurements, beliefs relating to the variables (i.e. behavioural, normative and control beliefs) are elicited from respondents during a pilot work. Responses are then used to identify personal and modal beliefs. Modal beliefs serve as a basis for constructing belief-based questions used in questionnaires.

3.3.2.3 Scaling questionnaire items

In scaling belief-based measures, the convention used by Francis et al. (2004) may be followed, where unipolar scales are used for unidirectional (probability-type) questions and bipolar scales for bidirectional (evaluation-type) questions. Direct measures on the other hand, are often drawn on bipolar scales. Where bipolar scales are used, responses would be evaluating an action or attribute as opposed to rating feelings or opinions about an item which is given as true. The advantage of this method is that the total score for each variable reflects the influence level of the variable on the behaviour e.g. for attitudes, depending on the type of scoring adopted, a score of zero will represent a neutral attitude, a positive score implies a favourable attitude and a negative score, an unfavourable attitude. Q1 and Q2 in 3.3.2.3.1 (below) show examples of both styles of measurement and scoring.

Due to response rate difficulties encountered during the data collection phase, only direct measures were used in this study. See appendix A.3 for A.4 the first and second questionnaires respectively. Summaries of key words and phrases used to elicit measures in the questionnaires are presented below in Figure 3.3 and Figure 3.4.

Combined, both questionnaires had 39 items measuring 10 constructs. 33 of these items were measured on a seven-point scale, 1 on a six-point scale, 2 on a four-point scale, 1 on a three-point scale and 1 on a two-point scale. According to Krosnick and Fabrigar (1997), longer scales can communicate information that may be more useful. However, they also warn that too many scale points may also hamper clear understanding of response options leading to reduced consistency of responses. Based on reliability studies conducted, they suggest that an ideal scale could be expected to be 5 to 7 points in length, for attitude and related constructs. In addition to items measuring ELM and TPB constructs, one item was included to measure attitude certainty because Rucker and Petty, (2006) highlighted this variable as a potential key influence on the outcomes of communication based interventions.

3.3.2.3.1 Examples of measures, scaling and scoring used for questionnaire items

Q1. Direct measurement of the Attitude construct

Saving energy in the workplace is:

Good	1	2	3	4	5	6	7	bad
Convenient (for me)	1	2	3	4	5	6	7	Inconvenient (for me)
Appealing	1	2	3	4	5	6	7	Unappealing

*Worthless 1 2 3 4 5 6 7 Worthwhile

Mean score = 3 *(*reverse coding applied because wording is in opposite direction i.e. 6 becomes 2)*

Q2. Indirect measurement of the Attitude construct

[Attitude (A) = Behavioural belief strength (b) x Outcome evaluation (e)

Assume one of the beliefs generated is "saving energy at work will reduce carbon emissions"

Behavioural belief strength (b)

When I save energy at work, I reduce carbon emissions.

Strongly disagree 1 2 3 4 5 6 7 Strongly agree

Outcome evaluation (e)

Reducing Carbon emissions is

Extremely undesirable -3 -2 -1 0 +1 +2 +3 Extremely desirable

Scoring: A= b x e= 21; Range =-21 to +21 *(The higher the score, the more positive the attitude and vice versa).* *<u>Here, attitude is extremely positive.</u>*

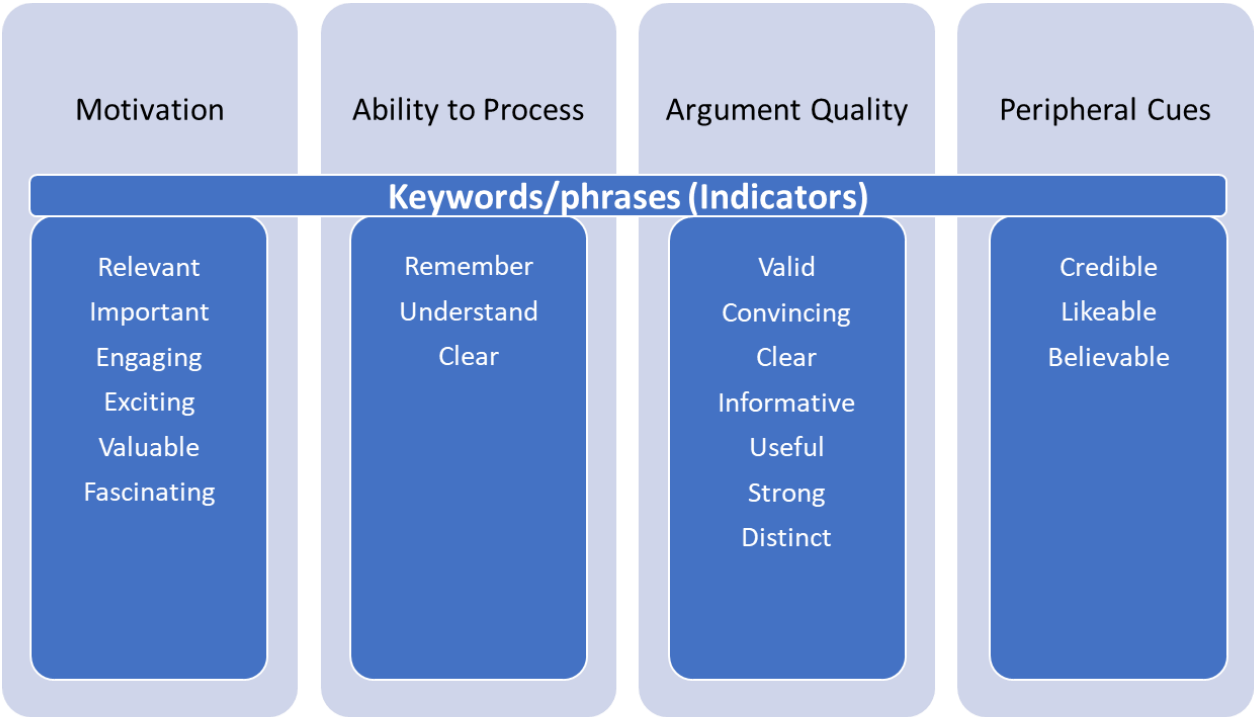


Figure 3.3 Summary of words used to elicit measures for variables in the first questionnaire

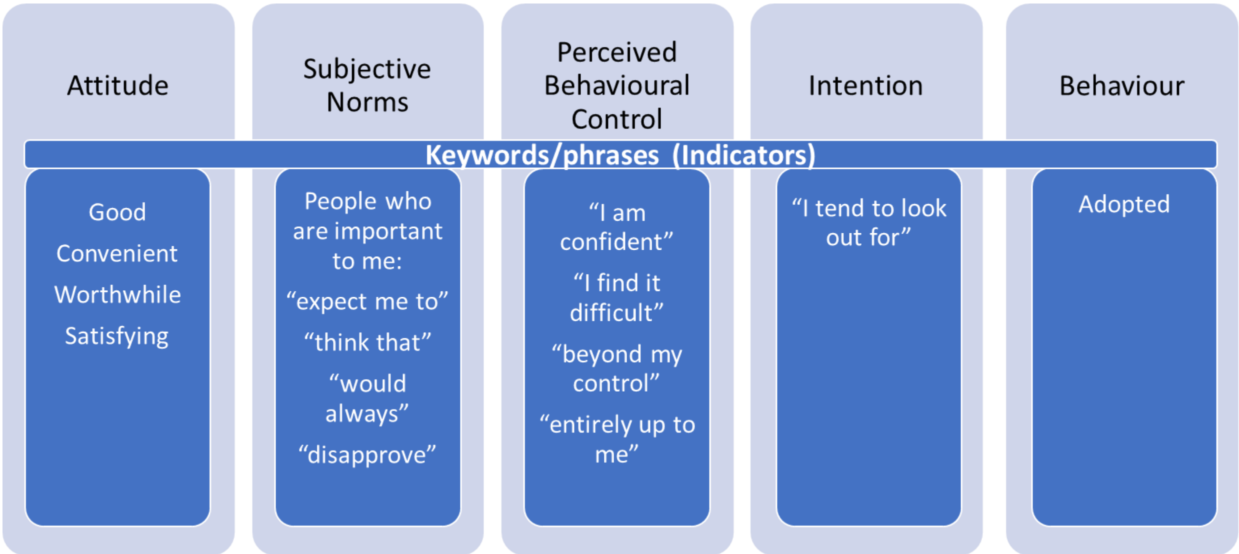


Figure 3.4 Summary of words and phrases used to elicit measures for variables in the second questionnaire

3.4 Data analysis and results

Statistical Package for Social Sciences (SPSS) version 22 for Windows was used to perform relevant statistical tests. See appendix A.5 for the survey data in SPSS. Analyses performed on data collected from the survey included data screening, factor analysis, multiple regression analysis and bivariate correlation analysis.

Pre-analysis screening of the data indicated that linear relationships existed among the variables. To understand these relationships in terms of strength and direction, correlation coefficients (*r*) were obtained. Of the various correlational methods, Spearman's correlation was chosen to reduce possible effects of deviations from normality in the data (Field, 2013). The correlation was two-tailed because no particular hypothesis was being tested; therefore, no direction was being suggested (Hanna and Dempster, 2012). The primary objective was to understand any existing relationships among variables. Regression analysis was also carried out on the survey data to further explain relationships between dependent and independent variables in the ELM-TPB framework and to explore the possibility of predicting the dependent variables in the framework.

3.4.1 Demographic data

Data from a total number of 21 respondents was used in this study. Participants were students from higher education institutions (HEIs) in the United Kingdom; 11 were from Cranfield University while 10 attended other universities in North-West England. 33.3% were male and 66.7% were female. Nearly half of the respondents were in the age group 20-24. 61.9% of respondents were African, 28.6% European; Asians and North Americans each 4.8%. 81% of respondents lived on campus while the remaining lived off-campus. Only 40% of the 21 participants had knowledge of the “student switch off” campaign prior to the survey; however, there was a link in the questionnaire to direct people to the campaign website before continuing with the survey. Table 3.1 shows the number of responses received for each variable studied.

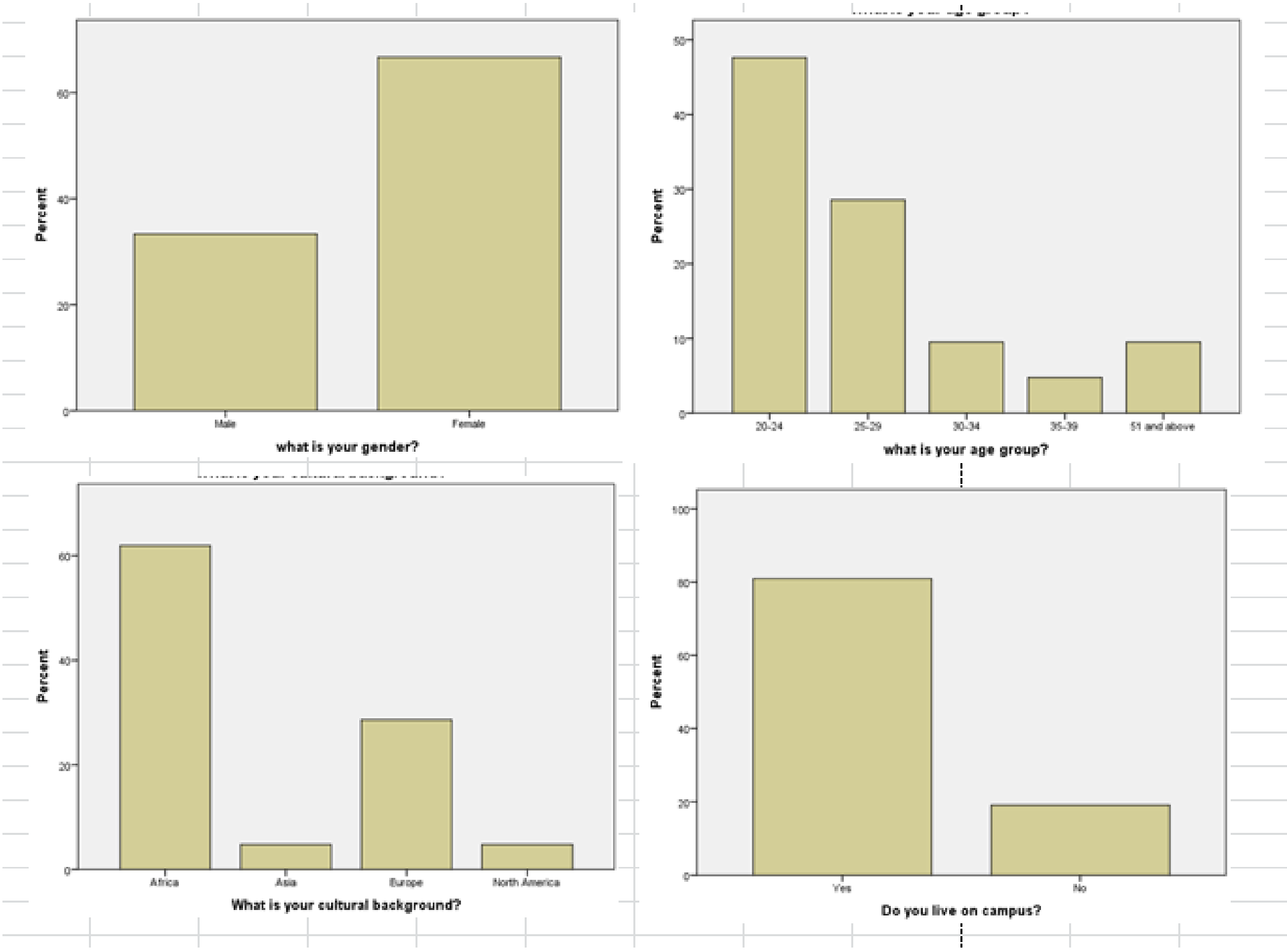


Figure 3.5 Bar charts showing frequencies of gender, age group, cultural background and residence

Table 3.1 Number of responses against variables measured in the questionnaire

Question	No of responses
What is your gender?	21
What is your age group?	21
Do you live on campus?	21
What is your cultural background?	21
Awareness of student switch off campaign	20
Knowledge of sponsor	21
Peripheral cues	5
Perceived behavioural control	21
Motivation	21
Subjective norms	21
Intention	17
Elaboration	18
Argument quality	21
Attitude	21
Ability to process	21
Behaviour	19

3.4.2 **Questionnaire Reliability**

The primary measurement instrument for this study was the questionnaire. Consequently, it is essential to establish that it was valid and reliable. To achieve this, a reliability analysis of questionnaire items was performed on data obtained from the pilot study as well as from the actual study. Validity refers to the questionnaire measuring what it is designed to measure while reliability ensures consistent measurement of a construct (Field, 2013; Tavakol and Dennick, 2011).

To be valid, the instrument (questionnaire) must first be reliable (Deniz and Alsaffar, 2013). Reliability may be assessed by getting the same group of people to complete the questionnaire twice; a reliable instrument will produce similar scores at both times. This is called test-retest reliability (Field, 2013).

A more practical method may be to perform a test of internal consistency e.g., Cronbach's alpha. Cronbach's alpha can be used to ascertain if a group of questionnaire items measure the same underlying construct. For this reliability test to be valid, items must be coded the same way i.e. values across all the items must reflect the same levels of the construct e.g. high values reflecting high levels of the construct across all items and so on (Field, 2013; Pallant, 2013). Generally, Cronbach alpha (α) scores of above 0.8 are considered preferable while values of 0.7 to 0.8 are acceptable. Values below 0.7 may imply the scale is unreliable.

A Cronbach alpha test of internal consistency was carried out on initial results from the pilot questionnaires and some questionnaire items were excluded from the main questionnaire as a result. Reliability results for constructs measured with multiple items are summarised in Table 3.2 .

Table 3.2 Summary of reliability results

Construct	No of Items	No of responses based on	Cronbach's Alpha (α)	Reliability
Motivation	7	19	0.905	Excellent
Ability to process	4	19	0.93	Excellent
Argument quality	7	19	0.867	Very good
Peripheral cues	3	4	1	Excellent
Elaboration	3	17	0.753	Acceptable
Attitude	3	18	0.779	Acceptable
Subjective norms	4	21	0.754	Acceptable
Perceived behavioural control	4	21	0.69	Acceptable

Questionnaire items measuring respective constructs *motivation, ability to process, argument quality, peripheral cues, elaboration, attitude, subjective norms* all had reliabilities ranging from satisfactory (Cronbach's α = .753) to high (Cronbach's α = 1). These results suggest that each of these constructs was adequately measured by the questions and scales used to elicit and measure its underlying characteristics. However, items measuring *perceived behavioural control* had just below high reliability (Cronbach's α = 0.69). Although this result may suggest a lack of homogeneity in the items used to elicit and measure the construct, Kline (2000) advises that psychological constructs may realistically produce values below 0.7 due to variability of constructs being measured. Also, Hinton et al. (2004) deem Cronbach's α = 0.6 as moderately reliable. Furthermore, it is advised that other considerations such as number of items in a scale and correlation between items, should be made when interpreting α scores before rejecting items due to low scores (Field, 2013). Based on these assertions, the questionnaire items used to elicit *perceived behavioural control* were not changed.

3.4.3 Factor Analysis (FA)

Factor analysis is a means of understanding correlations between variables. It may be used to test the construct validity of questionnaire items (Rattray and Jones, 2007). Similar to regression analysis but different as variables are not assigned dependent or independent status. As part of the analysis, a correlation matrix (R-matrix) is computed and clusters of highly intercorrelated variables can be seen. Here, factors are theoretical constructs based on underlying variables, created to account for the intercorrelation among variables and which replace the original set of variables. This is particularly useful when dealing with very large sets of variables as the number of factors are fewer than that of the original variables while preserving as much original information as possible. Also during the formation of measures and scales e.g. in a questionnaire, factor analysis assesses the degree to which items measure the same variables (through intercorrelation strength) or the relationship between responses to different questionnaire items.

Factor analysis is characteristically used as an exploratory tool (exploratory factor analysis) for summarising variables and understanding interrelationships among them as opposed to being used to find out variables which have a significant effect on others. To be applicable, the number of respondents should be more than the number of variables, with a recommended ratio of 5:1. On the other hand, factor analysis can also be used for confirmatory purposes but this is differentiated as ‘confirmatory factor analysis’. Confirmatory factor analysis is particularly useful in situations where the aim is to check the degree to which the outcome matches a known or hypothesized model or relationship (Robson, 2005).

Exploratory Factor Analysis (EFA) reduces a large group of correlated variables by accounting for the pattern of correlations in variables. This reduction is expressed in terms of a fewer number of **latent variables** or **factors** which could be viewed as “condensed variables”. A variable is considered latent when it cannot be measured directly but is understood to be related to a number of observable and measurable variables termed **manifest indicators** (Ajzen, 2002). For instance, to obtain information about *attitude* (latent variable) towards a certain product , questions could be asked relating to how much a people enjoy using the product, how often they use the product, if they would recommend the product to a friend and so on (manifest variables).

In this study, a factor analysis was performed with mean scores of constructs as variables, rather than with each questionnaire item score. This was done to align closer with Robson (2005) recommended respondent to variable ratio of 5:1. Outputs from the analysis performed on *elaboration,* Theory of Planned Behaviour variables and a*ttitude certainty* are presented and discussed below.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett’s Test of Sphericity are preliminary tests which are run as first steps in a factor analysis.

They determine if the FA is worth performing and jointly serve as a minimum standard to be passed prior to performing a factor analysis i.e. gauging the factorability of the data (Pallant, 2013; Williams et al., 2010). Table 3.3 is the SPSS output table for both tests.

Table 3.3 SPSS KMO and Bartlett's Test output

KMO and Bartlett's Test

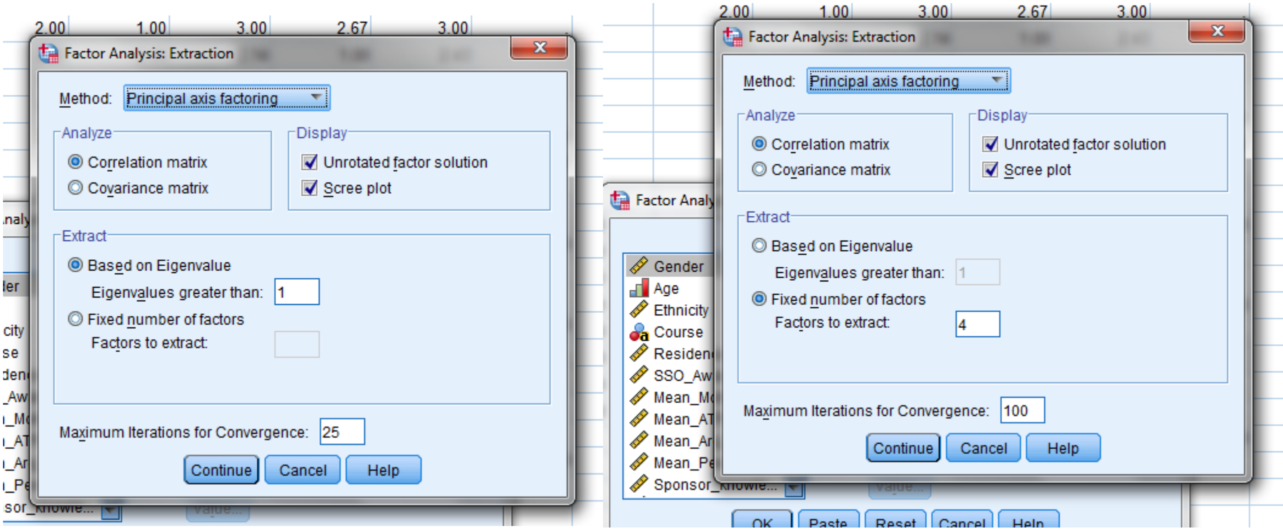
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.637
Bartlett's Test of Sphericity	Approx. Chi-Square	47.431
	df	21
	Sig.	.001

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) can range from 0 to 1. If partial correlations are small, the values are closer to one. A minimum value of 0.6 is recommended for a good factor analysis. The KMO is a ratio of the sum of squared correlations to the sum of squared correlations plus the sum of squared partial correlations (Tabachnick and Fidell, 2007). The KMO value for the data (i.e. 0.637) is just above the minimum recommended level, so at this stage, it is safe to assume that the data will provide a good factor analysis.

Bartlett's Test of Sphericity (BTS) tests a null hypothesis that all off-diagonal correlations in a correlation matrix are zero. Since this hypothesis cannot be accepted, the desired significance value should be zero. It is reputed to be very sensitive and tends to be significant in large sample sizes. For this reason, it is recommended only for use in samples of less than 5 cases per variable (Tabachnick and Fidell, 2007). This is ideal as the data to be factor analysed contains 21 cases and 7 variables, resulting in 3 cases per variable. The BTS for the sample is statistically significant at p = 0.001 which means the null hypothesis (stated above) is false and can be rejected.

The Scree Test. This is a plot of eigenvalues against factors. Eigenvalues represent variance. An eigenvalue is the total of squared factor loadings for a specific variable on the factor with which the eigenvalue is associated. By default, SPSS uses an eigenvalue of one to determine the number of factors which will best represent the pattern of correlations in the data. However, the decision to use eigenvalues as determinants of optimum factors is for the researcher to make (Williams et al., 2010), particularly where there is prior knowledge of the expected number of factors from theory (Tabachnick and Fidell, 2007). The factors computed are observable from the scree plot. The number of points in line with higher eigenvalues denotes the number of factors which can often be clearly distinct from other factors.

When factors were extracted using the “eigenvalue above one” setting (Figure 3.6a) only two factors were extracted i.e. the first two points on the scree plot in Figure 3.7. However, based on theoretical knowledge of latent variables present, in addition to the number of factors observed from the scree plot (above and just below the bend), the extraction determinant was then specified as a fixed number (Figure 3.6b). Four factors were successfully extracted with the fixed number specified as four. These are highlighted in Figure 3.7.



(a) (b)

Figure 3.6 SPSS Factor Analysis extraction windows

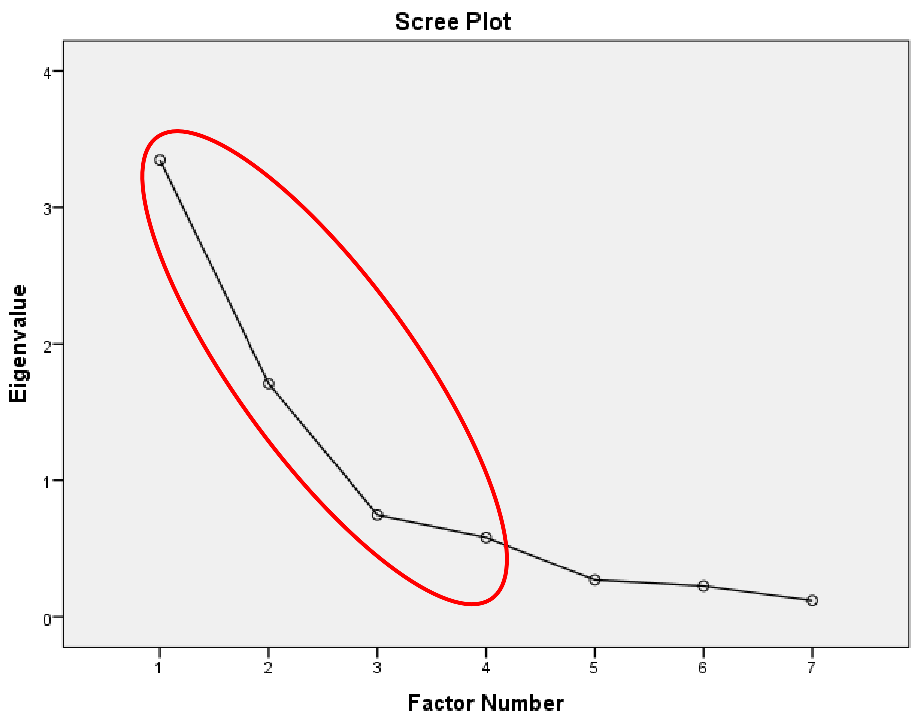


Figure 3.7 Scree plot showing factors

From the cumulative figures of rotation sums of squared loadings in Table 3.4, it can be deduced that the four factors extracted account for 79% of the variance. This implies that 79% of the questionnaire items load on the first four factors.

Table 3.4 Explanation of total variance

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.347	47.814	47.814	3.167	45.238	45.238	1.940	27.716	27.716
2	1.708	24.403	72.217	1.481	21.152	66.390	1.840	26.289	54.004
3	.747	10.670	82.887	.698	9.975	76.365	1.365	19.498	73.502
4	.582	8.318	91.205	.245	3.496	79.861	.445	6.359	79.861
5	.270	3.861	95.066						
6	.225	3.221	98.288						
7	.120	1.712	100.000						

Extraction Method: Principal Axis Factoring.

<u>Factor Matrix:</u> Table 3.5 shows the factor matrix for questionnaire items. This title is regarded as slightly misleading, as this is not the matrix used to interpret the factors (Field, 2013). However, it gives an idea of how variables load on factors and is consistent with the percentage of variance each factor accounts for in Table 3.4.

Table 3.5 Factor Matrix for questionnaire items

Factor Matrix[a]

	Factor			
	1	2	3	4
Mean_SN	.814		.546	
ATT_CERT	.757	.399		
Mean_ELAB	-.673	.543		
Mean_ATT	-.659	-.506	.530	
Mean_PBC	.652	.542		
Intention	.617	-.533		
Behaviour	-.489	.426		.335

Extraction Method: Principal Axis Factoring.

a. 4 factors extracted. 48 iterations required.

Rotated Factor Matrix: The purpose of rotating factors is to aid ease of interpretation (Costello and Osborne, 2005). This is achieved by distributing factor loadings such that each variable loads highly on only one factor (Pallant, 2013). In Table 3.6, *Intention, Elaboration, and Behaviour* correlate highly with each other and load on Factor 1. *Attitude, Attitude certainty* and *Perceived behavioural control* load on Factor 2 because they correlate highly with each other and so on. The relevance of rotated factor loadings to a questionnaire survey is that it verifies if the items measure the intended constructs (Osborne, 2014). For example, the results show that there is a relationship between *Elaboration* and *Behaviour*, which is expected, as implied in the theoretical framework. Perhaps more importantly, a possible problem is also exposed with *Intention* and *Behaviour* which contrary to theory are negatively correlated; however, the smallness of the sample size may be responsible for the inconsistency.

Table 3.6 Rotated Factor Matrix for questionnaire items

Rotated Factor Matrix[a]

	Factor			
	1	2	3	4
Intention	-.830			
Mean_ELAB	.784		-.345	
Behaviour	.684			
Mean_ATT		-.980		
ATT_CERT		.688	.473	
Mean_PBC		.588	.423	.553
Mean_SN	-.360		.909	

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

3.4.3.1 Summary of factor analysis results

A principal axis factor analysis was carried out on 7 items with orthogonal rotation (varimax). The Kaiser-Meyer-Olkin measure verified the sampling adequacy for the analysis, KMO = 0.637, p = 0.001. An initial analysis was run to obtain eigenvalues for each factor in the data. Four factors were extracted by specifying a fixed number of 4 and altogether explained 79.9% of the variance. Two of these factors had eigenvalues above Kaiser's criterion of 1 and together explained 54% of the variance. The scree plot showed inflexions that can explain retaining either 2 or 4 factors. 4 factors were retained based on theory. The item groupings suggest that Factor 1 relates to outcomes; Factor 2 appears related to personal viewpoint; Factor 3, social and Factor 4 control oriented. This interpretation indicates that on a high level, expected outcomes, personal perspectives, social influence and perceived behavioural control are factors that determine intervention success in the context of energy saving.

3.4.4 Data Screening

Careful screening of data prior to analysis is an important step, necessary to prevent problems during the main analysis. It is also vital to the reliability of results obtained from the analysis. The screening process includes checks for accuracy, missing data, outliers, normality, linearity, homoscedasticity, multicollinearity and so on (Tabachnick and Fidell, 2007). Some of these have been applied to the data collected and are discussed below.

3.4.4.1 Normality check

While the requirement that data is normally distributed is not always mandatory during data analysis, checking data for normality when dealing with multiple variables can be vital in early stages of analysis, especially when the purpose of the analysis is to draw inference from a sample to a population. One reason for this is that if variables are not normally distributed or show extreme differences in any non-normality present (e.g. some positively and some negatively skewed), outcomes or inferences reached will be less reliable (Tabachnick and Fidell, 2007).

The normality check can be done for skewness (i.e. symmetry of distribution) or kurtosis (i.e. how peaked a distribution is). In a perfectly normal distribution, skewness and kurtosis have values of zero. However, the absence of kurtosis in a distribution can be given a value of 3, where a statistical package is not used, as statistical packages subtract 3 during computation to give an expected value of zero (Field, 2013; Tabachnick and Fidell, 2007).

Skewness in the data distribution is checked either visually from a histogram or box and whisker plot, or by means of a skewness statistic. As a general guideline, a data distribution is regarded to significantly differ from a symmetrical distribution if the skewness statistic is twice its standard error (Hanna and Dempster, 2012).

Kurtosis can also be assessed graphically or by means of a kurtosis statistic, where positive kurtosis (values above zero) indicate a distribution that is too peaked, and values below zero, one that is too flat. The presence of kurtosis in a distribution implies an underestimation of its variance.

The skewness statistics (see **Error! Reference source not found.**) for all variables except *ability to process* were less than twice the respective standard error of skewness, with *ability to process* having a skewness statistic of 1.038 and a standard error of skewness of 0.501 (0.501x2=1.002). With only one variable as an exception, the skewness of the overall data set is deemed acceptable.

Table 3.7 Skewness and kurtosis statistics for Elaboration Likelihood Model and Theory of Planned Behaviour variables

Statistics

		Mean_Motivated	Mean_ATProcess	Mean_Arg_Quality	Mean_Peripheral_Cues	Mean_ELAB	Mean_ATT	Mean_SN	Mean_PBC	Intention	Behaviour	ATT_CERT	SSO_Awareness	Sponsor_knowledge
N	Valid	21	21	21	5	18	21	21	21	17	19	21	20	21
	Missing	0	0	0	16	3	0	0	0	4	2	0	1	0
Std. Error of Mean		.25446	.24194	.20135	.48990	.13056	.28824	.21497	.18921	.37145	.10956	.36234	.11239	.09524
Std. Deviation		1.16607	1.10871	.92269	1.09545	.55391	1.32090	.98513	.86706	1.53153	.47757	1.66046	.50262	.43644
Variance		1.360	1.229	.851	1.200	.307	1.745	.970	.752	2.346	.228	2.757	.253	.190
Skewness		.017	1.038	.347	-1.293	-.017	.899	-.620	-.169	-.738	.862	-.754	-.442	-1.327
Std. Error of Skewness		.501	.501	.501	.913	.536	.501	.501	.501	.550	.524	.501	.512	.501
Kurtosis		-1.236	-.315	-.547	2.917	-.865	.056	.988	-.565	-.291	-1.419	-.750	-2.018	-.276
Std. Error of Kurtosis		.972	.972	.972	2.000	1.038	.972	.972	.972	1.063	1.014	.972	.992	.972

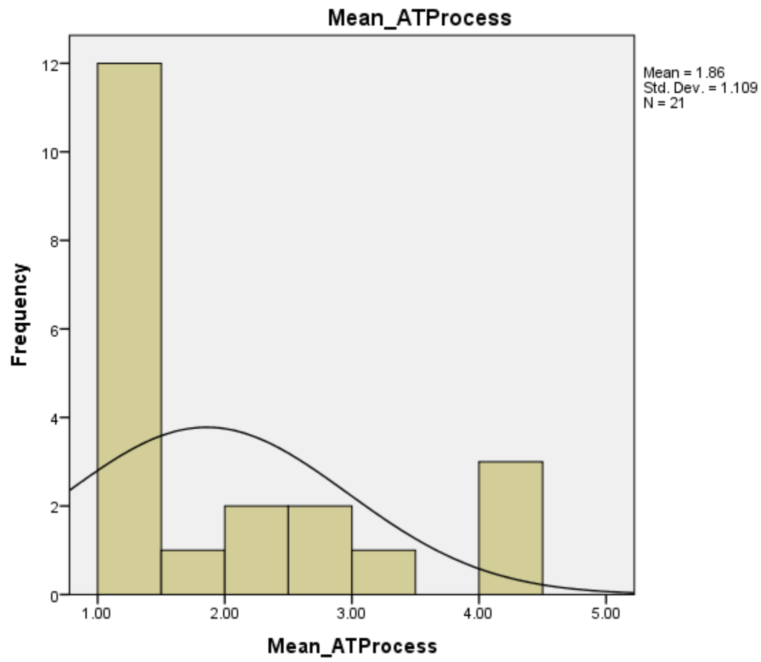


Figure 3.8 Histogram showing skewness in Ability to process

Kurtosis statistics showed negative kurtosis for variables *motivated*, *ability to process*, *argument quality, elaboration*, *perceived behavioural control*, *intention, behaviour* and *attitude certainty*, implying that these distributions are slightly flatter than normal. *Peripheral cues*, *attitude* and *subjective norms* on the other hand have more peaked distributions than normal with positive kurtosis values.

Overall, standardised (z) values for skewness and kurtosis of the variables (except for skewness of *ability to process*) fall within the range of +/- 1.96. This implies that values are within 95% confidence interval of a normal distribution. . See Table A.2 in appendix A.6 for the z values obtained by dividing each statistic by their respective standard errors.

3.4.4.2 Linearity

This is a check for a linear relationship between two variables and can be assessed visually on a scatterplot. If a linear relationship exists between two variables, which also have normal distributions, the scatter plot will be oval-shaped. However, if one of two linearly related variables does not have a normal distribution, the scatterplot obtained will not be oval.

Correlational analysis such as Pearson's *r* only captures linear relationships among variables, while overlooking sunstantial non-linear relationships among variables. Hence, the importance of a linearity check (Tabachnick and Fidell, 2007).

In checking for linearity, outcome variables (in this case, *elaboration, attitude, intention* and *behaviour* respectively) should be linearly related to the respective predictor variables.

Based on the framework being tested, three sets of dependent variables with their respective predictors have been created. The first TPB dependent variable is *Intention* with predictor variables *attitude, subjective norms,* and p*erceived behavioural control.* The second TPB dependent variable *Behaviour* has *Intention* as it's direct predictor while ELM variables *elaboration, motivated, ability to process*, *argument quality* and *peripheral cues* act as predictor variables for the outcome variable *attitude* (which is a predictor variable in the *TPB*). If an information-based intervention results in a positive change in attitude towards the desired behaviour, it is implied that persuasion was achieved, therefore the *attitude* variable can be a measure of persuasion and serves as the link between the Elaboration Likelihood Model and the Theory of Planned Behaviour in the suggested framework. The scatterplots below show the linearity in these relationships.

SET 1: Outcome variable – *Intention*, Predictor variables – *Attitude, Subjective norms,* and P*erceived behavioural control*

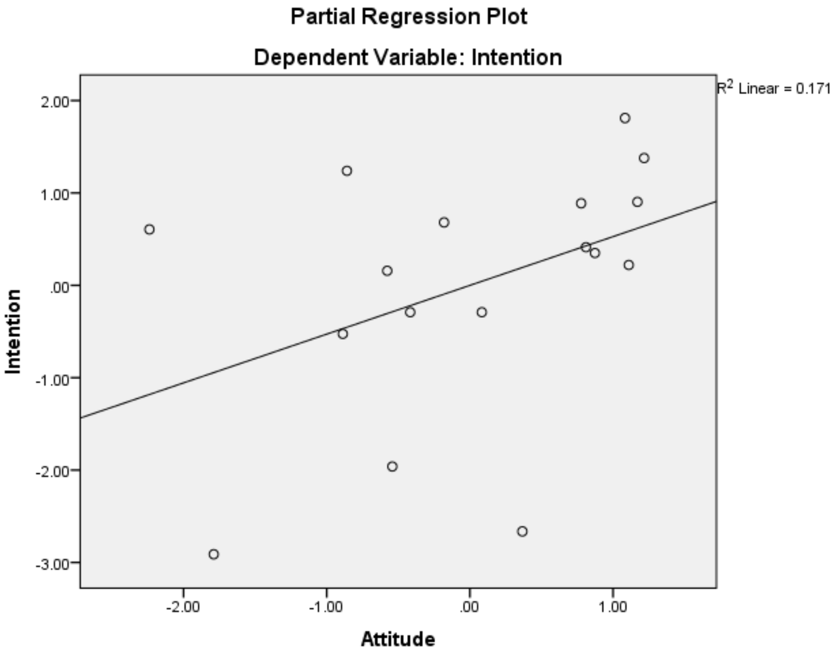


Figure 3.9 Scatterplot showing relationship between outcome variable, *intention* and predictor variable, *attitude*

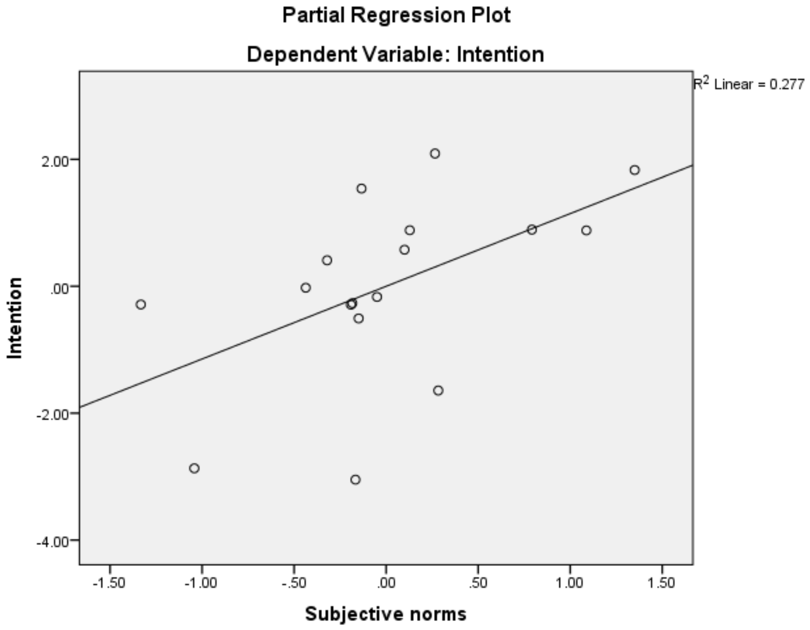


Figure 3.10 Scatterplot showing relationship between outcome variable, *intention* and predictor variable, *subjective norms*

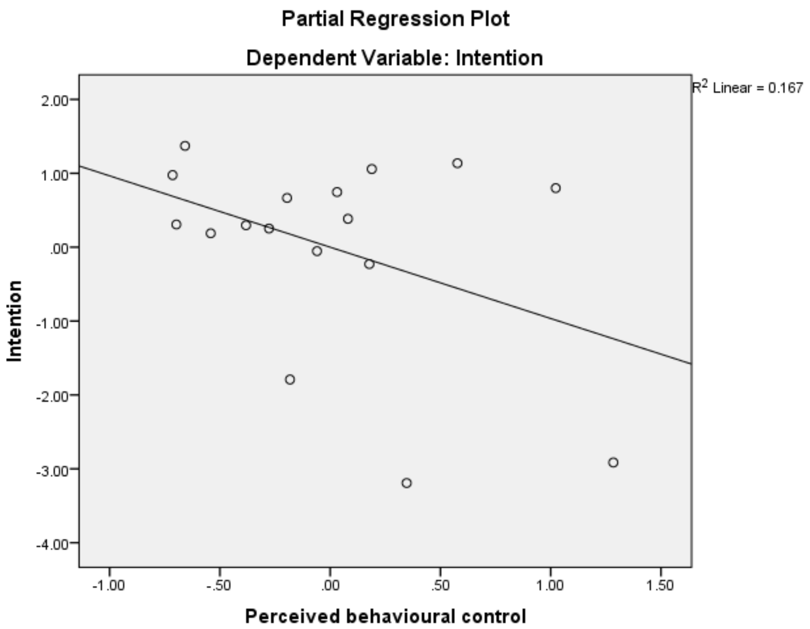


Figure 3.11 Scatterplot showing relationship between outcome variable, *intention* and predictor variable, *perceived behavioural control.*

Figure 3.9 shows a clear positive linear trend in the *Intention-Attitude* relationship, indicating that positive attitudes strengthen the intention to save energy. However the spacing out of the data points suggest that the relationship is not very strong. With the sample size (N=17) being small, this is understandable.

Figure 3.10 also shows a positive linear relationship between *intention* and *subjective norms.* This suggests that social norms inspires the intention to save energy on campus. A higher number of points are closer to the line suggesting a stronger relationship than *Intention-Attitude*. *.*

The *Intention-Perceived Behavioural Control* scatterplot in Figure 3.11 shows a negative trend, implying that a higher level of perceived behavioural control does not strengthen the intention to save energy.

<u>Set 2: Outcome variable – Attitude; Predictor variables – *Motivated, Ability to process*, *Argument quality*, *Peripheral cues, Elaboration*</u>

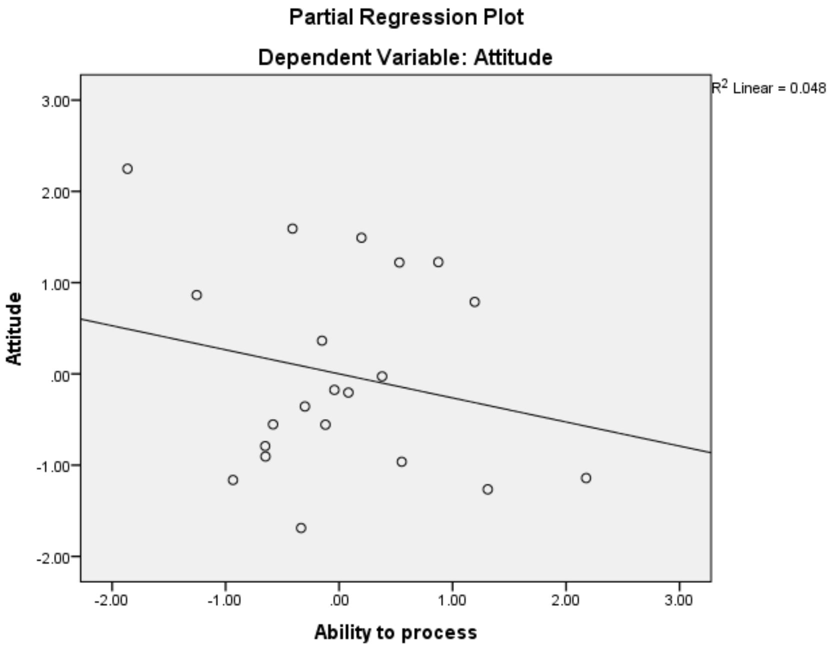


Figure 3.12 Scatterplot showing relationship between outcome variable Attitude and predictor variable Ability to process

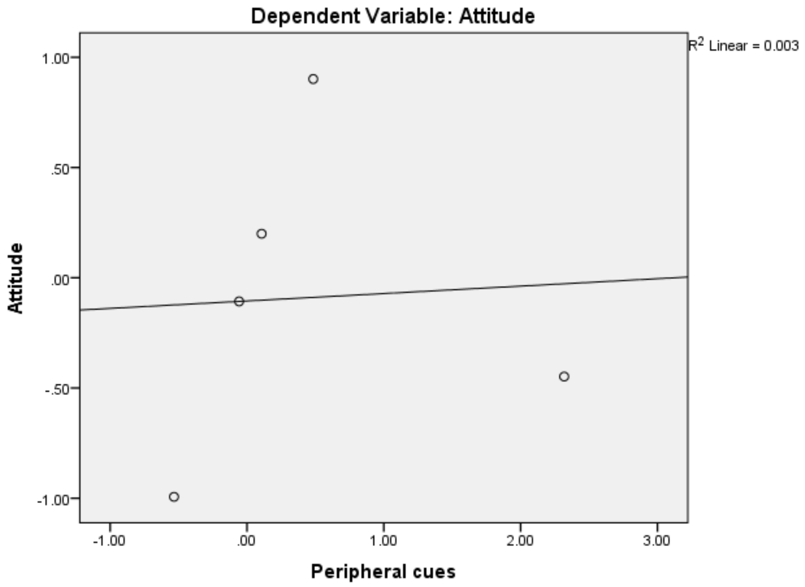


Figure 3.13 Scatterplot showing relationship between outcome variable Attitude and predictor variable Peripheral cues

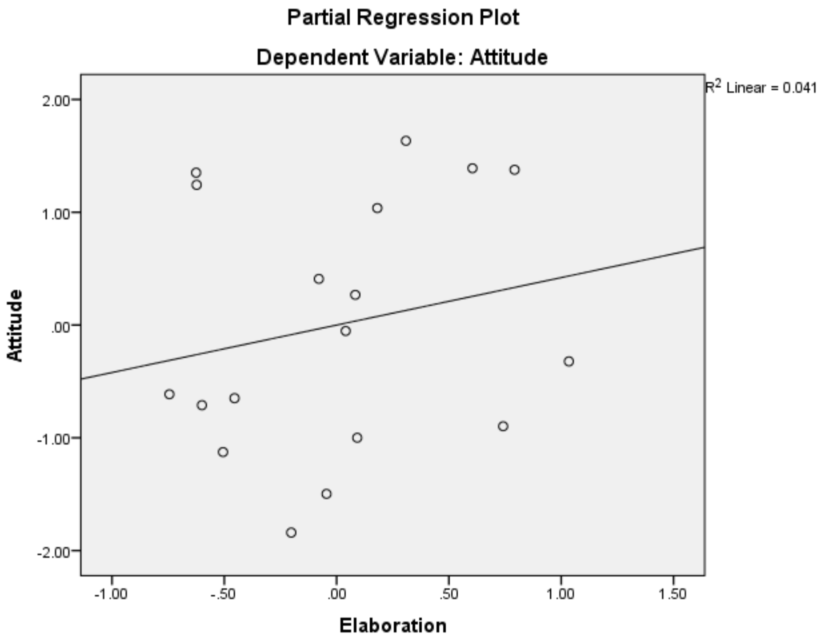


Figure 3.14 Scatterplot showing relationship between outcome variable Attitude and predictor variable Elaboration

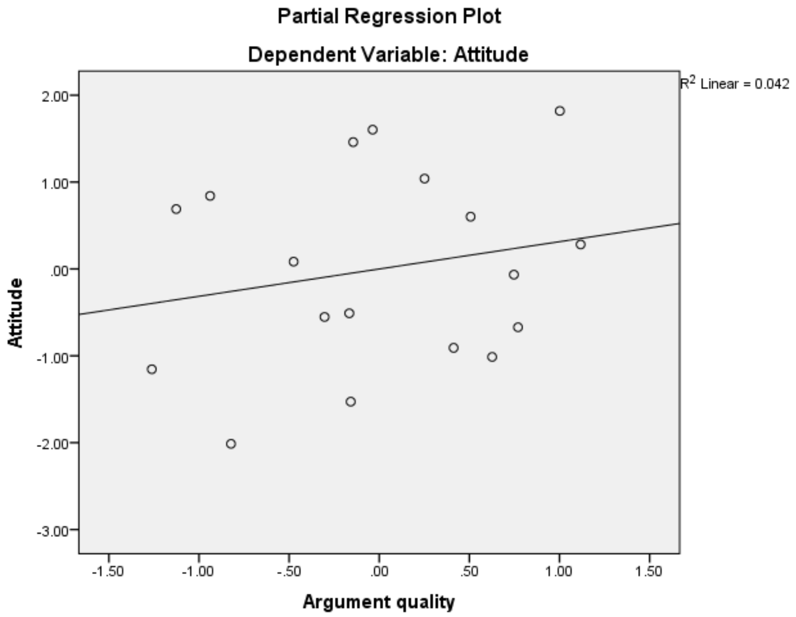


Figure 3.15 Scatterplot showing relationship between outcome variable Attitude and predictor variable Argument Quality

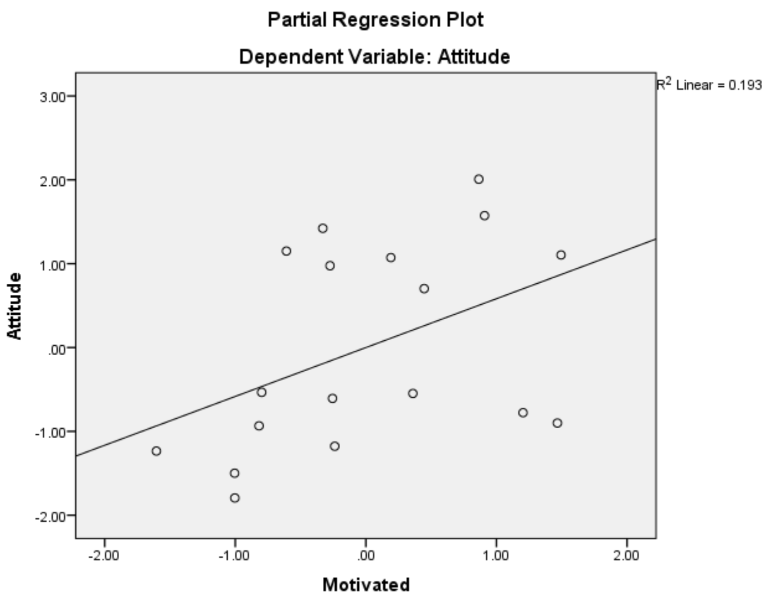


Figure 3.16 Scatterplot showing relationship between outcome variable Attitude and predictor variable Motivated

Figure 3.12 suggests a negative relationship between *Attitude* and *Ability to process,* implying that students' ability to understand the information given in the 'student switch off' campaign does not result in a more positive attitude towards energy saving on campus.

Figure 3.13 shows a very mild positive, arguably neutral linear relationship between *Attitude* and *Peripheral cues.*Only 5 respondents were familiar with the sponsors of the *student switch off* campaign, hence limiting the number of data points.

Attitude-Elaboration linear relationship in Figure 3.14 is a positive one, indicating that a deeper understanding or rationalisation of the intervention improves attitudes towards energy saving among the sample population. Similarly, a rise in *Argument Quality* is seen to improve energy saving attitudes (Figure 3.15).

The scatterplot in Figure 3.16 suggest that being motivated about the *student switch off* campaign has a clearly positive effect on energy saving attitudes among the sample population.

SET 3: Outcome variable – *Behaviour,* Predictor variable – *Intention*

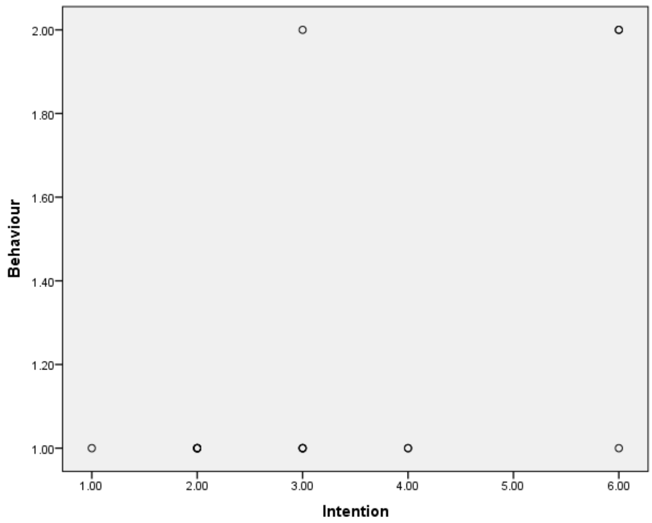


Figure 3.17 Scatterplot showing relationship between outcome variable Behaviour and predictor variable Intention

The *Behaviour*-*Intention* relationship shown in Figure 3.17 above does not look linear; however, this may be expected as *Behaviour* is a dichotomous variable, having only two possible values —“yes”or “no” (Hanna and Dempster, 2012).

3.4.4.3 Multicollinearity

This refers to a state of perfect correlation among variables. This check tests the extent to which predictor variables correlate highly with each other. Even though some correlation could be expected among predictor variables, very high correlations mean that the distinctive effect of a predictor on the outcome cannot be singled out as the predictor variables may just be measuring similar attributes. SPSS gives two measures of multicollinearity namely *Tolerance* and *Variance Inflation Factor (VIF).* These measures are inverted forms of one another i.e. Tolerance=1/VIF and VIF=1/Tolerance. It is generally accepted that a *Tolerance* and *VIF* value of 1 means the absence of multicollinearity (which is ideal) and the lesser than 1 the Tolerance values are, the higher the multicollinearity. Values below 0.2 are indicative of problems with the slope of the regression line (meaning that the predictor variable will not adequately predict the outcome). Conversely, *VIF* values above 1 indicate higher levels of multicollinearity and values above 5 are deemed problematic.

The collinearity figures in Table 3.8 and Table 3.9 show that all predictor variables have acceptable multicollinearity. The variable—*peripheral cues*—was left out of set 2 (Figure 3.15) because with only 5 data points, it will distort the real state of multicollinearity. Therefore, holding all other influences constant, it should be possible to determine the effect of each predictor variable on respective outcome variables – *Intention* and *Attitude.*

Collinearity statistics are not computed for *Intention (*the direct predictor of *Behaviour)* as it is a single predictor variable.

Table 3.8 SPSS Collinearity statistics for SET 1 predictor variables

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.240	2.358		.526	.608		
	Attitude	.528	.323	.473	1.635	.126	.597	1.674
	Perceived behavioural control	-.965	.598	-.552	-1.615	.130	.428	2.338
	Subjective norms	1.146	.514	.619	2.231	.044	.648	1.543

a. Dependent Variable: Intention

Table 3.9 SPSS collinearity statistics for SET 2 predictor variables

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.212	1.255		-.169	.868		
	Motivated	.583	.331	.512	1.761	.102	.597	1.675
	Ability to process	-.505	.432	-.428	-1.170	.263	.376	2.658
	Argument quality	.314	.416	.225	.757	.463	.569	1.758
	Elaboration	.421	.563	.267	.748	.468	.395	2.532

a. Dependent Variable: Attitude

3.4.4.4 Homoscedasticity

This refers to homogeneity of variance between the output variable and all predictor variables. In other words, the variance of the output variable should not change irrespective of the number of data groups. Checking for homoscedasticity helps in choosing the right type of analysis especially where linear regression is being considered as the analysis of choice. If this criterion is absent, linear regression is not the appropriate type of analysis. The absence of a homoscedastic relationship among data is called heteroscedasticity and may be the result of a variable not having a normal distribution, the transformation of a related variable or a significant error in measurement of predictor variables. Formal tests for homoscedasticity include Levene's test, which is a one-way ANOVA of the deviation scores to test that variances across all groups of data are equal. Another is the variance ratio (a.k.a. Hartley's Fmax) test. In Hartley's Fmax, the ratio of the largest variance to the smallest is matched against critical values in a table published by Harley; however, this method is not commonly used.

A fairly simple and more up-to-date method of assessing homoscedasticity is to fit a model e.g. a straight line, to the data on a scatterplot and subsequently generate a second plot of residuals against predicted outcomes (both in standardised formats) or vice versa. If the data is homoscedastic, the generated plot should be a random array of dots with no "systematic relationship" observed (between errors and predicted values). Conveniently, this yardstick also holds true for linearity. (Field, 2013).

Figure 3.18 and Figure 3.19 are scatterplots of standardised predicted outcomes vs. standardised residuals of Set 1 and Set 2 variables respectively. In both cases, points are randomly spaced out with no specific pattern and so the data are deemed as being homoscedastic.

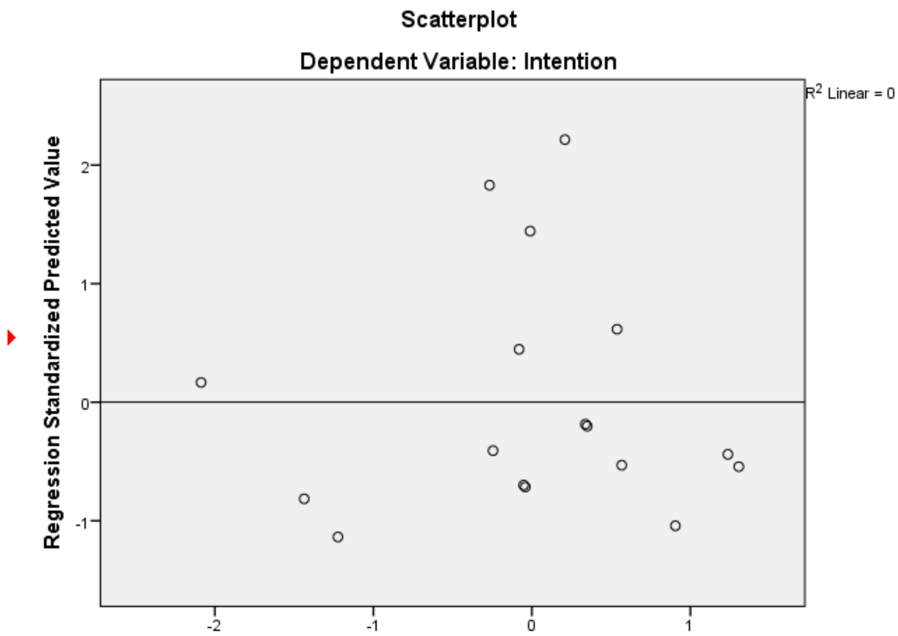


Figure 3.18 Scatterplot of predicted outcomes vs. residuals (standardised) for dependent variable Intention

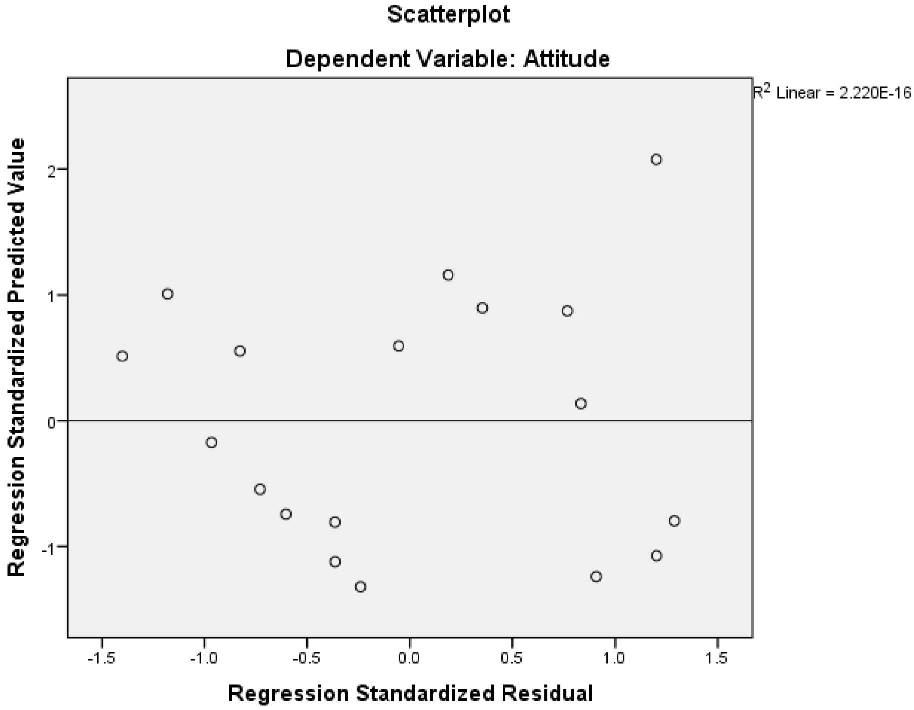


Figure 3.19 Scatterplot of predicted outcomes vs. residuals (standardised) for dependent variable Attitude

<u>Outliers:</u> No outliers by distance for Sets 1 and 2, evidenced by the absence of a "casewise diagnostics" output table from SPSS. No outliers by influence; maximum value for Cook's distance is less than 1 in both cases. Maximum centred leverage value for both sets is less than 3 times the mean (Table 3.10 and Table 3.11). For Set 3, *behaviour - intention,* there are no outliers by distance and maximum value for Cook's distance is less than 1 (Table 3.12). However, the maximum centred leverage value is marginally higher than 3 times the mean. Looking at the leverage values and Cook's distances (N=17) generated by SPSS in the data file, there are 3 cases with the maximum centred leverage value (0.204). However, the corresponding Cook's distances are low (0.366). These data points were retained for analysis.

Table 3.10 Set 1 Residuals statistics table showing Cook's distance and Centred Leverage Value

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.6751	6.7146	4.7059	.90696	17
Std. Predicted Value	-1.137	2.215	.000	1.000	17
Standard Error of Predicted Value	.391	.943	.639	.188	17
Adjusted Predicted Value	2.6023	6.5453	4.7152	1.09006	17
Residual	-2.85731	1.78702	.00000	1.23411	17
Std. Residual	-2.087	1.305	.000	.901	17
Stud. Residual	-2.247	1.800	-.004	1.086	17
Deleted Residual	-3.35104	3.39772	-.00931	1.83212	17
Stud. Deleted Residual	-2.761	1.996	-.042	1.215	17
Mahal. Distance	.361	6.644	2.824	2.164	17
Cook's Distance	.000	.730	.144	.243	17
Centered Leverage Value	.023	.415	.176	.135	17

a. Dependent Variable: Intention

Table 3.11 Set 2 Residuals statistics table showing Cook's distance and centred leverage value

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.9566	3.7437	2.1786	.75729	21
Std. Predicted Value	-1.614	2.067	.000	1.000	21
Standard Error of Predicted Value	.321	.736	.499	.120	21
Adjusted Predicted Value	.5798	3.4755	2.1673	.76246	21
Residual	-1.77728	1.75628	.00000	1.08226	21
Std. Residual	-1.514	1.496	.000	.922	21
Stud. Residual	-1.787	1.921	.004	1.043	21
Deleted Residual	-2.47550	2.89566	.01131	1.39895	21
Stud. Deleted Residual	-1.924	2.106	.014	1.082	21
Mahal. Distance	.542	6.917	2.857	1.771	21
Cook's Distance	.000	.599	.079	.138	21
Centered Leverage Value	.027	.346	.143	.089	21

a. Dependent Variable: Attitude

Table 3.12 Set 3 Residuals statistics table showing Cook's distance and centred leverage value

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.8682	1.5777	1.1875	.22285	16
Std. Predicted Value	-1.433	1.751	.000	1.000	16
Standard Error of Predicted Value	.088	.180	.118	.035	16
Adjusted Predicted Value	.8354	1.7880	1.1818	.23047	16
Residual	-.57770	.84797	.00000	.33591	16
Std. Residual	-1.661	2.439	.000	.966	16
Stud. Residual	-1.940	2.521	.007	1.055	16
Deleted Residual	-.78802	.90614	.00569	.40345	16
Stud. Deleted Residual	-2.187	3.288	.051	1.221	16
Mahal. Distance	.025	3.066	.938	1.168	16
Cook's Distance	.000	.685	.109	.199	16
Centered Leverage Value	.002	.204	.062	.078	16

a. Dependent Variable: Behaviour

3.4.5 Correlational Analysis

Bivariate correlation analysis performed on survey data are presented in this section. Pre-analysis screening of the data indicated that linear relationships existed among the variables. To understand these relationships in the light of strength and direction, correlation coefficients (*r*) were obtained. Of the various correlational methods, Spearman's correlation was chosen to reduce any potential effects of deviations from normality in the data (Field, 2013). The correlation was two-tailed because no hypothesis was being tested; therefore, no direction was being suggested (Hanna and Dempster, 2012). The primary objective was to understand any existing relationships among variables. Correlation coefficients range from +1 to -1. The sign is indicative of direction (0 means no relationship) and the number, strength. As a guide, (Cohen, 1988) stipulates that +/-0.1 represents a small effect; +/-0.3, medium and +/-0.5 is a large effect. However, it is recommended to always interpret correlation coefficients in the context of the study being done (Field, 2013). In a written commentary, Hemphill (2003) argued that it is overly simplistic to have only a set of guidelines for interpreting the magnitudes of correlation coefficients, especially as the current guidelines (above) were formed by splitting the distribution into lower, upper and middle thirds. He maintained that other cut offs could have been used and different sets of guidelines produced. This inference was made from reviewing two meta-analytic studies on psychological assessment (Lipsey and Wilson, 1993; Meyer et al., 2001). Findings from the review indicated that Cohen's (1988) guideline for a large effect size (+/- 0.5) was hardly observed in many significant psychology research studies; rather a lower value seemed to be more typical. Table 3.13 shows correlations at 1% statistical significance, while Table 3.14 shows correlations at 5% statistical significance.

Table 3.13 Variables that correlated at 1% significance with Spearman's 2-tailed correlation

Variables	Attitude			Motivation			Perceived Behavioural control			Subjective Norms		
	r	R^2	N	r	R^2	N	r	R^2	N	r	R^2	N
Attitude				0.56	0.31	21	0.67	0.44	21			
PBC				0.58	0.34	21						
Attitude Certainty	0.78	0.60	21	0.56	0.31	21	0.75	0.57	21	0.61	0.37	21
ATP				0.57	0.33	21						

Table 3.14 Variables that correlated at 5% significance with Spearman's 2-tailed correlation

Variables	Argument Quality			Subjective Norms			Ability to Process		
	r	R^2	N	r	R^2	N	r	R^2	N
Elaboration	0.51	0.26	18				0.56	0.31	18
Argument Quality				0.53	0.28	21			
Motivation	0.53	0.28	21						
Intention	0.59	0.35	17	0.54	0.29	17			
PBC	0.52	0.27	21	0.49	0.24	21			

To further understand the relationship between correlated variables, each *r* was squared to produce a coefficient of determination (R^2). R^2 "is a measure of the amount of variability in one variable that is shared by another" (Field, 2013). Presenting R^2 as a percentage may make it more meaningful and although it helps to explain shared variances between variables, it does not imply causality. All statistically significant correlations at the $p = 0.01$ level were strong and positive, ranging from 0.56 to 0.78. At $p = 0.05$, r ranged from 0.49 to 0.59. Outcomes of the analysis at 1% statistical significance levels are discussed below:

Attitude and *Attitude certainty*

There was a strong, positive, statistically significant relationship between *attitude* and *attitude certainty;* r (19) = 0.78, p = .000

With a shared variance of 60%, this indicates that people with positive energy conservation attitudes were more convinced that their attitudes were correct. Attitude certainty lends strength to the attitude construct and together, both constructs could serve as a measure of attitude strength (Kokkinaki, 1999). However, this may be too simplistic a measure as other dimensions of attitude strength have been identified by researchers which together improve the measurement of the attitude construct (Raden, 1985). Attitudes borne with high levels of conviction are known to be more resistant to change, longer lasting and more influential in causing behaviour change (Bassili and N., 1996; Fazio and Zanna, 1978; Tormala and Petty, 2002).

Attitude certainty and *Perceived behavioural control*; *Attitude* and *Perceived behavioural control*

The relationship between *Attitude certainty* and *Perceived behavioural control* was strong and positive r (19) = 0.75, p = .000, having a shared variance of 57%, implying that respondents who felt they could exercise the self-control required to save energy, were more certain that saving energy was the right thing to do. Being underpinned by the role of “self”, this outcome is consistent with research findings on paradigms of perceived self-efficacy which plays a significant role in people’s thoughts, feelings, motivations and ultimately behaviour (Bandura, 1993).

The relationship between *Attitude* and *Perceived behavioural control* was also strong and positive; r (19) = 0.67, p = .001, having a shared variance of 44% and suggests a link between being positive about energy saving and the feeling of being able to apply self-discipline to prevent wasting energy. Going by the TPB and considering attitude strength (discussed above), both outcomes indicate an increased likelihood of energy saving behaviour among the sample, especially if *subjective norms* are positive as well.

Attitude certainty and *Subjective norms*

The relationship between *Attitude certainty* and *Subjective norms* was strong and positive; r (19) = 0.61, p = .004, having a shared variance of 37%. This outcome implies that the influence of important relationships on energy saving is more effective where an individual has firm convictions that energy saving is justified.

Thus, where the target behaviour is deemed unnecessary by an individual, social influence may be less effective. This suggests that a focus on attitude change will be necessary to fully harness the potential strength in social influence to achieve energy saving among HEI students.

Another interpretation could be that an individual is more certain of his/her attitude towards energy saving when important people in their lives share the same convictions, which also implies being certain of their subjective norm. This inter-relationship potentially benefits energy conservation and is consistent with a study by (Trafimow, 1994) where certainty mediated the relationship between subjective norms and intention.

Perceived behavioural control and Motivation

The relationship between *Perceived behavioural control and Motivation* was strong and positive, r (19) = 0.58, p = .005, with a shared variance of 34%. This suggests that being motivated about energy saving may strengthen an individual's self-perception of being able to save energy. It may also suggest the reverse, where the feeling of being able to achieve energy saving motivates an individual to engage in the behaviour. Considering that perceived behavioural control on its own can predict behaviour in situations where it reflects actual control (Sheeran et al., 2003), this outcome lends relevance to motivation as a potential precursor to behaviour in the context of this study at the least.

Ability to process and Motivation

The relationship between Ability to process and Motivation was strong and positive, r (19) = 0.57, p = .006, with a shared variance of 33%. This outcome suggests that people that were motivated were able to process the messages in the intervention. This result is consistent with the *ELM* for achieving the desired attitude change. Considering that information availability does not guarantee attitude or behaviour change, the above correlation is regarded as encouraging because it suggests that the intervention did not result in de-motivation caused by being confused or overwhelmed from excessive information (e.g. thoughts that the problem is too complex and cannot be resolved by small contributions from individuals)(Prager, 2012)

<u>*Attitude and Motivation; Attitude certainty and Motivation*</u>

Motivation correlated in the same way with *Attitude* and *Attitude certainty*, respectively. The relationships were strong and positive r (19) = 0.56, p = .009, with a shared variance of 31%. This suggests that respondents who had a positive attitude towards energy saving felt motivated and were sure that saving energy is worthwhile. Instead of viewing *motivation* simply as a trigger for elaboration (thinking) on a message, these results suggest that motivation could be directly linked to attitudes and certainty. It is reasoned that (perhaps) indirectly and depending on the context, motivation could be viewed as an outcome of the message (motivating positive attitudes) rather than a determinant of how a message is received or processed.

3.4.6 **Regression Analysis**

Regression analysis is a statistical tool for exploring relationships between variables. It is often used to determine the causal effect of one or more variables (predictor or independent variables) on another (response or dependent variable). In regression analysis, the relationship between variables is expressed as an equation for a line or curve. Different types of regression analysis exist, however linear regression (simple linear regression and multiple linear regression) is used in this study as the variables fulfil the assumptions of this method.

Linear regression calculates the way variations in the dependent variable relate to changes in the independent variable. Significantly, by design, regression controls for all variables included in the model i.e. the effect of each independent variable is computed holding constant all other predictors in the model.

A simple linear regression equation is as follows:

$$y = a + bx$$

Where:

y=Dependent variable

a=y- intercept or constant

b=Slope or regression coefficient

x=Predictor variable

The equation for multiple linear regression is:

$$\boldsymbol{y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n + \varepsilon}$$

Where:

y = dependent variable

x_n = independent variables

b_0 = intercept or constant

b_n = regression coefficients

ε = error

Having carried out relevant pre-analysis checks in section 3.4.4 regression analyses are carried out on the data sets. The purpose of this is twofold:

1) To explain relationships between dependent and independent variables in the ELM-TPB framework.
2) To explore the possibility of predicting the dependent variables in the framework.

To understand possible effects of ELM and TPB variables on one another, several sets of regression analysis were performed[1].

3.4.6.1 Regression Set 1: Intention vs. Attitude, Subjective Norms, and Perceived Behavioural Control

In the Theory of Planned Behaviour, Intention is suggested to be antecedent to Behaviour. A combination of attitude, subjective norms and perceived behavioural control are in turn antecedent to Intention. A multiple regression analysis was carried out to determine the effect of these core variables on the intention to save energy among students. There were no outliers by distance; however, 3 probable outliers by influence were identified. These were retained because the corresponding Cook's distances were acceptable (see Table 3.10) having been examined using SPSS casewise diagnostics, Cook's distance test

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[1] Only 5 respondents were conversant with the sponsors of the *student switch off* campaign, therefore only 5 responses were obtained for the variable *peripheral cues*. Therefore, some of the analyses were performed omitting peripheral cues to prevent limiting the data set.

and centred leverage values. The data showed acceptable normality, assessed by inspection of a histogram and statistics for skewness and kurtosis.

Mild but acceptable collinearity was observed among variables on inspection of computed Tolerance and VIF values. The requirement for homogeneity of variance was met, assessed by inspection of the scatter plot for standardised predicted values and residuals. The model showed that the probability (p value) that R^2 occurred by chance is 12.1 % ($F(3, 13) = 2.340$, $p = 0.121$). The adjusted R^2 indicated that only 20% of the variance in *Intention* could be explained by the variances in the three predictor variables. *Subjective norms* (β=0.619) was the most influential predictor, followed by *attitude* (β=0.473). Perceived behavioural control had no positive influence on the intention to save energy on campus (β= -0.552; see Table 3.15a, b, c and Table 3.16 for the output tables from SPSS). Going by the generally accepted p value for statistical significance ($p<0.05$), only *Subjective norms* ($t = 2.23$; $p = 0.04$) was shown to be a statistically significant predictor of *Intention.*

From the coefficient values given in

Table 3.16, the regression model for intention is:

Intention = 1.240 + (0.528 * *Attitude*) + (1.146 * *Subjective norms*) + (-0.965 *PBC*)

(3.1)

The model suggests that among the student sample, every unit change in attitude affects the intention to save energy b y 0.528 points. Similarly, a unit increase in the influence of *subjective norms* strengthens *Intention* by 1.146 points. A unit increase in *perceived behavioural control* however, weakens the intention to save energy. Overall, the model implies that *perceived behavioural control does* not inspire the intention to save energy on campus. However, *subjective norms* and *attitude* positively influence energy saving intentions.

Table 3.15 a, b, c Set 1 SPSS regression output tables for variables entered, model summary and ANOVA.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Perceived behavioural control, Subjective norms, Attitude[b]	.	Enter

a. Dependent Variable: Intention

b. All requested variables entered.

a

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.592[a]	.351	.201	1.36912	2.213

a. Predictors: (Constant), Perceived behavioural control, Subjective norms, Attitude

b. Dependent Variable: Intention

b

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.161	3	4.387	2.340	.121[b]
	Residual	24.368	13	1.874		
	Total	37.529	16			

c

Table 3.16 Set 1 regression coefficients' table

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part
1	(Constant)	1.240	2.358		.526	.608	-3.853	6.333			
	Attitude	.528	.323	.473	1.635	.126	-.170	1.225	.301	.413	.365
	Subjective norms	1.146	.514	.619	2.231	.044	.036	2.255	.430	.526	.499
	Perceived behavioural control	-.965	.598	-.552	-1.615	.130	-2.257	.326	.106	-.409	-.361

a. Dependent Variable: Intention

3.4.6.2 Regression Set 2: Attitude vs. Motivated, Ability to process, Argument quality[2].

Attitude, a dependent variable in the ELM and an antecedent in the TPB, is the link between both theories. Accordingly, multiple regression analysis was carried out to determine the influence of ELM variables *ability to process*, *motivation* and *argument quality* on attitudes toward energy saving among participants. There were no outliers in the data, examined using SPSS casewise diagnostics, Cook's distance test and centred leverage values. The data showed acceptable normality, assessed by inspection of a histogram. Mild but acceptable collinearity was observed among variables on inspection of computed Tolerance and VIF values. The requirement for homogeneity of variance was met, assessed by inspection of the scatter plot for standardised predicted values and residuals. The model showed that the probability (p value) that R^2 occurred by chance is 7.3% ($F=2.775$, $p=0.073$). The adjusted R^2 indicated that only 21% of the variance in *Attitude* could be explained by the variances in the three predictor variables. *Motivated* ($\beta=0.464$) was the most influential predictor and *Ability to process* ($\beta=-0.221$), the least influential predictor in the model. SPSS output tables of the analysis are shown below in Table 3.17a, b, c and Table 3.18.

Going by the generally accepted p value for statistical significance ($p<0.05$), none of the independent variables were shown to be statistically significant predictors of Attitude. The regression model for attitude is shown in **(3.2)** below.

[2] Elaboration and Peripheral cues excluded

$$\textit{Attitude} = 0.235 + (0.526^{*}\ \textit{motivated}) + (-0.264 * \textit{Ability to process}) + (0.403 * \textit{Argument quality}) \tag{3.2}$$

The unstandardized coefficients show that among the student sample, variables *motivated* and *argument quality* strengthened *Attitude* towards energy saving. For every unit increase in feeling motivated, attitudes are strengthened by 0.526 points. Similarly, a unit increase in *argument quality* strengthens *Attitude* by 0.403 points. The ability to process information given in the student switch off campaign however weakens attitudes towards energy saving by 0.264 points. Overall, the model suggests that being motivated and the quality of the message argument have greater influence on energy saving attitudes than the ability to process the intervention.

Table 3.17 a, b, c Set 2 SPSS regression output tables for variables entered, model summary and ANOVA.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Argument quality, Ability to process , Motivated[b]	.	Enter

a. Dependent Variable: Attitude

b. All requested variables entered.

a

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.573[a]	.329	.210	1.17388

a. Predictors: (Constant), Argument quality, Ability to process , Motivated

b. Dependent Variable: Attitude

b

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.470	3	3.823	2.775	.073[b]
	Residual	23.426	17	1.378		
	Total	34.896	20			

a. Dependent Variable: Attitude

b. Predictors: (Constant), Argument quality, Ability to process , Motivated

c

Table 3.18 Set 2 regression coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.235	.816		.288	.777	-1.486	1.955
	Motivated	.526	.282	.464	1.864	.080	-.069	1.120
	Ability to process	-.264	.285	-.221	-.925	.368	-.865	.338
	Argument quality	.403	.363	.282	1.111	.282	-.363	1.170

a. Dependent Variable: Attitude

P values above 0.05; deemed not statistically significant

3.4.6.3 Regression set 3: *Behaviour* vs. *Intention*

Behaviour is the outcome variable in the Theory of Planned Behaviour. Having *Intention* as its direct antecedent, this may be used as a proxy where measures of behaviour are unavailable. With both variables having fulfilled the assumptions of regression, a simple linear regression was performed to determine the influence of the intention to save energy in halls of residence on the focal behaviour—energy saving among students. There were no outliers in the data, examined using SPSS casewise diagnostics, Cook's distance test and centred leverage values. The data showed mild skewness in distribution but did not violate normality, assessed by inspection of a histogram alongside skewness and kurtosis statistics. The model was statistically significant ($F (1, 14) = 6.162$, $p < 0.05 (p = 0.026)$). The adjusted R^2 shows that 25.6% of the variance in *Behaviour* can be explained by the variance in *Intention*. *Intention* was shown to be a statistically significant predictor of *Behaviour* ($t = 2.482$, $p < 0.05$ ($p =0.026$)). Output tables from SPSS are presented in Table 3.19 a, b, c and Table 3.20

From the coefficient values derived (see Table 3.20), the regression equation for the model is:

$$\textit{Behaviour} = 7.26 + 0.142 * \textit{Intention}. \tag{3.3}$$

The model suggests that a unit increase in *Intention* was related to an increase of 0.142 units in behaviour, contributing to an improvement in behaviour albeit mild. The model is therefore deemed consistent with the *TPB*.

Table 3.19 a, b, c Set 3 SPSS regression output tables for variables entered, model summary and ANOVA.

Variables Entered/Removed[a]

a

Model	Variables Entered	Variables Removed	Method
1	Intention[b]	.	Enter

a. Dependent Variable: Behaviour

b. All requested variables entered.

Model Summary[b]

b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.553[a]	.306	.256	.34770	.729

a. Predictors: (Constant), Intention

b. Dependent Variable: Behaviour

ANOVA[a]

c

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.745	1	.745	6.162	.026[b]
	Residual	1.693	14	.121		
	Total	2.438	15			

a. Dependent Variable: Behaviour

b. Predictors: (Constant), Intention

Table 3.20 Set 3 SPSS regression coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.726	.205		3.541	.003	.286	1.166					
	Intention	.142	.057	.553	2.482	.026	.019	.264	.553	.553	.553	1.000	1.000

a. Dependent Variable: Behaviour

3.4.7 **Summary of results**

Key results from the analyses presented in the preceding sections are summarised in the bullet points below.

- A strong, positive, statistically significant relationship between *attitude* and *attitude certainty* with a shared variance of 60% suggests that people with positive energy conservation attitudes were more convinced that their attitudes were correct.
- A strong, positive, statistically significant relationship between *Attitude certainty* and *Perceived behavioural control* with a shared variance of 57%, implies that respondents who felt they had control of their energy use behaviours, were more certain that saving energy was the right thing to do.
- The relationship between *Attitude* and *Perceived behavioural control* was also strong and positive with a shared variance of 44%, suggesting a link between being positive about energy saving and the feeling of being in control of the behaviour.
- A strong, positive and statistically significant relationship between *Attitude certainty* and *Subjective norms* with a shared variance of 37% implies that the impact of important relationships on energy saving is more effective where a person's attitude toward the behaviour is resolute.
- The relationship between *Perceived behavioural control and Motivation* is strong, positive and significant. It suggests that being motivated about

energy saving may strengthen an individual's self-perception of being able to save energy. The reverse could also be the case, where the feeling of being able to achieve energy saving motivates an individual to engage in the behaviour

- *The relationship between Ability to process and Motivation* suggests that people that were motivated were also able to deliberate on the intervention's message.
- *Motivation correlates* with *Attitude* and *Attitude certainty in the same way—strong, positive and significant.*
- The regression model implies that *perceived behavioural control* has a negative effect on the *intention* to save energy on campus. However, *subjective norms* and *attitude* positively influence energy saving intentions. Also, it suggests that motivation and argument quality have greater influence on energy saving attitudes than cognitive ability i.e. *ability to process*

4 AGENT-BASED MODELLING FOR UNDERSTANDING INFORMATIONAL ENERGY SAVING INTERVENTIONS.

In the past two decades, agent-based models have been widely used across various fields to study the interactions of various types of agents and resulting effects over time. Examples of these are in economics (Boero, 2015; Morini and Pellegrino, 2015), healthcare (Barnes et al., 2013), policy analysis (Berger and Troost, 2011) and so on. As opposed to reductionist methods where the aggregate is used to provide information about individual components, ABM provides a bottom-up approach for understanding aggregate phenomena such as behaviour. Typically, an agent-based model is built from simple behavioural or decision rules at the level of individual agents and can be used to explore collective behaviour which cannot be determined from the simplest level but can emerge as a result of many interactions and possibly, complexities among individual elements of a system (Barnes and Chu, 2010; Bianchi et al., 2007).

4.1 An overview of current energy saving intervention studies containing agent-based modelling.

This section summarises selected studies that have used agent-based modelling in an energy-saving context. The purpose here is to highlight the diversity of ABM approaches that have been used in the energy saving domain. This study's justification for using ABM has been provided in section 1.1.6.

Azar and Menassa (2014) used ABM to simulate the effect of energy saving interventions (peer pressure, training and green social marketing) on total energy consumption of a standard commercial building with different companies. The aim of the study was to “develop a framework to evaluate the energy saving potential of occupancy interventions in commercial buildings by using real data to simulate a typical commercial building environment in the United States while accounting for its social subnetworks (i.e. companies)” (p. 65). To achieve this, peer pressure was studied within the context of sub-networking to understand how social interactions affect interventions. Comparable to this, Bale et al. (2014) used ABM to investigate diffusion of energy innovations in a real-world social system (city) while Jensen et al.(2015) identified ways by which behaviour diffusion spread the effects of feedback devices from adopters to non-adopters and boosted the rate of behaviour change among households.

Studies like these can offer insight into how social networks and subnetworks respond to interventions for energy demand reduction, guiding decision and/or policy makers in designing interventions that are more effective. In a similar vein, Savarimuthu et al. (2012) employed agent-based modelling to investigate social norms as a promoter of energy saving with particular focus on the respective and combined effects of descriptive and injunctive norms. Three agent-based models were developed, and a meta-norm based intervention approach proposed and explored based on their initial findings. This was done in a household context as opposed to organisational, where the influence of these norms was already being harnessed for marketing.

With a focus on identifying model features most critical for predicting typical patterns of the technology adoption process of residential solar photovoltaics, Robinson and Rai (2015) developed four adaptations of an agent-based model with varying levels of empirical characteristics and complexities. Their findings indicated the importance of defining attitudes and social interactions in agents for accurately predicting spatial and demographic adoption patterns.

Tran, (2012) built an agent-based model to investigate effects of individual behaviours and network influence on energy innovation diffusion. His findings indicated that risk-averse behaviour can counter network influence in quickening the diffusion of new energy innovations. However, larger populations can have a greater effect on an individuals' adoption of energy innovations than direct personal interactions.

In ABM, agents can represent a diverse range of entities. The key characteristic to note is that agents are the component of the model that act dynamically or make decisions in the simulated system (Barnes and Chu, 2010; Borshchev, 2013). For example, in Azar and Menassa (2014), agents were occupants (with specified energy use characteristics) in different companies within a commercial building; in Jensen et al. (2015) and Natarajan et al. (2011), households consuming energy; and office occupants in Zhang et al. (2011).

Real life data is mostly favoured over assumptions for defining ABM characteristics such as behaviour, environments and interactions. This has the obvious advantage of capturing any significant complexities present in the real system that could be missed if simplistic assumptions are made, thereby strengthening the applicability of the model. However, a key issue often overlooked is the continued relevance of the "real life" data for future purposes (Natarajan et al., 2011). Since most data are often collected in a snap-shot of time e.g. surveys, issues surrounding how to account for any changes to the original data may arise. For example, Azar and Menassa (2014) used real life data from a U.S. Energy Information Administration (2003) survey on commercial buildings energy consumption to define characteristics of their model built about a decade later. This could compromise the model's likelihood of predictive success and raise questions of validity for any assumptions deduced from the model output for present and future purposes. Nonetheless, it does not necessarily detract from the robustness of the framework itself. Several studies have highlighted that the effect of interventions on energy saving behaviour tend to wane in the long run (Abrahamse et al., 2005; Peschiera and Taylor, 2012; Staats et al., 2004, 2000). These underscore the importance of up-to-date real-life data in simulating energy intervention effects on behaviour.

Agent rules, states and decision processes typically govern the way agents choose between behavioural alternatives (Jager and Mosler, 2007). In developing these, some studies—e.g. this one—employ behavioural theories while others do not (see Table 4.1). An observed benefit of the theoretical approach is that it gives a clear hypothetical context to the agent-based model within the area being studied. In addition, agent based models can be indirectly useful for testing the applicability of the theories being used (Epstein, 1999; Smaldino et al., 2015). So far, theories have commonly been tested using methods such as survey results, case studies or experiments (e.g. (Ajzen, 1991; Cacioppo et al., 1985; Miniard and Cohen, 1981; Petty et al., 2009a). While these may be suitable for some theories, it may not be appropriate or beneficial for others. For example, behavioural theories in which contextual factors influence outcomes would have to be tested in many case studies before reliable conclusions can be drawn. This is a limitation of the case study approach which agent based modelling can overcome (Janssen et al., 2014). Other approaches that have been used in characterising agent states and decision processes include empirical analysis of the subject and logical assumptions (Janssen and Ostrom, 2006; Tran, 2012). Table 4.1 shows input characteristics of some identified ABM studies in the energy domain.

Table 4.1 Input characteristics of agent-based models in some energy behaviour/ intervention studies

Authors	Data source	Age of data source	Use of behavioural theory
Azar and Menassa (2014)	Survey	>10 years	✓
Chen et al. (2012)	Experiment	<2 years	×
Snape (2011)	Inference from another study	3 years	✓
Bale et al. (2014)	Survey Assumptions	2-3 years	×
Jensen et al. (2015)	Existing ABM Assumptions	1 year 5 years	✓
Natarajan et al. (2011)	Survey	>10 years	×
Zhang et al. (2011)	Survey Estate management	<1 year	×

Authors	Data source	Age of data source	Use of behavioural theory
Savarimuthu et al. (2012)	Government data	Not specified	✗
Robinson and Rai (2015); Rai and Robinson (2015)	Survey Energy provider Local authority	2-11 years	✓
Tran (2012)	Empirical analysis	Not specified	✓

4.2 Developing the agent-based model

As previously expressed in sections 1.1.6 and 1.3.1, this study uses agent-based modelling to integrate elements of theory and practice in a simulated environment for understanding energy behaviours.

In addition to the rationale already provided, the uniqueness of this approach as used herein is twofold. Firstly, at the heart of the model are two theories which have been around for a long time and have been tested and proven to be empirically sound by numerous studies (Alt and Lieberman, 2010). This means that the validity of the simulation and its exploratory worth can be more readily assessed within the existing research area as opposed to if a new theory/framework was being produced or tested (Mosler et al., 2001). Therefore, implying the potential of the approach as an explanatory method suitable for theory testing, development and perhaps, formation.

Secondly, even though the two theories—the Theory of Planned Behaviour and the Elaboration Likelihood Model—have been jointly but sparsely used to understand several types of behaviours including energy saving (Bae, 2008; Beale and Bonsall, 2007; Brown et al., 2010; Wilson, 2014), they are not known to have previously been jointly integrated in a computer simulation—particularly in an agent-based model—for understanding energy saving or other behaviours. By applying agent-based modelling within this context, the study contributes an original approach.

Survey data obtained from the first phase of the study were adapted for use as input parameters in the agent-based model. The development of the agent-based model consists of two main steps which are: designing and evaluating the model. This chapter focuses on describing the design aspects of the model development process. Figure 4.1 shows a summary of the complete modelling process and where this chapter fits in.

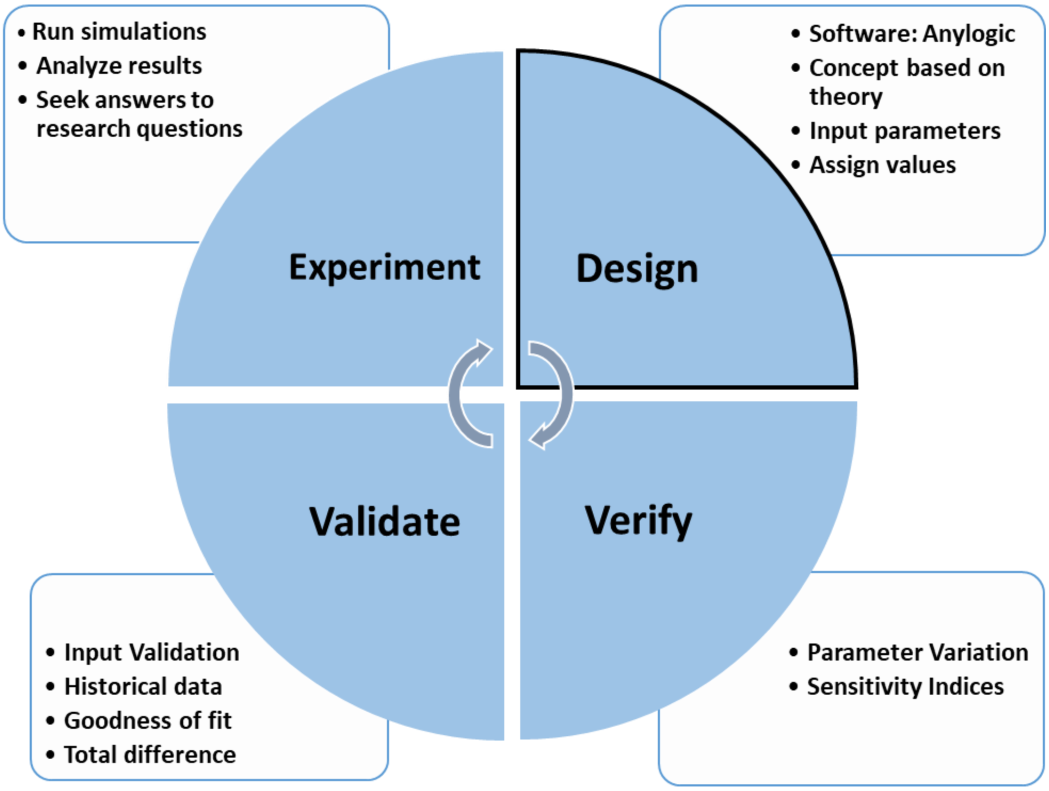

Figure 4.1 The modelling process

4.2.1 **Model-specific Research Questions**

In addition to the 2nd research question posed in 1.3.2 and as an offshoot of the 4th objective in 1.3.3, model-specific research questions were formulated to guide the development and application of the model. These are outlined below and the extent to which these questions are answered are discussed in section 7.2

Key Question: In view of the Theory of Planned Behaviour and the Elaboration Likelihood Model, how do informational interventions influence energy-saving behaviour in a social system? (*Objective 4*)

Sub-Questions:

1. What outcomes or trends can be observed from using the TPB and ELM to explain energy saving behaviour and intervention success?
2. To what extent do the constructs of the TPB and ELM influence energy saving behaviour?
3. Under what conditions do elements of the TPB and ELM produce energy saving behaviours?

4.3 Describing the model

Figure 4.2 summarises the various elements of the developed model. One of the challenges faced in agent-based modelling is in describing the model. This is possibly because of the absence of generally acknowledged standards on how to do so (Rand and Rust, 2011). Nonetheless, this aspect is crucial to the use of agent-based modelling as a scientific tool because replicability can only be possible if the model is adequately described. Many published ABM studies are impossible to replicate because of incomplete or disorganised information (Altaweel et al., 2010; Grimm and Railsback, 2012; Groeneveld et al., 2012; Müller et al., 2013). Also, where agent-based models are developed to support decision making in the real world, it is important that clear descriptions of model structure and assumptions are available for those decision makers. To tackle this issue (Grimm et al., 2006) proposed a standard protocol for describing individual-based and agent-based models called the ODD protocol which consists of three main parts: Overview, Design concepts, and Details.

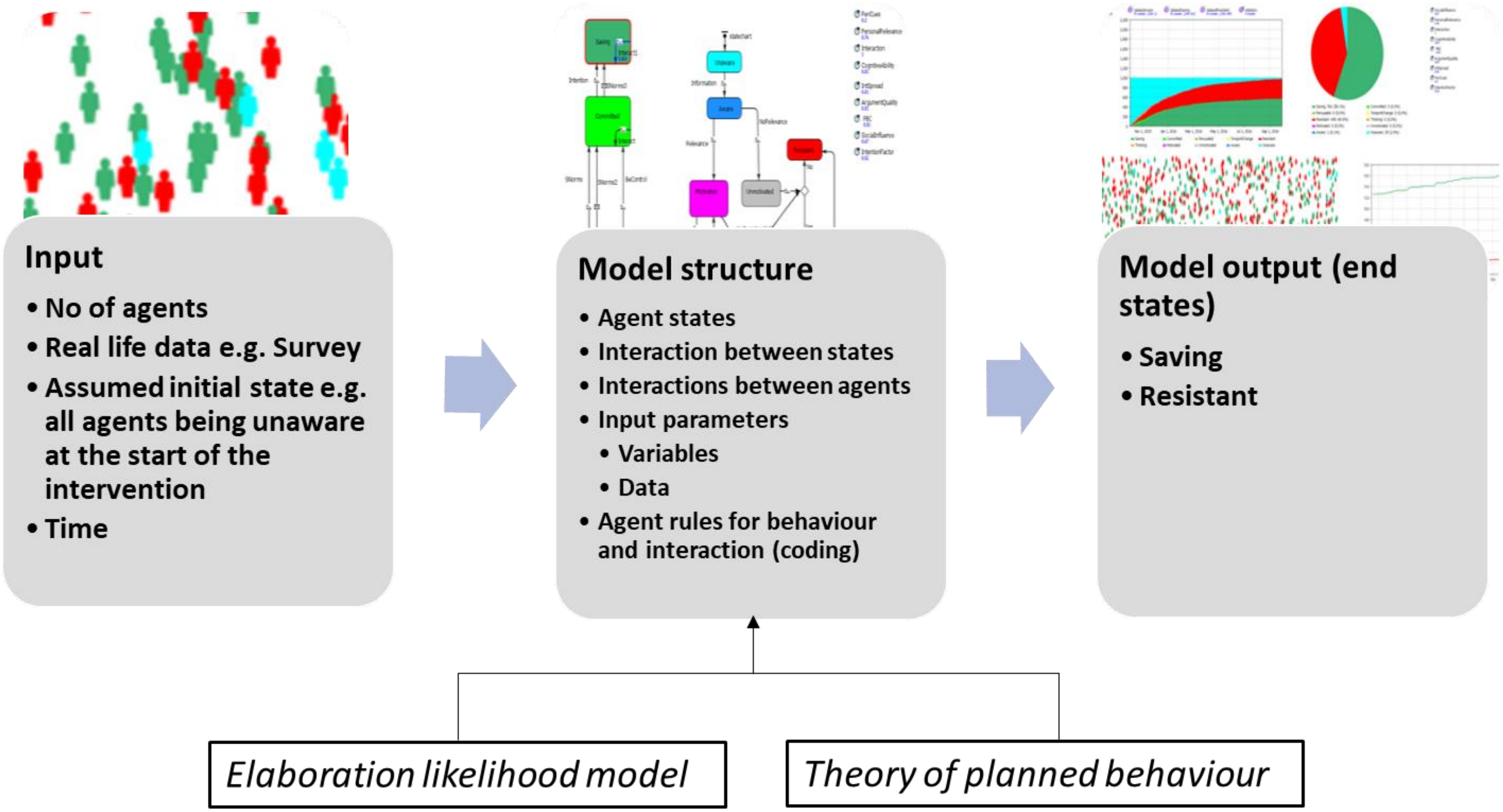

Figure 4.2 Schematic showing different elements of the agent-based model

Over the years, the , ideas from the ODD protocol have been implemented across ABMs in several disciplines and refined (Grimm et al., 2017, 2010; Grimm and Railsback, 2012; Polhill et al., 2008). Ideas from the ODD protocol are used to further describe the model in succeeding sections.

4.3.1 Purpose

1) To provide a means of integrating and simulating concepts and variables within the ELM-TPB framework and research methodology.

2) To support the understanding of how informational interventions can produce favourable attitudes and behaviours towards energy saving in a social system.

3) To generate new data for understanding possible long-term effects of interventions for energy saving.

4.3.1.1 Scope and limitations of the model

The scope of the model is mainly descriptive. The intent is to use it for exploring and understanding, thereby providing explanations for energy saving behaviour (or the lack of it) within the joint context of the Elaboration Likelihood Model and the Theory of Planned Behaviour. However, it can also be used for research and learning e.g. the model can be applied to other behaviours apart from energy saving to study emergent patterns that could occur because of interactions between model parameters in a virtual, agent world. Also, to further understand the scope of applicability of the TPB and ELM, model results could be compared across different behavioural contexts.

The model also has the potential to be used beyond the scope of the current experiment—for predicting responses to planned interventions. In such scenarios, surveys or interviews will first need to be conducted among the target population, to measure the relevant theoretical variables. Values obtained from the measurement exercise can then be converted for use as model parameters. For example, in this study, all model parameters except *intSpread* have their origin in the ELM and TPB variables (Ajzen, 2002a; Petty and Cacioppo, 1986b). The parameter *intSpread*, has its origin in Rogers' (2003) diffusion of innovations theory. Sections 4.3.3 and 4.3.7 provide more details on these.

Model output from simulation runs can then be analysed to provide some guidance on possible responses to the intervention within the population sampled.

Within the model, individual agent characteristics such as age, gender etc. are not defined. Also, although agent to agent interaction is modelled, social network structures not detailed. Although regarded as limitations of the model, these do not stand in the way of the model achieving its purpose (as outlined in **Error! Reference source not found.**).

The primary survey data used as an early phase input for validating the model was from a small sample (n=21). This is also considered a limitation to the model. However, secondary data from a larger sample i.e. n=199 was obtained from Wilson (2014) and used to further validate the model (See section 5.2.2). The depth of survey responses also poses a limitation to the model as contexts to survey questions were not provided in the questionnaire. Contexts were not provided in order to prevent wordiness which could discourage recipients from completing the questionnaire. However, SMART objectives created for developing the questionnaire together with guidance from Ajzen (2002a) and Francis et al. (2004) provided confidence in questionnaire items being able to elicit sufficient levels of information on the theoretical constructs, especially as the main purpose of the model is to provide explanations.

4.3.2 Entities, State variables and scales

The model's layout is arbitrarily allocated, and there is no defined network for agents. The model consists of one type of entity i.e. individuals, called energyUsers. There are two agent types: Main and energyUser. Main is the environment which contains energyUsers. The model is populated with agents of the same agent type (energyUsers) which are characterised by 10 state variables (subsequently referred to as states): *Unaware, Aware, Motivated, Unmotivated, Resistant, TempAttChange, Thinking, Persuaded, Committed, Saving.*

4.3.3 Process overview, scheduling

The model consists of people (agents) who have the potential to save energy but initially do not do so and are assumed to be unaware of energy saving methods. However, the energy saving intervention and interaction e.g. word of mouth will attempt to persuade them to adopt energy saving.

The first step in the adoption process is initiating awareness. People's awareness of the intervention is modelled in the context of the rate at which the intervention reaches agents by setting a specific percentage of agents to receive the message per day. *IntSpread* is the parameter responsible for this and is set to an assumed default of 0.01 i.e. 1% of agents will be reached by the intervention daily. The idea for this parameter comes from the diffusion of innovations theory which establishes that innovations have a rate at which they spread in a social system (Rogers, 2003).

A state chart describes event and time driven behaviour. In the model, it is used to define the behaviour of an energyUser. The states depict the stages a person goes through before and after receiving persuasive information and are based on the Elaboration Likelihood Model and the Theory of Planned Behaviour (Ajzen, 1991; Petty and Cacioppo, 1986b). At any given time, an agent can only be in one state and each state is depicted by a colour. An agent's change into each state is controlled by a code which assigns the state's colour to the agent e.g. when an agent enters the aware state, the entry action (`shapeBody.setFillColor(dodgerBlue`) is performed. The entry action is written in java code and simply means an agent's colour animation changes to 'dodger blue' when they enter that state. All the other states have similar entry actions defined. The colours representing the different states can be seen in the state chart shown in Figure 4.3.

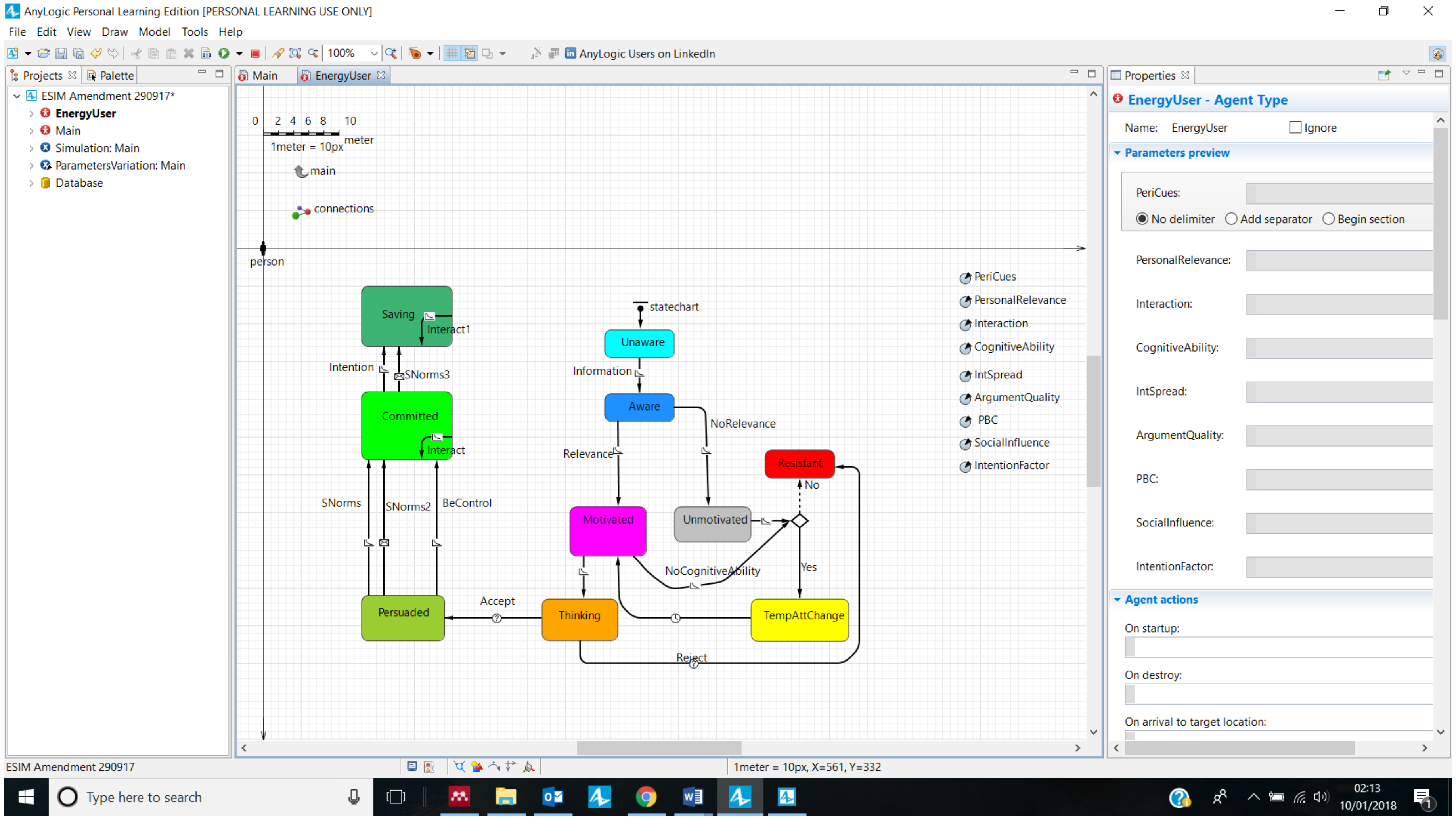

Figure 4.3 Model screen showing the state chart

Transitions connect one state to another. Agent states are updated when a transition is executed. In some cases, state changes are further determined by written java code. Table 4.2 presents a summary of how and when agents transition from one state to another in the model.

Time is modelled as a continuum over which both continuous and discrete events can occur. Each time step is one day, and each model run is set to a default of 0 to 365 days as it is assumed that one year is enough time for the intervention to spread and yield some results. For simulation experiments done to understand behaviour over time, the time was adjusted accordingly.

Another assumption the model makes relates to the starting point of the model where it is assumed that agents are unaware of energy saving information or have not previously come across the intervention. This assumption is made because it prevents complication of the model's structure and is not considered to detract from its main purpose of understanding the effect of individual level variables on collective behaviour (An, 2012; Sun et al., 2016).

Table 4.2 Model transitions and their triggers

Transition name	Transition from state to state	Triggered by	Code
Information	Unaware to Aware	Rate; IntSpread per day	
Relevance	Aware to Motivated	Rate; PersonalRelevance per day	
NoRelevance	Aware to Unmotivated	Rate; 1-PersonalRelevance per day	
Yes	Unmotivated to TempAttChange	Rate; PeriCues per day Condition; `randomTrue(PeriCues)`	`randomTrue(PeriCues)`
No	Unmotivated to Resistant	Rate; PeriCues per day Condition; if default i.e. `randomTrue(PeriCues)` is	
--	TempAttChange to Motivated	Timeout; 1 day	
--	Motivated to Thinking	Rate; CognitiveAbility per day	
Reject	Thinking to Resistant	Condition; `randomFalse(ArgumentQuality)`	`randomFalse(ArgumentQuality)`
Accept	Thinking to Persuaded	Condition; `randomTrue(ArgumentQuality)`	`randomTrue(ArgumentQuality)`
SNorms	Persuaded to Committed	Rate; socialInfluence per day	
SNorms2	Persuaded to Committed	Message; "save energy"	`randomTrue(SocialInfluence)`
BeControl	Persuaded to Committed	Rate; PBC per day	
Interact	Within Committed	Rate; Interaction per day	Action; `sendToRandom("save")`
SNorms3	Committed to Saving	Message; `"save energy"`	Guard; `randomTrue(SocialInfluence)`
Intention	Committed to Saving	Rate; Intention per day	Guard; `randomTrue(IntentionFactor)`
Interact1	Within Saving	Rate; Interaction per day	Action; `sendToRandom("save energy")`

4.3.4 **Design concepts**

Basic principles: The core concepts built into the model are from the Elaboration Likelihood Model and the Theory of Planned Behaviour. The variables from these theories were included in the model as parameters governing the model's state variables. These occur in sequence, with ELM elements first, followed by the TPB.

Output: The magnitude of behaviour for and against energy saving among the population is the main output emerging from various interactions between agents and elements of the central theories used.

Adaptation: The adaptive traits agents possess are limited to the ability to become convinced by other agents who are in the committed and saving states to take on their respective states. These are governed by the rate of interaction between these committed/saving agents and random agents

Interaction: This is predetermined by an arbitrarily chosen parameter value of 1, implying that each agent interacts with one other agent. The aspects of the model where interaction plays a role are those transitions governed by social influence such as transitions between *Persuaded* and *Committed* and *Committed* to *Saving*.

Stochasticity: The transition from *Unmotivated* to either *Resistant* or temporary attitude change (*TempAttChange*) is randomly determined. From *Thinking* to either *Persuaded* or *Resistant* is randomly chosen. The transition from *Persuaded* to *Committed* guided by social norms is randomly chosen. Transitions between *Committed* and *Saving* are also randomly chosen. Agents in the committed and saving states can send a message to save energy to a randomly chosen recipient who subsequently changes to the state of the sender.

Observation: The model output can be visualised via four mediums: a time stack chart, a pie chart, a time plot and a 2D pictorial chart. Although the output data of interest are the end states (*Saving* and *Resistant*), the number and percentage of agents in all other states are also available at the end of each simulation run.

4.3.5 **Initialisation**

At time t=0, the model contains a given number of agents, specified by the user. This was sometimes chosen arbitrarily or obtained from existing data depending on the purpose for which the simulation was being run. For the analysis aspects, 1000 agents were specified. At t=0, all agents are assumed unaware of energy saving information. Initialisation is always the same for each simulation run except where a random seed is used for the number generator e.g. during model validation where outputs of random multiple runs needed to be assessed.

4.3.6 **Input data**

"The model does not use input data from external sources to represent time varying processes" (Grimm et al., 2010, p.11).

4.3.7 **Sub models**

The model contains two main processes, which may be regarded as sub models. The first, comprises of ELM variables and the second, TPB variables. These variables are translated to model parameters which are assigned values obtained from survey data. To obtain parameter values, hypotheses testing was used in converting survey data. This process also doubled as a form of input validation and is discussed in the validation section (5.2.1). Table 4.3 describes the theoretical variables used and shows how they are represented as parameters. Table 4.4 summarises how parameter values were obtained from survey data.

Table 4.3 A description of theoretical variables used as model parameters

Variable	**Parameter in model**	**Description**
Peripheral cues	PeriCues	Cues separate from the strength of the message
Personal relevance	PersonalRelevance	This is the perceived relevance of the message to a recipient.
Cognitive ability	CognitiveAbility	Mental aptitude or capacity to understand the message.
Argument quality	ArgumentQuality	How well a case is made for the intervention and its subject
Perceived behavioural control	PBC	An individual's opinion of how difficult or easy it is to perform a behaviour.
Subjective/social norms	SocialInfluence	Influence of close or important people
Intention	IntentionFactor	Intent to perform the target behaviour

Table 4.4 Converting survey data to parameter values

Variable	Parameter	Survey mean score ($\bar{x}$)	Standard deviation	Null hypothesis (H_0)	Alternate hypothesis (H_A)	Considerations for hypotheses	t statistic	Responses used to calculate parameter value	Parameter value
Motivation	*PersonalRelevance*	2.62	1.166	μ=4	μ<4	Scoring of 1 - 3 = relevance; 4 = indifference	-5.4245	16 out of 21	0.76
Peripheral cues	*PeriCues*	1.7619	0.4364	μ=1	μ>1	1=familiar with sponsors; 2=not familiar with sponsors	8.0032	4 out of 20	0.2
Ability to process	*CognitiveAbility*	1.86	1.10871	μ=4	μ<4	1=Good; 4=neutral; 7=poor	-8.8466	17 out of 21	0.81
Argument quality	*ArgQuality*	2.62	0.92269	μ=4	μ<4	1=strong; 4= neutral; 7= weak	-6.8513	17 out of 21	0.81
Subjective norms	*SocialInfuence*	4.7619	0.98513	μ=4	μ>4	1= no influence; 4= neutral; 7= strong influence	3.5442	14 out of 21	0.67
Perceived behavioural control	*PBC*	5.4643	0.86706	μ=4	μ>4		7.7391	17 out of 21	0.81
Intention	*IntentionFactor*	3.2941	1.53153	μ=4	μ>4	1= no intention; 4=neutral; 7=strong intention	-1.9004	11 out of 21	0.52

4.3.7.1 The ELM sub model

When the model is run, agents first go through ELM aspects i.e. from becoming aware of the intervention to either becoming persuaded or resistant to the intervention's message. Decision making rules guiding agents in the ELM sub model are summarised below in Table 4.5.

Table 4.5 Decision table for the ELM sub model

		RULE 1	RULE 2	RULE 3	RULE 4	RULE 5	RULE 6	RULE 7	RULE 8	RULE 9
Conditions	Motivation	Y	Y	Y	Y	Y	N	N	N	N
	Ability to Process (AtP)	Y	Y	Y	N	N	Y	Y	N	N
	Cognitive Processing (Argument Quality)	Y	Y	N	N	N	Y	N	N	N
	Peripheral Cues	Y	N	Y	Y	Y	Y	Y	Y	Y
Decisions	Long term Attitude change	Y	Y	N	N	N	Y	N	N	N
	Temporary Attitude change	N	N	Y	Y	Y	N	Y	Y	Y

When an unaware agent encounters the intervention, the next state, *Aware* becomes active and its entry action (`shapeBody.setFillColor(dodgerBlue)`) is performed. Awareness is modelled in the context of the rate at which the intervention spreads (parameter: *IntSpread*). The idea for this parameter is supported by the diffusion of innovations theory (Rogers, 2003), which highlights initial contact with a message as a first step in adopting an innovation. Other possible metrics are percentage exposure to or percentage engagement with the information.

From *Aware*, agents can transition randomly to either *Motivated* or *Unmotivated*. This transition is triggered by the relevance of the message as perceived by the agent. In the Elaboration Likelihood Model (ELM), motivation is explained by perceived relevance or how involved a recipient feels in the context of the message. If agents feel that the energy saving message is directly relevant to them, they transition to *Motivated*. This transition is determined by the rate at which the parameter *PersonalRelevance* occurs daily.

When agents transition to *Unmotivated*, a stochastic process occurs where agents look for the presence of peripheral cues such as credibility of the message source. At this stage agents can either have a short-term attitude change or remain unmotivated, in which case they are deemed resistant to the intervention. This is driven by a condition code—`randomTrue(PeriCues)`

If agents have the mental ability to understand the message (controlled by the parameter *CognitiveAbility*), they transition from *Motivated* to *Thinking*, where they can either agree with or reject the message.

If agents agree with the message, they transition to *Persuaded* or else become *Resistant* to the message. The parameter *ArgumentQuality* randomly triggers the acceptance or rejection of the intervention message. This is controlled by condition codes; `randomFalse(ArgumentQuality)` for rejection and `randomTrue(ArgumentQuality)` for acceptance of the message.

The *Persuaded* state represents both long-term attitude change in the ELM and the attitude construct in the TPB. As is commonly known, attitude alone does not guarantee behaviour change (Bhattacherjee and Sanford, 2009; Carrington et al., 2010; Mohiyeddini et al., 2008; Steg et al., 2005). Therefore, to achieve energy saving behaviour in the model, other factors need to be considered. This is the rationale for the second sub-model which is based on the TPB.

4.3.7.2 The TPB sub model

A summary of the decision-making rules guiding agents in the TPB sub model are presented in the table below.

Table 4.6 Decision table for the TPB sub model

		RULE 1	RULE 2	RULE 3	RULE 4	RULE 5
Conditions	Attitude	Y	Y	Y	N	N
	Subjective Norms	Y	Y	N	Y	Y
	Percieved behavioural control	Y	N	Y	Y	N
Decision 1	Intention	Y	Y	?	?	?
Decision 2	Energy Saving (Behaviour)	Y	?	?	?	?

According to Ajzen's (1991) Theory of Planned Behaviour, *Subjective norms* and *Perceived behavioural control* are key variables to consider alongside *Attitude*. Together, these three are predictive of *Intention* which is a direct predictor of *Behaviour*. In some contexts, actual behavioural control could also directly predict behaviour.

In this sub model, *subjective norms* are modelled as three separate transitions. The first of these is *SNorms* which is triggered by the rate of *SocialInfluence* per day. The parameter *SocialInfluence* represents an agent's influence on other agents and is expressed as the percentage of agents who will become committed to saving energy because of social influence. The rationale is that people close to each other exert some amount of influence on one another's decision making. This reasoning is supported by the focus theory of norms (Cialdini et al., 2006; Cialdini and Goldstein, 2004).

An agent in the *Committed* state is set up with an internal transition (*interact*). Every time this transition takes place, it sends a random agent a "save energy" message. This action is enabled by a code—`sendToRandom("save")`. This models the peer-to-peer communication aspects of the intervention. At this stage, if the receiving agent is in the *Persuaded* state, it will become *Committed*. However, realistically, a persuaded agent will not always become committed. To accommodate this, an additional external transition *SNorms2* is used to model commitments made in response to peer influence and assigned a guard `randomTrue(SocialInfluence)`, which will allow for randomness, thereby preventing agents in *Persuaded* from always transitioning to *Committed* on receiving a message from a committed agent.

The third core variable of the Theory of Planned Behaviour—*Perceived behavioural control*—is modelled via a transition (*BeControl*) from *Persuaded* to *Committed* which is triggered by rate at which parameter *PBC* occurs daily. *PBC* determines the number of agents that feel able to perform the target behaviour. Typically, situational factors contribute to this variable.

The *Saving* state represents the target behaviour—energy saving—and is set up with an internal transition (*interact1*) which allows agents in *Saving* to randomly send any agent a message to save energy. Here, agents in *Committed*, will become *Saving*. This models the nudge to take the final step that can come from peer-to-peer communication. A transition *SNorms3* also sends committed agents a message to save energy but prevents agents in the preceding *Committed* state from always transitioning to *Saving* on interaction with an agent in *Saving*. This is achieved by assigning a guard—`randomTrue(SocialInfluence)`.

The *Intention* variable from the Theory of Planned Behaviour is modelled as a transition from *Committed* to *Saving*. The rate at which parameter "*IntentionFactor*" occurs daily is the trigger for this transition. *IntentionFactor* is the percentage of agents who have the intention to save energy. This transition is assigned a guard—`randomTrue(IntentionFactor)` to model the reality that not all agents with the intention to save energy do so.

5 MODEL EVALUATION

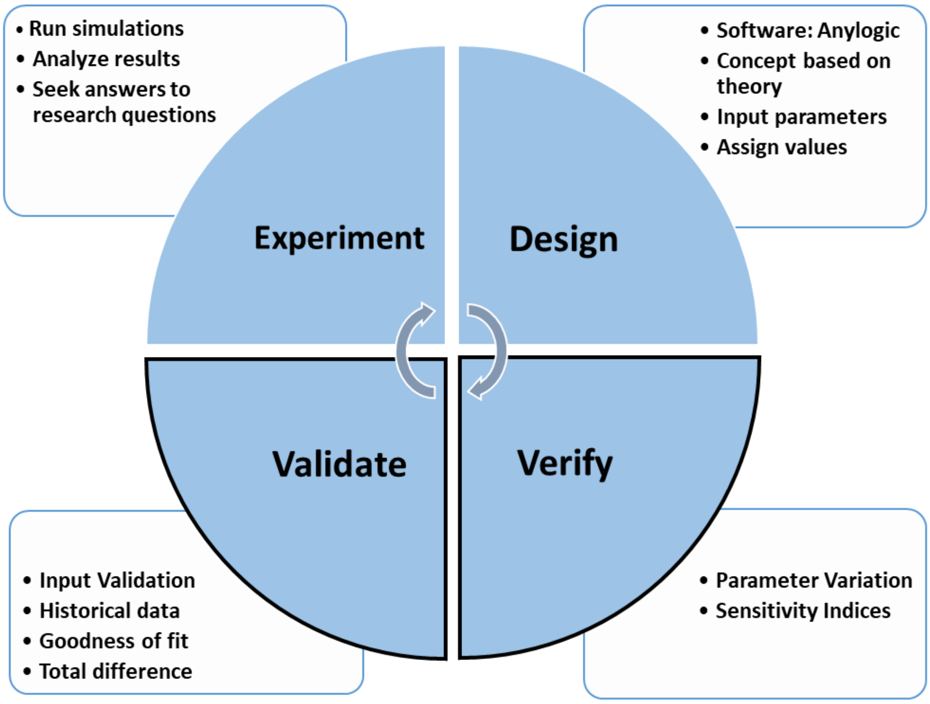

Figure 5.1 Showing how evaluation fits into the modelling process

As illustrated in the figure above (Figure 5.1), after the model design (and building) stage, a detailed evaluation is done. This provides answers to questions surrounding simulation accuracy and model behaviour e.g. how does the model react to variations in simulation settings?(Smith and Smith, 2007). In addition to on-going adjustments typical of model development, this type of information provides much needed guidance during the process. Model evaluation may be regarded as iterative, exposing any issues with the model and ultimately provides feedback for improving the model design or structure. For example, initial verification of this study's agent-based model exposed an inconsistency which led to a seemingly small but vital amendment in the model's structure (see Appendix B).

A model whose correctness (within a realistic boundary of error) is unknown is limited in its usefulness (Barnes and Chu, 2010). Model evaluation can involve analysing the model in many ways. In this study, the methods used for evaluation are broadly categorised into verification and validation.

5.1 **Verification**

Parameter variation and sensitivity indices were used to verify the model. This involved changing the input parameters of the model to observe any associated effects and checking that these conform to the concept on which the model was built (Ormerod and Rosewell, 2009; Xiang et al., 2005). Effects may be considered either quantitatively—magnitude and direction— or qualitatively—direction only (Sargent, 2013). Parameters that have significant effects on model behaviour would have to be deemed sufficiently accurate for any useful deductions to be made from the model. In addition to assessing that the model output is consistent with its concept, varying parameters help to understand how the model responds to small changes in parameter values. Figure 5.2 shows a range of effects obtained by varying each model parameter on the number of agents performing the target behaviour. A key observation is that energy saving is highest when *peripheral cues* is at the maximum. This is consistent with the model's theoretical concept and suggests that in the presence of strong peripheral cues, energy saving is achieved via the peripheral route. The model's response to varying other parameters also shows consistence with its concept i.e. higher levels of energy saving are observed with high to maximum levels of *personal relevance*, *cognitive ability*, *argument quality*, *perceived behavioural* *control* and *social influence*. As parameter variations were also done as part of the simulation experiments, these are further discussed in 6.1.3.1.

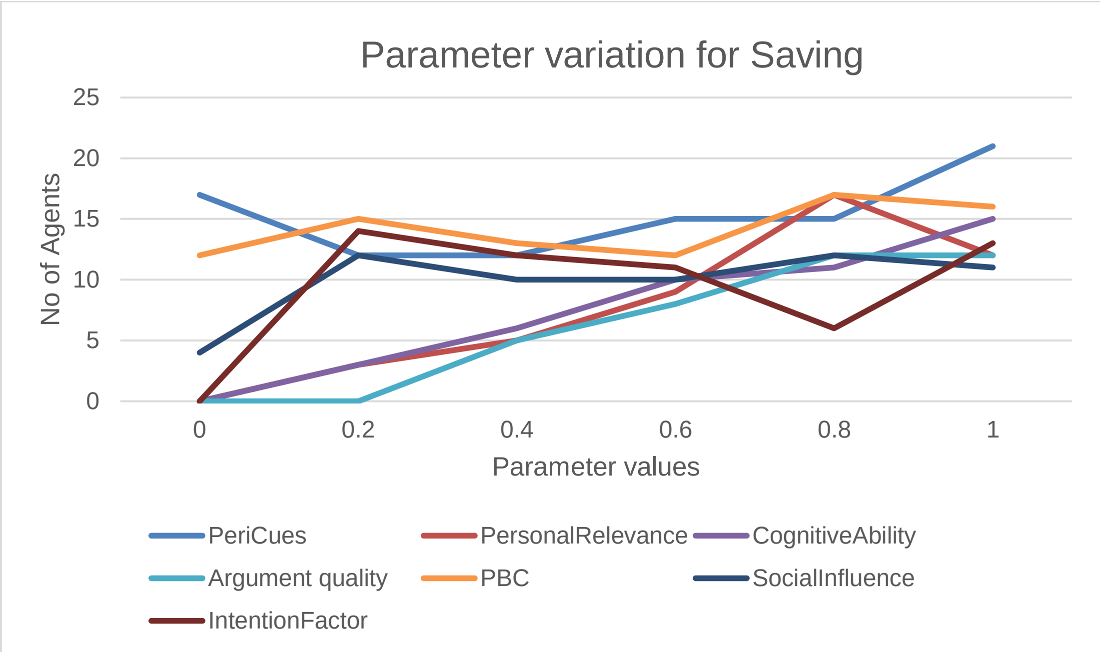

Figure 5.2 ***Chart showing effects of varying the values of model parameters.***

To further verify the model and to understand the extent to which the model is sensitive to changes in parameter values, a simple and tested formula proposed by Hoffman & Gardner (1983) was used to calculate the sensitivity indices for model parameters with respect to the two outputs: *Saving* and *Resistant*.

$$SI = 1 - \frac{P_{min}}{P_{max}}$$

Where:

P_{max} = Output obtained when the parameter under consideration is at its maximum value.

P_{min}= Output obtained when the parameter under consideration is at its minimum value.

SI= Sensitivity Index.

Tables 5.1a and b below show the sensitivity indices, ranked according to magnitude for all parameters.

Tables 5.1 ***a and b: Ranked sensitivity indices***

Saving	
Parameter	**Sensitivity Index**
PersonalRelevance	1
CognitiveAbility	1
ArgumentQuality	1
IntentionFactor	1
IntSpread	1
SocialInfluence	0.636
Interaction	0.583
PBC	0.25
PeriCues	0.19

a

Resistant	
Parameter	**Sensitivity Index**
CognitiveAbility	-2.5
ArgumentQuality	-1.333
PersonalRelevance	-1.333
IntSpread	1
PeriCues	-1
PBC	-0.8
IntentionFactor	0.125
SocialInfluence	-0.1
Interaction	0

b

Overall, the magnitudes and direction of the sensitivity indices all correspond to the theoretical concept of the model. According to the ELM, variables *Motivated,* *Ability to process* and *Cognitive Processing* are significantly deterministic in the formation of desirable attitudes i.e. persuasion. These variables represented respectively by the model parameters *PersonalRelevance*, *CognitiveAbility* and *Argument quality*, all have a sensitivity index of 1 for the target behaviour—energy saving. Based on the range of parameter variation values, this is the highest sensitivity index possible, suggesting that *Saving* is highly sensitive to changes in these three parameters. This implies a strong influence in determining the target behaviour and is consistent with the model concept. *Intention* in the TPB is the immediate precursor of behaviour and some studies have suggested that it could be a proxy for behaviour, especially where data on behaviour is unavailable (Eccles et al., 2006; Godin et al., 2008; Kostelijk, 2017). Also having a sensitivity index of 1, the related parameter (*IntentionFactor*) substantiates that the model is consistent with the TPB. The values of *SocialInfluence* and *Interaction* suggest that *Saving* is moderately sensitive to changes in both parameters, which are expressions of the TPB variable *subjective norms*. Where peripheral cues bring about positive attitude change, it is usually short term; therefore, its low sensitivity index is consistent with the *Saving* target behaviour of the model implying that for producing long term energy saving, the model is insensitive to changes in peripheral cues (*PeriCues*).

For *Resistant*—the undesirable end state, the high and negative sensitivity index for *CognitiveAbility* supports the theory that without the cognitive ability to process the information being disseminated e.g. in an intervention, the desired behavioural changes cannot be achieved. Similarly, the sensitivity index for *Argument quality* suggests that for *Resistant* outcomes, the model is highly sensitive to changes in this parameter in the reverse order i.e. the weaker the argument for energy saving, the more resistant the output. This supports the ELM which proposes that the quality of a persuasive message brings about desired attitude change. This also holds true for *PersonalRelevance* i.e. motivation. A high and negative sensitivity index for *PeriCues* suggests that the model is sensitive to weak peripheral cues and causes resistance to energy saving where this is the case. With a magnitude of 0.8, the model is sensitive to *perceived behavioural control (PBC)* for producing *Resistant* outcomes. This provides some support for the concept of the TPB which proposes that *PBC* increases predictive power of behaviour compared to the theory of reasoned action (which is the TPB without *PBC*). Although it appears not to be as strong for predicting *Saving,* the directions of both *PBC* sensitivity indices offer strong support for their respective end states i.e. positive for the desired behaviour and negative for the undesirable behaviour.

The logic on which the above deductions are based are visually represented in the ELM-TPB framework in Figure 3.1.

5.2 **Validation**

The model was validated to provide confidence in the results of the model (Natarajan et al., 2011). Validity refers to the extent to which a model corresponds to a real system. Validation of an agent based model can be done in several ways. Liu (2011) suggests that both internal and external validation should be done to term an ABM valid. Several methods of validation have been discussed and used by researchers for validating ABMs (Liu, 2011; Sargent, 2013; Xiang et al., 2005). Some of these are presented below:

Face validation: This entails getting expert approval for the model's adequacy with respect to attributes such as its logic, behaviour, relationships and accuracy. Although face validity may be regarded as subjective, the use of animation and graphs of statistical outputs help to provide a clearer picture of the model behaving correctly, making it easy for reasonable conclusions to be drawn.

Validation by historical data: Here, historical data could simply be data collected specifically for building and testing the model e.g. survey data from the real system being modelled; or other existing real system data that corresponds with the model outputs e.g. periodic performance data. In this method, available data is used to inform the model e.g. for assigning parameter values and to test the model e.g. comparing model output to relevant real-world data. This method was used in this study.

Comparison to other models: This method involves comparing model outputs with outputs from similar validated models e.g. the same conceptual model, modelled and validated using a different platform. The benchmark model may be analytic or simulated. It has been referred to as back to back testing or docking. This method is beneficial for scenarios where data required for validation cannot be obtained from the system being modelled.

Multiphase validation: As the name implies, this technique consists of several stages of validation. The first is to develop the model based on theory, observations or common knowledge. Where possible, validating model assumptions (input validation) through empirically testing provides another layer of validation. A final layer of validation would involve comparing model input/ output relationships to the real system being modelled.

Internal validation: This type of validation can also be referred to as output validation. It is done by using randomly generated seeds for several runs of the model. If there is significant variability present among the run results, it implies that there is a problem, possibly with the conceptual or coding aspects of model development.

Statistical tests: Being quantitative**,** using statistical analysis in the validation process can give considerable credibility to a model. Rather than being a standalone technique, statistical analyses tend to be used as part of other validation methods. For example, statistical tests could be used to compare the model's output to that of the real system being studied (validation by historical data) or to understand results from different runs of the same model (internal validation). In fact, most of the techniques mentioned above would require some statistical input for credible conclusions to be drawn. Examples of useful statistical techniques range from simple measures such as variance, to more complex methods such as hypothesis testing. Generally, statistical analyses provide a standard means for understanding the extent of a model's accuracy.

The validation carried out in this study are mostly statistical in nature and fall under a joint umbrella of validation by historical data, internal validation and multiphase validation.

5.2.1 **Input validation**

Due to the small survey sample size (n=21) and considering that the data for all variables showed acceptable normality (see 3.4.4.1), all model parameters were statistically validated by hypotheses testing using one sample t-tests. The purpose of using a one sample t-test is to establish the possibility that sample came from a population with a given mean (μ). A summary is presented in Table 5.2. However, two examples (*PersonalRelevance* and *Pericues*) are also outlined below to provide an understanding of the process used.

PersonalRelevance: This parameter represents the percentage of aware agents that will find the message relevant and is a measure of motivation. From survey results, a sample mean score of 2.62 was obtained for the *motivation* variable.

A one sample t-test was used to test the hypothesis of having a mean *motivation* score of less than 4. The following considerations were made:

- A scoring of 1 to 3 implies personal relevance, 4 is indifferent, and 5-7 means no personal relevance. See questionnaire items in appendices A.3 and A.4.
- From the survey sample, the mean motivation score is 2.62.
- Sample standard deviation is 1.166

Table 5.2 Input validation summary

Parameter	Survey mean score ($\bar{X}$)	Standard deviation	Null Hypothesis (H_0)	Alternate hypothesis (H_A)	Considerations for hypotheses	t statistic	No of responses used to calculate parameter value
Personal Relevance	2.62	1.166	μ=4	μ<4	Scoring of 1 - 3 = relevance; 4 = indifference	-5.4245	16 out of 21
PeriCues	1.7619	0.4364	μ=1	μ>1	1=familiar with sponsors; 2=not familiar with sponsors	8.0032	4 out of 20
CognitiveAbility	1.86	1.10871	μ=4	μ<4	1=Good; 4=neutral; 7=poor	-8.84663	17 out of 21
ArgQuality	2.62	0.92269	μ=4	μ<4	1=strong ; 4= neutral; 7= weak	-6.8513	17 out of 21
SocialInfuence	4.7619	0.98513	μ=4	μ>4	1= no influence; 4= neutral; 7= strong influence	3.5442	14 (4.5 and above) out of 21
PBC	5.4643	0.86706	μ=4	μ>4		7.7391	17 out of 21
IntentionFactor	3.2941	1.53153	μ=4	μ>4	1= no intention; 4=neutral; 7=strong intention	-1.9004	11 out of 21

- A scoring of 4 is hypothesised as the population mean (μ) because it is the middle point score for personal relevance i.e. scores < 4 imply motivation. The three-sigma rule was used to determine the validity/significance of this estimation. μ - (2 x standard deviations) was greater than zero, implying that this estimation is valid and significant with a confidence interval of 95%.

A t-statistic was then calculated for $H_o: \mu = 4 \; and \; H_A: \mu < 4$ (i.e. the null and alternative hypothesis respectively) as follows.

$$\boldsymbol{t_{n-1}} = \frac{\left(\bar{\boldsymbol{x}} - \boldsymbol{\mu}\right)}{\frac{\boldsymbol{\sigma}}{\sqrt{\boldsymbol{n}}}};$$

$$\therefore t_{20} = \frac{(2.62-4)}{\frac{1.166}{\sqrt{21}}} = -5.4245$$

The null Hypothesis $H_o: \mu = 4$ is rejected because the t value for a 0.05 significance level for t_{20} is 1.725 and the calculated t statistic is -5.425

The corresponding one-tail P value for $t_{20} = -5.425$ is 0.000013. This result is significant at P<0.05.

This implies that the ratio of respondents with a motivation score below 4 to the total number of respondents can be assigned as the default *PersonalRelevance* value in the model. This value is ${}^{16}/_{21} = 0.76$

PeriCues (Peripheral Cues): According to the ELM, when people are unable to cognitively process or are unmotivated by a persuasive message, there could be other superficial avenues of persuasion present e.g. credibility of the message source. If present, these could lead to a short-term attitude change. *PeriCues* therefore defines the proportion of unmotivated agents that will become convinced due to the presence of peripheral cues in the message.

Sponsor credibility was used as a measure of peripheral cues and from n=21, only 5 respondents were familiar with the intervention's sponsors. Four out of the five respondents agreed that the sponsors made the SSO campaign more credible, with the remaining one respondent indifferent. Consequently, the value of *PeriCues* is specified as the ratio of agreeing respondents to the total sample size minus the indifferent respondent i.e. $\frac{4}{21-1} = 0.2$

To test the validity of the specified value, a one sample t-test was used to test the following hypotheses $H_o: \mu = 1 \; and \; H_A: \mu > 1$ (where 1 is the score assigned to familiarity with sponsors)

- From the survey sample, the mean score for peripheral cues is 1.7619
- Standard deviation of the sample is 0.4364
- The three-sigma rule was used to determine the validity/significance of this estimation. μ - (2 x standard deviations) was greater than zero, implying that this estimation is valid and significant with a confidence interval of 95%.

A t-statistic is calculated as follows:

$$t_{n-1} = \frac{(\bar{x} - \mu)}{\frac{\sigma}{\sqrt{n}}}; \therefore t_{20} = \frac{(1.7619-1)}{\frac{0.4364}{\sqrt{21}}} = 8.0032$$

The null Hypothesis $H_o: \mu = 1$ is rejected because the t value for a 0.05 significance level for t_{20} is 1.725 and the calculated t statistic is greater than that at ~ 8.

The corresponding one-tail P value for $t_{20} = 8$ is < .00001. This result is significant at P<0.05.

This means that the *PeriCues* default value of 0.2 specified can be assumed valid.

5.2.2 **Validation using external data**

Due to the smallness of the primary data set, a larger data set from an external source (Wilson, 2014) was also used to validate the model. Data on similar variables to that of this study were presented on p. 304 of Wilson's journal paper (Table 5.3 below). The data was collected from 199 respondents (p. 303) and showed the average rating score for each variable tested. The data was adapted into parameter values and used to run the model. See

Table 5.4.

Table 5.3 Data from Wilson (2014)

Variable	Cronbach alpha	No. of items/Min possible rating score	Max possible rating score	Variable mean	Variable Std. Deviation
Ability to process	.886	6	30	23.1	4.834
Involvement	.893	6	30	24.47	5.248
Source credibility	.907	6	30	22.52	4.899
Argument quality	.795	5	25	21.1	3.054
Intention	.767	2	10	7.65	1.842
Attitude	.799	3	15	12.69	2.532
Perceived Control	.812	4	20	15.94	3.929
Subjective norm	.795	4	16	11.7	2.391
Behaviour	.734	4	16	10.1	2.805

To obtain the parameter values, the extent to which each variable was present among the sample was determined by calculating the ratio of the variable means to the maximum possible rating scores. These were entered in the model and run randomly 300 times. The number of runs was chosen following recommendations of a minimum of 100 events for validating prognostic models (Collins et al., 2016).

Table 5.4 Adaptation of Wilson's (2014) data for use as input parameters in the model.

Variable (Wilson, 2014)	Equivalent Model Parameter	Mean Variable Score	Maximum Possible Score	Level of variable present (Parameter value)
Ability to Process	CognitiveAbility	23.1	30	0.77
Involvement	PersonalRelevance	24.47	30	0.815666667
Source Credibility	PeriCues	22.52	30	0.750666667
Argument Quality	ArgumentQuality	21.1	25	0.844
Intention	IntentionFactor	7.65	10	0.765
Percieved Control	PBC	15.94	20	0.797
Subjective Norms	SocialInfluence	11.7	16	0.73125

Model output obtained is presented in Figure 5.3 in comparison with the actual data. The mean for energy-saving behaviour from the 300 model runs was 69.64%; whereas, the level of behaviour obtained from Wilson's data was 63%. This shows a difference of 6.64%. However, some of the items Wilson used to elicit responses for the variable *intention* appear to be identical to those used for *behaviour.* This is understandable because in some instances, intention may be used as a proxy for actual behaviour in the TPB. When taking this into consideration, the combined value for behaviour and intention from Wilson's data is 69.8%. Comparing this to the mean model output, there is a small difference of 0.16%.

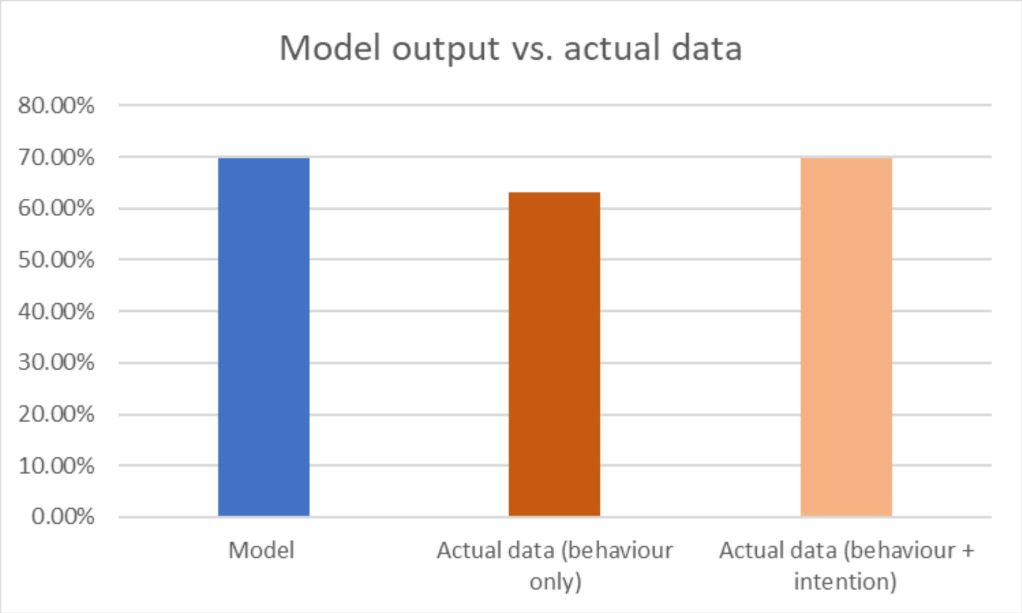

Figure 5.3 Comparing model output and actual data

5.2.3 **Output Validation**

To provide further validation of the model, random seeded runs based on the external data and the study's own survey data were statistically assessed using IBM SPSS Statistics software (version 24). The goal of this assessment was to check the extent of variability among model outputs and to also assess the distribution of data. z-scores were computed to find out if they fall outside the 95% confidence interval (which would suggest the presence of large variability and the possibility of a problem with the model). Histograms and Q-Q plots were used to assess normality and goodness of fit. These are discussed below

5.2.3.1 *Goodness of Fit: Normality of model output based on own survey data*

The histograms shown in Figure 5.4 and Figure 5.6 appear to be approximately normal in distribution, having mild skewness. Values of the skewness statistic for both *Saving* and *Resistant* demonstrate that the skewness in the data is acceptable as both values produced are less than twice the standard error of skewness i.e. 0.130 x2=0.26 (Hanna and Dempster, 2012). Also, both skewness statistics being quite close to zero provide further support to accept the distribution as reasonably symmetrical. The rationale being that the skewness for a normal distribution is zero.

Kurtosis statistics for both end states show negative kurtosis, implying that the distributions have lighter tails than a perfectly normal distribution.

The standardised (z) values for skewness and kurtosis were obtained by dividing each statistic by their respective standard errors. z-values obtained fall within the range of +/- 1.96, showing that all values fall with the 95% confidence interval of a normal distribution.

Furthermore, the Q-Q plots (Figure 5.5 and Figure 5.7) do not show significant deviations from the straight line; this gives validity to the distributional assumption of normality.

Based on the above, the conclusion is drawn that the data produced from the model do not differ significantly from normality.

Table 5.5 Descriptive statistics for 350 model runs based on data own survey

Statistics			
		Saving	Resistant
N	Valid	350	350
	Missing	0	0
Mean		56.4898	41.1293
Std. Error of Mean		0.56398	0.56291
Std. Deviation		10.55114	10.53111
Variance		111.327	110.904
Skewness		-0.082	0.061
Std. Error of Skewness		0.130	0.130
Kurtosis		-0.384	-0.499
Std. Error of Kurtosis		0.260	0.260
Range		57.14	57.14
Minimum		23.81	14.29
Maximum		80.95	71.43

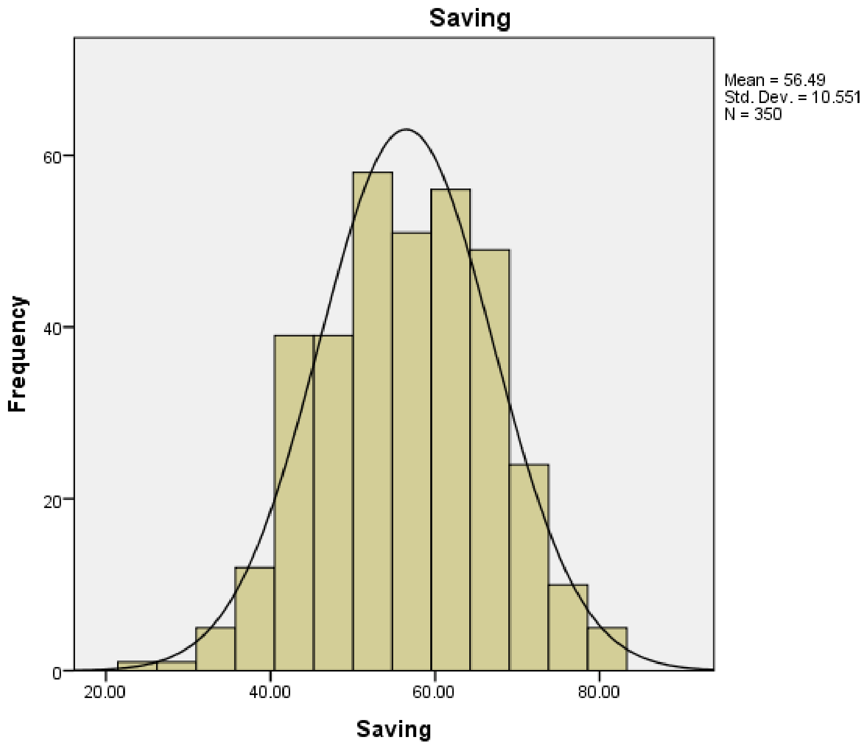

Figure 5.4 ***Histogram of model output "Saving" from own data***

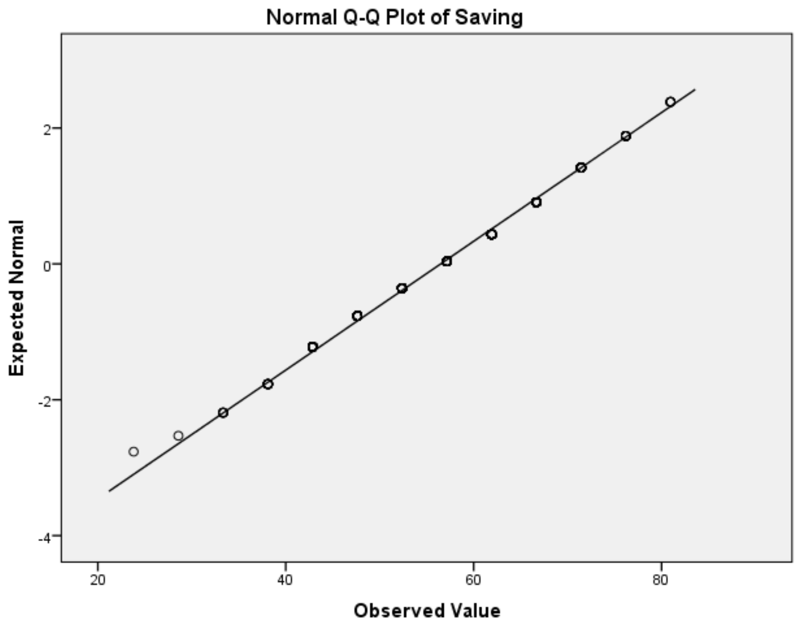

Figure 5.5 ***Normal Q-Q plot of model output "Saving" from own data***

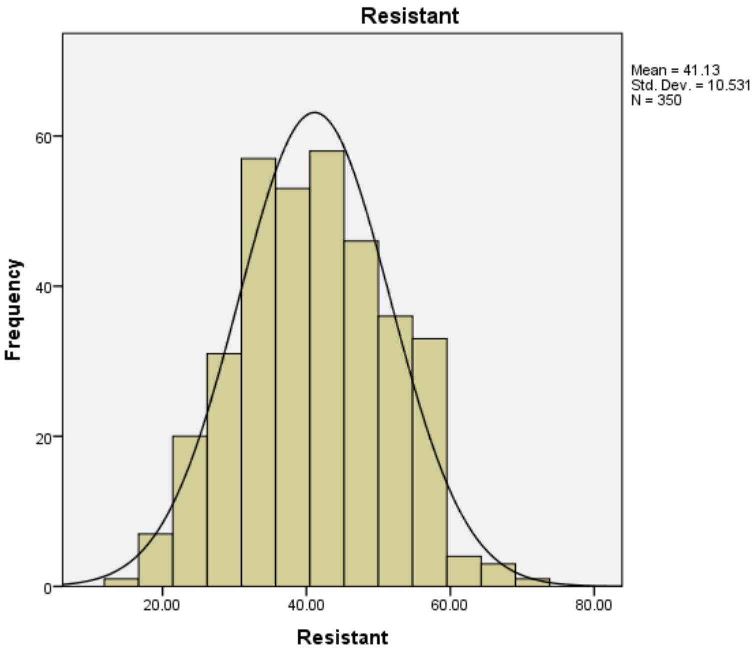

Figure 5.6 ***Histogram of model output "Resistant" from own data***

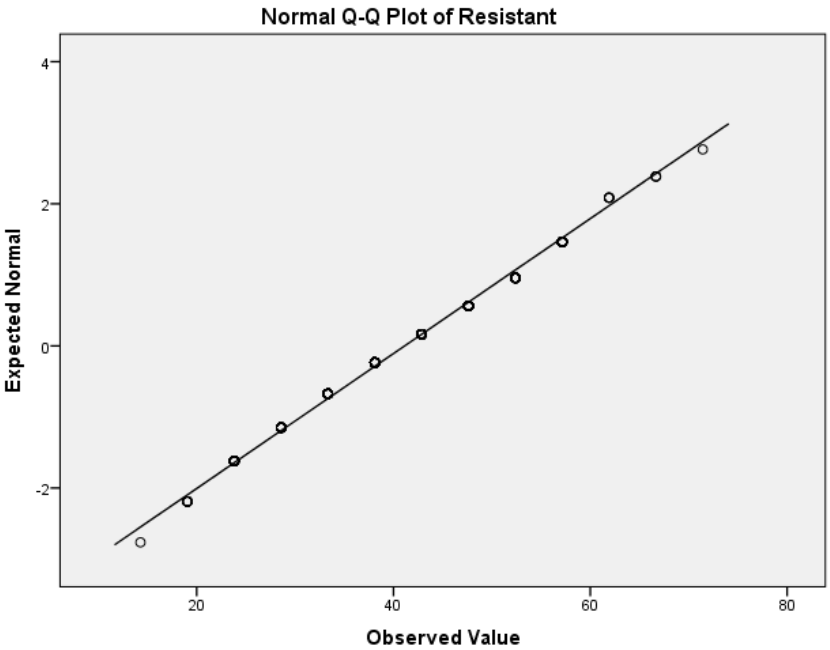

Figure 5.7 ***Normal Q-Q plot of model output "Resistant" from own data***

5.2.3.2 Goodness of Fit: Normality of model output based on data from external source

The histogram (Figure 5.8) is normal in distribution. Having a skewness statistic of -0.004 (see Table 5.6) demonstrates acceptable skewness, considering that the skewness for a normal distribution is zero.

The kurtosis statistics imply that the distributions have slightly lighter tails than a perfectly normal distribution.

The standardised (z) values for skewness and kurtosis also fall within the range of +/- 1.96, showing that all values fall with the 95% confidence interval of a normal distribution.

The Q-Q plot (Figure 5.9) shows most of the data points clustering around the straight line. This further supports the distributional assumption of normality.

Therefore, the conclusion is drawn that the data produced from the model do not differ significantly from normality.

Table 5.6 Descriptive statistics for 300 model runs based on data from external source.

Statistics		
Saving		
N	Valid	300
	Missing	0
Mean		69.6430
Std. Error of Mean		0.19444
Std. Deviation		3.36776
Variance		11.342
Skewness		-0.004
Std. Error of Skewness		0.141
Kurtosis		0.263
Std. Error of Kurtosis		0.281
Range		22.60
Minimum		58.30
Maximum		80.90

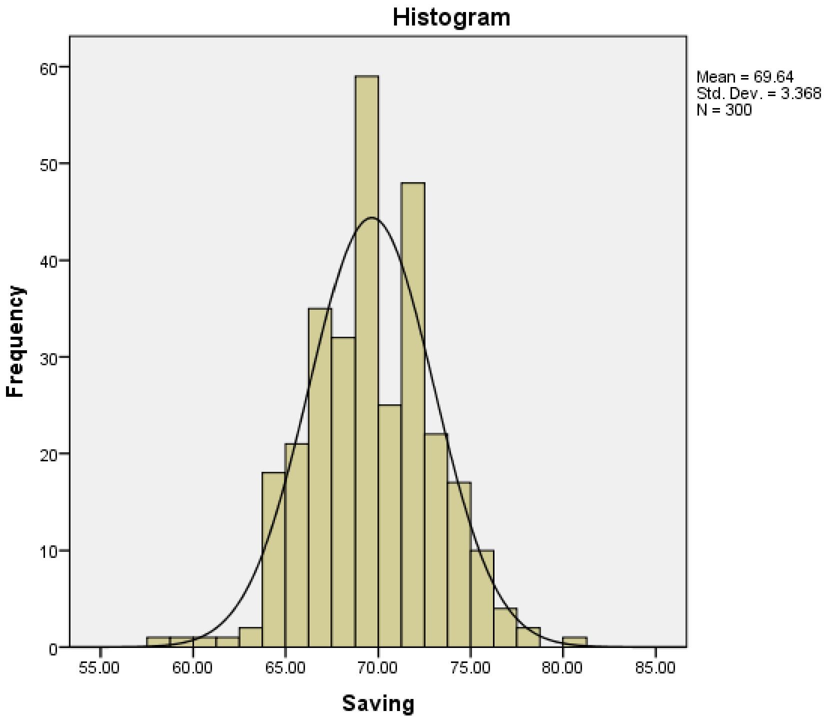

Figure 5.8 Histogram of model output from external data

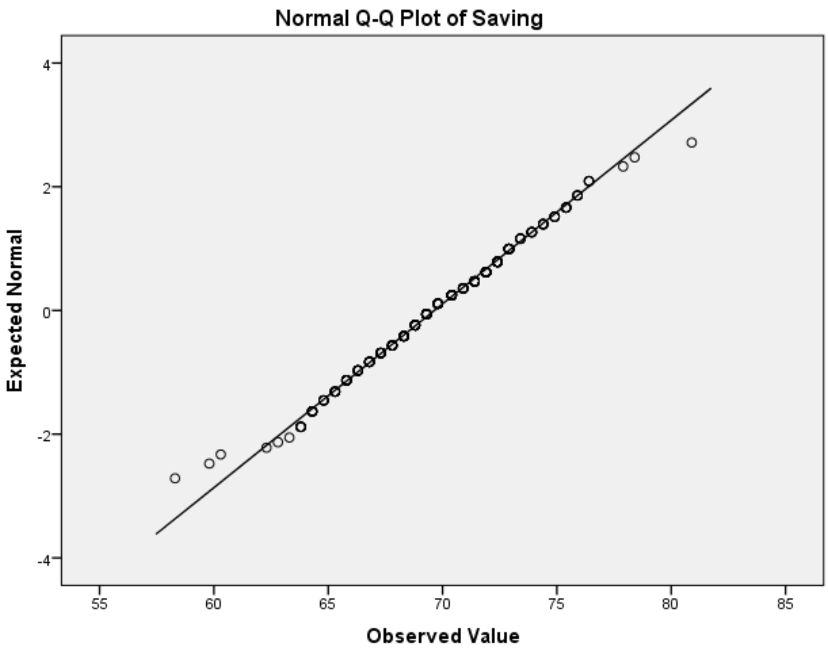

Figure 5.9 Normal Q-Q plot of model output from external data

5.2.3.3 Total difference expressed as a percentage

To further understand the extent to which between model output differs from historical (external) data, the root mean squared error expressed as a percentage was calculated from a fixed seed run of the model. The formula below was used:

Root mean squared error = $\frac{\mathbf{100}}{\boldsymbol{s}} * \sqrt{\boldsymbol{S}-\boldsymbol{M}}$

Where *S* is the survey value and *M* is the model value. This formula was adapted from the RMSE equation in Smith & Smith (2007, p.87), to account for single data values available. The total difference between the model and external survey results was 7.69%.

6 SIMULATION RESULTS AND DISCUSSION

Following verification and validation of the model (chapter 5), simulations were run to explore and provide explanations for the behaviour of the modelled system under different conditions. These were done in view of the research objectives and questions. This chapter presents and discusses results from the simulation experiments.

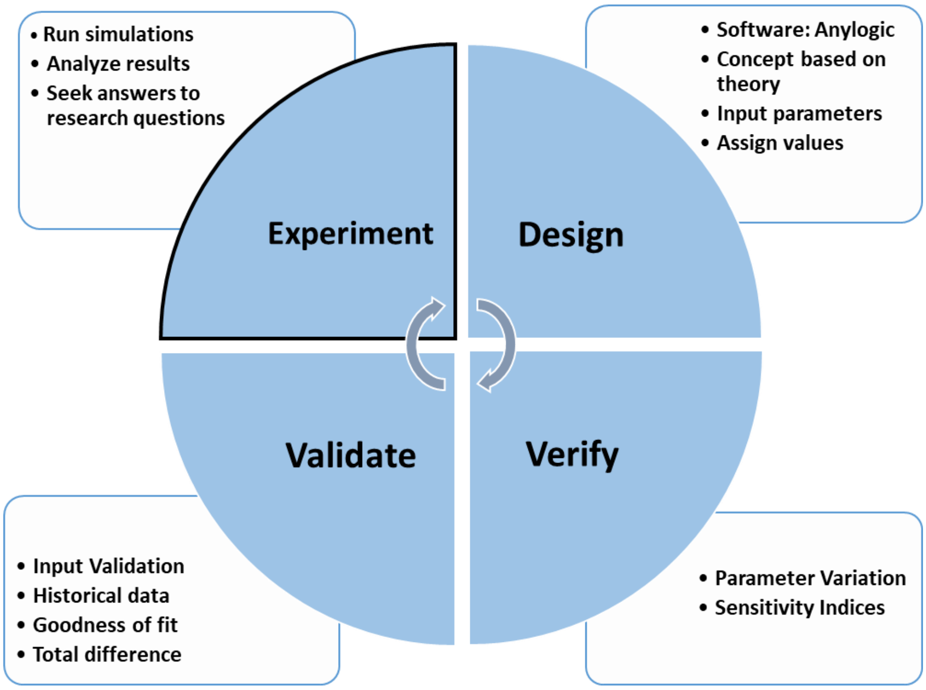

Figure 6.1 Illustrating how simulation experiments fit into the modelling process

6.1 Simulation Experiments, Results and Analysis

Scenarios were formulated to investigate the research questions underpinning the purpose of the model (see section 4.2.1). Three sets of experiments were conducted to respectively investigate each of the research questions i.e. behaviour over a specified time frame, the extent to which theoretical variables of interest influence energy saving and the conditions in which these variables result in substantial energy saving behaviour. Each of these experiments are presented in the following sub-sections.

6.1.1 Intervention uptake[3] over time

The model was run with the default[4] parameter values for each of the population sizes[5] 100, 500, 1000, 5000, 10000 and 20000 over a period of 4 years i.e. 1460 days, and output values for each end behaviour—energy saving and resistant—were obtained. Behaviours across different sizes of agent population were then observed over this period. To provide an equal basis of comparison, percentage values were used. Across all population sizes, both behaviours gradually increased over time, peaking and then stabilising (see Figure 6.2). Generally, model outputs showed that a higher proportion of agents saved energy compared to those who did not.

Among a population size of 100 agents, an increase in both behaviours occurred over time and peaked equally at two years with 50% for each behaviour. Similarly, energy saving and resistant behaviour each peaked at 2 years among a population of 500 agents but at 52.4% and 47.6 % respectively, remaining steady over the next two years. Energy saving and resistant behaviour among populations of 5,000, 10,000 and 20,000 agents respectively peaked at 3 years.

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[3] Intervention uptake is the proportion of people saving energy

[4] Default parameter values are those obtained from the study's own survey data

[5] The population sizes were not based on any specific data and were intuitively chosen and deemed reasonable for demonstrating any related effects or trends.

Among the population of 1000 agents, Energy saving peaked at 4 years while resistant behaviour peaked at 3 years. These are summarised below in Table 6.1.

Table 6.1 Behaviour peak times per population size

	Saving		Resistant	
Population	**Peak time (years)**	**% at peak time**	**Peak time (years)**	**% at peak time**
100	2	50%	2	50%
500	2	52.40%	2	47.60%
1000	4	57.90%	3	42.10%
5000	3	56.96%	3	43.04%
10000	3	57.27%	3	42.73%
20000	3	56.64%	3	43.37%

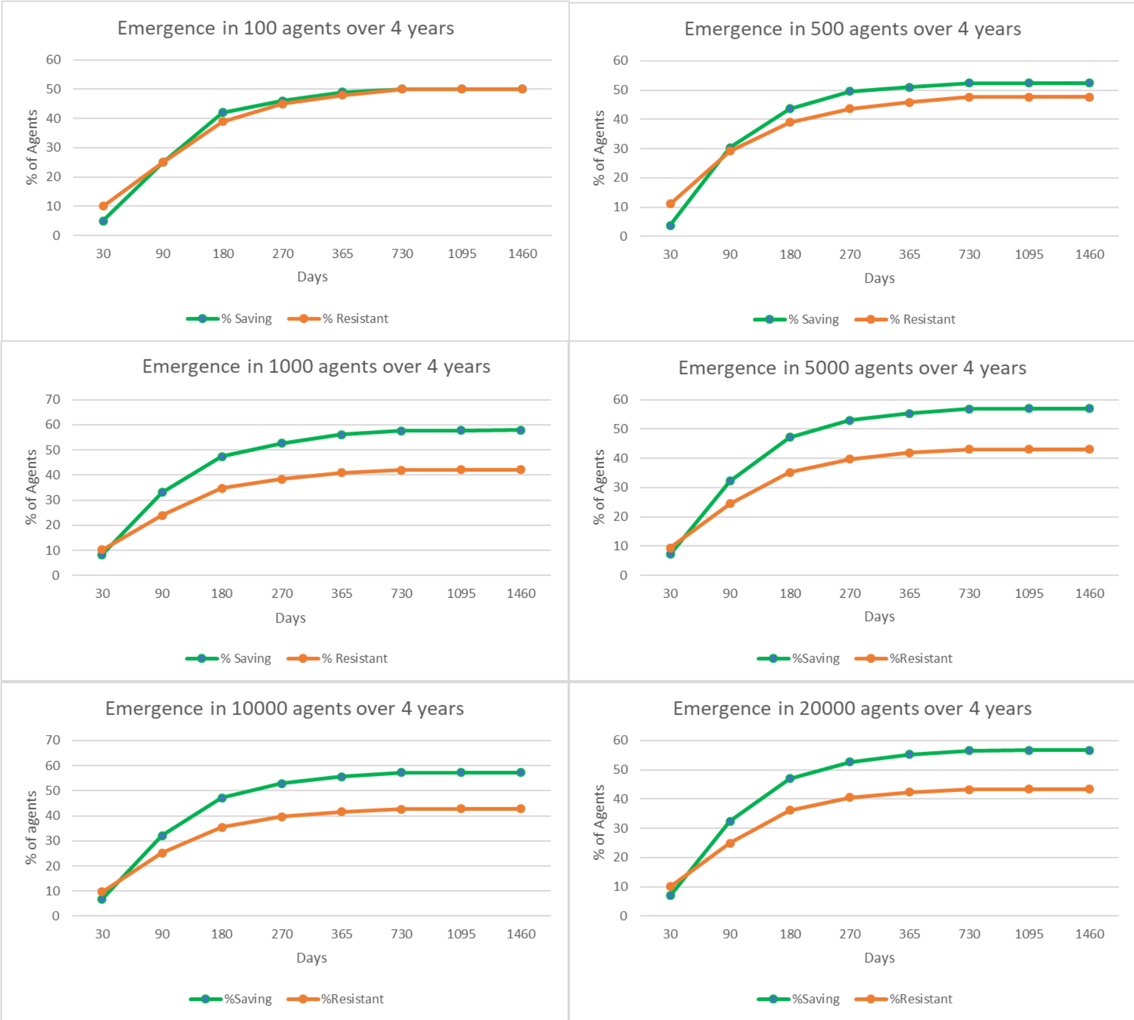

Figure 6.2 ***Energy use behaviours over four years for different agent population size***

6.1.1.1 Key observations

In the results presented above, behavioural trends are observed even though increase in the end behaviours are neither proportional to population size nor to time. The results are summarised as follows:

- In each population size, intervention uptake increased with time.
- Energy saving is stronger than resistant behaviour for all population sizes.

- Growth in uptake slows down after the first year. Across all population sizes, at least half had taken up energy savings by the end of the first year, except for that of 100 agents, where this occurred shortly after the first year (day 371)
- Although intervention uptake peaked at different times (2-3 years) for different population sizes, it stabilised by the third year.

6.1.2 The impact of population size on intervention uptake.

Model output was obtained for specified time periods namely 1 month, 3 months, 6 months, 9 months, 1 year, 2 years, 3 years and 4 years. Percentage values for the behaviours of interest were calculated for different agent population sizes (100, 200, 300, 400, 500, 1000, 5000, 10,000 and 20,000). In the first month, there was more resistance to the intervention than responsiveness, across all population sizes. However, subsequently, agents become more responsive and the percentage of responsiveness i.e. energy saving grows and becomes consistently higher than that of resistance among all population sizes.

As seen below in Figure 6.3, the shapes of the graphs are reasonably consistent across all time periods apart from the first month. From the 3rd month onwards, the two behaviours tend to converge at a population of 500 where energy saving dips and resistant behaviour increases, making the ratio of energy saving to resistant behaviour lower, compared to other population sizes (excluding 100).

From 9 months, the population size of 10000 has the highest percentage of energy saving among the various population sizes; whereas in the first 6 months, this was the case for population size of 1000. Resistant behaviour on the other hand recorded its highest percentage among the population size of 100 from 6 months onwards. Although at 6 months, population sizes of 400 and 500 also had equally high percentages and in the first six months, the population of 400 agents recorded the highest percentage for resistant behaviour.

Overall, both behaviours stabilised as agent population increased to 20000 and the effect of population size on behaviour can be considered consistent over time.

In summary,[6]

- Ratios of uptake to resistance[7] are higher among population sizes above 500 compared to those below, with the population size of 200 as an exception. See
- Table 6.2.
- Uptake did not occur incrementally with population size.
- Behavioural trend is consistent over time across all population sizes.
- Energy saving is lowest in the population of 500 agents across all periods
- Energy saving is highest in the population size of 200.

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[6] The first month is not taken into consideration as this is deemed the take off period.

[7] Uptake to resistance ratio = $\frac{\%energy\ saving}{\%resistance}$

Table 6.2 Uptake-resistance ratios per population over time

	Uptake:Resistance							
Population size	1 month	3 months	6 months	9 months	1 year	2 years	3 years	4 years
100	0.50	1.00	1.08	1.02	1.02	1.00	1.00	1.00
200	0.61	1.44	1.32	1.47	1.43	1.41	1.41	1.41
300	0.72	1.23	1.22	1.25	1.26	1.27	1.27	1.27
400	0.63	1.13	1.16	1.19	1.17	1.17	1.17	1.17
500	0.34	1.04	1.12	1.14	1.11	1.10	1.10	1.10
1000	0.81	1.38	1.36	1.38	1.37	1.37	1.37	1.38
5000	0.77	1.32	1.34	1.33	1.35	1.32	1.32	1.32
10000	0.70	1.28	1.33	1.34	1.36	1.34	1.34	1.34
20000	0.69	1.30	1.30	1.30	1.35	1.31	1.31	1.31

Figure 6.3 Percentage behaviour across agent population size over time

6.1.3 Understanding the influence of TPB and ELM variables on energy saving.

To investigate the influence of the theoretical variables on energy saving, model parameters were varied and resulting effects observed. Consequently, parameters observed to have greater effects on energy saving were combined to investigate potentially favourable scenarios for energy saving. The results are presented in 6.1.3.1 and 6.1.3.2 respectively.

6.1.3.1 Varying model parameters

In using the model to understand how variables from the Theory of Planned Behaviour and Elaboration Likelihood Model can influence energy saving, each parameter (variables are expressed as parameters in the model) was varied over a one-year period at 0, 0.5 and 1 i.e. minimum, medium and maximum values, while keeping other parameters constant at their default values. The purpose of doing this was to investigate the impact of different levels of specific variables on the target behaviour, within the context of the model's set-up. Results are presented in Figure 6.4. These show that energy saving is highest when *Peripheral Cues* = 1, followed by *Personal Relevance* = 1 and lastly, when *Cognitive Ability* = 1. Understandably, a low value of 13.8% energy saving is observed when there is no Personal Relevance. When *Cognitive Ability* and *Argument quality* are each absent, energy saving behaviour is not produced at all. The absence of peripheral cues however, did not have a similar effect, with 56.4% energy saving still achieved. Moderate levels of *peripheral cues*, *personal* *relevance*, *cognitive ability* and *argument quality* produced 56.9%, 40.9%, 35.8% and 31.6% energy saving, respectively. `

At 29.2%, the absence of social influence had a considerable impact on energy saving but did not appear to have a similar effect on resistance (40%), when compared to values of 55.7% saving and 41.2% resistant obtained at moderate presence and 56.4% saving and 40.6% resistant when fully present. Although there were differences in the % end behaviours when intention was varied, these are deemed only slight as can be seen in the chart below (Figure 6.4). A moderate level of perceived behavioural control yielded more energy saving (56.2%) than when at its maximum (54.9%) and interestingly, when absent, 55.1% energy-saving behaviour was still achieved. As can be expected, a lack of interaction resulted in low energy saving of 20.3%, compared to 53% with moderate interaction and 56.1% with absolute interaction.

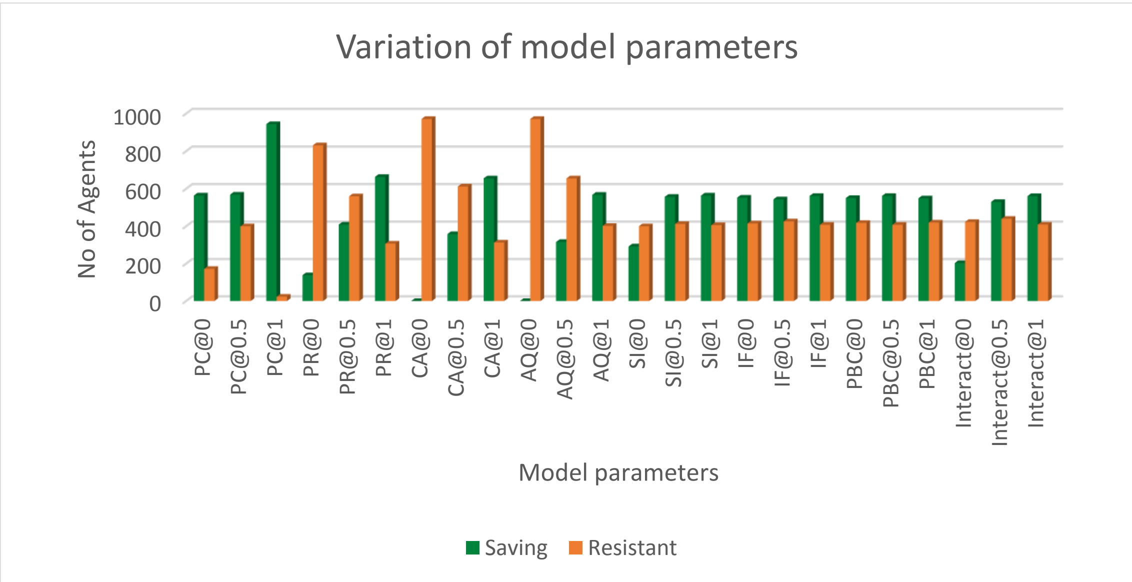


Figure 6.4 ***Results from varying model parameters***

Consistent with the *ELM*, resistant behaviour is highest at 97.1% when *Cognitive ability* and *Argument quality* are respectively absent. This is followed by 83.1% when there is no *Personal relevance*. The lowest values for resistant behaviour (2.3% and 17.2%) were produced by maximum and minimum levels of *Peripheral cues*, respectively. These results suggest that compared to when moderately present, a lack of peripheral cues cannot be significantly linked to resistant behaviour.

6.1.3.2 Investigating conditions for producing energy saving behaviours

To further understand how theoretical variables can affect energy saving, model parameters at levels which produced the highest instance of each behaviour were selected and combined, allowing for further investigation of best conditions for producing energy saving behaviour.

For energy saving these are PC@1, PR@1 and CA@1 while for resistant behaviour these are CA@0, AQ@0 and PR@0. Thirteen pairs of possible variable combinations were derived using Microsoft Excel. Each combination was fed into the model while other parameters were kept at their default values.

Observing that the absence of *Argument Quality* (AQ) yielded the highest value for resistant behaviour, two more combinations were derived, each testing the effect of the total absence and presence of *Argument Quality* alongside other parameter conditions that favour energy saving. Worth noting is that this variable is an intervention feature, not characteristic of the recipient and when absent results in the highest resistance to energy saving as seen in Figure 6.4.

PC @1 which produced the highest energy saving was also combined with the three factors that produced the highest resistance figures. The purpose of this was to understand the impact of peripheral cues in the face of strong resisting factors. In all, 17 combinations were entered in the model, the last being a combination of the three parameters which resulted in the highest energy saving values i.e. PC@1, PR@1 and CA@1. Model outputs from these parameter combinations are presented in Figure 6.5 and Table 6.3

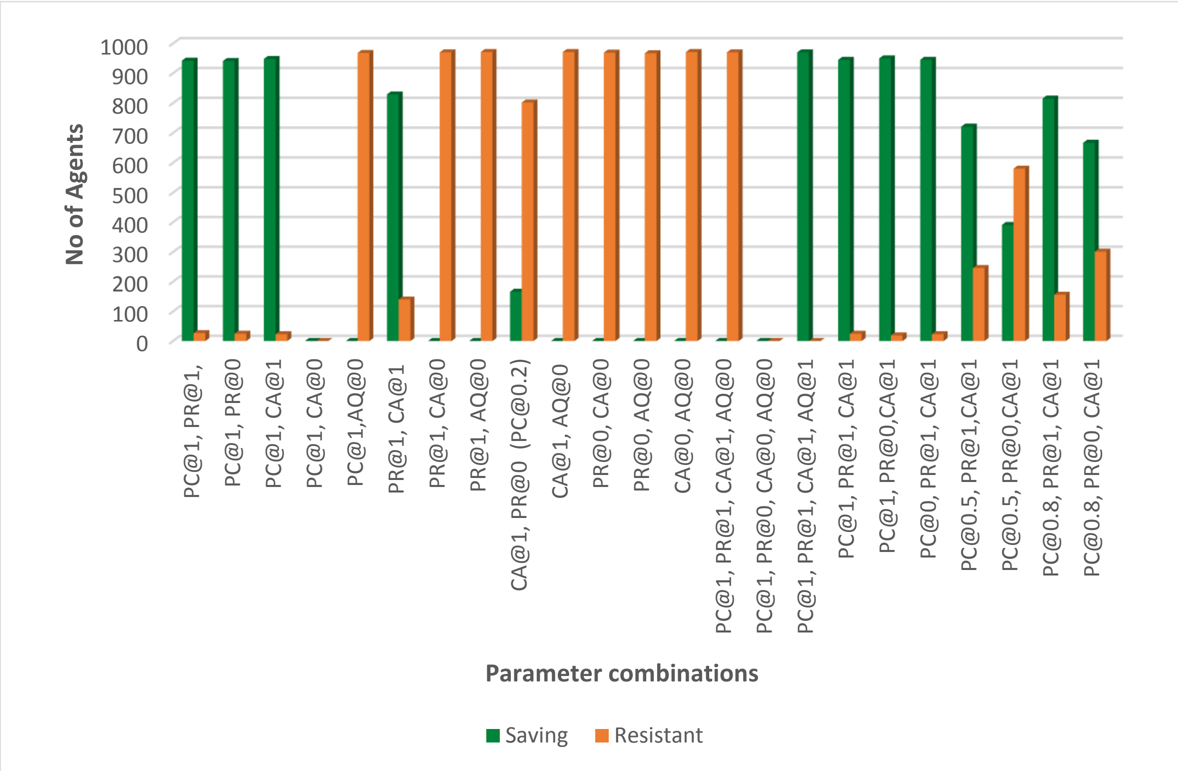


Figure 6.5 ***Parameter combinations and behavioural outcomes for energy use***

Table 6.3 Model results of parameter combinations

Parameter combinations	Energy saving	Resistant
PC@1, PR@1,	942	27
PC@1, PR@0	941	25
PC@1, CA@1	948	23
PR@1, CA@1	829	140
CA@1, PR@0 (PC@0.2)	166	802
PC@1, PR@1, CA@1, AQ@1	970	0
PC@1, PR@1, CA@1	945	25
PC@1, PR@0,CA@1	950	19
PC@0, PR@1, CA@1	945	23
PC@1, CA@0	0	0
PC@1,AQ@0	0	968
PR@1, CA@0	0	970
PR@1, AQ@0	0	971
CA@1, AQ@0	0	971
PR@0, CA@0	0	969
PR@0, AQ@0	0	967
CA@0, AQ@0	0	971
PC@1, PR@1, CA@1, AQ@0	0	970
PC@1, PR@0, CA@0, AQ@0	0	0
PC@0.5, PR@1,CA@1	721	246
PC@0.5, PR@0,CA@1	391	580
PC@0.8, PR@1, CA@1	815	156
PC@0.8, PR@0, CA@1	667	301

Additional simulation experiments were conducted to investigate the effects of personal relevance on energy saving in the presence of varying levels of peripheral cues. These are presented in Figure 6.6 below.

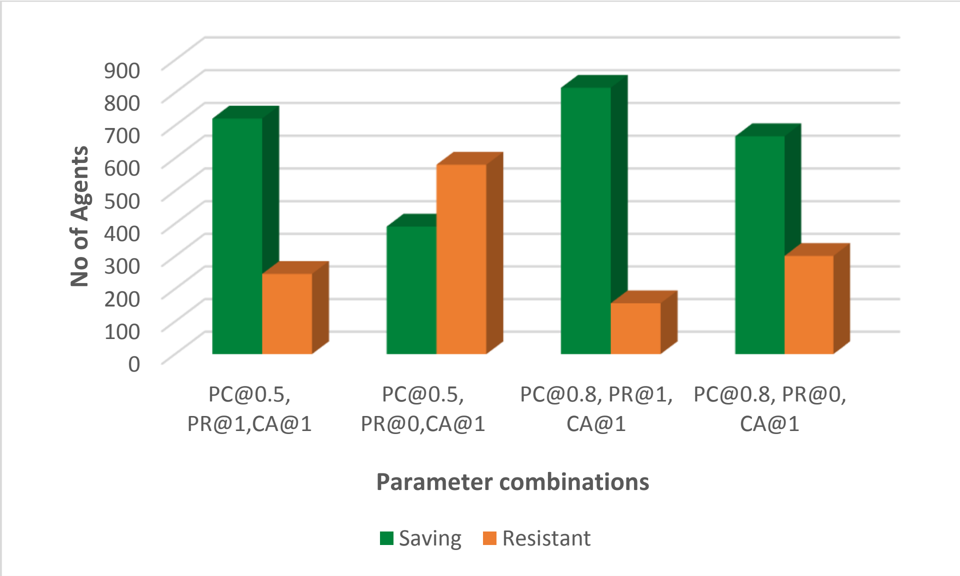


Figure 6.6 Investigating the effect of *Personal relevance* on energy saving with medium to high levels of *Peripheral cues.*

7 SYNTHESIS OF FINDINGS AND CONCLUSION

The results from both phases of the research are presented in this chapter. Results from the survey are first discussed followed by those from the agent-based model. The potential influence of the findings and the value of the methods used are then discussed next. The study's contribution to knowledge is discussed in 7.5, followed by an evaluation of the methodology where the limitations of the study are presented.

7.1 Phase 1: Survey

Results from the correlation and regression analysis carried out on survey data are discussed here. These have previously been presented in sections 3.4.5 and 3.4.6 and summarised in section 0.

The presence of shared variances between variables from the Theory of Planned Behaviour and the Elaboration Likelihood Model demonstrate that both models can jointly serve as a useful framework for understanding energy use behaviours (objective 2); this corroborates the work of Wilson (2014). Statistically significant correlations with large effect sizes between certain variables of the TPB and the ELM (e.g. *PBC* and *Motivation*: r= 0.58; *Argument quality* and *Subjective norms* r=0.53; *Intention* and *Argument quality*: r= 0.59; *PBC* and *Argument quality*: r=0.52) demonstrate this (Cohen, 1988).

Contrary to findings from a study conducted by (Wilson et al., 2010, p.100), *Subjective norms* were found to be a statistically significant predictor of *intention* (objective 1). *Intention* was also found to be a statistical predictor of behaviour;

although they found a significant (assumed non-causal) relationship between *Intention* and *Behaviour.* This is consistent with the SSO campaign's key strategies of peer influence and word-of-mouth; and could be regarded as evidence of its effectiveness. The intervention's focal activities—energy saving competitions between halls of residences and posting personal photos showing engagement in an energy saving action—suggest that descriptive norms have been targeted as the main agent of change. Research shows that this descriptive element of subjective (social) norms motivates people to do what others do to achieve favourable results (Cialdini et al., 2006, 1990; Reno et al., 1993). Also, the competitive element of the SSO strategy ensures that participants are focused on outdoing their rivals in achieving a joint goal of energy saving for a prize.

According to the focus theory of normative conduct, "norms are only likely to influence behaviour directly when they are focal in attention and, thereby, salient in consciousness" (Cialdini et al., 2006, p.4). This suggests that the success of the SSO is achieved because participants are conscious of what others are doing (the norm) i.e. partaking in the competition and posting photos, thereby adopting the desired energy saving behaviours (Kallgren, Reno, & Cialdini, 2000).

Specific energy saving tips given on the SSO website are however injunctive in nature (see 3.3.1). The fact that these tips are mainly accessed via the website show that descriptive norms are only a first tactic. When people visit the website for more information, the energy saving tips are likely to further convince them.

This suggests that where descriptive norms have not achieved much success, injunctive norms are utilised as a second ‘line of attack’. This further strengthens the intervention since studies confirm that when either type of norms is triggered, notably different behavioural responses are yielded compared to what previously existed (Cialdini and Goldstein, 2004; Kallgren et al., 2000; Nolan et al., 2008; Schultz et al., 2007). In practical terms, this has consequences for communicators trying to convince an audience to behave in a certain way. They must acknowledge that injunctive and descriptive norms have distinct influences and steer the target audience towards the specific type of norm that is most consistent with their goals, to achieve success (Cialdini et al., 2006).

By showing that the success of the ‘*Student Switch Off*’ does not depend only on standalone factors but on relationships and variation among these (objective 3), the ELM-TPB framework sheds some light on inter-relationships that are potentially significant behavioural influences in energy use. Thereby, informing the understanding of intervention success and highlighting its would-be value in an energy saving context, particularly if used with a larger data set. It also demonstrates that successfully persuading people to save energy depends on more than simply disseminating relevant information. The degree to which factors—cognitive, social, environmental, situational etc.—interact in the face of persuasive information may be more significant in achieving energy saving than communicating useful information or even, the information itself (Petty et al., 2009).

7.2 Phase 2: ABM

The primary purpose of the model is explanatory in nature. Therefore, the extent to which it sheds light on the research questions and overall topic of informational interventions for energy saving is paramount. In this section, results obtained from the simulation experiments are discussed in the light of the model-specific research questions posed in 4.2.1.

7.2.1 What behavioural outcomes or trends can be observed from using the TPB and ELM to explain energy-saving intervention success?

A trend of aggregate energy-saving and resistant behaviours over time is observed to show progressive increase in energy saving, peaking and then steadying in a shape reasonably comparable to Rogers' (2003) well-known s-shaped diffusion of innovations curve (see Appendix B).

In seeking answers to this question, two factors—population size and time—were examined.

7.2.1.1 The impact of time on intervention uptake

Recipients' collective response to any intervention determines its success. However, for issues with far reaching consequences such as energy use, this does not rest with initial or short-term response but with enduring change. From theories of innovation diffusion, it is known that new ideas and technology take time to spread (Darley, 1977; Rogers, 2003). As time progresses and people become more aware of an intervention, they start to consider its message and other supporting factors and decide whether to adopt or not. Results from the model support this fact, also showing that after intervention impact peaked, it steadied over the remaining period studied i.e. 4 years. When planning for an intervention, understanding the possible time frames required to achieve optimal success would be useful for deciding the length of time in which, and how an intervention should be actively managed. Therefore, estimating the life span of an intervention should be an informed choice and not arbitrarily chosen.

Although there is an abundance of empirical research on energy saving and interventions (Sweeney et al., 2013), recent studies into long-term effects of informational interventions for energy saving are scant. Considering that informational interventions are still a much-used means of encouraging energy saving, it is necessary that long term effects be understood. Findings from Staats et al. (2000) longitudinal study (previously mentioned in section 2.2) showed that in roughly half of the cases studied, there were temporary relapses in the target behaviours, suggesting that applying the intervention at intervals may have helped in achieving energy savings. Conversely, this implies that if the interventions were not re-applied, success would not have been achieved. This provides a possible explanation for the reduction in intervention uptake observed from the model’s results and is not surprising because the importance of regular and relevant feedback for inducing change from habitual behaviours have been highlighted by several studies (e.g. Darby 2006; Ehrhardt-martinez 2010; Faruqui et al. 2010; Nye & Hargreaves 2009).

In a real-world situation (as opposed to a study), interventions of this type could benefit from prior understanding of potential peak times and causes of relapses. Informed modelling of the target population's response to the intervention (e.g. via surveys, interviews etc.) should be useful for providing such guidance. Different modelling types may be explored for this purpose. However, as already discussed in section 1.1.6, the use of agent-based modelling is recommended because of its capacity to model details such as social complexities and interactions which other modelling types may not be able to capture adequately. While the intervention is live and actively being maintained but before the predicted peak, maintenance investigations can be carried out to further understand drivers and barriers most responsible for uptake achieved so far. These can subsequently be built upon for increasing the adoption rate or the intervention's peak figures; thus, helping to direct the intervention's effort while minimizing loss of resources and maximising energy savings.

In a similar vein, data obtained from the Staats et al. (2000) study implied that the interventions not only needed re-administering but would also need to be boosted if the energy savings initially achieved were to be sustained. Although due to methodology limitations, they advised caution in applying their results, their preliminary findings buttress the viewpoint that response to energy saving interventions wane over time. Also, understanding the potential behaviour of the target population in relation to this is important for guiding intervention efforts which is vital to intervention success. Bator & Cialdini (2000) also support this view point expressing that when developers of public service announcements—a type of informational intervention—overlook such guiding principles which are backed up by relevant research, “their efforts to bring about behavioural change are likely to be unsuccessful” (p.528)

Overall, results from the model demonstrate that using the TPB and ELM framework within an agent-based model for explaining energy-saving behaviour provides useful information on intervention induced energy-saving uptake by showing how responses emerge in a population over time.

7.2.1.2 The impact of population size on intervention uptake

Although intervention uptake (measured by the number of agents saving energy) is seen to increase over time in all population groups, the relationship between population size and intervention uptake is not incremental. This suggests that the size of the target population has little or no significance to the adoption of energy saving interventions. This is somewhat interesting as it could be expected that in a larger population, there will be more opportunities for social interactions. Going by research evidence of the positive effect of social influence on pro-environmental behaviours (Abrahamse and Steg, 2013; Farrow et al., 2017a; Nolan et al., 2008), this should imply more social influence to bring about consistently higher adoption ratios. In an ABM innovation diffusion study of hybrid electric vehicles, Tran (2012) found that indirect influence from a larger population had a stronger effect on individual adoption than person-to-person interaction. In spite of these, the influence of social norms should not be assumed as there is still a lot to understand about its dynamics (Abrahamse and Steg, 2013; Hahn and Metcalfe, 2016). Social influence can have mixed effects for several reasons e.g. varying motivation levels, no perceived effect on reputation, or if an individual is already overachieving compared to the norm (Delmas and Lessem, 2014). A study by Schultz et al.(2007) showed that social norms could have a rebound effect depending on what type it is. In their case, descriptive norms conveyed by giving information on average collective energy use, yielded a rebound effect subject to whether people where already saving energy or not. In the case of a study conducted in China, urbanisation—and by inference population increase—had a negative impact on energy saving (Ji and Chen, 2017). However, this was not measured in direct response to an intervention.

Several factors can contribute to a variety of reactions to interventions within a population; therefore population size may not necessarily determine energy saving or pro-environmental behaviours (Quaglione et al., 2017; Xu et al., 2017). Even within a community of people with seemingly similar characteristics, response to energy saving can differ significantly due to a range of possible reasons as in the case of mixed effects of social influence mentioned in the preceding paragraph. These differences—which imply that different intervention strategies may be required—include intellectual differences (Corradi et al., 2013; Stephenson et al., 2010), motivation (Li et al., 2017; Sweeney et al., 2013), previous environmental awareness (Schultz, 2002; Trombley and Halawa, 2017), context (Han et al., 2013; Šćepanović et al., 2017) and so on. Considering these, identifying and targeting specific characteristics present in a population is likely to yield greater intervention success (Casado et al., 2017). For instance, in the case of Staats et al. (2000) (earlier cited in 7.2.1.1), the offices studied could be separated into two categories—those that were already behaving in line with the intervention and those that were not. At the end of the intervention period i.e. 2 years, 58.6% of the group that were already acting mostly in line with the intervention’s requirements did not do anything different; however, the remaining 41.4% showed improvements in their energy saving behaviour. The other category i.e. the ‘newbies’, all adopted the target behaviour at different levels—54% showed the adoption of one target behaviour while 46% adopted more than one energy saving behaviour. It could be argued that intervention efforts were wasted on the 58.6% of offices that didn’t change because applying the intervention did not yield further savings with this group. Findings from a study conducted by Trombley & Halawa (2017) corroborate this, showing that in instances where people were already aware of energy saving, informational interventions were not significantly beneficial. In such cases, it is likely that a different but suited type of intervention or even a combination will achieve better success (Casado et al., 2017; G. Thondhlana and Kua, 2016).

The Theory of Planned Behaviour and Elaboration Likelihood Model which underpin this research also highlight motivation, context, social influences, cognitive factors etc. as possible contributors to behaviour. Identifying and understanding such contributors within a target population and focusing on these as key change agents within an intervention could be critical to achieving optimal intervention success. This means that even within a given population, interventions would have to be tailored to specific groups or audiences to achieve maximum energy savings. (Abrahamse et al., 2007; Han et al., 2013; Khosrowpour et al., 2016).

A recent study from the health domain used structural analysis to hone in on influential community members as a potentially strong inspiration for community-wide behaviour change and subsequently targeted this for intervention (Shakya et al., 2017). In addition to reinforcing the support for tailored interventions, the study (and several others e.g. Hahn and Metcalfe, 2016; Miniard et al., 1992; Mosler, 2006; Rosenthal, 2012) highlights the value of peripheral cues such as social influence—constructs of the ELM and TPB respectively—in attaining behavioural change. The role of these and other constructs in allowing for optimum conditions for energy saving as determined from results of the model are discussed in 7.2.2 below.

7.2.2 To what extent do the constructs of the TPB and ELM influence energy saving behaviour?

Results from the model show that constructs of both theories influence energy saving behaviour in varying degrees (see Figure 6.4 and Figure 6.5). Generally, findings appear consistent with the standpoint of the theoretical framework which underpins the study. Constructs shown (in section 6.1.3.1) to have the most significant effects on energy-saving are discussed.

Peripheral Cues

According to the ELM, peripheral cues provide an alternate route for persuasion where recipient motivation is lacking, they are unable to think through a message or the ability to do so is compromised (Bhattacherjee and Sanford, 2009; Briñol and Petty, 2015; Petty et al., 2009b; Petty and Cacioppo, 1986a). Without this alternate route, cognitive barriers are likely to result in negative behavioural outcomes. In some cases, however, such limitations may result in positive outcomes for example enabling an individual to focus and make sense of a few good sources of information (Savolainen, 2015). Depending on context, such cognitive limitations may be due to illiteracy, lack of concentration, a reluctance to admit to having an information need, being ignorant of information sources, inability to deal with excessive information and so on (Rosenthal, 2012; Savolainen, 2015). Many types of peripheral cues exist and some of these have been identified by Cialdini (2001) as reciprocation, consistency, social proof, liking, authority, and scarcity.

A study by Graffeo et al. (2015) showed that in addition to being informed about the energy saving behaviour of others, the knowledge of who they were resulted in less energy consumption. Such evidence strengthens the role of social norms, an example of peripheral cues (Krcmar et al., 2016), in enabling favourable energy use behaviour. Results from the model corroborate this, with energy saving behaviour highest when *Peripheral cues* were highest.

In the complete absence of the variable and when it was semi-present (@ 0.5), similar values (56.4% and 56.9% respectively) were obtained for energy saving with more than half of the population still saving energy. This suggests that the success achieved when *Peripheral cues* was fully present has other contributory factors. Going by these findings, it is considered precarious to make it the sole foundation of an intervention especially as the ELM theorises that change achieved via the peripheral route is often short-term. Bator & Cialdini (2000) also consider it a risky path for informational interventions, particularly pro-environmental campaigns. This is mainly because it can be expected that behaviours such as energy saving would require some thought and commitment, as opposed to cognitive shortcuts which characterise the peripheral route. Nonetheless, it may be argued that peripheral cues can result in long term change by triggering cognitive processing while in the state of short-term attitude change associated with the peripheral route. However, this is likely to be dependent on factors such as the type of peripheral cue involved and specific scenarios.

The extent to which peripheral cues are effective can be dependent on cultural orientation such as individualist or collectivist (Kim et al., 1994; Triandis, 1994, 1989). In individualist cultures, people are primarily independent and “self” is determined by an individual’s internal qualities (Geertz, 1975). Therefore, social cues such as the opinion of others are only effective to the extent to which it provides self-validation, introspective evaluation or a yardstick for comparison. On the other hand, collectivist cultures tend to be defined by social interactions, where people depend on each other. This implies that in a collectivist population, others are fundamental in the definition of “self” and are therefore important considerations in the choices a person makes (Aaker and Maheswaran, 1997; Markus and Kitayama, 1991). Apart from cultural orientations, people’s personal individualistic or collectivistic tendencies have been shown to have significant impact on choices made (Cialdini et al., 1999; Joireman et al., 2001; Van Lange and Joireman, 2008). Differences like these would therefore require separate approaches from an intervention. Understanding issues of this nature are therefore vital for intervention success.

*Personal Relevance (*a.k.a. *Involvement or motivation).*

In the literature, this construct has also been referred to as involvement and the motivation to process information (Li et al., 2017; Poiesz and Bont, 1995). In this study, it is used in an experiential context i.e. as perceived by the individual (Petty and Cacioppo, 1986b). In the ELM, it is one of two triggers of the central route to persuasion, the second being thinking ability. Regardless of any differences in the operationalisation of this construct, it has been established in the literature that motivation/involvement/personal relevance plays a firm role in the journey to attitude change, not only in energy saving or pro-environmental domain but across many other fields. In a study which involved investigating the design of web-based interfaces for engaging users in energy saving, participants of a focus group all indicated the importance of having energy saving strategies that were relevant to them in some way e.g. lifestyle, values or circumstance (Burrows et al., 2015). However, the motivation that comes from finding energy saving personally relevant doesn't guarantee change in attitude or behaviour. It has been shown that the aspiration to save energy can be challenged by an array of factors which could be within or outside of the consumer's control.

A key consideration in the touting of motivation as a major influencer of energy saving behaviour lies in the fact that motivational orientations may be varied. This suggests that factors like morality, rationality and power which are central to motivation are likely to be perceived differently by different people depending on their orientation (Joireman et al., 2003). This poses a real challenge for intervention planners because prevalent orientation types will need to be systematically identified and considered during intervention design (Kok et al., 2011). However, it is recognised that other practical or situational limitations may stand in the way of this being achieved in real life. For some reason, it appears that evidence from research does not in many cases translate to real world practice. Taking rationality as an example; although it is acknowledged in the literature that energy use does not always involve rational thought, this appears to often be overlooked during intervention design and planning (Abrahamse et al., 2005; Kok et al., 2011; Uitdenbogerd et al., 2007). Unfortunately, the notion of rationality tends to ignore other far-reaching elements like cultural and social factors which have been shown to influence energy use and assume that when presented with relevant information, people will reduce their consumption because of the resulting awareness or knowledge gained.

These identified issues put a crack in the strength of personal relevance as a determining factor of energy saving behaviour.

Also, a person could find an energy-saving information relevant to their situation but choose not to deliberate further on it for a number of reasons (Corradi et al., 2013; Steg, 2008) e.g. strong cultural implications. In such a case, personal relevance does not do anything for energy saving. However, if the same individual realises that other people in his social or cultural circle are reducing their energy use, given the evidence for social norms and peripheral cues in the literature, there is a likelihood that they would begin to practice energy saving (Abrahamse and Steg, 2013; Axsen and Kurani, 2012; Farrow et al., 2017; Gifford and Nilsson, 2014). Results from the model support this view with maximum peripheral cues producing considerable higher energy saving (94.4%) than personal relevance at the same value (66.3%).

Cognitive ability (Ability to process or think)

From the model's results, when *Cognitive ability* is highest, and all other parameters are at default values, 65% of energy saving behaviour is produced.

However, in its absence, energy saving does not occur at all. This suggests that cognitive ability is a strong determinant of energy saving. However, this also indicates that energy saving did not occur via the peripheral route, most likely because the default value for *Peripheral cues* is low, at 0.2. While the importance of cognitive ability is acknowledged, it only accounts for rational aspects of the decision making process and is considered most beneficial when the information to be processed is perceived as personally or issue relevant (Cacioppo et al., 1985).

The ability to think through a message (as a key determinant of energy saving) may hinge not so much on a person's intellectual or educational level, but on other considerations which could obstruct the thinking process instead of enabling it. Other actions may compete for mental resource e.g. reducing the setting on a pressing iron (or even leaving it on) instead of unplugging it when instinctively running of a room in response to the oven's alarm going off in the kitchen. In such a scenario, responding to the alarm trumped the energy-saving action of unplugging the iron. Other real issues like inability to pay close attention to activities which are susceptible to energy wastage (e.g. charging a battery), tiredness—which can cause temporary cognitive impairment, distractions and even absent-mindedness can all contribute to energy wasting, thereby weakening the role of *cognitive ability* in energy saving.

From the discussion so far, it is reasonable to assert that a combination of the theoretical variables identified and discussed above are best considered when designing informational interventions for energy-saving. In view of this, combinations of these variables were derived and simulated (see 6.1.3.2).

Conditions which resulted in the highest levels of resistance were also included in some of the combinations to account for any effects on energy saving. The results are discussed below in 7.2.3

7.2.3 In what conditions do elements of the TPB and ELM produce energy saving behaviours?

Results presented in Figure 6.5 and Table 6.3 are discussed here.

Consistent with the Elaboration Likelihood Model, almost the entire population (97%) saved energy in an ideal situation of maximum *Peripheral cues*, *Motivation*, *Cognitive ability* and *Argument quality*. This combination demonstrates that when both the central and peripheral pathways are fully engaged in processing a message containing superior quality arguments, a high intervention success rate may be expected. In the absence of such a message, a difference of 2.5% is observed with both pathways fully engaged. Interestingly, when personal relevance is at the default level, maximum levels of *peripheral cues* and *cognitive ability* result in more energy saving than at its highest. The implication (of both peripheral and cognitive pathways being engaged) for intervention success is three-fold. Firstly, the energy saving achieved is likely to be long-term since cognition is involved. Secondly, behaviour change achieved via cognition can be sustained by the presence of *peripheral cues* like celebrity involvement etc. The rationale here is that the presence of *peripheral cues* can reinforce actions already committed to. Thirdly, continuing in the behaviour (achieved via cognition) can encourage those persuaded via the peripheral route to begin to rationally consider their energy saving actions, resulting in firmer commitment.

When either central and peripheral pathways are fully engaged, *Personal relevance* does not appear to make much difference for energy saving. When *Peripheral cues* are fully present, a lack or full presence of *Personal relevance* does not appear to make any significant difference (0.1%). This might raise questions regarding the case for *personal relevance* as a prerequisite for the cognitive processing of energy saving information, especially considering that with the default level of *personal relevance*, optimal levels of *Peripheral cues* and *Cognitive ability* combined, yielded 94.8% energy saving and when equal to zero, 95%.

Maximum *Cognitive ability* with zero *Personal relevance* yielded only 16.6% of the desired behaviour. This may appear to contradict the preceding stance; however, it must be noted that these variations are done against a back drop of default values (i.e. holding other parameters constant at their default values). Therefore, the default *Peripheral cue* value (0.2) means that energy saving via the peripheral route will be minimal in such an instance. In addition to questioning the effect of *Personal relevance*, this finding strengthens the position of *Peripheral cues* as a strong determinant of energy saving. Nevertheless, combining full *Cognitive ability* with full *Personal relevance* resulted in 82.9% energy saving suggesting that in a situation of high cognitive ability, personal relevance is most beneficial for energy saving when peripheral cues are low. To test this premise, the model was run with maximum levels of *Cognitive ability* and *Personal relevance* and zero *peripheral cues*. Interestingly, this resulted in 94.5% energy saving, the same as when peripheral cues are at their highest. Rejecting the premise, this outcome instead suggests that at both extremes of *peripheral* *cues* (i.e. 0 and 1) and high *cognitive ability*, *personal relevance* does not have a considerable effect on energy saving. Further experiments with other levels of *Peripheral cues* (0.5 and 0.8) yielded substantially different results (see Figure 6.6) which suggests that *Personal relevance* has an impact on energy saving only when *Cognitive ability* is present and *Peripheral cues* are not at extreme states. By suggesting that being motivated only results in energy saving when a person has the cognitive capacity to think about the intervention, this finding partly reinforces the ELM's central route of persuasion. However, it also demonstrates that unexpected and seemingly inexplicable properties can emerge from collective behaviour, especially over time.

In all combinations where either *Cognitive ability* or *Argument quality* had zero value, energy saving was not achieved. However, this does not imply total resistance to energy saving in every case. Depending on the extent to which other parameters were present, other states were also achieved. For example, in the absence of both *Cognitive ability* and *Argument quality*, even with high *Peripheral cues*, neither energy saving, nor resistant behaviour occurred as may be expected. However, 66.9% temporary attitude change occurred, which is indicative of persuasion by *Peripheral cues*. 30.2% where motivated but did not have the ability to process the information. For the model output page showing these, see Figure **D.1** in Appendix C.

7.3 Potential influence of findings on the theoretical method for understanding behavioural responses to informational interventions for energy saving.

In the first phase of this study, observed inter-relationships between variables of the Elaboration Likelihood Model and the Theory of Planned Behaviour contribute to theoretical knowledge. Of interest are correlations between *Attitude* and *Motivation*; *Attitude certainty* and *Motivation*; *Perceived behavioural control* and *Motivation.* Although these relationships are non-causal, the presence of *Motivation* in each of these suggest its potential as a strong precursor to *Attitude* and *Behaviour* and further links both theories for use in understanding energy saving behaviour. Sheeran et al. (2003) showed that *Perceived behavioural control* can by itself predict *behaviour* in situations where it reflects actual control. Together with the correlation above, this suggests that *Motivation* could also be a direct precursor of *Behaviour,* which is likely to be lasting. This is supported by findings from the agent-based model which showed that when the ability to process the information was present, *Personal relevance* i.e. *Motivation* resulted in energy saving. These suggestions buttress the ELM's assertion that being motivated is the start-off condition that determines the elaboration process (Petty & Cacioppo 1986) i.e. without *Motivation*, persuasive information cannot result in lasting attitude change.

Furthermore, the correlations between the attitudinal constructs (*Attitude* and *Attitude certainty*) and *Motivation* suggest that (perhaps) indirectly and depending on the context, *Motivation* may also be regarded as an outcome of the message rather than solely as the determinant of whether a message is processed on receipt. Where motivation is initially non-existent and the peripheral route to attitude change is fully engaged, a person could begin to appreciate the significance of their actions and become motivated to continue. Also, motivation already present is likely to be strengthened. As this type of motivation is regarded as being fully persuaded, it is expected to be more deeply seated, further ratifying the attitude change. It has been suggested that these type of ratified attitudes appear to be better predictors of behaviour (Glasman and Albarracín, 2006).

Secondly, the correlation between A*rgument quality* and *Subjective norms* appears to be an unusual one, considering that the former is a message characteristic while the latter directly relates to the recipient. More so, each variable belongs to a distinctly different theory. The TPB does not have a message component and *Subjective norms* are an antecedent to *Intention* and do not directly influence attitudes; whereas in the ELM, *Argument quality* is theorised to directly influence attitudes. The observed correlation between A*rgument quality* and *Subjective norms* suggest that *Subjective norms* may (possibly, to some extent) strongly influence *Attitudes* in a similar vein as *Argument quality* and not only *Intention* as proposed by the TPB. Although the aforementioned correlation is uncommon, it should be noted that correlations between *Attitudes* and *Subjective norms* are not unusual (O'Keefe, 1990). Several studies have shown positive and significant relationships between *Attitudes* and *Subjective norms* (e.g. Greene et al., 1997; Wan et al., 2017). This suggests a lack of singularity in attributing the effect of either variable on *Intention*. However, Fishbein and Ajzen (1981) in response to criticisms from

(Miniard and Cohen, 1981) maintain that both variables correlate more strongly with *Intention* than with each other. They supported their stance with evidence from a manipulation experiment intended to influence *Attitude* which did not have any effects on *Subjective norms* (Fishbein and Ajzen, 1975).

In providing further explanations about the attitude-subjective norms association, Park (2000) categorised attitudes into personal attitudes and social attitudes and investigated relationships between both categories and subjective norms. His findings showed a strong relationship only between social attitudes and subjective norms. When seen from this perspective, the premise that subjective (social) norms influence attitudes in a similar fashion (i.e. directly) to argument quality is justifiable. However, it must be noted that attitudes influenced by the quality of an argument is personal in nature as opposed to social type implied above.

Furthermore, it is argued that *Subjective norms* could be regarded as a type of peripheral cue[8] (Krcmar et al., 2016) because subjective norms are often about other people's opinions or actions e.g. "people important to me are doing it so it must be a good thing to do". This suggests that it can influence short term attitude change. (Conner and Armitage, 1998) have already highlighted not accounting for affective processes as a weakness of the TPB. The affective bias of subjective norms being suggested, and the short-term attitude change associated with it may be contributory to the intention-behaviour gap often observed in real life

[8] an ELM construct that does not require cognition but tends to be more affective and could lead to temporary attitude change

which has been acknowledged by several studies (Bhattacherjee and Sanford, 2009; Carrington et al., 2010; Mohiyeddini et al., 2008). These submissions could be foundational to extending the ELM-TPB framework for application in predicting the behavioural responses to informational interventions for energy saving. Future work to explore this possibility is encouraged.

Overall, results from the model are consistent with the theories studied. However, the effect of social influence (subjective norms) on energy saving did not seem as strong as could be expected. Although, it has been reasoned to be a type of peripheral cue, at its highest it resulted in 56.4% energy saving. Compared to the actual *Peripheral cue* variable which at maximum influence resulted in 94.4% energy saving, it did not have as much impact. A possible explanation for this is how the variable is operationalised in the model. In the TPB, *Subjective norms* are at par with *Attitude* and *Perceived behavioural control* in terms of direct impact on intention. It represents the influence of important others on a person's behaviour. This implies relationship and therefore in the model, it is accounted for based on interaction only. *Peripheral cues* on the other hand is not limited to interaction with other people but is more broadly defined, encompassing a range of affective tendencies like celebrity buy-in, improved reputation etc. Although the TPB has been updated in recent years to accommodate descriptive social norms, these are still in relation to important others. This ignores external influences like source credibility which can be regarded social norm. By suggesting a possible limitation in the scope of subjective norms and a resultant implication for investigating energy saving, a real issue in the sole use of the Theory of Planned Behaviour for predicting energy-saving behaviours is exposed. Thus, providing further support for studies that criticise the theory's scope of application (see Bamberg and Möser, 2007; Conner and Armitage, 1998; Klöckner, 2013; Rivis et al., 2009). Some of these have also been highlighted in 1.1.4 and 2.8. The objective here is not to undermine the usefulness of the TPB—as it has been widely used successfully for understanding behaviours—but to advocate that the drawbacks exposed should be considered and accounted for during application where necessary. Furthermore and in light of this, extending the theory e.g. by including relevant personal and social factors can enhance its predictive and explanatory validity (Gifford and Nilsson, 2014).

In summary, the study's findings contribute to theory within the context of understanding success factors of a UK-based HEI informational intervention for energy saving by:

- Suggesting that *motivation* (*personal relevance, involvement*) could be an outcome of the elaboration process as opposed to the precursory role it currently plays in the Elaboration Likelihood Model
- Exposing a correlation between the quality of a message and subjective norms, therefore highlighting the possibility of subjective norms having a direct influence on attitude change towards energy saving.
- Indicating that the context in which subjective norms is applied in the Theory of Planned Behaviour may pose a limitation to its predictive and explanatory power in some contexts; thereby suggesting that its scope be extended to include other social factors like peripheral cues where relevant.

7.4 A brief appraisal of the study in view of previous studies

The ELM-TPB framework is known to have previously been applied to energy saving only in research conducted on six communication-based interventions—Wilson et al. (2010), Wilson & Irvine (2013) and Wilson (2014)—the key objectives were to investigate the plausibility of the combined framework for evaluating communication approaches for energy conservation. Although similarly, the usefulness of the framework for evaluative purposes may be inferred from the findings of this research, the focus here was to understand factors which could influence the success of informational interventions for encouraging energy saving within the context of UK HEI where in many cases, energy bills are not borne directly by the student, having been pre-paid in accommodation charges. This context rules out the effect of external factors such as cost savings on the decision to save energy.

Although the joint use of ELM and TPB in energy conservation studies may be regarded as still in infancy, it has been used in the work of several researchers across other fields. For example: Beale & Bonsall (2007)—in transportation research; Brown et al. (2010)—in Tourism related pro-environmental behaviour; Bae (2008)—in health communication research; Hill et al. (2007)— for an intervention to encourage exercise in children. Wilson et al. (2010) however pointed out that in most of these studies the ELM aspects were not actually measured but only used to provide insight needed for designing the respective interventions with recommendations for further empirical work on both elements of the framework.

7.5 Contribution to knowledge

Combining the use of a theoretical framework and agent-based modelling, this study developed an original method for testing theory and explaining how known persuasion and behavioural variables can interact to produce behavioural outcomes. Therefore, it contributes to the knowledge of how theory may be used in conjunction with agent-based modelling to understand the success of information-based interventions for energy saving. This is discussed in more detail below. Findings from the study will be beneficial for informing decision-making aspects of energy-saving intervention design.

Wilson (2014) demonstrates that using the ELM-TPB framework in the design, monitoring and evaluation of energy conservation interventions is a promising approach and calls for further research as “repeated use of the framework would confirm more detail about the relationship between the two theories and highlight differences in communication acceptance according to situation and context” (p.307). This research supports and responds to that call.

Findings from the first phase of the study suggest that subjective norms can influence not only behaviour but also attitudes towards energy saving. This is not currently accounted for in the TPB and suggests that due to its social features, subjective norms may have value as a type of peripheral cue, hence its influence on attitude change. This contributes to knowledge by highlighting the potential value of peripheral cues for extending the theory of planned behaviour and strengthens the role of social norms as a peripheral cue in enabling favourable energy use behaviour (Krcmar et al., 2016). Results from the model corroborate these thoughts, showing that energy saving behaviour was highest when *Peripheral cues* were fully present (section 7.2.2).

Following on from the discussion in 7.4, this study also makes an original contribution to knowledge by measuring individual variables of the Elaboration Likelihood Model and the Theory of Planned Behaviour and investigating these in relation to each other within the context of energy saving interventions in Higher Education Institutions.

The use of agent-based modelling to gain further insights for answering the research questions also provides a secondary benefit of further testing the suitability of the ELM-TPB framework for understanding attitude and behaviour change as agent rules and behaviour in the model are specified based on both theories. This is not only considered useful from a theory development and testing perspective but the method with which the different elements of the framework are represented in the model are original and thereby contributes to the agent-based modelling body of knowledge.

Overall, developing an agent-based model in the context of the ELM-TPB framework for investigating energy saving provides a different means of analysing the framework. It allows for varied experiments, thereby providing more facts about the relationship between the two theories which will be relevant for future use within and outside the domain of energy conservation behaviours.

Table **7.1** below gives a summary of how the study addresses research gaps highlighted in 1.2.

Table 7.1 Summary of research gaps and contributions

Research gap/need	Contribution to bridging the gap
Limited research that applies both theory and agent based modelling in the uderstanding of informational interventions for energy saving.	This study demonstrates how this approach could be applied within the given context.
Scant information on how individual level factors contribute to the impact of behavioural interventions for energy saving at a group level (Staats et al. 2000; Scherbaum et al. 2008; Dixon et al. 2015; Lo et al. 2012).	The theories used address individual level factors via their constructs which form the basis for findings in the first phase of the research. Also, as agent rules are based on these individual-level variables, the model sheds more light on how interactions between such factors influence energy saving in response to interventions.
New methods for empirical testing of ABMs and methods that allow for more generalizable ABMs (Janssen & Ostrom 2006)	The agent based model was verified and validated statistically with a combination of methods including hypothesis testing, sensitivity analysis, input validation, external validation. Also, Agent decision rules are based on established theories (TPB & ELM). Therefore, the extent to which the model re-produces a known or theorized outcome as a result of specific input provides a means of empirically testing the model and applying it in different contexts.
Limited use of theory and measurement of impacts for evaluating energy use behavioural change projects (Wilson 2014).	The research demonstrates how the *Theory of planned behaviour* and *Elaboration Likelihood Model* may be used as a framework to understand factors that impact on the success of energy saving interventions. Findings also suggest how the TPB can be extended with specific variables from the ELM for this purpose.
Decline in studies on social aspects of energy use over the years UKERC website (2016); (Wilhite et al. 2000)	The study provides an additional information resource for demonstrating factors that could influence energy saving from a social perspective.
A vital need for relevant information required for the planning and design of successful energy-saving interventions (Wilson and Chatterton, 2011).	Findings from the study offer explanations and information on influences to consider during planning and design of informational intereventions for energy saving.

7.6 Evaluating the methodology

One of the criticisms of the TPB is that in spite of the insight that it provides, measures of its key constructs are largely by means of self-reports, and these may not always capture actual states (Gifford, 2014). However, the results of the study were reasonably consistent with the intervention strategy and supports that using the TPB-ELM to investigate the intervention's success was an effective methodology. Although the study did not set out to measure tangible energy savings as proof of intervention success, feedback provided from the SSO indicate that the intervention is making good impact (see 3.3.1).

Wilson (2014) highlighted a lack of theoretically and impact-based evaluations of behavioural change projects for energy saving. By using two established theories —the *Theory of Planned Behaviour* and the *Elaboration Likelihood Model*— conventionally and within an agent-based model to investigate and provide a visual demonstration of the impact of their constructs within the stated context, this study contributes to filling that gap. Also, with findings specific to an HEI-focused energy demand reduction scheme, it provides information that could be further investigated for creating tailored interventions to achieve increased energy savings in the sector. Such information could be a source of additional motivation in the continual striving for energy conservation (Altan, 2010).

7.6.1 Value of methods used

Wilson et al. (2009) advocate Zanna and Fazio's (1982) approach to investigating by asking questions relating to 'when?' and 'how?' rather than following only either line of questioning. In the *ELM-TPB* framework, output from the ELM informs the "how" (i.e. how attitudes change) while the TPB provides explanations for the "when" (e.g. behaviour change is achieved when influencing factors interact favourably) and may be useful in explaining situations where despite positive attitudes toward the behaviour, actual behaviour change is not achieved (Ozawa-Meida and Fleming, 2016; Petty et al., 2009a)

A criticism of the TPB is that even though it can help identify beliefs that influence behaviour (Ajzen and Manstead, 2007), it does not provide information on how such beliefs may be changed (Sutton, 2010). With respect to attitudes, The ELM is able to fill this gap (Petty and Cacioppo, 1986b). On the other hand, even though the ELM provides information on external and internal variables which influence attitudes, it does not proffer explanations on the extent to which attitudes can result in behaviour (Conner and Armitage, 1998; Devine and Hirt, 1989).

Variables of the ELM and TPB jointly encompass key elements of communication—source, message, receiver and channel (Shannon and Weaver, 1948)—and therefore it seems justifiable to assert that the framework fulfils to a considerable degree, requirements necessary for investigating information based interventions.

Although the use of questionnaire surveys has been criticised for reasons such as validity, subjectivity, inaccuracy and a host of other possible issues that could arise with self-reporting (Alt and Lieberman, 2010; Gifford, 2014; Kormos and Gifford, 2014), it provided quantitative data which could be analysed objectively via statistical methods. Also, unlike interviews, the electronic questionnaires used provided an anonymous means by which useful data could be collected suggesting that responses were likely to be more truthful and relaxed. Smart objectives (see appendix A.1) were formulated to guide questionnaire development and to ensure that the questionnaires achieved their purpose.

Taking the drawbacks of the survey methodology into consideration, the additional use of agent-based modelling lends robustness to the overall methodology, providing further means by which the theories used can be assessed within the context of the research.

By demonstrating and exploring behaviour which tends to arise from the adaptive way by which individual agents change their decision rules (Balke and Gilbert, 2014; Bianchi et al., 2007; Wilensky and Rand, 2015), agent-based modelling as used in this study shows how multiple factors in the TPB-ELM framework interact to produce outcomes beneficial for understanding informational interventions for energy-saving.

The use of the Theory of Planned Behaviour and the Elaboration Likelihood Model provides an empirically sound backing for the model's decision-making rules (Greaves et al., 2013b; Jager and Mosler, 2007; Mosler, 2006). In addition to this, the model provides a straightforward means by which both single and multiple theoretical variables can be varied, and their dynamic effects observed in a virtual social system. This holds an advantage over mathematical models in which varying multiple parameters can quickly become complicated, unmanageable and prone to error (Jager and Mosler, 2007; Law, 2015). That said, Tran (2012) noted that in spite of the variability characteristic of agent-based models, they are not necessarily superior to mathematical models such as differential equations for predicting. Moreover, calibration and validation issues also challenge the credibility of ABM results. Notwithstanding, the capacity to produce a range of possible outcomes from non-linear relationships is considered a benefit associated with agent-based modelling.

Acknowledging that social systems can be complex and unpredictable, using an agent-based model helps to demonstrate and perhaps, understand how the whole can become more than a sum of its parts. For example, in Figure 6.2 and Figure 6.3, reasonably consistent patterns can be observed from the results even though the adoption of, and resistance to energy saving were neither proportional to population size nor to time. Such information can be of benefit in intervention design and planning.

7.6.2 Comparing the findings

Considering that the regression analysis and agent-based modelling aspects of the study (i.e. phase 1 and phase 2 respectively) are both geared towards demonstrating causal relationships, a comparison of their key findings was done and are set out below. To achieve this, versions of the ABM were created with the end states being the dependent variable from each regression model. i.e.

Intention in the regression model = *Committed* in ABM; *Attitude* in the regression model = *Persuaded* in ABM. These model versions are illustrated in 7.7Appendix E, Figure **E.1** and Figure **E.3** respectively. Effects of *Intention* on *Behaviour* were deduced from the complete model.

Similarities:

- *Subjective norms* and *Attitudes* had a positive effect on *Intention*. At the end of the relevant simulation, no agent was left in the persuaded state. Considering that *Persuaded* (i.e. attitude), *Subjective norms* and *PBC* play a precursory role to *Committed* in the model, it shows that these independent variables resulted in agents' intention to save energy. See Figure E.1 and Figure E.**2** in Appendix E for the state chart and output window.
- Consistent with the regression model, argument quality has a positive effect on attitude in the model. (Appendix E, Figure E.5)
- Motivation had a positive effect on attitude in both cases. See Appendix E, Figure E.6. All Committed agents in the ABM became energy-savers indicating that intention positively influenced behaviour as suggested by the regression model. (Appendix E, Figure E.7)

Differences:

- Model output (Appendix E, Figure E.8) shows that without *Cognitive ability*, all aware agents demonstrated resistant behaviour, suggesting that the variable has a positive effect on *Attitude*. However, results from the second set of regression analysis in 1.1.1.1 suggest that cognitive ability has a negative effect on attitudes.

- The ABM demonstrates that *PBC* does not have a negative effect on *Intention* unlike in the regression model. See Appendix E, Figure E.9

Reasons for the inconsistences identified may be investigated in further research; however, these may also be attributed to limitations of the study, some of which are identified and discussed next.

7.6.3 Limitations of the study

Limitations to the study have been identified from both phases of the research and are discussed here. These provide opportunities for future research (discussed in 7.6.4).

The response rate for the survey conducted was low (32 responses); consequently, the sample size (21 respondents) used for the study was small. Although, the model was validated using representative data from an external source, default values for model parameters were calculated from these responses. Although necessary statistical tests were conducted to ascertain data reliability and validity, a larger sample size, especially one representative of the population, would have made the findings from this study more generalisable.

Although the intervention is within a HEI context, using student subjects may pose a limitation in terms of generalising findings of the study as other groups in the society may respond differently to the same or similar interventions. Conducting similar studies with other groups or sectors will provide additional insight and a basis for comparative studies.

The focal intervention (the Student Switch Off campaign) targets student behaviour within their living areas. In view of this, findings of this study should not be generalised to include students' energy-saving behaviour elsewhere e.g. behaviour in study areas; although, it is hoped that desired behaviours adopted would be carried over where applicable. Nevertheless, the study could be extended to investigate the influence of the intervention in establishing general and long-term energy saving behaviour.

The agent-based model does not include details of network effects i.e. how information and norms spread. This is because the aim was to keep it simple and to focus on understanding the effect of individual level variables on collective behaviour.

Model simulations occurred over time whereas survey results represent only responses in obtained at a specific point in time. This means that model results account for changes in behavioural states over time whereas survey results do not. This should be considered when reflecting on the comparisons made.

In discussing results of the study, subjective norms were assumed in the context of peer influence. However, social influence may also come from different sources such as family, groups and so on (McDonald and Crandall, 2015). Cultural background may also play a role because sources of social pressure vary in different cultures. Several studies imply that it would be erroneous to ignore the way culture influences social behaviour (Quaglione et al. 2017; Aaker & Maheswaran 1997; Han & Shavitt 1994). For example social influence in some cultures lean towards collectivism, while others are individualistic (Kim et al., 1994). However, as already argued earlier in the discussion, this is likely to be more adequately represented by *peripheral cues*.

Regardless of these limitations, the methods used promote constructive deliberation on using theories within agent-based modelling to explain how individual level variables can interact to produce collective outcomes. Also, findings from the research proffer practical and valuable considerations for planning informational interventions for energy saving.

7.6.4 Recommendations

Suggestions for future research are proffered following on from the study's findings and limitations.

Further studies combining theory and agent-based modelling will be beneficial for visualizing the dynamic effect of theoretical variables on energy-saving behaviour and contribute to the literature on both agent-based modelling and the understanding of energy-saving behaviours.

The TPB-ELM framework will benefit from more empirical use with large enough data sets in the energy conservation domain, to better explore its potential and to further develop its use as a theoretical tool useful for explaining and evaluating information-based behavioural interventions. In addition, other approaches to using the framework could also be explored e.g. extending the framework to include established theories which provide insightful and reasonable explanations for the subjective norms and perceived behavioural control elements of the Theory of Planned Behaviour. This will potentially give a deeper understanding of factors that can significantly influence energy use behaviour change.

Future studies can be carried out to determine the strongest reference groups for specific societies or national cultures in relation to energy use behaviour. Such findings can be useful for designing targeted energy-saving interventions for multi-cultural societies.

Further research to investigate the (suggested) affective tendencies of subjective norms and any effects on attitude and the intention-behaviour gap will be beneficial for gaining more insight to this notion which may prove valuable for expanding the Theory of Planned Behaviour, especially for use in the energy saving domain.

Other analytical methods may be used to investigate interactions between variables of the theoretical framework used. This will provide a basis for comparison which can be useful for evaluating the effectiveness of the theoretical frame work for explaining the adoption of energy saving.

As combining the use of the TPB and ELM for understanding energy-saving behaviour is still somewhat uncommon, the applicability of the framework could be explored using other simulation methods and contexts. This would contribute to the diversity of the literature available on the subject.

7.7 **Summary and Implications for Policy and Practice**

This research has demonstrated how the use of theory can aid in understanding the influence of behavioural interventions on outcomes for energy conservation projects. By jointly using the Theory of Planned Behaviour, Elaboration Likelihood Model and agent-based modelling, it informs a gap in the use of theory and measurement of impacts in evaluating behavioural change projects for energy saving as identified by Wilson (2014). By presenting findings applicable to an HEI-focused energy demand reduction scheme, it provides information on potential areas of focus, serving as added motivation in the continual striving for energy conservation, in line with submissions by Altan (2010). Interactions between behavioural and informational variables shown facilitate an understanding of potential mechanisms of change vital to the purposeful planning required for successful intervention design.

The project set out to achieve 4 objectives which have been realised and set out in this thesis. To achieve the first objective, literature searches were conducted to identify theoretical factors that affect energy saving intentions and behaviour; a questionnaire survey was conducted to elicit responses for measuring these. Correlation and regression analysis were performed on survey data to realise the second objective. These helped to determine relationships between the core constructs of the TPB and ELM and demonstrated that the two theories could be used effectively for behavioural responses to informational interventions for energy saving. The analyses also shed light on the effect of the theories' constructs on one another; therefore, achieving the third objective by showing how variations in one construct can bring about changes in the target behaviour. Varying parameters in an agent-based model also contributed to achieving this objective.

With agent-based modelling being a burgeoning technique, a literature search was done to gain an understanding of the extent of its use in the energy conservation domain and the different approaches used. Subsequently, the fourth objective was achieved by developing an agent-based model. In doing this, research questions specific to the purpose of the model were first created to guide the development process. Part of the modelling process included validation and verification by external data and parameter variation, respectively.

Based on the findings, the aim of the research was achieved, and some key conclusions drawn:

- By linking information, attitudes and behaviour, the ELM-TPB framework can expose interactions which offer explanations (for different processes of behavioural choices) necessary for targeted planning and design of successful interventions—a vital need from a policy perspective (Wilson and Chatterton, 2011). However, it needs to be put to further empirical use with large enough data sets, to fully explore its potential and to develop its use as a theoretical tool useful for explaining and evaluating information-based behavioural interventions.
- Intervention success is a gradual process which peaks; Gaining prior evidence of potential scenarios through methods such as preliminary surveys combined with agent-based modelling can be beneficial in guiding intervention planning and design e.g. by indicating areas and periods to focus on.

- Energy saving intervention success is most guaranteed when an excellent case is made for energy saving alongside high levels of peripheral cues, motivation and cognitive ability in the target population.
- Accounting for peripheral cues within the subjective norm construct of the Theory of Planned Behaviour is likely to accord the theory better predictive value.

In terms of direct implications for policy, the findings of this study suggest that programmes designed to encourage energy conservation behaviours should target using peripheral cues and social norms as key change agents. This may be achieved by seeking to understand prevalent sources of social pressure and dominant types of subjective norms among targeted groups or sectors, and then guide intervention efforts using this knowledge. Also, understanding the dominant level of cognitive ability in a population and tailoring the rationale for energy saving to appeal to this group could contribute significantly to intervention success.

REFERENCES

Aaker, J.L., Maheswaran, D., 1997. The Effect of Cultural Orientation on Persuasion. J. Consum. Res. 24, 315–328.

Abelson, J., Forest, P.G., Eyles, J., Smith, P., Martin, E., Gauvin, F.P., 2003. Deliberations about deliberative methods: Issues in the design and evaluation of public participation processes. Soc. Sci. Med. 57, 239–251. https://doi.org/10.1016/S0277-9536(02)00343-X

Abraham, C., Sheeran, P., Henderson, M., 2011. Extending social cognition models of health behaviour. Health Educ. Res. 26, 624–637. https://doi.org/10.1093/her/cyr018

Abrahamse, W., Steg, L., 2013. Social influence approaches to encourage resource conservation: A meta-analysis. Glob. Environ. Chang. 23, 1773–1785. https://doi.org/10.1016/J.GLOENVCHA.2013.07.029

Abrahamse, W., Steg, L., Gifford, R., Vlek, C., 2009. Factors influencing car use for commuting and the intention to reduce it: A question of self-interest or morality? Transp. Res. Part F Traffic Psychol. Behav. 12, 317–324. https://doi.org/10.1016/j.trf.2009.04.004

Abrahamse, W., Steg, L., Vlek, C., Rothengatter, T., 2007. The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. J. Environ. Psychol. 27, 265–276. https://doi.org/10.1016/j.jenvp.2007.08.002

Abrahamse, W., Steg, L., Vlek, C., Rothengatter, T., 2005. A review of intervention studies aimed at household energy conservation. J. Environ. Psychol. 25, 273–291. https://doi.org/10.1016/j.jenvp.2005.08.002

Adams, R., 1990. Green Consumerism and the Food Industry: Early Signs of Big Changes to Come. Br. Food J. 92, 11–14.

Adua, L., 2010. To cool a sweltering earth: Does energy efficiency improvement offset the climate impacts of lifestyle? Energy Policy 38, 5719–5732. https://doi.org/10.1016/j.enpol.2010.05.021

Ajzen, I., 2002a. Constructing a TpB questionnaire: Conceptual and methodological considerations.

Ajzen, I., 2002b. Constructing a TpB Questionnaire: Conceptual and Methodological Considerations.

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., 1985. From Intentions to Actions: A Theory of Planned Behavior, in: Action Control. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 11–39. https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I., Manstead, A.S.R., 2007. Changing health-related behaviours: An approach based on the Theory of Planned Behaviour. scope Soc. Psychol. Theory Appl. 43–63. https://doi.org/10.4324/9780203965245

Allcott, H., 2011. Social norms and energy conservation. J. Public Econ. 95, 1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003

Allcott, H., Mullainathan, S., 2010. Behavioral Science and Energy Policy.

Alt, J.K., Lieberman, S., 2010. Modeling the Theory of Planned Behavior from Survey Data for Action Choice in Social Simulations. 19th Annu. Conf. Behav. Represent. Model. Simul. 2010, BRiMS 2010 21–24.

Altan, H., 2010. Energy efficiency interventions in UK higher education institutions. Energy Policy 38, 7722–7731. https://doi.org/10.1016/j.enpol.2010.08.024

Altaweel, M.R., Alessa, L.N., Kliskey, A., Bone, C., 2010. A Framework to Structure Agent-Based Modeling Data for Social-Ecological Systems. Struct. Dyn. Dyn. eJournal Anthropol. Relat. Sci. 4.

An, L., 2012. Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecol. Modell. 229, 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010

Araujo-Soares, V., Rodrigues, @bullet A, Presseau, @bullet J, Sniehotta, F.F., 2013. Adolescent sunscreen use in springtime: a prospective predictive study informed by a belief elicitation investigation. J. Behav. Med. 36, 109–123. https://doi.org/10.1007/s10865-012-9415-3

Armitage, C.J., Conner, M., 2001. Efficacy of the Theory of Planned Behaviour: A meta-analytic review. Br. J. Soc. Psychol. 40, 471–499. https://doi.org/10.1348/014466601164939

Aronson, E., 1969. The Theory of Cognitive Dissonance: A Current Perspective. Adv. Exp. Soc. Psychol. 4, 1–34. https://doi.org/10.1016/S0065-

2601(08)60075-1

Aronson, E., 1968. Dissonance theory: Progress and problems, in: Abelson, R.P., Aronson, E., Mcguire, W.J., Newcomb, T.., Rosenberg, M.J., Tannenbaum, P.H. (Eds.), In Theories of Cognitive Consistency: A Sourcebook. Rand-McNally, Chicago., pp. 5–27.

Axsen, J., Kurani, K.S., 2012. Social Influence, Consumer Behavior, and Low-Carbon Energy Transitions. Annu. Rev. Environ. Resour. 37, 311–340. https://doi.org/10.1146/annurev-environ-062111-145049

Azar, E., Menassa, C.C., 2014. Framework to Evaluate Energy-Saving Potential from Occupancy Interventions in Typical Commercial Buildings in the United States. J. Comput. Civ. Eng. 28, 63–78. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000318

Bae, H.-S., 2008. Entertainment-Education and Recruitment of Cornea Donors: The Role of Emotion and Issue Involvement. J. Heal. Commun. 13, 20–36. https://doi.org/10.1080/10810730701806953

Bale, C.S.E., Mccullen, N.J., Foxon, T.J., Rucklidge, A.M., Gale, W.F., 2014. Modeling diffusion of energy innovations on a heterogeneous social network and approaches to integration of real-world data. Complexity 19, 83–94. https://doi.org/10.1002/cplx.21523

Balke, T., Gilbert, N., 2014. How do agents make decisions? A survey. JASSS. https://doi.org/10.18564/jasss.2687

Bamberg, S., Möser, G., 2007. Twenty years after Hines, Hungerford, and

Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. J. Environ. Psychol. 27, 14–25. https://doi.org/10.1016/j.jenvp.2006.12.002

Bamberg, S., Schmidt, P., 2003. Incentives, Morality, Or Habit?: Predicting Students' Car Use for University Routes With the Models of Ajzen, Schwartz, and Triandis. Environ. Behav. 35, 264–285. https://doi.org/10.1177/0013916502250134

Bandura, A., 2001. Social Cognitive Theory of Mass Communication. Media Psychol. 3, 265–299.

Bandura, A., 1993. Perceived Self-Efficacy in Cognitive Development and Functioning. Educ. Psychol. https://doi.org/10.1207/s15326985ep2802_3

Bandura, A., 1977. Social learning theory. Prentice Hall.

Barnes, D.J., Chu, D., 2010. Introduction to Modelling for Biosciences. Springer. https://doi.org/10.1007/978-1-84996-326-8

Barnes, S., Golden, B., Price, S., 2013. Applications of Agent-Based Modeling and Simulation to Healthcare Operations Management. Springer, New York, NY, pp. 45–74. https://doi.org/10.1007/978-1-4614-5885-2_3

Bassili, J.N., N., J., 1996. Meta-judgmental versus operative indexes of psychological attributes: The case of measures of attitude strength. J. Pers. Soc. Psychol. 71, 637–653. https://doi.org/10.1037/0022-3514.71.4.637

Bator, R.J., Cialdini, R.B., 2000. The Application of Persuasion Theory to the

Development Of Effective Proenvironmental Public Service Announcements. J. os Soc. Issues 56, 527–541.

Beale, J.R., Bonsall, P.W., 2007. Marketing in the bus industry: A psychological interpretation of some attitudinal and behavioural outcomes. Transp. Res. Part F Traffic Psychol. Behav. 10, 271–287. https://doi.org/10.1016/j.trf.2006.11.001

Berger, T., Troost, C., 2011. Insights for Climate Change Policy from Agent-Based Modeling of Land-Use. OECD Expert Meet.

Bhattacherjee, a., Sanford, C., 2009. The intention–behaviour gap in technology usage: the moderating role of attitude strength. Behav. Inf. Technol. 28, 389–401. https://doi.org/10.1080/01449290802121230

Bianchi, C., Cirillo, P., Gallegati, M., Vagliasindi, P.A., 2007. Validating and Calibrating Agent-Based Models: A Case Study. Comput. Econ. 30.

Boero, R., 2015. A Few Good Reasons to Favor Agent-based Modeling in Economic Analyses, in: Agent-Based Models of the Economy. Palgrave Macmillan UK, London, pp. 3–9. https://doi.org/10.1057/9781137339812_1

Borshchev, A., 2013. The Big Book of Simulation Modeling — AnyLogic Simulation Software [WWW Document]. Book. URL http://www.anylogic.com/big-book-of-simulation-modeling (accessed 9.12.16).

Briñol, P., Petty, R.E., 2015. Elaboration and Validation Processes: Implications for Media Attitude Change. Media Psychol. 18, 267–291.

https://doi.org/10.1080/15213269.2015.1008103

Brown, T.J., Ham, S.H., Hughes, M., 2010. Picking up litter: an application of theory-based communication to influence tourist behaviour in protected areas. J. Sustain. Tour. 18, 879–900. https://doi.org/10.1080/09669581003721281

Bruch, E., Atwell, J., 2015. Agent-based models in empirical social research. Sociol. Methods Res. 44, 186–221. https://doi.org/10.1177/0049124113506405

Bull, R., Lemon, M., Everitt, D., Stuart, G., 2015. Moving beyond feedback: Energy behaviour and local engagement in the United Kingdom. Energy Res. Soc. Sci. 8, 32–40. https://doi.org/10.1016/j.erss.2015.04.006

Burrows, R., Johnson, P., Johnson, H., 2015. Value Sensitive Design Approach to Influence Energy-use Behaviour, in: Beckmann, C., Gross, T. (Eds.), Interact 2015 Adjunct Proceedings : 15th IFIP TC. 13 International Conference on Human-Computer Interaction 14 - 18 September 2015, Bamberg, Germany. Univ. of Bamberg Press, Bamberg, pp. 547–552.

Cacioppo, J.T., Petty, R.E., 1989. Effects of Message Repetition on Argument Processing, Recall, and Persuasion. Basic Appl. Soc. Psych. 10, 3–12. https://doi.org/10.1207/s15324834basp1001

Cacioppo, J.T., Petty, R.E., Stoltenberg, C.D., 1985. Processes of social influence: The elaboration likelihood model of persuasion, Advances in Cognitive-Behavioral Research and Therapy. https://doi.org/10.1016/B978-

0-12-010604-2.50012-4

Cagno, E., Trianni, A., Abeelen, C., Worrell, E., Miggiano, F., 2015. Barriers and drivers for energy efficiency: Different perspectives from an exploratory study in the Netherlands. Energy Convers. Manag. 102, 26–38. https://doi.org/10.1016/j.enconman.2015.04.018

Carmona-Moreno, E., Céspedes-Lorente, J., Martinez-del-Rio, J., 2012. Environmental human resource management and competitive advantage. Manag. Res. J. Iberoam. Acad. Manag. 10, 125–142. https://doi.org/10.1108/1536-541211251607

Carrico, A.R., Riemer, M., 2011. Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education. J. Environ. Psychol. 31, 1–13. https://doi.org/10.1016/j.jenvp.2010.11.004

Carrington, M.J., Neville, B.A., Whitwell, G.J., 2010. Why ethical consumers don't walk their talk: Towards a framework for understanding the gap between the ethical purchase intentions and actual buying behaviour of ethically minded consumers. J. Bus. Ethics 97, 139–158. https://doi.org/10.1007/s10551-010-0501-6

Casado, F., Hidalgo, M.C., García-Leiva, P., 2017. Energy efficiency in households: The effectiveness of different types of messages in advertising campaigns. J. Environ. Psychol. 53, 198–205. https://doi.org/10.1016/j.jenvp.2017.08.003

Chai, K.H., Baudelaire, C., 2014. Understanding the energy efficiency gap in

Singapore: A Motivation, Opportunity, and Ability perspective. J. Clean. Prod. 100, 224–234. https://doi.org/10.1016/j.jclepro.2015.03.064

Chan, L., Bishop, B., 2013. A moral basis for recycling: Extending the theory of planned behaviour. J. Environ. Psychol. 36, 96–102. https://doi.org/10.1016/j.jenvp.2013.07.010

Chen, S.-H., Lee, K.-P., 2008. The Role of Personality Traits and Perceived Values in Persuasion: an Elaboration Likelihood Model Perspective on Online Shopping. Soc. Behav. Personal. an Int. J. 36, 1379–1399. https://doi.org/10.2224/sbp.2008.36.10.1379

Cialdini, R.B., 2001. Influence : science and practice, 4th Editio. ed. Allyn & Bacon: 2001.

Cialdini, R.B., Demaine, L.J., Sagarin, B.J., Barrett, D.W., Rhoads, K., Winter, P.L., 2006. Managing social norms for persuasive impact. Soc. Influ. 1, 3–15. https://doi.org/10.1080/15534510500181459

Cialdini, R.B., Goldstein, N.J., 2004. Social Influence: Compliance and Conformity. Annu. Rev. Psychol. 55, 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Cialdini, R.B., Reno, R.R., Kallgren, C. a., 1990. A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. J. Pers. Soc. Psychol. 58, 1015–1026. https://doi.org/10.1037/0022-3514.58.6.1015

Cialdini, R.B., Wosinska, W., Barrett, D.W., Butner, J., Gornik-Durose, M., 1999.

Commitment/Consistency on Collectivists and Individualists Compliance with a Request in Two Cultures: The Differential Influence of Social Proof and. Personal. Soc. Psychol. Bull. 25. https://doi.org/10.1177/0146167299258006

Clarity Sustainability, 2015. Communications for Energy Behaviour Change.

Cohen, J., 1988. Statistical power analysis for the behavioral sciences. L. Erlbaum Associates.

Collins, G.S., Ogundimu, E.O., Altman, D.G., 2016. Sample size considerations for the external validation of a multivariable prognostic model: a resampling study. Stat. Med. 35, 214–26. https://doi.org/10.1002/sim.6787

Conner, M., Armitage, C.J., 1998. Extending the Theory of Planned Behavior: A Review and Avenues for Further Research. J. Appl. Soc. Psychol. 28, 1429–1464. https://doi.org/10.1111/j.1559-1816.1998.tb01685.x

Corradi, N., Priftis, K., Jacucci, G., Gamberini, L., 2013. Oops, I forgot the light on! The cognitive mechanisms supporting the execution of energy saving behaviors. J. Econ. Psychol. 34, 88–96. https://doi.org/10.1016/j.joep.2012.11.002

Costanzo, M., Archer, D., Aronson, E., Pettigrew, T., 1986. Energy conservation behavior: The difficult path from information to action. Am. Psychol. 41, 521–528. https://doi.org/10.1037/0003-066X.41.5.521

Costello, A.B., Osborne, J.W., 2005. Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. Pract.

Assessment, Res. Eval. 10.

D’Souza, C., Taghian, M., 2017. Small and medium size firm’s marketing competitive advantage and environmental initiatives in the Middle East. J. Strateg. Mark. 1–15. https://doi.org/10.1080/0965254X.2017.1318945

Dainton, M., Zelley, E.D., 2004. Explaining theories of persuasion., in: Applying Communication Theory for Professional Life: A Practical Introduction. Sage Publications Inc., Thousand Oaks.

Dale, B.G., Y-Wu, P., Zairi, M., T Williams, A.R., Van Der Wiele, T., 2001. Total Quality Management Total quality management and theory: An exploratory study of contribution Total quality management and theory: An exploratory study of contribution 12, 439–449. https://doi.org/10.1080/09544120123930

Darby, S., 2006. The Effectiveness of Feedback on Energy Consumption a Review for Defra of the Literature on Metering , Billing and Direct Displays. Environ. Chang. Inst. Univ. Oxford 22, 1–21. https://doi.org/10.4236/ojee.2013.21002

Darley, J.M., 1977. Energy Conservation Techniques as Innovations, and their Diffusion 178, 339–343.

de Leeuw, A., Valois, P., Ajzen, I., Schmidt, P., 2015. Using the theory of planned behavior to identify key beliefs underlying pro-environmental behavior in high-school students: Implications for educational interventions. J. Environ. Psychol. 42, 128–138. https://doi.org/10.1016/j.jenvp.2015.03.005

De Young, R., 1996. Some Psychological Aspects of Reduced Consumption

Behavior: The Role of Intrinsic Satisfaction and Competence Motivation. Environ. Behav. https://doi.org/10.1177/0013916596283005

Delmas, M. a., Fischlein, M., Asensio, O.I., 2013. Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. Energy Policy 61, 729–739. https://doi.org/10.1016/j.enpol.2013.05.109

Delmas, M., Kaiser, W., 2013. Behavioral responses to real-time individual energy usage information : A large scale experiment. California.

Delmas, M.A., Lessem, N., 2014. Saving power to conserve your reputation? The effectiveness of private versus public information. J. Environ. Econ. Manage. 67, 353–370. https://doi.org/10.1016/j.jeem.2013.12.009

Deniz, M.S., Alsaffar, A.A., 2013. Assessing the validity and reliability of a questionnaire on dietary fibre-related knowledge in a Turkish student population. J. Health. Popul. Nutr. 31, 497–503.

Dennis, M.L., Soderstrom, J.E., Koncinski, W.S.J., Cavanaugh, B., 1990. Effective Dissemination of Energy-Related Information Applying Social Psychology and Evaluation Research Limitations of the Rational-Economic Model. Am. Psychol. 45, 1109–1117.

Dermody, J., Hanmer-Lloyd, S., 2011. Saving Energy within the Workplace An Overview of Behavioural Theory.

Dietz, T., Stern, P.C., Guagnano, G.A., 1998. Social Structural and Social Psychological Bases of Environmental Concern. Environ. Behav. 30, 450–

471. https://doi.org/10.1177/001391659803000402

Dixon, G.N., Deline, M.B., McComas, K., Chambliss, L., Hoffmann, M., 2015. Saving energy at the workplace: The salience of behavioral antecedents and sense of community. Energy Res. Soc. Sci. 6, 121–127. https://doi.org/10.1016/j.erss.2015.01.004

Eccles, M.P., Hrisos, S., Francis, J., Kaner, E.F., Dickinson, H.O., Beyer, F., Johnston, M., 2006. Do self- reported intentions predict clinicians' behaviour: a systematic review. Implement. Sci. 1, 28. https://doi.org/10.1186/1748-5908-1-28

Ehrhardt-martinez, K., 2010. Changing Habits , Lifestyles and Choices : The Behaviours that Drive Feedback-Induced Energy Savings, in: ACEEE Summer Study on Energy Efficiency. American Council for an Energy Efficient Economy Summer Study, Asilomar, CA, pp. 202–507.

Eldabi, T., Irani, Z., Paul, R.J., Love, P.E.D., 2002. Quantitative and qualitative decision - making methods in simulation modelling. Manag. Decis. 40, 64–73. https://doi.org/10.1108/00251740210413370

Energy efficiency interventions in UK higher education institAltan, H., 2010. Energy efficiency interventions in UK higher education institutions. , 38, pp.7722–7731. Available at: http://eprints.whiterose.ac.uk/42780/2/Altan_42780.pdf.utions, 2010. 38, 7722–7731. https://doi.org/10.1016/j.enpol.2010.08.024

Epstein, J.M., 1999. Agent-based computational models and generative social science. Gener. Soc. Sci. Stud. Agent-Based … 4, 41–60. https://doi.org/10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.0.CO;2-F

Etzion, D., 2007. Research on Organizations and the Natural Environment, 1992-Present: A Review. J. Manage. 33, 637–664. https://doi.org/10.1177/0149206307302553

European Environent Agency, 2016. Communication, environment and behaviour: A scpoing study on the links between public communication, environment policy implementation and behavioura science. Luxembourg. https://doi.org/10.2800/062336

Fagiolo, G., Windrum, P., Moneta, A., 2007. A Critical Guide to Empirical Validation of Agent-Based Economics Models: Methodologies, Procedures, and Open Problems. Comput. Econ. 30, 195–226.

Farrow, K., Grolleau, G., Ibanez, L., 2017a. Social Norms and Pro-environmental Behavior: A Review of the Evidence. Ecol. Econ. 140, 1–13. https://doi.org/10.1016/J.ECOLECON.2017.04.017

Farrow, K., Grolleau, G., Ibanez, L., 2017b. Social Norms and Pro-environmental Behavior: A Review of the Evidence. Ecol. Econ. 140, 1–13. https://doi.org/10.1016/j.ecolecon.2017.04.017

Faruqui, A., Sergici, S., 2010. Household response to dynamic pricing of electricity: a survey of 15 experiments. J. Regul. Econ. 38, 193–225. https://doi.org/10.1007/s11149-010-9127-y

Faruqui, A., Sergici, S., Sharif, A., 2010. The impact of informational feedback on energy consumption-A survey of the experimental evidence. Energy 35, 1598–1608. https://doi.org/10.1016/j.energy.2009.07.042

Fazio, R.H., Zanna, M.P., 1978. Attitudinal Qualities Relating to the Strength of the Attitude-Behavior Relationship. J. Exp. Soc. Psychol. 14, 398–408.

Festinger, L., 1957. A Theory of cognitive dissonance. Stanford University Press, Stanford, CA.

Festinger, L., Back, K., Schachter, S., Kelley, H.H., Thibaut, J., 1951. THEORY AND EXPERIMENT IN SOCIAL COMMUNICATION. J. Abnorm. Soc. Psychol. 46, 92–99.

Festinger, L., Maccoby, N., 1964. On resistance to persuasive communications. J. Abnorm. Soc. Psychol. 68, 359–366. https://doi.org/10.1037/h0049073

Field, A., 2013. Discovering Statistics using IBM SPSS Statistics, 4th ed. Sage, London.

Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A., 2013. Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environ. Model. Softw. 45, 1–7. https://doi.org/10.1016/j.envsoft.2013.03.017

Fischer, C., 2008. Feedback on household electricity consumption: A tool for saving energy? Energy Effic. 1, 79–104. https://doi.org/10.1007/s12053-008-9009-7

Fishbein, M., Ajzen, I., 2010. Predicting and changing behavior : the reasoned action approach. Psychology Press.

Fishbein, M., Ajzen, I., 1981. On Construct Validity: A Critique of Miniard and Cohen's Paper. J. Exp. Soc. Psychol. 17, 340–350.

Fishbein, M., Ajzen, I., 1975. Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research. Read. MA AddisonWesley.

Fishbein, M., Ajzen, I., 1975. Measurement techniques. Belief, Attitude, Intention, Behav. An Introd. to Theory Res.

Francis, J.J., Eccles, M.P., Johnston, M., Walker, A., Grimshaw, J., Foy, R., Kaner, E.F.S., Smith, L., Bonetti, D., Francis, J., 2004. Contructing questionnaires based on the theory of planned behaviour: a manual for Health Services Researchers, Centre for Health Services Research and Quality of Life and Management of Living Resources. https://doi.org/0-9540161-5-7

Frederiks, E.R., Stenner, K., Hobman, E. V., 2015. Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. Renew. Sustain. Energy Rev. 41, 1385–1394. https://doi.org/10.1016/J.RSER.2014.09.026

Frey, B.S., Oberholzer-Gee, F., 1997. The Cost of Price Incentives: An Empirical Analysis of Motivation Crowding- Out. Am. Econ. Rev. 87, 746–755.

Froehlich, J., 2009. Promoting Energy Efficient Behaviors in the Home through Feedback: The Role of Human-Computer Interaction, in: HCIC Workshop.

pp. 0–10.

Gatersleben, B., Steg, L., Vlek, C., 2002. Measurement and Determinants of Environmentally Significant Consumer Behavior. Environ. Behav. 34, 335–362. https://doi.org/10.1177/0013916502034003004

Geertz, C., 1975. On the Nature of Anthropological Understanding: Not extraordinary empathy but readily observable symbolic forms enable the anthropologist to grasp the unarticulated concepts that inform the lives and cultures of other peoples. Am. Sci. 63, 47–53. https://doi.org/10.2307/27845269

Geller, E.S., Winett, R.A. (Richard A., Everett, P.B. (Peter B., 1982. Preserving the environment : new strategies for behavior change. Pergamon Press.

Gifford, R., 2014. Environmental Psychology Matters. Annu. Rev. Psychol. 65, 541–579. https://doi.org/10.1146/annurev-psych-010213-115048

Gifford, R., Nilsson, A., 2014. Personal and social factors that influence pro-environmental concern and behaviour: a review. Int. J. Psychol. 49, 141–57. https://doi.org/10.1002/ijop.12034

Gilbert, N.G., 2007. Agent-based models. Sage Publications Inc., Thousand Oaks, United States.

Glasman, L.R., Albarracín, D., 2006. Forming attitudes that predict future behavior: a meta-analysis of the attitude-behavior relation. Psychol. Bull. 132, 778–822. https://doi.org/10.1037/0033-2909.132.5.778

Godin, G., B?langer-Gravel, A., Eccles, M., Grimshaw, J., Perneger, T., Pittet, D., Steen, N., Grimshaw, J., Maclennan, G., Clarkson, J., Walker, A., 2008. Healthcare professionals' intentions and behaviours: A systematic review of studies based on social cognitive theories. Implement. Sci. 3, 36. https://doi.org/10.1186/1748-5908-3-36

Godin, G., Conner, M., Sheeran, P., 2005. Bridging the intention–behaviour "gap": The role of moral norm. Br. J. Health Psychol. 44, 497–512. https://doi.org/10.1348/014466604X17452

Godin, G., Kok, G., 1996. The theory of planned behavior: a review of its applications to health-related behaviors. Am. J. Heal. Promot. 11, 87–98.

Goodland, R., 1995. The Concept of Environmental Sustainability. Annu. Rev. Ecol. Syst. https://doi.org/10.1146/annurev.es.26.110195.000245

Graffeo, M., Ritov, I., Bonini, N., Hadjichristidis, C., 2015. To make people save energy tell them what others do but also who they are: a preliminary study. Front. Psychol. 6, 1287. https://doi.org/10.3389/fpsyg.2015.01287

Greaves, M., Zibarras, L.D., Stride, C., 2013a. Using the theory of planned behavior to explore environmental behavioral intentions in the workplace. J. Environ. Psychol. 34, 109–120. https://doi.org/10.1016/j.jenvp.2013.02.003

Greaves, M., Zibarras, L.D., Stride, C., 2013b. Using the theory of planned behavior to explore environmental behavioral intentions in the workplace. J. Environ. Psychol. 34, 109–120. https://doi.org/10.1016/j.jenvp.2013.02.003

Green, K., Morton, B., New, S., 2000. Greening Organizations: Purchasing, Consumption, and Innovation. Organ. Environ. 13, 206–225. https://doi.org/10.1177/1086026600132003

Greene, K., Hale, J.L., Rubin, D.L., 1997. A Test of the Theory of Reasoned Action in the Context of Condom Use and AIDS. Commun. REPORTS 10.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser, U., DeAngelis, D.L., 2006. A standard protocol for describing individual-based and agent-based models. Ecol. Modell. 198, 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023

Grimm, V., Berger, U., Deangelis, D.L., Polhill, J.G., Giske, J., Railsback, S.F., 2010. The ODD protocol : A review and first update. Ecol. Modell. 221, 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019

Grimm, V., Polhill, G., Touza, J., 2017. Documenting Social Simulation Models: The ODD Protocol as a Standard. Springer, Cham, pp. 349–365. https://doi.org/10.1007/978-3-319-66948-9_15

Grimm, V., Railsback, S.F., 2012. Designing, Formulating, and Communicating Agent-Based Models, in: Agent-Based Models of Geographical Systems. Springer Netherlands, Dordrecht, pp. 361–377. https://doi.org/10.1007/978-90-481-8927-4_17

Groeneveld, J., Müller, B., Angermüller, F., Drees, R., Drebler, G., Groeneveld, J.;, Müller, B.;, Angermüller, F.;, Klassert, C.;, Schulze, J.;, Weise, H., Schwarz, N., Klassert, C., Schulze, J., 2012. Good modelling practice: expanding the ODD model description protocol for socio-environmental agent based models based models Good modelling practice:, in: Seppelt, R., Voinov, A. A., Lange, S., Bankamp, D. (Ed.), International Environmental Modelling and Software Society (IEMSs) 2012 International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet, Sixth Biennial Meeting, Leipzig, Germany. pp. 1–5.

Hahn, R., Metcalfe, R., 2016. The Impact of Behavioral Science Experiments on Energy Policy.

Han, H., 2014. The norm activation model and theory-broadening: Individuals' decision-making on environmentally-responsible convention attendance. J. Environ. Psychol. 40, 462–471. https://doi.org/10.1016/J.JENVP.2014.10.006

Han, Q., Nieuwenhijsen, I., de Vries, B., Blokhuis, E., Schaefer, W., 2013. Intervention strategy to stimulate energy-saving behavior of local residents. Energy Policy 52, 706–715. https://doi.org/10.1016/j.enpol.2012.10.031

Han, S., Shavitt, S., 1994. Persuasion and culture: Advertising appeals in individualistic and collectivistic societies. J. Exp. Soc. Psychol.

Handgraaf, M.J.J., Van Lidth de Jeude, M.A., Appelt, K.C., 2013. Public praise vs. private pay: Effects of rewards on energy conservation in the workplace. Ecol. Econ. 86, 86–92. https://doi.org/10.1016/J.ECOLECON.2012.11.008

Hanna, D., Dempster, M., 2012. Psychology statistics for dummies. Wiley.

Heilbroner, R.L., Thurow, L.C., 1982. Economics explained. Prentice-Hall.

Hemphill, J.F., 2003. Interpreting the magnitudes of correlation coefficients. Am. Psychol. 58, 78–79. https://doi.org/10.1037/0003-066X.58.1.78

Herrmann, C., Thiede, S., Kara, S., Hesselbach, J., 2011. Energy oriented simulation of manufacturing systems - Concept and application. CIRP Ann. - Manuf. Technol. 60, 45–48. https://doi.org/10.1016/j.cirp.2011.03.127

Higher Education Statistics Agency, 2016. Estates | HESA [WWW Document]. URL https://www.hesa.ac.uk/data-and-analysis/providers/estates (accessed 9.15.16).

Hill, C., Abraham, C., Wright, D.B., 2007. Can theory-based messages in combination with cognitive prompts promote exercise in classroom settings? Soc. Sci. Med. 65, 1049–1058. https://doi.org/10.1016/j.socscimed.2007.04.024

Hinton, P.R., Brownlow, C., McMurray, I., Cozens, B., 2004. SPSS explained. Routledge, East Sussex.

Hoffman, F.O., Gardner, R.., 1983. Evaluation of uncertainties in environmental radiological assessment models, in: Till, J.E., Meyer, R.H. (Eds.), Radiological Assessment : A Textbook on Environmental Dose Analysis. US Nuclear Regulatory Commission, Washington, D.C, pp. 11-1-11–46.

House of Lords, 2011. Science and Technology Select Committee report. J.

Radiol. Prot. 26, 331. https://doi.org/10.1088/0952-4746/26/3/L01

Hovland, C.I., Janis Irving L, Kelley, H.H., 1953. Communication and persuasion psychological studies of opinion change,. Yale University Press, New Haven.

Hu, Y., Shyam Sundar, S., 2010. Effects of Online Health Sources on Credibility and Behavioral Intentions. Communic. Res. 37, 105–132. https://doi.org/10.1177/0093650209351512

Illingworth, L., Williams, D., Burnett, S., 2002. The costs and benefits of the Internet as a marketing and communications tool: the attitudes, perceptions and experiences within the non-profit environmental sector in Scotland. Aslib Proc. 54, 280–293. https://doi.org/10.1108/00012530210448235

Jackson, T., 2005. Motivating Sustainable Consumption. A Rev. Evid. Consum. Behav. Behav. Chang. A Rep. to Sustain. Dev. Res. Netw. as part ESRC Sustain. Technol. Program. Cent. Environ. Strateg. Univ. Surrey Guildf. 15, 1027–1051. https://doi.org/10.1260/0958305043026573

Jager, W., Mosler, H.J., 2007. Simulating Human Behavior for Understanding and Managing Environmental Resource Use. J. Soc. Issues 63, 97–116. https://doi.org/10.1111/j.1540-4560.2007.00498.x

Janssen, M. a, Ostrom, E., Editorial, G., 2014. Empirically Based , Agent-based models. Ecol. Soc. 11, 37. https://doi.org/yes

Janssen, M.A., Ostrom, E., 2006. Empirically Based , Agent-based models. Ecol. Soc. 11, 37. https://doi.org/yes

Jensen, T., Holtz, G., Chappin, É.J.L., 2015. Agent-based assessment framework for behavior-changing feedback devices: Spreading of devices and heating behavior. Technol. Forecast. Soc. Change 98, 105–119. https://doi.org/10.1016/j.techfore.2015.06.006

Ji, X., Chen, B., 2017. Assessing the energy-saving effect of urbanization in China based on stochastic impacts by regression on population, affluence and technology (STIRPAT) model. J. Clean. Prod. 163, S306–S314. https://doi.org/10.1016/j.jclepro.2015.12.002

Johnson, B.T., Eagly, A.H., 1989. Effects of Involvement on Persuasion: A Meta-Analysis. Psychol. Bull. 106, 290–314.

Joireman, J. a, Lasane, T.P., Bennett, J., Richards, D., Solaimani, S., 2001. Integrating social value orientation and the consideration of future consequences within the extended norm activation model of proenvironmental behaviour. Br. J. Soc. Psychol. 40, 133–155. https://doi.org/10.1348/014466601164731

Joireman, J.A., Kuhlman, D.M., Van Lange, P.A.M., Doi, T., Shelley, G.P., 2003. Perceived rationality, morality, and power of social choice as a function of interdependence structure and social value orientation. Eur. J. Soc. Psychol. 33, 413–437. https://doi.org/10.1002/ejsp.155

Jones, L.W., Sinclair, R.C., Rhodes, R.E., Courneya, K.S., 2004. Promoting exercise behaviour: an integration of persuasion theories and the theory of planned behaviour. Br. J. Health Psychol. 9, 505–521. https://doi.org/10.1348/1359107042304605

Kaiser, F.G., Wolfing, S., Fuhrer, U., 1999. ENVIRONMENTAL ATTITUDE AND ECOLOGICAL BEHAVIOUR. J. Environ. Psychol. 19.

Kallgren, C., Reno, R., Cialdini, R., 2000. A focus theory of normative conduct: When norms do and do not affect behavior Leveraging Social N... Personal. Soc. Psychol. Bull. 1002–1012.

Kallgren, C.A., Reno, R.R., Cialdini, R.B., 2000. A Focus Theory of Normative Conduct: When Norms Do and Do not Affect Behavior. Personal. Soc. Psychol. Bull. 26, 1002–1012. https://doi.org/10.1177/01461672002610009

Kals, E., Schumacher, D., Montada, L., 1999. Emotional Affinity toward Nature as a Motivational Basis to Protect Nature. Environ. Behav. 31, 178–202. https://doi.org/10.1177/00139169921972056

Kerr, G.F., Beede, Park, Proud, William, Schultz, 2010. The Elaboration Likelihood Model in the New Millennium: An exploratory study, in: American Academy of Advertising European Conference, 4 - 6 June, 2010, Milan, Italy. Milan, pp. 1–26.

Khosrowpour, A., Xie, Y., Taylor, J.E., Hong, Y., 2016. One size does not fit all: Establishing the need for targeted eco-feedback. Appl. Energy 184, 523–530. https://doi.org/10.1016/j.apenergy.2016.10.036

Kiesling, E., Günther, M., Stummer, C., Wakolbinger, L.M., 2012. Agent-based simulation of innovation diffusion: a review. Cent. Eur. J. Oper. Res. 20, 183–230.

Kim, U. (Ed), Triandis, H.C. (Ed), Kâğitçibaşi, Ç. (Ed), Choi, S.-C. (Ed), Yoon, G.

(Ed), 1994. Individualism and collectivism: Theory, method, and applications. Sage Publications, Inc.

Kitchen, P.J., Kerr, G., Schultz, D.E., Mccoll, R., Pals, H., 2014. The elaboration likelihood model: review, critique and research agenda. Eur. J. Mark. Young Consum. Eur. J. Mark. 481212, 2033–2050.

Kline, P., 2000. The handbook of psychological testing, 2nd ed. Routledge, London.

Klöckner, C.A., 2015. The Psychology of Pro-Environmental Communication: Beyond Standard Information Strategies. Palgrave Macmillan, LOndon, UK.

Klöckner, C.A., 2013. A comprehensive model of the psychology of environmental behaviour—A meta-analysis. Glob. Environ. Chang. 23, 1028–1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014

Kluger, A.N., DeNisi, A., 1996. The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. Psychol. Bull. 119, 254–284. https://doi.org/10.1037/0033-2909.119.2.254

Kok, G., Hing Lo, S., Peters, G.-J.Y., Ruiter, R.A., 2011. Changing energy-related behavior: An Intervention Mapping approach. Energy Policy 39, 5280–5286. https://doi.org/10.1016/j.enpol.2011.05.036

Kokkinaki, F., 1999. Predicting Product Purchase and Usage: the Role of Perceived Control, Past Behavior and Product Involvement. Adv. Consum. Res. Vol. 26.

Kormos, C., Gifford, R., 2014. The validity of self-report measures of proenvironmental behavior: A meta-analytic review. J. Environ. Psychol. 40, 359–371. https://doi.org/10.1016/j.jenvp.2014.09.003

Kostelijk, E., 2017. The influence of values on consumer behaviour : the value compass. Routledge, London and New York.

Krcmar, M., Roskos-Ewoldsen, D.R., Koerner, A., 2016. Communication science theory and research : an advanced introduction. Routledge, New York.

Krosnick, J.A., Fabrigar, L.R., 1997. Designing rating scales for effective measurement in surveys, in: Lyberg, L., Biemer, P., Collins, M., de Leeuw, E., Dippo, C., Schwarz, N., Trewin, D. (Eds.), Survey Measurement and Process Quality. John Wiley, New York, pp. 141–164.

Law, A.M., 2015. Simulation modeling and analysis, Fifth. ed, McGraw-Hill international edition. McGraw-Hill Education, New York.

Leth-Petersen, S., Togeby, M., 2001. Demand for space heating in apartment blocks: measuring effects of policy measures aiming at reducing energy consumption. Energy Econ. 23, 387–403. https://doi.org/10.1016/S0140-9883(00)00078-5

Lewin, K., 1951. Field Theory in Social Science : Selected Theoretical Papers. New York : Harper & Brothers.

Li, D., Menassa, C.C., Karatas, A., 2017. Energy use behaviors in buildings: Towards an integrated conceptual framework. Chem. Phys. Lett. 23, 97–112. https://doi.org/10.1016/j.erss.2016.11.008

Lien, N.-H., 2001. Elaboration Likelihood Model in Consumer Research: A Review. Proc. Natl. Sci. Counc. Part C Humanit. Soc. Sci. 11, 301–310.

Lindenberg, S., Steg, L., 2007. Normative, gain and hedonic goal frames guiding environmental behavior. J. Soc. Issues 63, 117–137. https://doi.org/10.1111/j.1540-4560.2007.00499.x

Lipsey, M.W., Wilson, D.B., 1993. The efficacy of psychological, educational, and behavioral treatment. Confirmation from meta-analysis. Am. Psychol. 48, 1181–209.

Littlejohn, S.W., Foss, K.A., 2010. Theories of Human Communication, Ninth Edition, 10th ed. Waveland Press, Inc., Long Grove, Illinois.

Liu, F.C.S., 2011. VALIDATION AND AGENT-BASED MODELING: A PRACTICE OF CONTRASTING SIMULATION RESULTS WITH EMPIRICAL DATA. New Math. Nat. Comput. 7, 515–542. https://doi.org/10.1142/S1793005711002050

Lo, S.H., Peters, G.J.Y., Kok, G., 2012. A Review of Determinants of and Interventions for Proenvironmental Behaviors in Organizations. J. Appl. Soc. Psychol. 42, 2933–2967. https://doi.org/10.1111/j.1559-1816.2012.00969.x

Lopes, M.A.R., Antunes, C.H., Martins, N., 2012. Energy behaviours as promoters of energy efficiency: A 21st century review. Renew. Sustain. Energy Rev. 16, 4095–4104. https://doi.org/10.1016/j.rser.2012.03.034

Lorenzoni, I., Nicholson-Cole, S., Whitmarsh, L., 2007. Barriers perceived to engaging with climate change among the UK public and their policy implications. Glob. Environ. Chang. 17, 445–459. https://doi.org/10.1016/J.GLOENVCHA.2007.01.004

Lynne, G.D., Franklin Casey, C., Hodges, A., Rahmani, M., 1995. Conservation technology adoption decisions and the theory of planned behavior. J. Econ. Psychol. 16, 581–598. https://doi.org/10.1016/0167-4870(95)00031-6

Macal, C., North, M., 2010. Tutorial on agent-based modelling and simulation. J. Simul. 4, 151–162. https://doi.org/10.1057/jos.2010.3

Mahler, A., Rogers, E.M., 1999. The diffusion of interactive communication innovations and the critical mass: the adoption of telecommunications services by German banks. Telecomm. Policy 23, 719–740.

Manning, M., 2009. The effects of subjective norms on behaviour in the theory of planned behaviour: a meta-analysis. Br. J. Soc. Psychol. 48, 649–705. https://doi.org/10.1348/014466608X393136

Manstead, A.S.R., Parker, D., 1995. Evaluating and Extending the Theory of Planned Behaviour. Eur. Rev. Soc. Psychol. 6, 69–95. https://doi.org/10.1080/14792779443000012

Markus, H.R., Kitayama, S., 1991. Culture and the self: Implications for cognition, emotion, and motivation. Psychol. Rev. 98, 224–253.

Marshall, D.A., Burgos-Liz, L., IJzerman, M.J., Crown, W., Padula, W. V., Wong, P.K., Pasupathy, K.S., Higashi, M.K., Osgood, N.D., 2015. Selecting a Dynamic Simulation Modeling Method for Health Care Delivery Research—Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good

Practices Task Force. Value Heal. 18, 147–160. https://doi.org/10.1016/J.JVAL.2015.01.006

Matthies, E., Trondheim, N., 2009. Planning interventions on a theoretical basis. Application of a new integrative influence model of pro-environmental behaviour to promote energy efficient behaviour, in: First European Conference Energy Efficiency and Behaviour. p. Vol 18.

McDonald, R.I., Crandall, C.S., 2015. Social norms and social influence. Curr. Opin. Behav. Sci. 3, 147–151. https://doi.org/10.1016/j.cobeha.2015.04.006

McGuire, W.J., 1962. Persistence of the resistance to persuasion induced by various types of prior belief defenses. J. Abnorm. Soc. Psychol. 64, 241–248. https://doi.org/10.1037/h0044167

McKenzie-Mohr, D., 2000. Fostering sustainable behavior through community-based social marketing. Am. Psychol. 55, 531–7.

McMichael, M., Shipworth, D., 2013. The value of social networks in the diffusion of energy-efficiency innovations in UK households. Energy Policy 53, 159–168. https://doi.org/10.1016/j.enpol.2012.10.039

Meyer, G.J., Finn, S.E., Eyde, L.D., Kay, G.G., Moreland, K.L., Dies, R.R., Eisman, E.J., Kubiszyn, T.W., Reed, G.M., 2001. Psychological testing and psychological assessment. A review of evidence and issues. Am. Psychol. 56, 128–65.

Miniard, P.W., Cohen, J.B., 1981. An examination of the Fishbein-Ajzen behavioral-intentions model’s concepts and measures. J. Exp. Soc. Psychol.

17, 309–339. https://doi.org/10.1016/0022-1031(81)90031-7

Miniard, P.W., Sirdeshmukh, D., Innis, D.E., 1992. Peripheral Persuasion and Brand Choice. J. Consum. Res. 19, 226. https://doi.org/10.1086/209298

Mohiyeddini, C., Pauli, R., Bauer, S., 2008. The role of emotion in bridging the intention–behaviour gap: The case of sports participation. Psychol. Sport Exerc. 10, 226–234. https://doi.org/10.1016/j.psychsport.2008.08.005

Morini, M., Pellegrino, S., 2015. Agent-based Dynamic Optimization of Fiscal Systems, in: Agent-Based Models of the Economy. Palgrave Macmillan UK, London, pp. 184–197. https://doi.org/10.1057/9781137339812_11

Mosler, H.-J., Schwarz, K., Ammann, F., Gutscher, H., 2001. Computer Simulation as a Method of Further Developing a Theory: Simulating the Elaboration Likelihood Model. Personal. Soc. Psychol. Rev. 5, 201–215.

Mosler, H.J., 2006. Better be convincing or better be stylish? A theory based multi-agent simulation to explain minority influence in groups via arguments or via peripheral cues. Jasss 9, 109–126. https://doi.org/4

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models - ODD+D, an extension of the ODD protocol. Environ. Model. Softw. 48, 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003

Natarajan, S., Padget, J., Elliott, L., 2011. Modelling UK domestic energy and carbon emissions: an agent-based approach. Energy Build. 43, 2602–2612. https://doi.org/10.1016/j.enbuild.2011.05.013

National Research Council, 2005. Decision Making for the Environment: Social and Behavioral Research Priorities. National Academies Press, Washington, D.C. https://doi.org/10.17226/11186

Nolan, J.M., Schultz, P.W., Cialdini, R.B., Goldstein, N.J., Griskevicius, V., 2008. Normative social influence is underdetected. Pers. Soc. Psychol. Bull. 34, 913–23. https://doi.org/10.1177/0146167208316691

Nye, M., Hargreaves, T., 2009. Exploring the Social Dynamics of Proenvironmental Behavior Change. J. Ind. Ecol. 14, 137–149. https://doi.org/10.1111/j.1530-9290.2009.00193.x

O'Keefe, D.J., 1990. Persuasion: Theory and research.

Office of national statistics, 2014. Labour market statistics [WWW Document]. URL www.ons.gov.uk/ons/dcp171778_363998.pdf

Olson, J.C., Jacoby, J., 1972. Cue Utilization in the Quality Perception Process. ACR Spec. Vol. SV-02.

Onwezen, M.C., Antonides, G., Bartels, J., 2013. The Norm Activation Model: An exploration of the functions of anticipated pride and guilt in pro-environmental behaviour. J. Econ. Psychol. 39, 141–153. https://doi.org/10.1016/J.JOEP.2013.07.005

Ormerod, P., Rosewell, B., 2009. Verification and Validation of Agent Based Models in the Social Sciences, in: Squazzoni, F. (Ed.), Epistemological Aspects of Computer Simulation in the Social Sciences. Springer Berlin Heidelberg, pp. 130–140. https://doi.org/10.1007/978-3-642-01109-2_10

Osborne, J.W., 2014. Best Practices in Exploratory Factor Analysis. Jason W. Osborne.

Ozawa-Meida, L., Fleming, P., 2016. Summative behaviour change evaluation of up-to-date metered energy feedback in European public buildings, in: 2016 International Energy Policies & Programmes Evaluation Conference, Amsterdam.

Pallant, J., 2013. SPSS survival manual : a step by step guide to data analysis using IBM SPSS, 5th ed. McGraw Hill, Berkshire.

Park, D.-H., Lee, J., Han, I., 2007. The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. Int. J. Electron. Commer. 11, 125–148. https://doi.org/10.2753/JEC1086-4415110405

Park, H.S., 2000a. Relationships among attitudes and subjective norms: Testing the theory of reasoned action across cultures. Commun. Stud. 51, 162–175. https://doi.org/10.1080/10510970009388516

Park, H.S., 2000b. Relationships among attitudes and subjective norms: Testing the theory of reasoned action across cultures. Commun. Stud. 51, 162–175. https://doi.org/10.1080/10510970009388516

Pegels, A., Figueroa, A., Never, B., 2015. The Human Factor in Energy Efficiency.

Peng, L., Zhang, Y., Wang, Y., Zeng, X., Peng, N., Yu, A., 2015. Energy efficiency and influencing factor analysis in the overall Chinese textile industry. Energy

93, 1222–1229. https://doi.org/10.1016/j.energy.2015.09.075

Perloff, R.M., 2003. The dynamics of persuasion: Communication and Attitudes in the 21st Century., 2nd ed. Lawrence Erlbaum Associates, Inc, Mahwah, New Jersey.

Peschiera, G., Taylor, J.E., 2012. The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems. Energy Build. 49, 584–590. https://doi.org/10.1016/j.enbuild.2012.03.011

Petty, R., Cacioppo, J., 1983. Central and peripheral routes to persuasion: Application to advertising, in: Percy, L., Woodside, A. (Eds.), Advertising and Consumer Psychology. Lexington Books, Massachusetts.

Petty, R., Ostrom, T.M., Brock, T.C. (Eds.), 1981. Thought Disruption and Persuasion: Assessing the Validity of Attitude Change Experiments, in: Cognitive Responses in Persuasion. Lawrence Erlbaum Associates, Inc, Hillsdale, New Jersey, pp. 55–79. https://doi.org/10.4324/9781315803012

Petty, R.E., 1997. The Evolution of Theory and Research in Social Psychology : From Single to Multiple Effect and Process Models of Persuasion, in: McGarty, C., Haslam, S. (Eds.), The Message of Social Psychology. Blackwell Publishing Ltd, Oxford, UK, pp. 268–290.

Petty, R.E., Brinol, P., Priester, J.R., 2009a. Mass media attitude change: Implications of the Elaboration Likelihod Model of persusaion, in: Bryant, J., Oliver, M.B. (Eds.), Media Effects: Advances in Theory and Research.

Routledge, New York, pp. 125–164.

Petty, R.E., Brinol, P., Priester, J.R., 2009b. Mass Media Attitude Change: Imlpications of the Elaboration Likelihood Model of Persuasion. Media Eff. Adv. theory Res.

Petty, R.E., Cacioppo, J.T., 1986a. The Elaboration Likelihood Model of Persuasion. Adv. Exp. Soc. Psychol. 19, 123–205. https://doi.org/10.1016/S0065-2601(08)60214-2

Petty, R.E., Cacioppo, J.T., 1986b. The Elaboration Likelihood Model of Persuasion. Adv. Exp. Soc. Psychol. 19, 123–205. https://doi.org/10.1016/S0065-2601(08)60214-2

Petty, R.E., Cacioppo, J.T., Kasmer, J.A., Haugtvedt, C.P., 1987a. A reply to Stiff and Boster. Commun. Monogr. 54, 257–263. https://doi.org/10.1080/03637758709390231

Petty, R.E., Kasmer, J.A., Haugtvedt, C.P., Cacioppo, J.T., 1987b. Source and message factors in persuasion: A reply to stiff's critique of the elaboration likelihood model. Commun. Monogr. 54, 233–249. https://doi.org/10.1080/03637758709390229

Petty, R.E., Unnava, R.H., Strathman, A.J., Robertson, T.S., Kassarjian, H.H., 1991. Theories of attitude change. Handb. Consum. Behav.

Petty, R.E., Wegener, D.T., 1999. The Elaboration Likelihood Model: Current Status and Controversies, in: Chaiken, S., Trope, Y. (Eds.), Dual Process Theories in Social Psychology. Guilford Press, New York, pp. 41–72.

Petty, R.E., Wells, G.L., Brock, T.C., 1976. Distraction can enhance or reduce yielding to propaganda: Thought disruption versus effort justification. J. Pers. Soc. Psychol. 34, 874–884. https://doi.org/10.1037/0022-3514.34.5.874

Poiesz, T.B.C., Bont, C.J.P.M. de, 1995. Do We Need Involvement to Understand Consumer Behavior? ACR North Am. Adv. NA-22.

Polhill, J.G., Parker, D., Brown, D., Grimm, V., 2008. Using the ODD Protocol for Describing Three Agent - Based Social Simulation Models of Land - Use Change. J. Artif. Soc. Soc. Simul. 1–31.

Prager, K., 2012. How to apply theories of behaviour change to SEWeb and related public engagement activities 1–24.

Quaglione, D., Cassetta, E., Crociata, A., Sarra, A., 2017. Exploring additional determinants of energy-saving behaviour: The influence of individuals' participation in cultural activities. Energy Policy 108, 503–511. https://doi.org/10.1016/j.enpol.2017.06.030

Raden, D., 1985. Strength-Related Attitude Dimensions. Soc. Psychol. Q. 48, 312. https://doi.org/10.2307/2786693

Rai, V., Douglas Henry, A., 2016. Agent-based modelling of consumer energy choices. Nat. Publ. Gr. 6. https://doi.org/10.1038/NCLIMATE2967

Rai, V., Robinson, S.A., 2015. Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. Environ. Model. Softw. 70, 163–177. https://doi.org/10.1016/j.envsoft.2015.04.014

Ramos, A., Gago, A., Labandeira, X., Linares, P., 2015. The role of information for energy efficiency in the residential sector. https://doi.org/10.1016/j.eneco.2015.08.022

RAND Europe, 2012. What Works in Changing Energy-Using Behaviours in the Home?

Rand, W., Rust, R.T., 2011. Agent-based modeling in marketing: Guidelines for rigor. Int. J. Res. Mark. 28, 181–193. https://doi.org/10.1016/j.ijresmar.2011.04.002

Rattray, J., Jones, M.C., 2007. Essential elements of questionnaire design and development. J. Clin. Nurs. 16, 234–243. https://doi.org/10.1111/j.1365-2702.2006.01573.x

Reno, R.R., Cialdini, R.B., Kallgren, C.A., 1993. The transsituational influence of social norms. J. Pers. Soc. Psychol. 64, 104–112. https://doi.org/10.1037//0022-3514.64.1.104

Rivis, A., Sheeran, P., 2003. Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. Curr. Psychol. 22, 218–233. https://doi.org/10.1007/s12144-003-1018-2

Rivis, A., Sheeran, P., Armitage, C.J., 2009. Expanding the affective and normative components of the theory of planned behavior: A meta-analysis of anticipated affect and moral norms. J. Appl. Soc. Psychol. 39, 2985–3019. https://doi.org/10.1111/j.1559-1816.2009.00558.x

Robinson, S.A., Rai, V., 2015. Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach. Appl. Energy 151, 273–284. https://doi.org/10.1016/j.apenergy.2015.04.071

Robson, C., 2005. Real world research: A resource for social scientists and practitioner-researchers., 2nd ed. Blackwell Publishing, Oxford.

Rogers, E.M., 2003. Diffusion of Innovations, 5th Edition, Book.

Rosenthal, E., 2012. Overcoming Cognitive and Motivational Barriers to Media Literacy: A Dual-Process Approach. Claremont Graduate University. https://doi.org/10.5642/cguetd/32

Rucker, D.D., Petty, R.E., 2006. Increasing the Effectiveness of Communications to Consumers: Recommendations Based on Elaboration Likelihood and Attitude Certainty Perspectives. J. Public Policy Mark. 25, 39–52. https://doi.org/10.1509/jppm.25.1.39

Sargent, R.G., 2013. Verification and validation of simulation models. J. Simul. 7, 12–24. https://doi.org/10.1057/jos.2012.20

Sargent, T.J., 2008. Evolution and intelligent design. Am. Econ. Rev. 98, 1–37.

Savarimuthu, B.T.R., Purvis, M., Verhagen, H., 2012. LNAI 7580 - An Agent-Based Simulation of Employing Social Norms in Energy Conservation in Households.

Savolainen, R., 2015. Cognitive barriers to information seeking: A conceptual analysis. Artic. J. Inf. Sci. 41, 613–623. https://doi.org/10.1177/0165551515587850

Šćepanović, S., Warnier, M., Nurminen, J.K., 2017. The role of context in residential energy interventions: A meta review. Renew. Sustain. Energy Rev. 77, 1146–1168. https://doi.org/10.1016/j.rser.2016.11.044

Scherbaum, C. a., Popovich, P.M., Finlinson, S., 2008. Exploring individual-level factors related to employee energy-conservation behaviors at work. J. Appl. Soc. Psychol. 38, 818–835. https://doi.org/10.1111/j.1559-1816.2007.00328.x

Schultz, P.W., 2002. Knowledge, Information, and Household Recycling: Examining the Knowledge-Deficit Model of Behavior Change, in: Dietz, T., Stern, P.C. (Eds.), New Tools for Environmental Protection: Education, Information, and Voluntary Measures. National Academies Press, Washington, D.C, pp. 67–81. https://doi.org/10.17226/10401

Schultz, P.W., Nolan, J.M., Cialdini, R.B., Goldstein, N.J., Griskevicius, V., 2007. The Constructive, Destructive, and Reconstructive Power of Social Norms. Psychol. Sci. 18, 429–434.

Schwartz, S.H., 1977. Normative Influences on Altruism. Adv. Exp. Soc. Psychol. 10, 221–279. https://doi.org/10.1016/S0065-2601(08)60358-5

Shah Alam, S., Mohamed Sayuti, N., 2011. Applying the Theory of Planned Behavior (TPB) in *halal* food purchasing. Int. J. Commer. Manag. 21, 8–20. https://doi.org/10.1108/10569211111111676

Shakya, H.B., Stafford, D., Alex Hughes, D., Keegan, T., Negron, R., Broome, J., McKnight, M., Nicoll, L., Nelson, J., Iriarte, E., Ordonez, M., Airoldi, E., Fowler, J.H., Christakis, N.A., 2017. Exploiting social influence to magnify population-level behaviour change in maternal and child health: study protocol for a randomised controlled trial of network targeting algorithms in rural Honduras Exploiting social influence to magnify population-lev. Honduras. BMJ Open 7. https://doi.org/10.1136/

Shannon, C.E., Weaver, W., 1948. A Mathematical Theory of Communication. Bell Syst. Tech. J. 27, 1–54. https://doi.org/10.1145/584091.584093

Sheeran, P., Traa Mow, D., Armitage, C.J., 2003. Predicting behaviour from perceived behavioural control: Tests of the accuracy assumption of the theory of planned behaviour. Br. J. Soc. Psychol. 42, 393–410.

Sheppard, B.H., Hartwick, J., Warshaw, P.R., Hartwick, J.O.N., 1988. The Theory of Reasoned Past Action : Meta-Analysis of with Modifications for Recommendations and. J. Consum. Res. 15, 325–343.

Shrivastava, P., 1995. Environmental technologies and competitive advantage. Strateg. Manag. 16, 183–200. https://doi.org/10.1002/smj.4250160923

Siero, F.W., Bakker, A.B., Dekker, G.B., van Den Burg, M.T.C., 1996. Changing organizational energy consumption behaviour through comparative feedback. J. Environ. Psychol. 16, 235–246. https://doi.org/10.1006/jevp.1996.0019

Simpson, M., Taylor, N., Barker, K., 2004. Environmental responsibility in SMEs: does it deliver competitive advantage? Bus. Strateg. Environ. 13, 156–171. https://doi.org/10.1002/bse.398

Smaldino, P.E., Calanchini, J., Pickett, C.L., 2015. Theory development with agent-based models. Organ. Psychol. Rev. 5, 300–317. https://doi.org/10.1177/2041386614546944

Smith, J., Smith, P., 2007. Environmental Modelling: An Introduction. OUP Oxford 180.

Snape, J.R., Irvine, K.N., Rynikiewicz, C., 2011. Understanding energy behaviours and transitions through the lens of a smart grid Agent Based Model Introduction: energy consumption in the environmentalJ context, in: Energy Efficiency First: The Foundation of a Low-Carbon Society - Proceeding of Eceee 2011 Summer Study.

Staats, H., Harland, P., Wilke, H. a. M., 2004. Effecting Durable Change: A Team Approach to Improve Environmental Behavior in the Household. Environ. Behav. 36, 341–367. https://doi.org/10.1177/0013916503260163

Staats, H., van Leeuwen, E., Wit, A., 2000. A Longitudinal Study of Informational Interventions to Save Energy in an Office Building. J. Appl. Behav. Anal. 33, 101–104. https://doi.org/10.1901/jaba.2000.33-101

Staats, H.J., Wit, A.P., Midden, C.Y.H., 1996. Communicating the Greenhouse Effect to the Public: Evaluation of a Mass Media Campaign from a Social Dilemma Perspective. J. Environ. Manage. 45, 189–203.

Steg, L., 2008. Promoting household energy conservation. Energy Policy 36, 4449–4453. https://doi.org/10.1016/j.enpol.2008.09.027

Steg, L., Berg, A.E. van den., De Groot, J.I.M., 2012. Environmental psychology :

an introduction. Wiley-Blackwell.

Steg, L., Dreijerink, L., Abrahamse, W., 2005. Factors influencing the acceptability of energy policies: A test of VBN theory. J. Environ. Psychol. 25, 415–425. https://doi.org/10.1016/j.jenvp.2005.08.003

Steg, L., Vlek, C., 2009. Encouraging pro-environmental behaviour: An integrative review and research agenda. J. Environ. Psychol. 29, 309–317. https://doi.org/10.1016/j.jenvp.2008.10.004

Stephenson, J., Barton, B., Carrington, G., Gnoth, D., Lawson, R., Thorsnes, P., 2010. Energy cultures: A framework for understanding energy behaviours. Energy Policy 38, 6120–6129. https://doi.org/10.1016/j.enpol.2010.05.069

Sterman, J.D., 2001. System Dynamics Modeling: Tools for Learning in a Complex World. Calif. Manage. Rev. 43.

Sterman, J.D., 2000. Business Dynamics: Systems Thinking and Modelling for a complex World. Irwin Mcraw-Hill.

Stern, P.C., 2000. Toward a Coherent Theory of Environmentally Significant Behavior. J. Soc. Issues 56, 407–424. https://doi.org/10.1111/0022-4537.00175

Stern, P.C., Dietz, T., Abel, T., Guagnano, G. a., Kalof, L., 1999. A value-belief-norm theory of support for social movements: The case of environmentalism. Hum. Ecol. Rev. 6, 81–97. https://doi.org/10.2307/2083693

Stern, P.C., Gardner, G.T., 1981. Psychological research and energy policy. Am.

Psychol. 36, 329–342. https://doi.org/10.1037/0003-066X.36.4.329

Stiff, J.B., 1986. Cognitive processing of persuasive message cues: A meta-analytic review of the effects of supporting information on attitudes. Commun. Monogr. 53, 75–89. https://doi.org/10.1080/03637758609376128

Stiff, J.B., Boster, F.J., 1987. Cognitive processing: Additional thoughts and a reply to Petty, Kasmer, Haugtvedt, and Cacioppo. Commun. Monogr. 54, 250–256. https://doi.org/10.1080/03637758709390230

Stokes, L.C., Mildenberger, M., Savan, B., Kolenda, B., 2012. Analyzing Barriers to Energy Conservation in Residences and Offices: The Rewire Program at the University of Toronto. Appl. Environ. Educ. Commun. 11, 88–98. https://doi.org/10.1080/1533015X.2012.751282

Stone, J., Cooper, J., 2000. A Self-Standards Model of Cognitive Dissonance. J. Exp. Soc. Psychol. 1–16. https://doi.org/10.1006/jesp.2000.1446

Stuart, G., Wilson, C., Irvine, K., Bull, R., 2013. Designing live energy performance feedback for public buildings in Leicester.

Sun, Z., Lorscheid, I., Millington, J.D., Lauf, S., Magliocca, N.R., Groeneveld, J., Balbi, S., Nolzen, H., Müller, B., Schulze, J., Buchmann, C.M., 2016. Simple or complicated agent-based models? A complicated issue. Environ. Model. Softw. 86, 56–57. https://doi.org/10.1016/j.envsoft.2016.09.006

Susan, D., Kirby John, R., Ureda Randall, L., Hussey, R.J., 1998. Peripheral Cues and Involvement Level: Influences on Acceptance of a Mammography Message. J. Health Commun. 3, 119–135.

https://doi.org/10.1080/108107398127418

Sutton, S., 2010. Using Social Cognition Models to Develop Health Behaviour Interventions. Heal. Psychol. 122–134.

Sweeney, J.C., Kresling, J., Webb, D., Soutar, G.N., Mazzarol, T., 2013. Energy saving behaviours: Development of a practice-based model. Energy Policy 61, 371–381. https://doi.org/10.1016/J.ENPOL.2013.06.121

Tabachnick, B.G., Fidell, L.S., 2007. Using multivariate statistics. Pearson/Allyn & Bacon, Boston Massachusetts.

Talbot, J., Love, J., 2014. I Will If You Will : A Replicable Strategy for Tenant Behavior Change, in: ACEEE Summer Study on Energy Efficiency in Buildings. pp. 338–350.

Tavakol, M., Dennick, R., 2011. Making sense of Cronbach's alpha. Int. J. Med. Educ. 2, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Thøgersen, J., 2004. A cognitive dissonance interpretation of consistencies and inconsistencies in environmentally responsible behavior. J. Environ. Psychol. 24, 93–103. https://doi.org/10.1016/S0272-4944(03)00039-2

Thondhlana, G., Kua, H.W., 2016. Promoting household energy conservation in low-income households through tailored interventions in Grahamstown, South Africa. https://doi.org/10.1016/j.jclepro.2016.05.026

Thondhlana, G., Kua, H.W., 2016. Promoting household energy conservation in low-income households through tailored interventions in Grahamstown, South Africa. J. Clean. Prod. 131, 327–340. https://doi.org/10.1016/j.jclepro.2016.05.026

Tormala, Z.L., Petty, R.E., 2002. What Doesn't Kill Me Makes Me Stronger: The Effects of Resisting Persuasion on Attitude Certainty. J. Pers. Soc. Psychol. 83, 1298–1313. https://doi.org/10.1037//0022-3514.83.6.1298

Trafimow, D., 1994. Predicting Intentions to Use a Condom From Perceptions of Normative Pressure and Confidence in Those Perceptions1. J. Appl. Soc. Psychol. 24, 2151–2163. https://doi.org/10.1111/j.1559-1816.1994.tb02377.x

Tran, M., 2012. Agent-behaviour and network influence on energy innovation diffusion. Commun. Nonlinear Sci. Numer. Simul. 17, 3682–3695. https://doi.org/10.1016/j.cnsns.2012.01.016

Triandis, H.C., 1994. Culture and social behavior. McGraw-Hill Ser. Soc. Psychol. 3, 330. https://doi.org/10.1016/j.cobeha.2015.02.001

Triandis, H.C., 1989. The self and social behavior in differing cultural contexts. Psychol. Rev. 96, 506–520. https://doi.org/10.1037/0033-295X.96.3.506

Triandis, H.C., 1977. Interpersonal Behaviour. Brooks/Cole Pub. Co., Monterey, CA.

Triandis, H.C., n.d. Culture and Social.

Trombley, J., Halawa, E., 2017. Can further energy reductions be achieved through behaviour changes in low income households? Energy Procedia

121, 230–237. https://doi.org/10.1016/J.EGYPRO.2017.08.022

Turaga, R.M.R., Howarth, R.B., Borsuk, M.E., 2010. Pro-environmental behavior: Rational choice meets moral motivation. Ann. N. Y. Acad. Sci. 1185, 211–224. https://doi.org/10.1111/j.1749-6632.2009.05163.x

Twomey, P., Cadman, R., 2002. Agent-based modelling of customer behaviour in the telecoms and media markets. Info 4, 56–63. https://doi.org/10.1108/14636690210426640

U.S. Energy Information Administration (EIA), 2003. Commercial Buildings Energy Consumption Survey (CBECS) [WWW Document]. URL https://www.eia.gov/consumption/commercial/ (accessed 1.6.17).

Uitdenbogerd, D., Egmond, C., Jonkers, R., Kok, G., 2007. Energy-related intervention success factors: a literature review, in: Eceee 2007 Summer Study Proceedings. France, pp. 1847–1853.

UKERC, 2016. Social and Organisational Aspects of Energy Use [WWW Document]. URL http://www.ukerc.ac.uk/programmes/energy-demand/social-and-organisational-aspects-of-energy-use.html (accessed 8.5.16).

United Nations, 2016. International Day for the Preservation of the Ozone Layer, 16 September [WWW Document]. URL http://www.un.org/en/events/ozoneday/background.shtml (accessed 3.7.18).

Updegraff, J.A., Sherman, D.K., Luyster, F.S., Mann, T.L., 2007. The effects of message quality and congruency on perceptions of tailored health communications. J. Exp. Soc. Psychol. 43, 249–257. https://doi.org/10.1016/j.jesp.2006.01.007

Van Lange, P. a M., Joireman, J. a., 2008. How we can promote behavior that serves all of us in the future. Soc. Issues Policy Rev. 2, 127–157. https://doi.org/10.1111/j.1751-2409.2008.00013.x

Wan, C., Shen, G.Q., Choi, S., 2017. Experiential and instrumental attitudes: Interaction effect of attitude and subjective norm on recycling intention. J. Environ. Psychol. 50, 69–79. https://doi.org/10.1016/j.jenvp.2017.02.006

Wang, W., Zhao, Y., Qiu, L., Zhu, Y., 2014. Effects of Emoticons on the Acceptance of Negative Feedback in Computer-Mediated Communication 15, 454–483.

Ward, I., Ogbonna, A., Altan, H., 2008. Sector review of UK higher education energy consumption. Energy Policy 36, 2929–2939. https://doi.org/10.1016/j.enpol.2008.03.031

Whitmarsh, L., Seyfang, G., O'Neill, S., 2011. Public engagement with carbon and climate change: To what extent is the public 'carbon capable'? Glob. Environ. Chang. 21, 56–65. https://doi.org/10.1016/J.GLOENVCHA.2010.07.011

Widman, R.O.N., Kaplan, R., Young, R.D.E., 1984. Behavioral Approaches to Energy Conservation in Organizations: A Selected Review of the Literature, CPL Biliographies. Chicago, Illinois.

Wilensky, U., Rand, W., 2015. An introduction to agent-based modeling : modeling natural, social, and engineered complex systems with NetLogo. MIT Press.

Wilhite, H., Shove, E., Lutzenhiser, L., Kempton, W., 2000. The Legacy of Twenty Years of Energy Demand Management: we know more about Individual Behaviour but next to Nothing about Demand, in: Society, Behaviour, and Climate Change Mitigation. Kluwer Academic Publishers, Dordrecht, pp. 109–126. https://doi.org/10.1007/0-306-48160-X_4

Williams, B., Onsman, A., Brown, T., 2010. Exploratory factor analysis: A five-step guide for novices. J. Emerg. Prim. Heal. Care 8, 2010–990399.

Wilson, C., 2014. Evaluating communication to optimise consumer-directed energy efficiency interventions. Energy Policy 74, 300–310. https://doi.org/10.1016/j.enpol.2014.08.025

Wilson, C., Chatterton, T., 2011. Multiple models to inform climate change policy: A pragmatic response to the “beyond the ABC” debate. Environ. Plan. A Econ. Sp. 43, 2781–2787. https://doi.org/10.1068/a44404

Wilson, C., Dowlatabadi, H., 2007. Models of decision making and residential energy use. Annu. Rev. Environ. Resour. 32, 169–203. https://doi.org/DOI 10.1146/annurev.energy.32.053006.141137

Wilson, C., Irvine, K.N., 2013. Bottom-up communication: Identifying opportunities and limitations through an exploratory field-based evaluation. Energy Effic. 6, 91–104. https://doi.org/10.1007/s12053-012-9161-y

Wilson, C., Irvine, K.N., Mill, G., 2011. Using theory-based evaluation to assess communications approaches., in: International Energy Program Evaluation Conference. Boston Massachusetts.

Wilson, C., Irvine, K.N., Mill, G., 2010. Behaviour change communication: does it live up to its name ?, in: IESD PhD Conference: Energy and Sustainable Development Institute of Energy and Sustainable Development, Queens Building, De Montfort University, Leicester, UK, 21st May 2010. Leicester, pp. 94–102.

Wilson, C., Irvine, K.N., Mill, G. a., 2009. The when and how of communicating climate change. 1–7. https://doi.org/ISBN 978-84-692-3179-1

Wilson, C., Stuart, G., 2013. Can persuasion theory help assess a deliberative communication approach?, 12th Int. Coll. on Arts, Social and Nonprofit Marketing.

Winett, R. a, Ester, P., 1983. Behavioral science and energy conservation: Conceptualizations, strategies, outcomes, energy policy applications. J. Econ. Psychol. 3, 203–229. https://doi.org/10.1016/0167-4870(83)90003-X

Winkler, R.C., Winett, R.A., 1982. Behavioral interventions in resource conservation: A systems approach based on behavioral economics. Am. Psychol. 37, 421–435. https://doi.org/10.1037/0003-066X.37.4.421

Xiang, X., Kennedy, R., Madey, G., Cabaniss, S., 2005. Verification and Validation of Agent-based Scientific Simulation Models, in: Agent-Directed Simulation Conference. pp. 47–55.

Xu, X., Maki, A., Chen, C.-F., Dong, B., Day, J.K., 2017. Investigating willingness to save energy and communication about energy use in the American workplace with the attitude-behavior-context model. Chem. Phys. Lett. 32, 13–22. https://doi.org/10.1016/j.erss.2017.02.011

Zanna, M.P., Fazio, R.., 1982. The attitude-behavior relation: Moving toward a third generation of research, in: Zanna, M.P., Higgins, E.T., Herman, C.P. (Eds.), Consistency in Social Behavior: The Ontario Symposium, Vol 2. Erlbaum, Hillsdale, NJ, pp. 283–301.

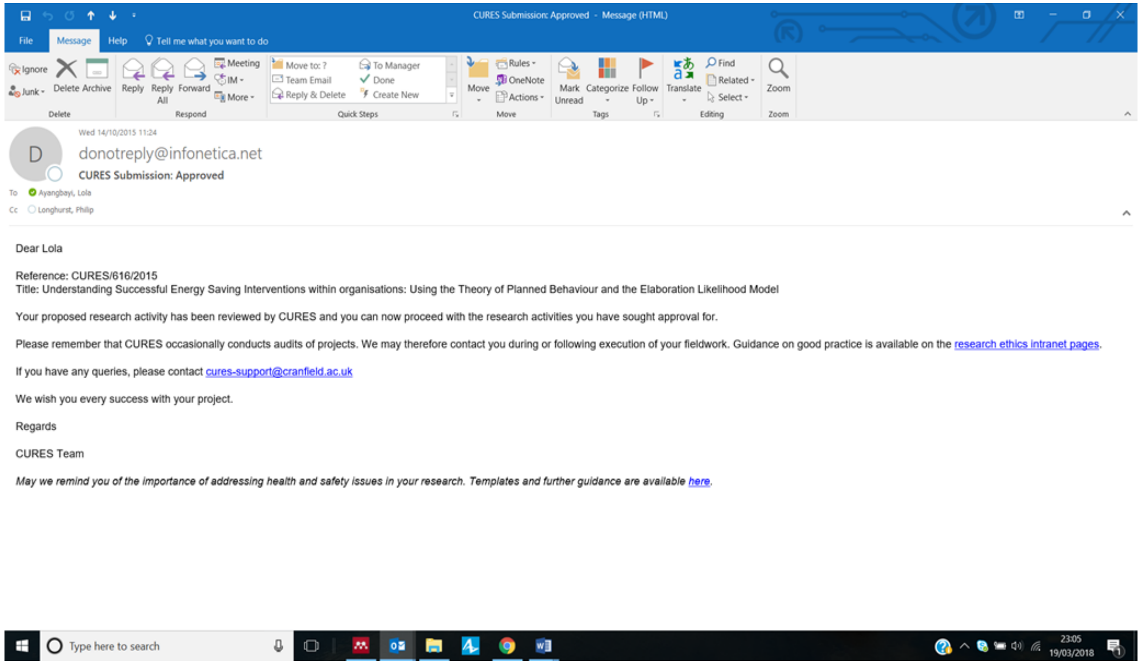
Zhang, T., Siebers, P.-O., Aickelin, U., 2011. Modelling electricity consumption in office buildings: An agent based approach. Energy Build. 43, 2882–2892. https://doi.org/10.1016/j.enbuild.2011.07.007

Zsifkovits, M., 2013. Agent-Based Modeling for Simulating Eco- Innovation Diffusion: A Review on the case of Green Mobility. Int. J. Sci. Res. ISSN (Online Index Copernicus Value Impact Factor 14, 2319–7064.

APPENDICES

Appendix A Further information originating from chapter 3

A.1 Ethics approval


CURES Submission: Approved - Message (HTML)

Wed 14/10/2015 11:24

donotreply@infonetica.net

CURES Submission: Approved

To Ayangbayi, Lola

Cc Longhurst, Philip

Dear Lola

Reference: CURES/616/2015
Title: Understanding Successful Energy Saving Interventions within organisations: Using the Theory of Planned Behaviour and the Elaboration Likelihood Model

Your proposed research activity has been reviewed by CURES and you can now proceed with the research activities you have sought approval for.

Please remember that CURES occasionally conducts audits of projects. We may therefore contact you during or following execution of your fieldwork. Guidance on good practice is available on the research ethics intranet pages.

If you have any queries, please contact cures-support@cranfield.ac.uk

We wish you every success with your project.

Regards

CURES Team

May we remind you of the importance of addressing health and safety issues in your research. Templates and further guidance are available here.

Figure A.1 Email confirming ethics approval from CURES

A.2 Objectives for a Theory of Planned Behaviour and Elaboration Likelihood Model questionnaire to understand factors influencing energy saving intentions and behaviours in the work place.

1. To elicit and record energy saving beliefs on a bipolar rating scale as a measure of the attitude, subjective norm, perceived behavioural control, source, message and receiver variables of the above theories and to determine combined effects on reducing energy demand among students in HEI.

   SMART Elements explained.

   Specific: attitude, subjective norm and perceived behavioural control constructs of the *Theory of Planned Behaviour* and source, message and receiver variables in the *Elaboration Likelihood Model*

   Measurable: beliefs

   Achievable: using bipolar adjectives in a rating scale e.g. semantic differential scale

   Relevant: to energy saving behavioural initiatives in the workplace

2. To understand the type of message elaboration suited to energy saving interventions by collecting information on associated attitudes, attitude certainty and thoughts

   SMART Elements explained.

   Specific: message elaboration (central i.e. deep processing or peripheral i.e. shallow processing)

Measurable: attitudes, attitude certainty and thoughts

Achievable: *attitude* and *attitude certainty* can be measured using bipolar adjectives on a semantic differential scale, *thoughts* about the intervention can be collected in a listed format (e.g. numbered or bullet points)

Relevant: to energy saving interventions in the workplace

A.3 Questionnaire 1

Questionnaire 1

Start of Block: Default Question Block

Thank you for choosing to participate in this survey. The following questionnaire is part of a research study at Cranfield University. Your responses will be kept confidential and anonymous. All information will be held securely.

The survey is in two parts. *Part 1* asks about demographic details. *Part 2* contains questions about an energy saving initiative. Some of the questions may seem similar or unnecessary, however these are all vital to testing the research framework. The survey should take approximately 10 minutes to complete. There are no right or wrong answers, all responses would be appreciated. Please click the ">>" button below to continue.

Page Break

PART 1 About your BACKGROUND

Page Break

Q1 what is your gender?

- Male (1)
- Female (2)

Q2 what is your age group?

- 20-24 (1)
- 25-29 (2)
- 30-34 (3)
- 35-39 (4)
- 40-45 (5)
- 46-50 (6)
- 51 and above (7)

Q3 What is your cultural background?

○ Africa (1)

○ Asia (2)

○ Australia (3)

○ Europe (4)

○ Middle East (5)

○ North America (6)

○ South America (7)

○ Other (8) ____

Q4 Please state your Cranfield University course of study and School *(**e.g.** MSc Energy from Waste, SEEA)*

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Q5 Do you live on campus?

- ◯ Yes (1)
- ◯ No (2)

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*<u>PART 2</u> Each question in this section refers to the **CRANFIELD STUDENT SWITCH OFF** campaign*

Q6 Are you aware of the Student Switch Off campaign?

- ◯ Yes (1)
- ◯ No (2)

Display This Question:

If Are you aware of the Student Switch Off campaign? = No

The Student Switch Off Campaign is an initiative designed to encourage energy saving behaviours in students. It raises energy saving awareness by engaging students in an inter-hall energy saving contest and other competitions, giving them a chance to win prizes. Specific information is given via four energy saving tips namely: Switch off lights and appliances Do not overfill the kettle Put a lid on it (when cooking) Put a layer on, not the heating (when feeling cold) For more information on the campaign kindly look it up (by following the link below or copy and paste it in your browser) before returning to complete the survey. http://www.studentswitchoff.org/unis/cranfield-university

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Page Break

Q7 The student switch off campaign is:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Relevant to me (1)	○	○	○	○	○	○	○	Irrelevant to me
Important to me (2)	○	○	○	○	○	○	○	Unimportant to me
Exciting to me (3)	○	○	○	○	○	○	○	Unexciting to me
Interesting to me (4)	○	○	○	○	○	○	○	Of no interest to me
Engaging to me (5)	○	○	○	○	○	○	○	Not engaging to me
Fascinating to me (6)	○	○	○	○	○	○	○	Repelling to me
Valuable to me (7)	○	○	○	○	○	○	○	Worthless to me

This Question elicits the theoretical construct "Motivation" (from the ELM).

Q8 The four energy saving tips given in the Student Switch Off campaign are:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Easy to remember (1)	○	○	○	○	○	○	○	Difficult to remember
Easy to understand (2)	○	○	○	○	○	○	○	Difficult to understand
Clear (3)	○	○	○	○	○	○	○	Unclear

This Question was used to elicit the theoretical construct "Ability to Process" (from the ELM).

Q9 The message of the Student Switch Off campaign is:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Valid (1)	○	○	○	○	○	○	○	Invalid
Convincing (2)	○	○	○	○	○	○	○	Unconvincing
Clear (3)	○	○	○	○	○	○	○	Unclear
Informative (4)	○	○	○	○	○	○	○	Uninformative
Useful (5)	○	○	○	○	○	○	○	Useless
Strong (6)	○	○	○	○	○	○	○	Weak
Distinct (7)	○	○	○	○	○	○	○	Right

This Question was used to elicit the theoretical construct "Argument Quality" (from the ELM).

Q10 I fully understand the message in the Student Switch Off campaign

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Somewhat Agree (4)
- Agree (5)
- Strongly Agree (6)

This question was used to elicit the theoretical construct "Ability to Process" (from the ELM).

Q11 Are you familiar with the sponsors of the Student Switch Off campaign?

- Yes (1)
- No (2)

Display This Question:

If Are you familiar with the sponsors of the Student Switch Off campaign? = Yes

Q12 The sponsors of the Student Switch Off campaign make it more

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
Credible (1)	○	○	○	○	○	○	○
Likeable (2)	○	○	○	○	○	○	○
Believable (3)	○	○	○	○	○	○	○

This question was used to elicit the theoretical construct "Peripheral cues" (from the ELM)

A.4 Questionnaire 2

Questionnaire 2

Start of Block: Default Question Block

Thank you for choosing to participate in this survey. This questionnaire is a follow-on to a previous survey about the Student Switch Off campaign. Please proceed ***only*** if you completed the preceding survey. As part of a research study at Cranfield University, your responses will be kept confidential and anonymous. All information will be held securely.

The survey is in two parts. *Part 1* asks about demographic details. *Part 2* contains questions about energy saving. Some of the questions may seem similar or unnecessary, however these are all vital to testing the research framework. The survey should take approximately 10 minutes to complete. Please answer openly, there are no right or wrong answers. Please click the ">>" button below to continue.

PART 1 About your BACKGROUND

Page Break

Q1 What is your gender?

- ○ Male (1)
- ○ Female (2)

Q2 What is your age group?

- ○ 20-24 (1)
- ○ 25-29 (2)
- ○ 30-34 (3)
- ○ 35-39 (4)
- ○ 40-45 (5)
- ○ 46-50 (6)
- ○ 51 and above (7)

Q3 What is your cultural background?

- ◯ Africa (1)
- ◯ Asia (2)
- ◯ Australia (3)
- ◯ Europe (4)
- ◯ Middle East (5)
- ◯ North America (6)
- ◯ South America (7)
- ◯ Other (8) ____

Q4 Please state your Cranfield University course of study and School ***(e.g.** MSc Energy from Waste, SEEA)*

____

____

____

____

____

Q6 Have you given further thought to the message of the student switch off campaign?

- ○ Not At All (1)
- ○ Occasionally (2)
- ○ Frequently (3)

This question was used to elicit the theoretical construct "Elaboration" (from the ELM).

Q5 Do you live on campus?

- ○ Yes (1)
- ○ No (2)

Skip To: Q9 If Do you live on campus? = No

Q7 Have you

	Yes (1)	Probably yes (2)	Probably not (3)	Not (4)
Spoken in favor of the Student Switch Off campaign to other students? (1)	○	○	○	○
Enquired further about the student switch off campaign? (2)	○	○	○	○

This question was used to elicit Attitude change (from the ELM).

Q8 I tend to look out for energy saving opportunities in the halls of residence more than in other areas on campus

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Somewhat Disagree (3)
- ○ Neither Agree nor Disagree (4)
- ○ Somewhat Agree (5)
- ○ Agree (6)
- ○ Strongly Agree (7)

This question was used to elicit the theoretical construct "Intention" (from the TPB).

Q9 Have you adopted any new energy saving habits (on or off campus) since you became aware of the student switch off campaign?

- ○ Yes (1)
- ○ No (2)

This question was used to elicit the theoretical construct "Behaviour" (from the TPB)

Q10 Saving energy on campus is

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Good (1)	○	○	○	○	○	○	○	Bad
Convenient (2)	○	○	○	○	○	○	○	Inconvenient
A waste of effort (3)	○	○	○	○	○	○	○	Worthwhile
Satisfying (4)	○	○	○	○	○	○	○	Dissatisfying

This question was used to elicit the theoretical construct "Attitude" (from the TPB).

Q11 People who are important to me

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
Expect me to always save energy on campus (1)	○	○	○	○	○	○	○
Think that consistently saving energy is important (2)	○	○	○	○	○	○	○
Would always save energy if they were in my shoes (3)	○	○	○	○	○	○	○
Disapprove of me taking part in Student Switch Off competitions (4)	○	○	○	○	○	○	○

This question was used to elicit the theoretical construct "Subjective Norms" (from the TPB).

Q12 Please select as appropriate

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
I am confident that I can consistently save energy on campus if I want to (1)	○	○	○	○	○	○	○
I find it difficult to consistently save energy on campus (2)	○	○	○	○	○	○	○
The decision to consistently save energy on campus is beyond my control (3)	○	○	○	○	○	○	○
Whether I consistently save energy on campus is entirely up to me (4)	○	○	○	○	○	○	○

This question was used to elicit the theoretical construct "Perceived Behavioural Control" (from the TPB).

Q13 I feel under social pressure to save energy on campus

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Somewhat Disagree (3)
- ○ Neither Agree nor Disagree (4)
- ○ Somewhat Agree (5)
- ○ Agree (6)
- ○ Strongly Agree (7)

This question was used to elicit the theoretical construct "Subjective Norms" (from the TPB).

Q14 How certain are you of your attitude towards energy saving on campus?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Not at all certain (1)	○	○	○	○	○	○	○	Very certain

This question was used to elicit Attitude certainty.

Q15 Please list any thoughts you have about saving energy on campus. Please list one thought per line.

A.5 Survey data in SPSS

Table A.1 Survey data in SPSS

	SSO_Awareness	Mean_Motivated	Mean_ATProcess	Mean_Arg_Quality	Mean_Peripheral_Cues	Mean_ELAB	Mean_ATT	Mean_SN	Mean_PBC	Intention_RC	Intention	Behaviour	ATT_CERT	Sponsor_knowledge
1	2.00	4.00	1.00	4.14	.	2.57	5.50	4.60	4.00	6.00	2.00	2.00	4.00	2.00
2	1.00	2.57	4.00	2.57	.	3.29	1.00	3.40	5.25	3.00	5.00	2.00	4.00	2.00
3	1.00	4.14	1.67	2.00	.	1.83	1.00	5.20	6.25	6.00	2.00	2.00	7.00	2.00
4	2.00	4.00	1.33	2.71	.	2.02	1.67	4.60	4.75	2.00	6.00	1.00	6.00	2.00
5	1.00	3.00	2.67	3.00	.	.	1.50	5.20	5.75	.	.	2.00	7.00	2.00
6	2.00	2.14	1.00	2.43	.	.	1.00	2.20	6.75	.	.	2.00	7.00	2.00
7	1.00	1.00	1.00	2.33	.	1.67	1.00	6.00	6.00	2.00	6.00	1.00	7.00	2.00
8	1.00	1.71	1.00	2.71	.	1.86	1.00	5.00	5.75	3.00	5.00	1.00	7.00	2.00
9	2.00	1.00	1.00	1.71	4.00	.	1.00	5.40	6.25	.	.	2.00	7.00	1.00
10	1.00	1.00	1.00	3.00	6.00	3.33	1.00	4.80	7.00	6.00	2.00	1.00	7.00	1.00
11	2.00	2.14	1.00	1.86	.	1.43	3.33	3.80	5.00	.	.	.	3.00	2.00
12	2.00	3.29	1.00	3.14	.	2.07	3.50	4.00	4.00	4.00	4.00	1.00	2.00	2.00
13	.	1.43	1.00	1.14	7.00	3.05	1.00	6.40	5.75	1.00	7.00	1.00	7.00	1.00
14	2.00	2.14	2.00	2.00	.	2.00	3.00	5.00	5.25	3.00	5.00	1.00	5.00	2.00
15	2.00	2.86	3.00	4.29	.	3.64	2.75	4.40	5.00	3.00	5.00	1.00	5.00	2.00
16	1.00	3.14	2.67	2.14	6.00	3.60	3.50	6.00	6.50	2.00	6.00	1.00	5.00	1.00
17	2.00	4.00	4.00	4.00	.	4.00	4.00	4.00	4.00	4.00	4.00	.	4.00	2.00
18	2.00	2.29	1.33	1.86	.	1.60	1.25	6.00	5.50	2.00	6.00	1.00	7.00	2.00
19	2.00	3.57	4.00	4.00	.	4.00	1.75	4.20	5.00	3.00	5.00	1.00	6.00	2.00
20	2.00	4.57	2.33	2.86	.	2.60	3.50	4.60	5.00	4.00	4.00	1.00	3.00	2.00
21	1.00	1.00	1.00	1.14	6.00	2.71	2.50	5.20	6.00	2.00	6.00	1.00	7.00	1.00

A.6 Standardised (z) values for assessing normality in questionnaire data

Table A.2 standardised (z) values for skewness and kurtosis in survey data

	Skewness			Kurtosis		
	statistic	standard error	standardised (z) value	statistic	standard error	standardised (z) value
Motivated	0.0170	0.5010	0.0339	-1.2360	0.9720	-1.2716
ATP	1.0380	0.5010	2.0719	-0.3150	0.9720	-0.3241
Argument Quality	0.3470	0.5010	0.6926	-0.5470	0.9720	-0.5628
Peripheral Cues	-1.2930	0.9130	-1.4162	2.9170	2.0000	1.4585
Attitude	0.8990	0.5010	1.7944	0.0560	0.9720	0.0576
Subjective Norms	-0.6200	0.5010	-1.2375	0.9880	0.9720	1.0165
PBC	-0.1690	0.5010	-0.3373	-0.5650	0.9720	-0.5813
Intention	-0.7380	0.5500	-1.3418	-0.2910	1.0630	-0.2738
Behaviour	0.8620	0.5240	1.6450	-1.4190	1.0140	-1.3994

Appendix B Updates resulting from model verification.

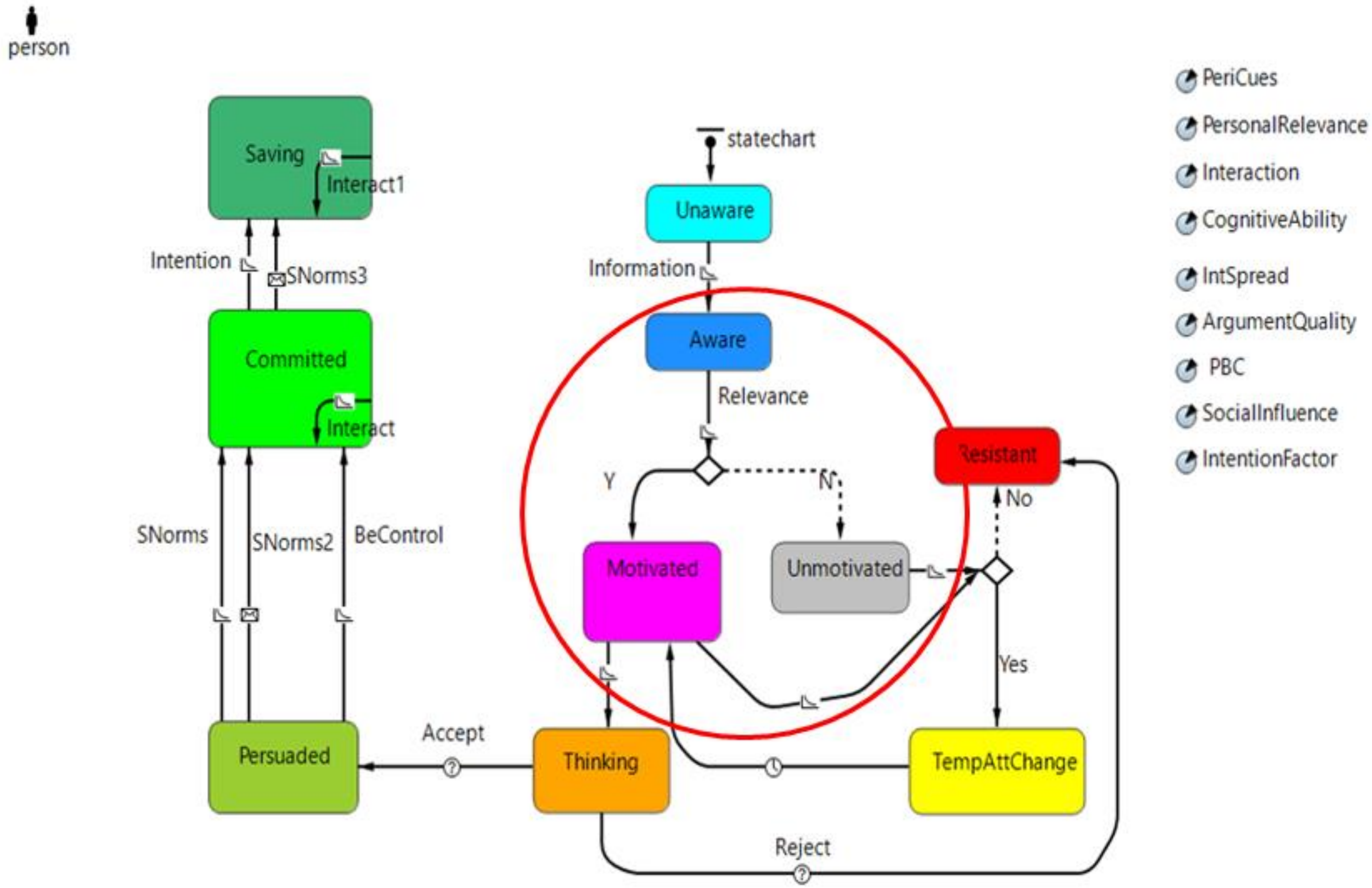

Figure B.1 Initial model state chart before verification

Following the parameter variation shown in Figure B.2, the area highlighted in the initial state chart in Figure B.1 was amended to rectify the error identified. The updated model state chart is shown in Figure B.3

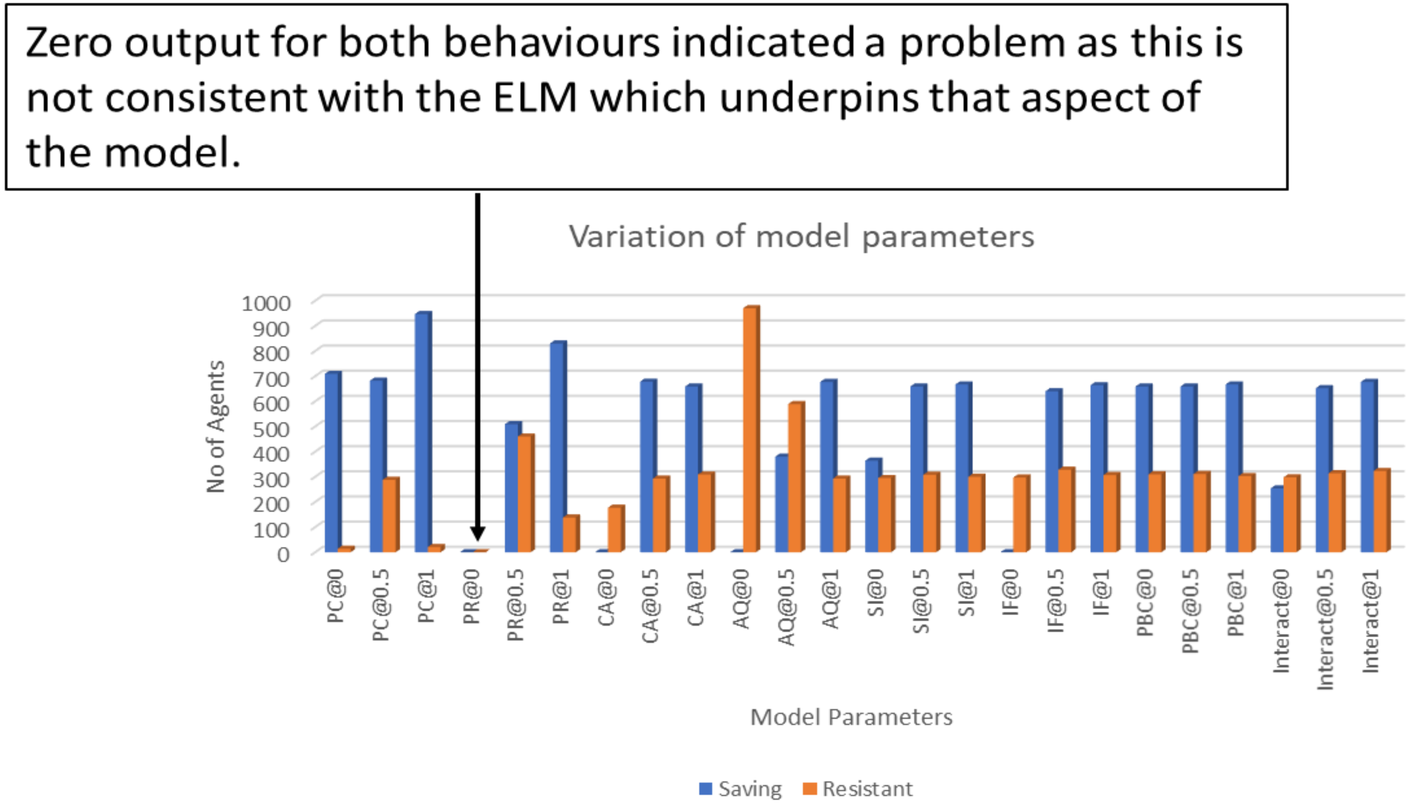

Figure B.2 Parameter variation on initial model

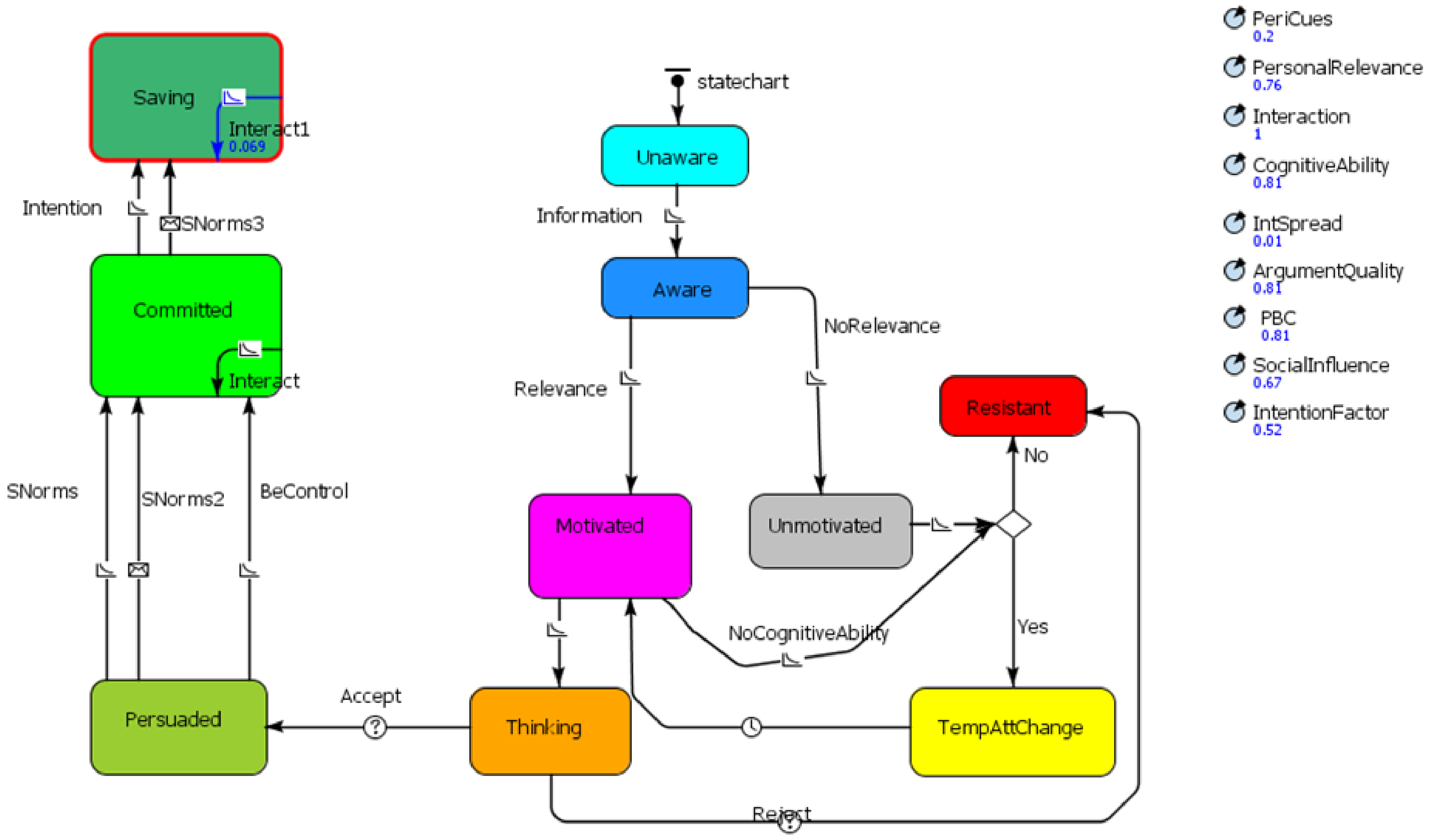

Figure B.3 Current Model (after amendment)

Appendix C The diffusion of innovations curve

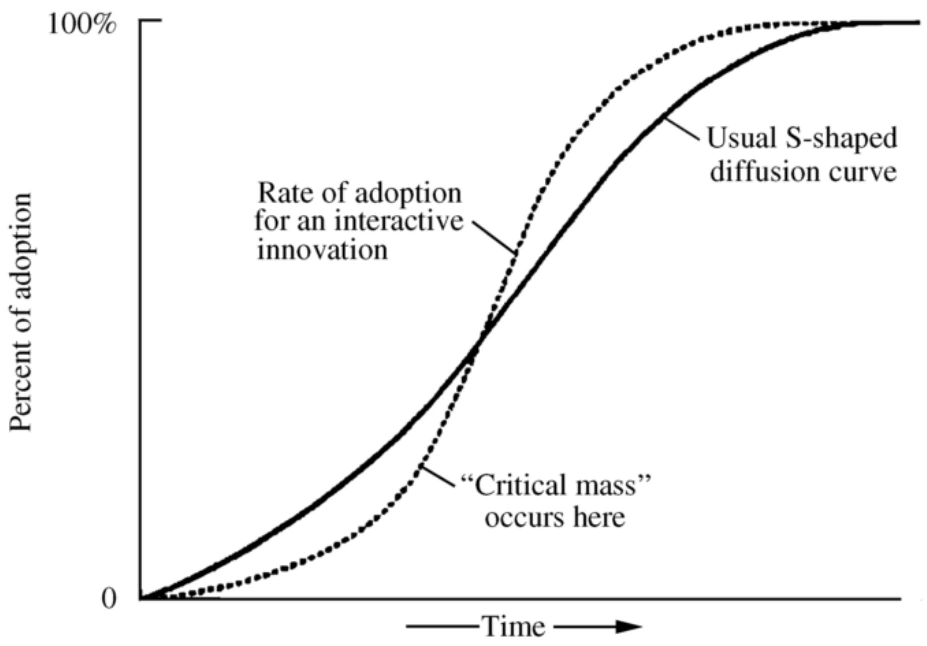

Figure C.1 The diffusion of innovations curve (Mahler and Rogers, 1999)

Appendix D Model output in the absence of *Cognitive ability* and *Argument quality*

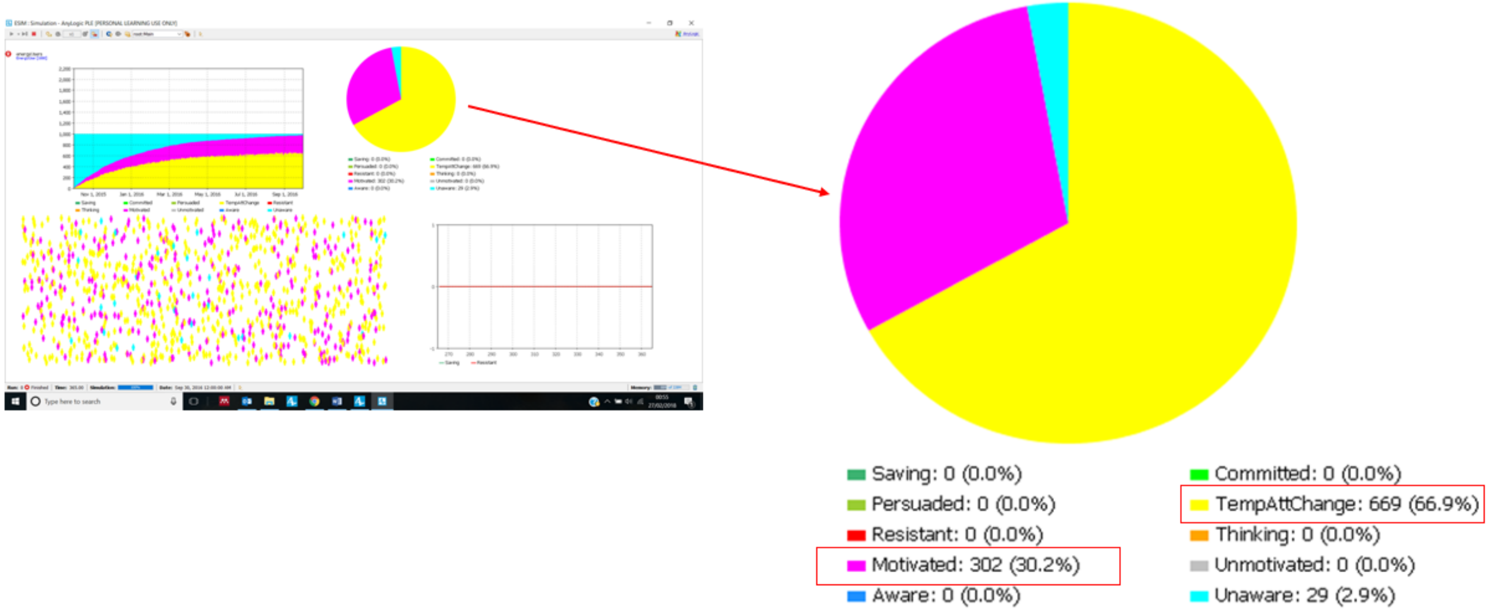

Figure D.1 Model output screen showing states achieved in the absence of *Cognitive ability* and Argument *quality*

Appendix E Model versions

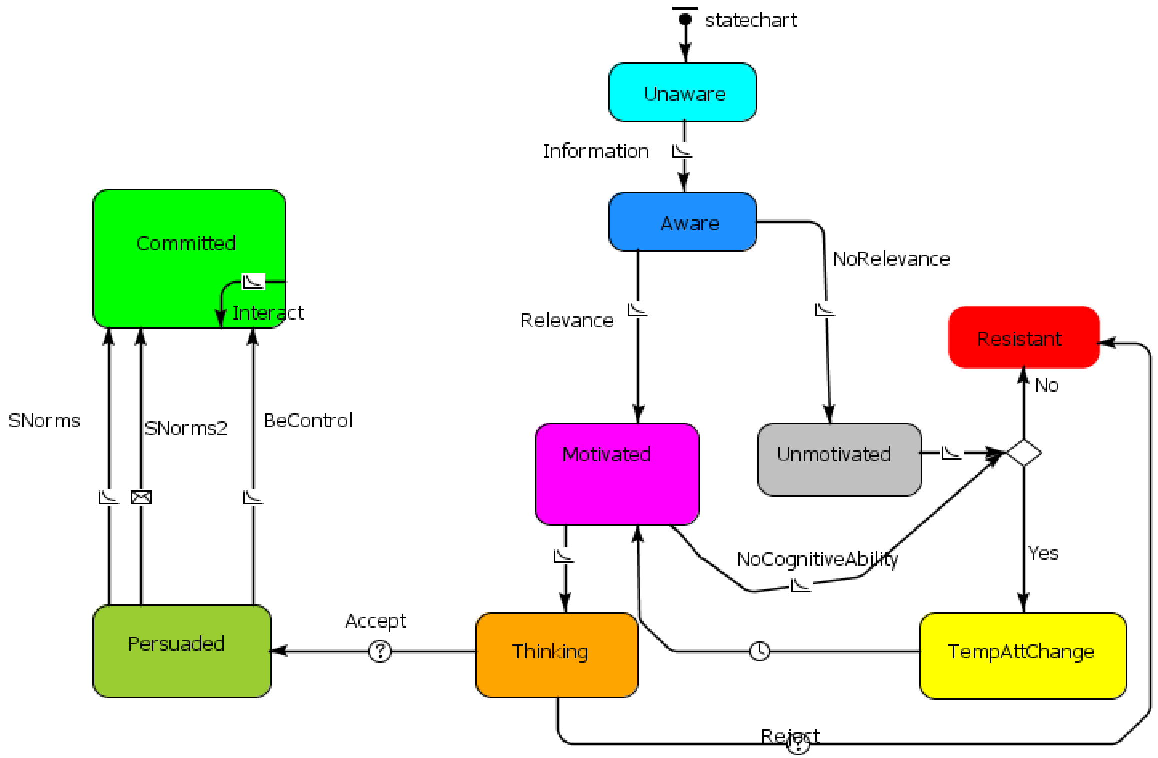

Figure E.1 Model with end state *Committed* (i.e. *Intention*)

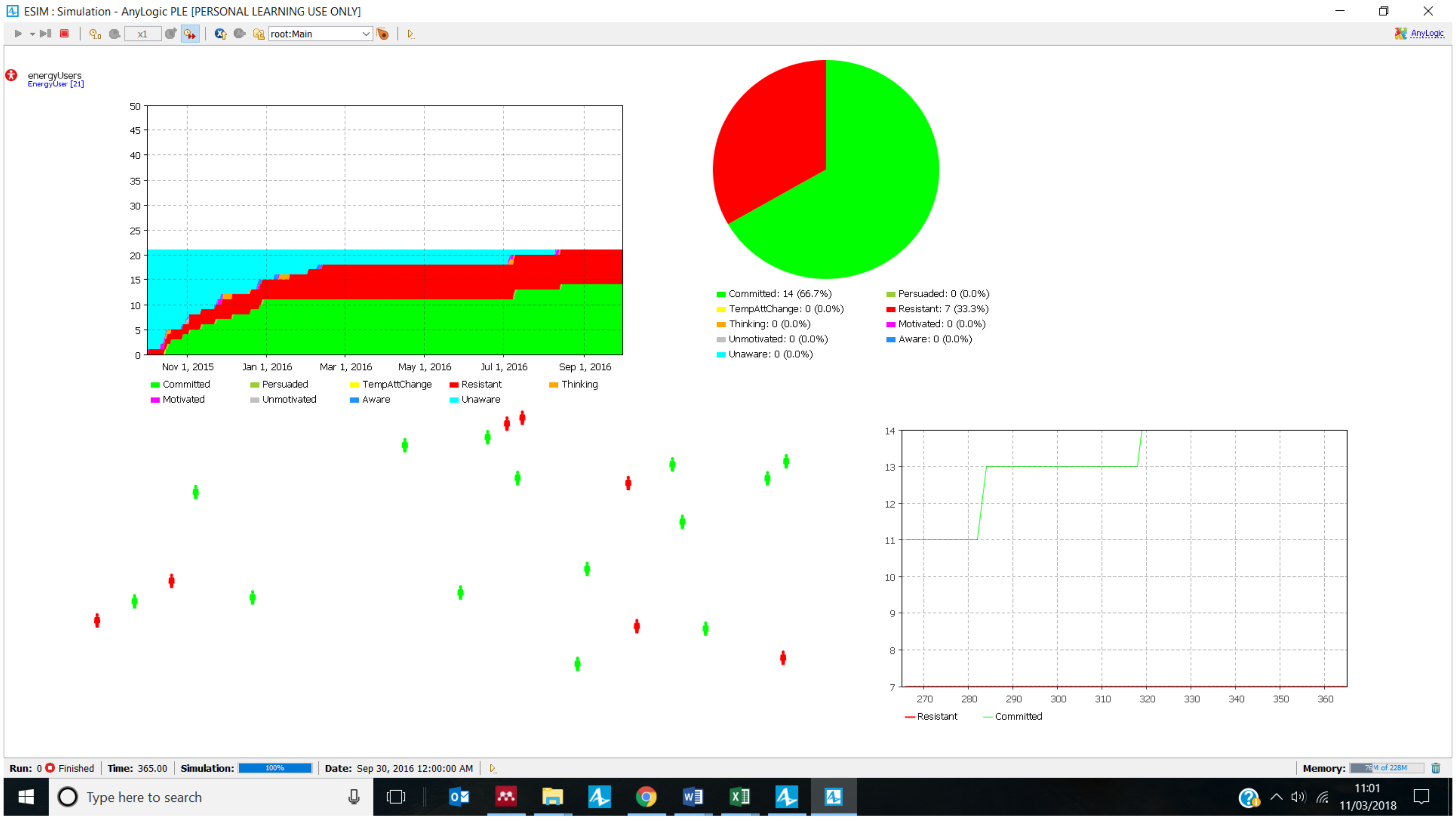

Figure E.2 Model output screen for end state *Committed* (*Intention*)

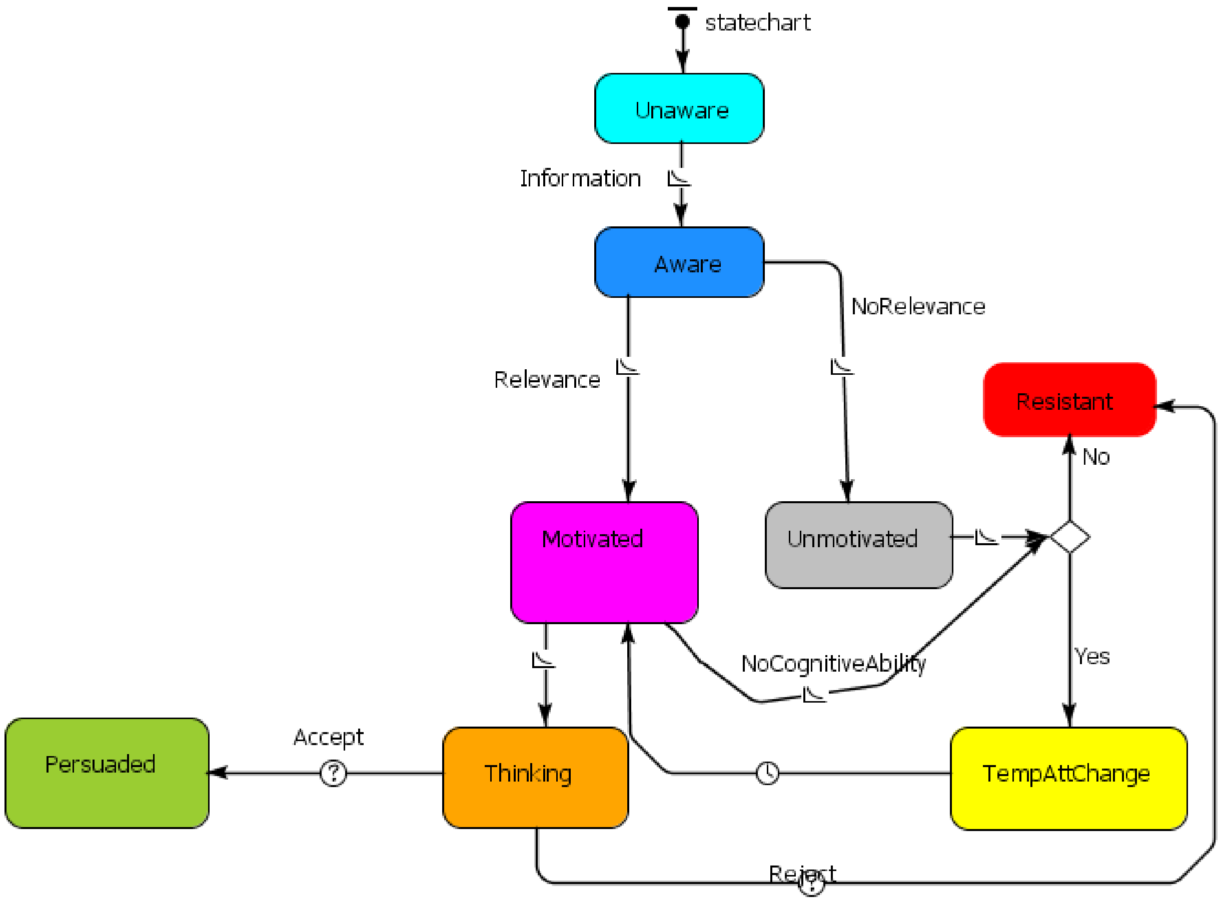

Figure E.3 Model version with end state *Persuaded* (i.e. *Attitude*)

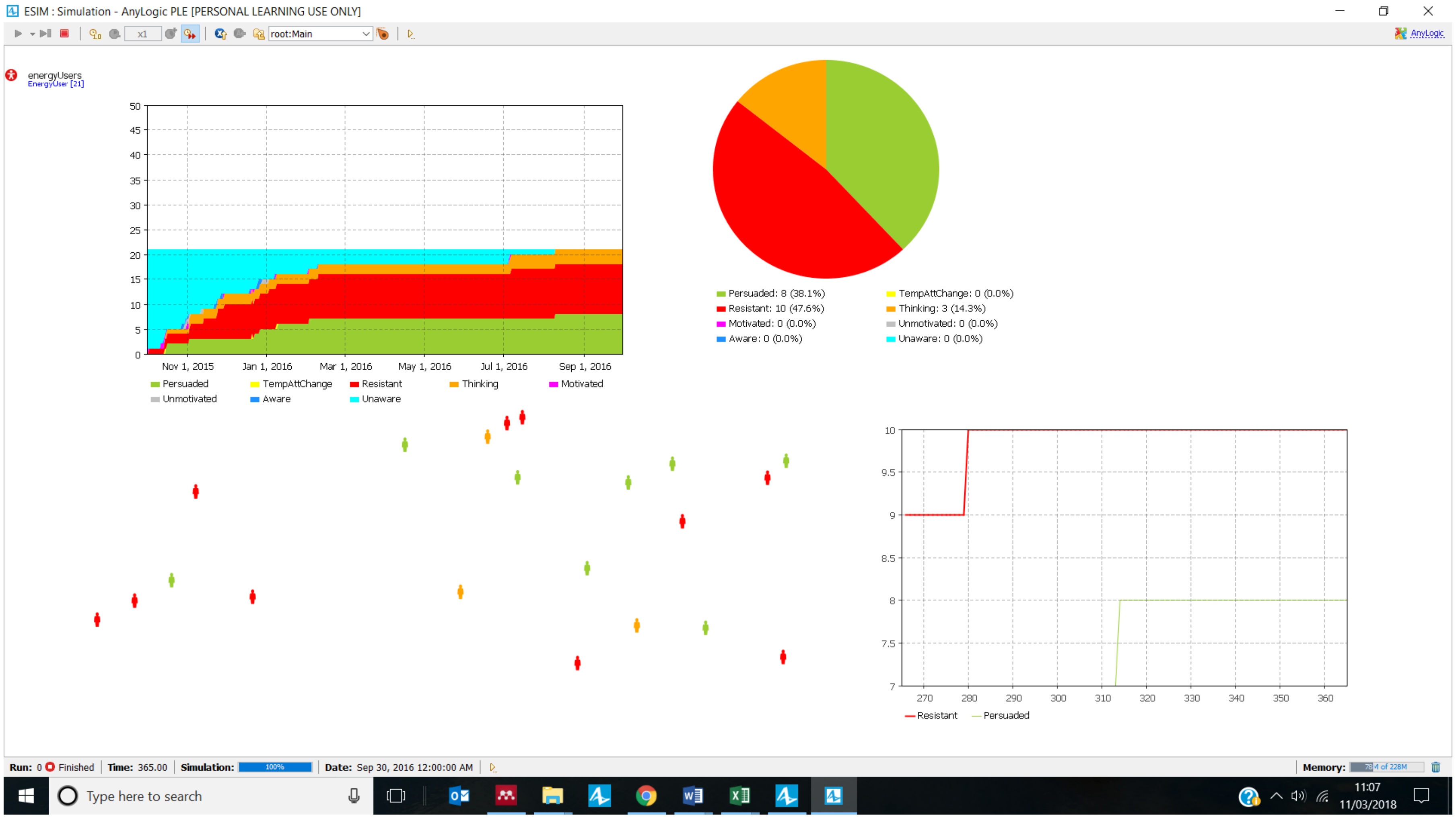

Figure E.4 Model output screen for *Attitude* as end state

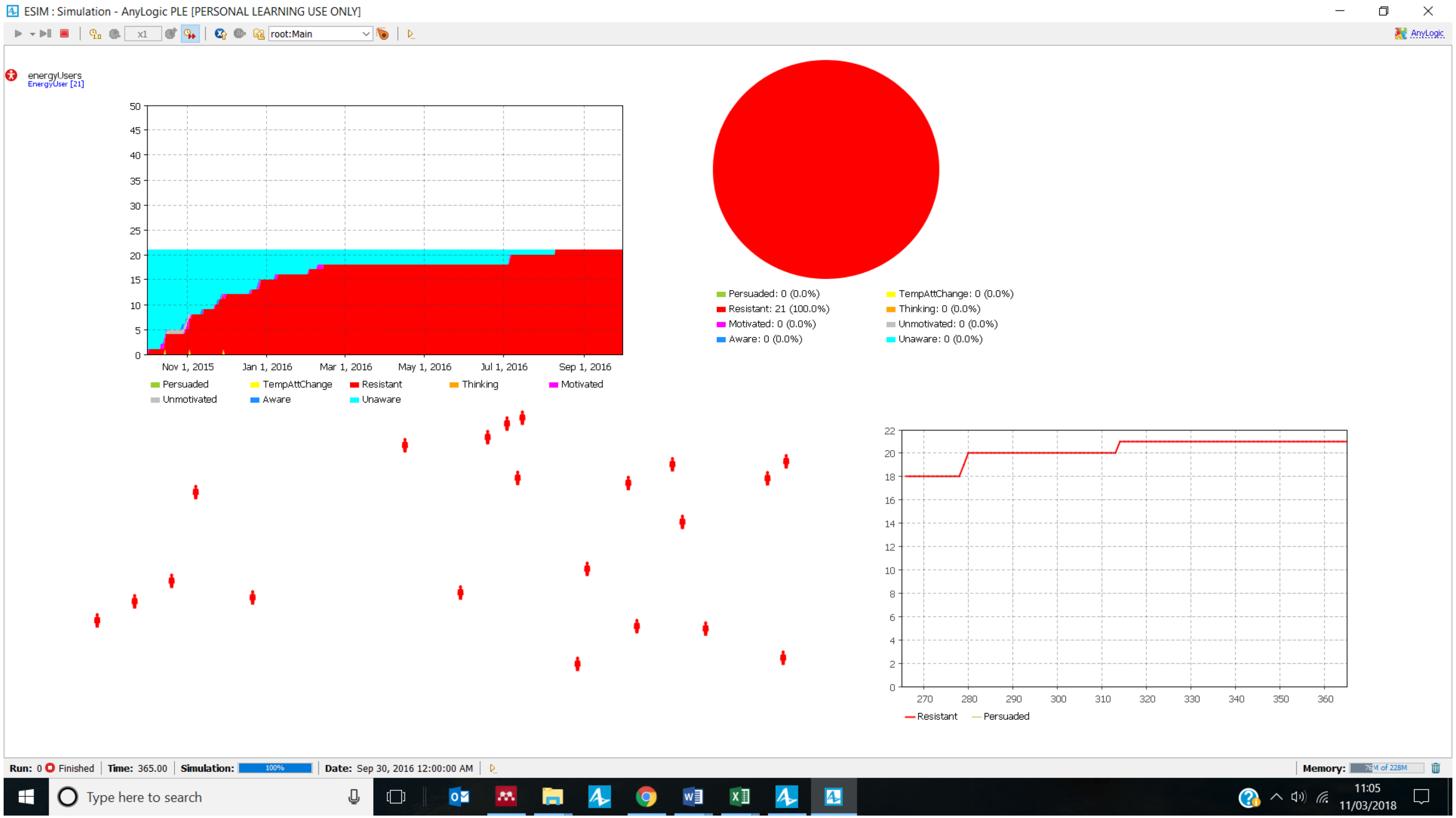

Figure E.5 Demonstrating that when *Argument quality* is lacking, there is no attitude change

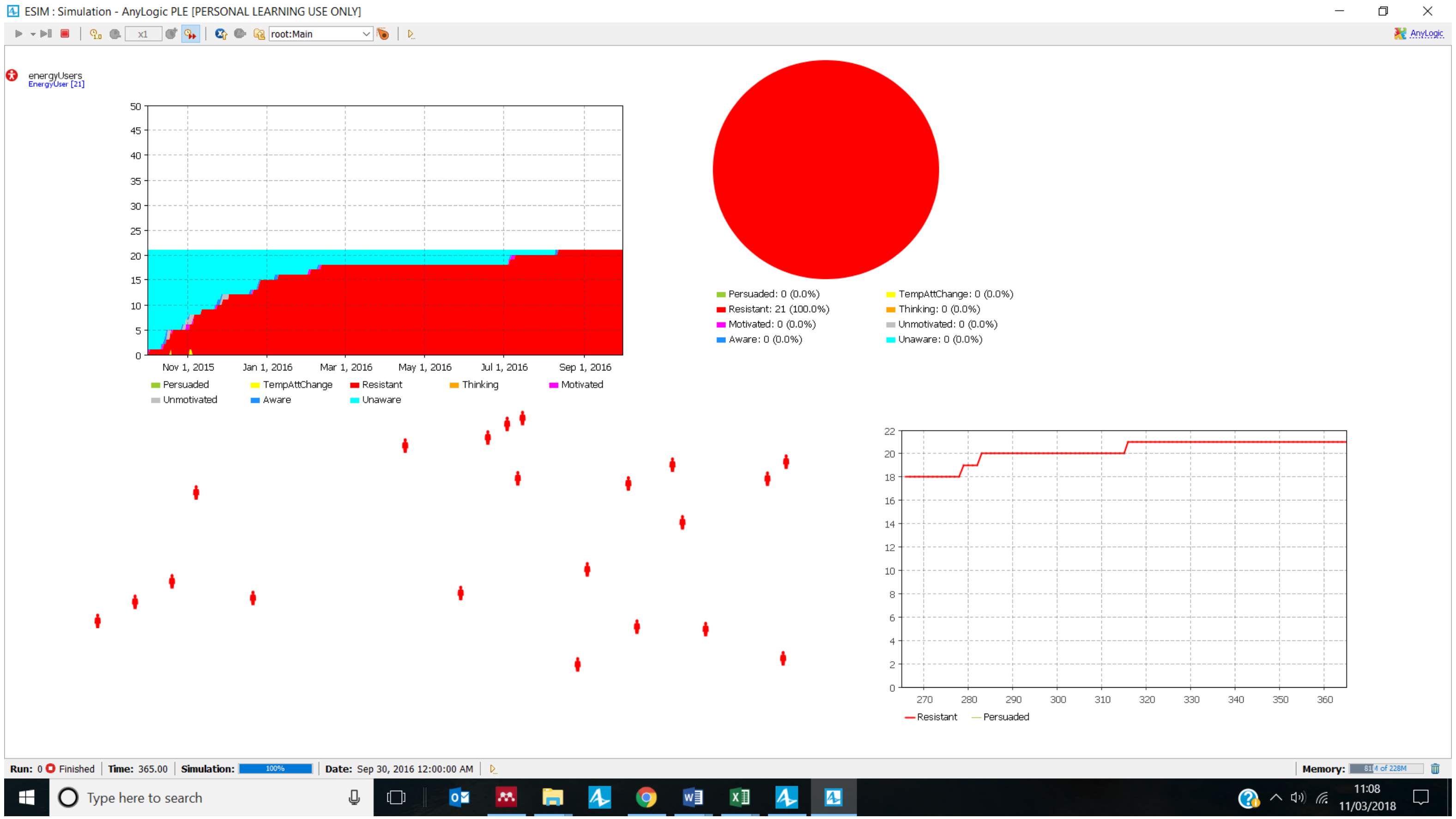

Figure E.6 Demonstrating that when *Motivation* is lacking, there is no attitude change

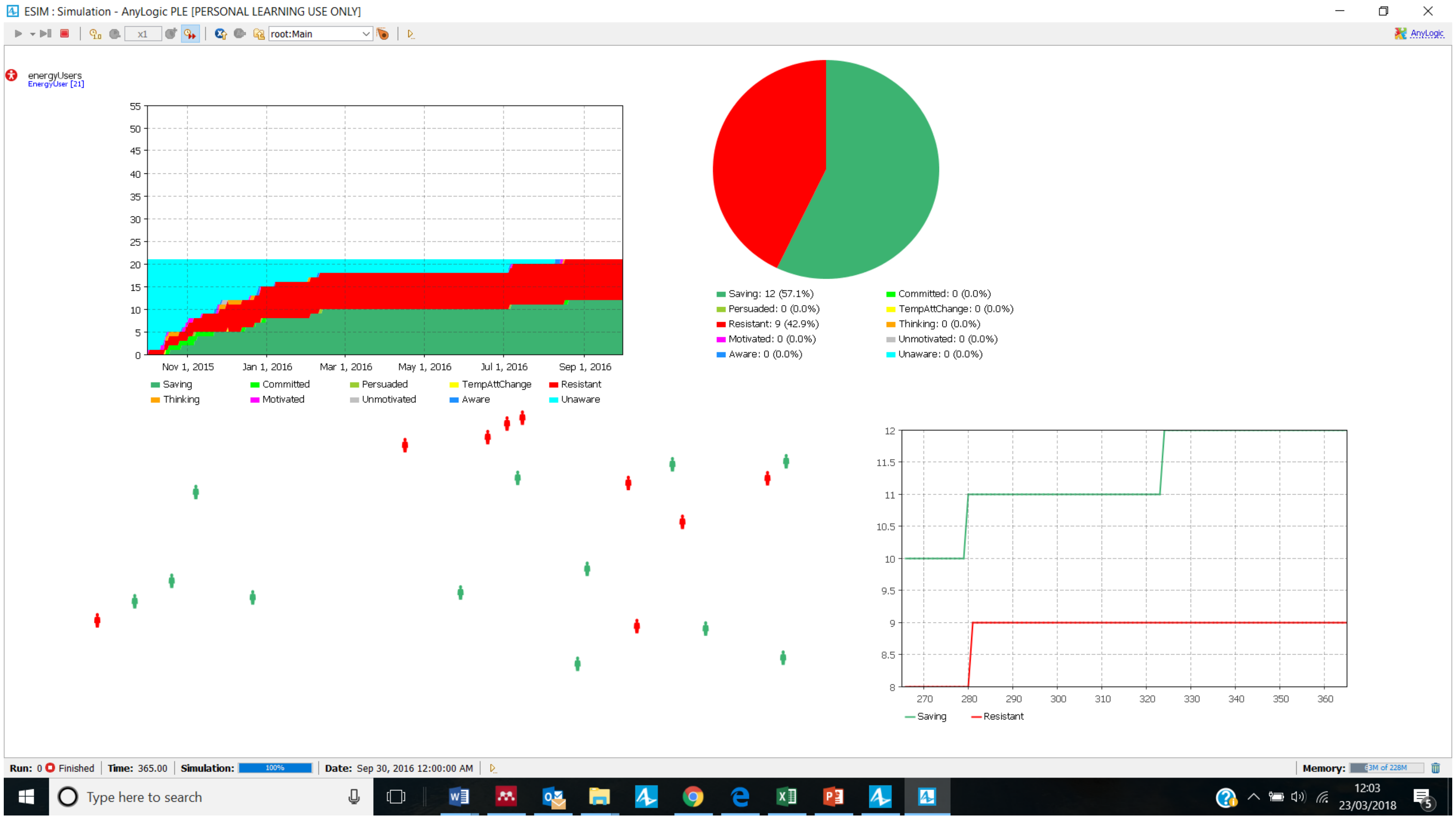

Figure E.7 Showing that all committed agents became energy savers

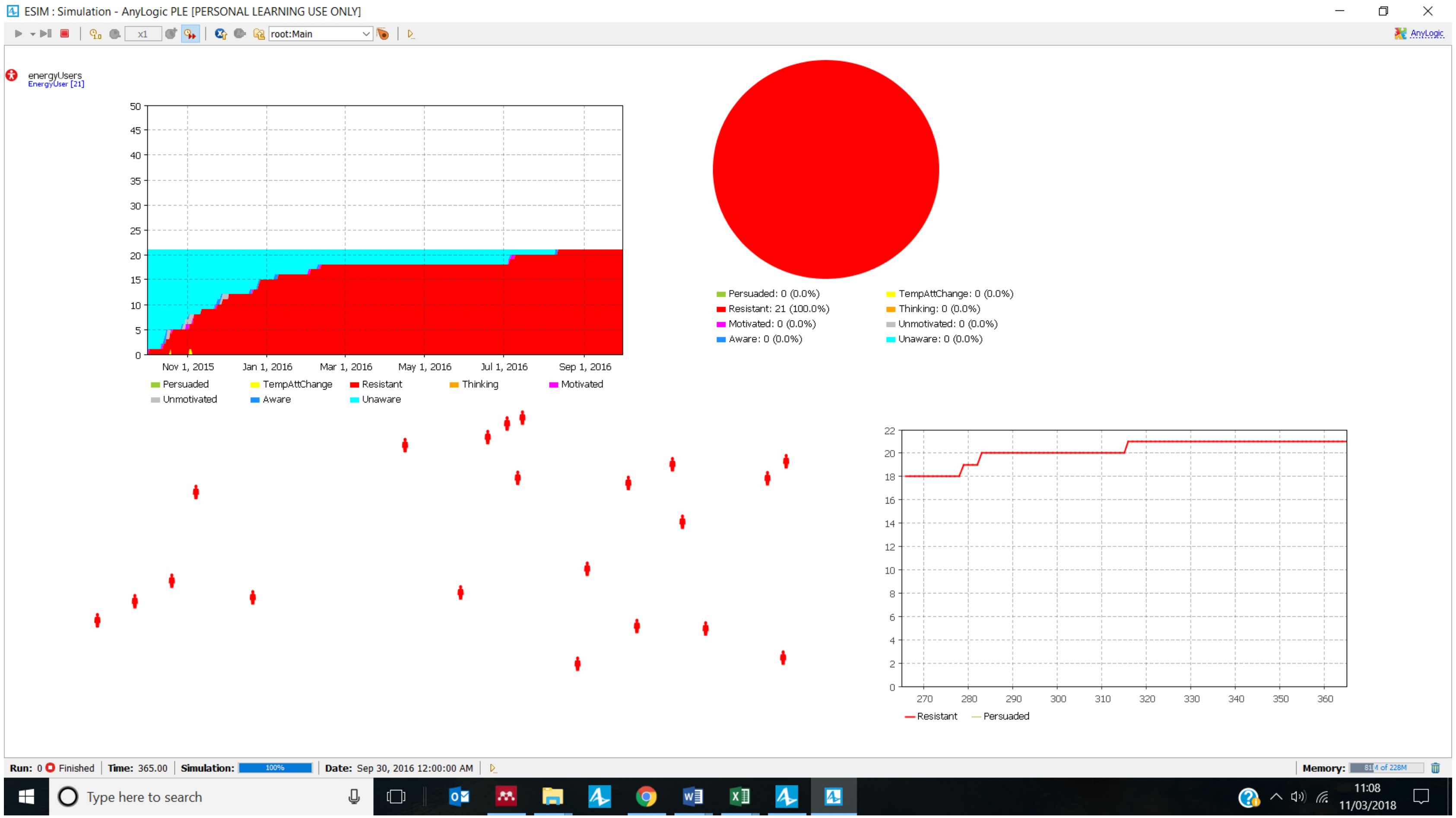

Figure E.8 Showing that attitude change is not achieved in the absence of *Cognitive ability*.

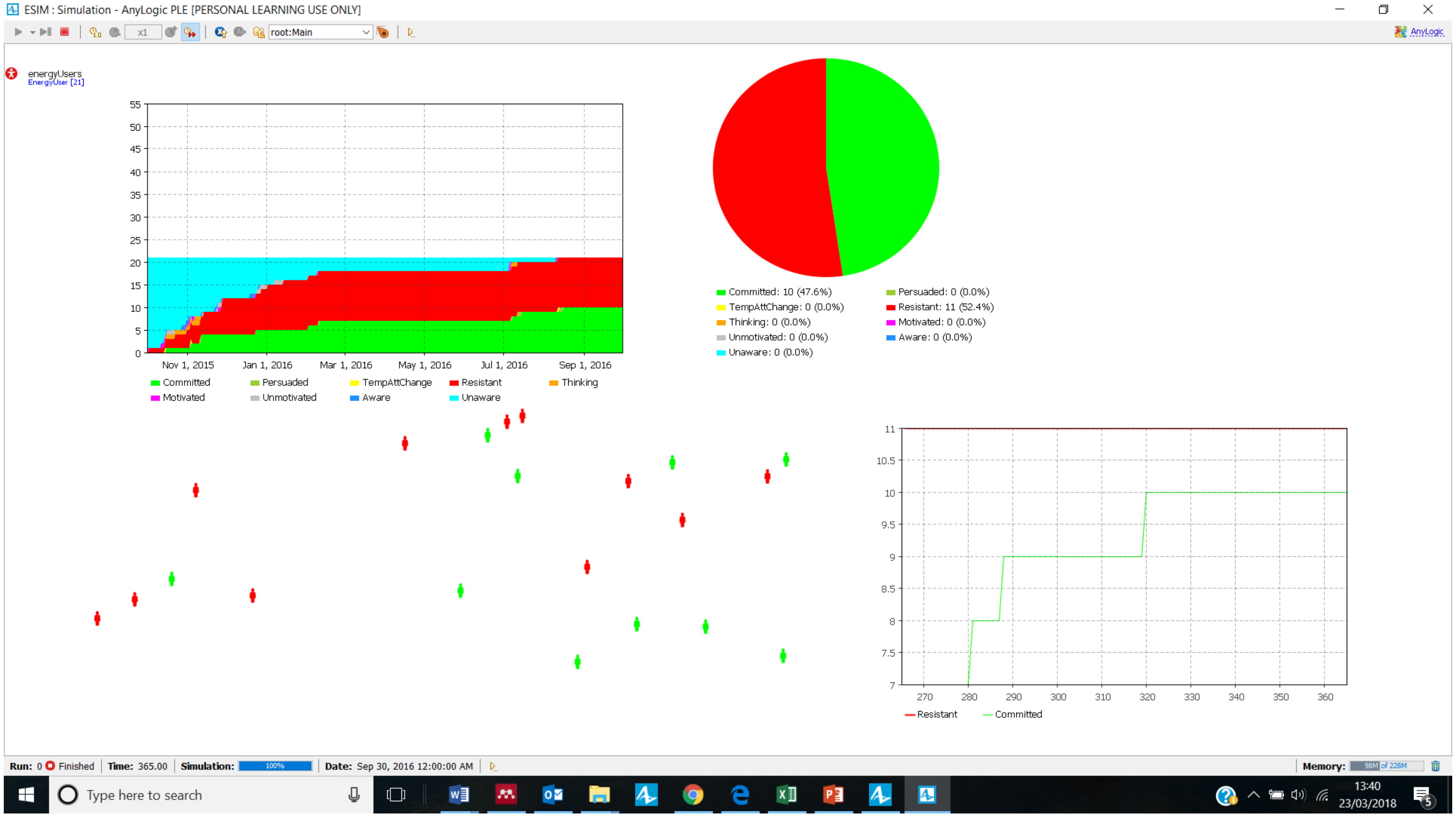

Figure E.9 Showing that *Intention* reduced in the absence of *Perceived behavioural control* (compare this to Figure E.2)