Breaking down silos: simulating consumer investment decisions in the multi-actor UK retrofit system

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Abstract

With energy use in UK domestic buildings accounting for nearly one-third of the country's total final energy consumption[1], there is a consistent interest in systems analysis research on the barriers and drivers to domestic building retrofit. The differences in how actor groups perceive and overcome retrofit barriers in the UK residential sector have been highlighted in previous research, and the importance of understanding them in creating robust policies and incentives has been highlighted. The purpose of our research is to identify, quantify and model actor-specific barriers and drivers to the uptake of energy efficiency measures, considering interactions between actors in the sector. This paper will focus on the conceptualization of an agent-based model (ABM) which seeks to simulate these barriers and drivers, and is integrated into MUSE ® (ModUlar energy systems Simulation Environment), a technology-rich, global 28-region simulation model of long-term energy transitions being developed at Imperial College London.

The purpose of this ABM is to simulate the adoption of energy-saving technologies by resident agents, considering their relationship with different actors in the retrofit system, including their peers. The decision to adopt is simulated as a deliberative decision-making process, based on the Theory of Planned Behavior[2]. Within this process, the impact of agents' interactions with their peers on their decision is simulated by incorporating subjective norm constructs (descriptive and injunctive norms) into the decision-making process. The impact of agent's relationships with other actors in the retrofit sector is simulated by assigning a level of exposure to and trust in these actors (such as public authorities, landlords and energy companies), thereby simulating the likelihood of the actors having an effect on the agent's decision to adopt a retrofit measure. These interactions of agents with their peers and with actors in the sector thus affect the decision of an agent to adopt a retrofit measure, in addition to the effect of the agent's characteristics (such as risk aversion and socio-demographic characteristics) and the characteristics of the technology (capital cost, availability of financing, payback period etc.).

By incorporating interactions into the agent decision-making framework, we aim to represent, as

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[1] BEIS, "Energy Consumption in the UK" (London, 2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/729317/Energy_Consumption_in_the_UK__ECUK__2018.pdf.
[2] Icek Ajzen, "The Theory of Planned Behavior," *Organizational Behavior and Human Decision Processes* 50, no. 2 (December 1, 1991): 179–211, doi:10.1016/0749-5978(91)90020-T.

realistically as possible, the heterogeneity of residential consumers in the UK retrofit sector. Once developed, it is hoped that the ABM will be able to support policy-makers and industrial actors in understanding how the interactions within the retrofit sector affect consumers' propensity to invest in energy-saving measures, thus identifying the gaps and opportunities for incentivising uptake of retrofit. Conceptually, this model aims to break down the "silos" within which decision-making for retrofit uptake is assumed to occur, and provide a better picture of the complex interactions within the sector, leading to improved design and delivery of policies and programmes to increase energy efficiency in the residential built environment.

Introduction

The UK residential retrofit sector offers an interesting test-bed for assessing and simulating energy efficiency in the housing retrofit sector, using innovative systems transitions theories and behavioral modelling frameworks. This is partly due to the complexity of interactions between actors in the residential retrofit sector[3], but also due to the poor understanding of non-technical and non-economic barriers to uptake of retrofit[4]. Incorporating the role of stakeholders in the retrofit sector (ranging from making energy consumption decisions to shifting wider market trends) is thus key to advancing reliable and robust frameworks for analyzing and projecting the future energy efficiency and carbon emissions of the housing sector.

The above call for evaluating energy consumption as an integral part of a complex system indicates a salient need for systems thinking in energy consumption research. The case for systems thinking is further supported by the fact that energy-saving interventions are also part of complex regimes, and rarely operate in isolation. This is characteristic of many environmental-related behavior change interventions, and was noted as early as the 1990s[5]. Another gap in the assessment of residential energy behavior and energy-saving interventions is the lack of methodological rigor across the literature. From a survey of peer-reviewed literature on residential energy consumption behavior, [6] conclude that, in many cases, the deployed methodologies are not capable of producing unbiased estimates of behavior change. As a result, they cannot form the basis of robust quantitative modelling frameworks, and thus research into energy efficiency behavior does not achieve its potential contribution to understanding and forecasting energy consumption and related carbon emissions, an area of research of great interest in the current climate change mitigation debate.

While some of the above methodological shortfalls are difficult to avoid, it becomes clear that current research on residential energy efficiency only weakly incorporates a deep understanding of the system within which this sector is embedded and its complexities. Our research seeks to implement a widely used behavioral framework, generally known as the Theory of Planned Behavior (TPB), into a quantitative model capable of being

[3] ARUP, "Towards the Delivery of a National Residential Energy Efficiency Programme," no. May (2016).
[4] Joanne Wade and Nick Eyre, "Energy Efficiency Evaluation : The Evidence for Real Energy Savings from Energy Efficiency Programmes in the Household Sector," 2015.
[5] John P. Dwyer, "The Use of Market Incentives in Controlling Air Pollution: California's Marketable Permits Program," *Ecology Law Quarterly* (University of California, Berkeley), accessed July 30, 2018, doi:10.2307/24113100.
[6] Elisha R. Frederiks et al., "Evaluating Energy Behavior Change Programs Using Randomized Controlled Trials: Best Practice Guidelines for Policymakers," *Energy Research & Social Science* 22 (2016): 147–64, doi:10.1016/j.erss.2016.08.020.

integrated into the MUSE ® modelling framework, a global bottom-up energy model under development at Imperial College London. In this paper, we review the potential for agent-based modelling to translate theoretical behavioral modelling frameworks into energy systems modelling frameworks. We then propose a methodology for using TPB to simulate investment by agents in energy-saving renovations of their homes, and translating this into an agent-based model (ABM) to be integrated into the Residential Building Sector (RBSM) module of the MUSE ® modelling framework. The remainder of this paper is structured into a background section, exemplifying relevant applications of the TPB framework and agent-based modelling, and a methodological proposal section, which outlines the conceptual ABM under development. The paper concludes on future steps and potential for further research in this area.

Background

Translating theoretical behavioral frameworks into quantitative modelling frameworks is a challenging task of research on housing energy retrofit, particularly when accounting for social networks and sectoral influences. Traditional bottom-up energy models for residential energy consumption either suffer from assumptions on occupant behavior (bottom-up engineering models) or the inability to model new technologies (bottom-up statistical models)[7]. Recently, various models based on empirical data have been applied in order to overcome these challenges on modelling occupant behavior and technological uptake: [8] use a discrete-choice model to investigate the impact of pro-environmental attitudes on the adoption of energy-saving measures, [9] proposes an explanatory model to explain the energy efficiency investment behaviors of small private landlords in Germany and [10] use a combination of diffusion-of-innovation and environmental psychology modelling to analyze consumer adoption of solar heating systems in Lebanon.

Several researchers have developed models for projecting the uptake of energy technologies, using TPB as the underlying framework for modelling the stages in decision-making of agents. The TPB framework constructs decision-making processes as a sequence of 3 stages, through which an individual moves in order to arrive at a certain behavior: (1) pre-existing state (based on personal attitude towards, and perceived control of, the outcomes of a behavior, and the attitude of the social network towards this behavior, or the “subjective norm”), (2) formulation of an intention to conduct the behavior and (3) implementation of the behavior itself. [11] used the TPB framework to propose a behavioral

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[7] Lukas G. Swan and V. Ismet Ugursal, “Modeling of End-Use Energy Consumption in the Residential Sector: A Review of Modeling Techniques,” *Renewable and Sustainable Energy Reviews* 13, no. 8 (2009): 1819–35, doi:10.1016/j.rser.2008.09.033.

[8] Ana Ramos, Xavier Labandeira, and Andreas Löschel, “Pro-Environmental Households and Energy Efficiency in Spain,” *Environmental and Resource Economics* 63, no. 2 (February 7, 2016): 367–93, doi:10.1007/s10640-015-9899-8.

[9] Steven März, “Beyond Economics—understanding the Decision-Making of German Small Private Landlords in Terms of Energy Efficiency Investment,” *Energy Efficiency*, September 20, 2017, 1–23, doi:10.1007/s12053-017-9567-7.

[10] Houda Elmustapha, Thomas Hoppe, and Hans Bressers, “Consumer Renewable Energy Technology Adoption Decision-Making; Comparing Models on Perceived Attributes and Attitudinal Constructs in the Case of Solar Water Heaters in Lebanon,” *Journal of Cleaner Production* 172 (January 20, 2018): 347–57, doi:10.1016/J.JCLEPRO.2017.10.131.

[11] Christian A. Klöckner and Alim Nayum, “Psychological and Structural Facilitators and Barriers to Energy Upgrades of the Privately Owned Building Stock,” *Energy* 140 (December 1, 2017): 1005–17, doi:10.1016/J.ENERGY.2017.09.016.

model for individuals conducting home energy upgrades. The authors added components to the original framework in order to better describe the morals, innovativeness and belief that their behavior will make a difference, of individuals. Figure 1 shows the resulting behavioral model, within which the different stages of the original TPB framework can be identified.

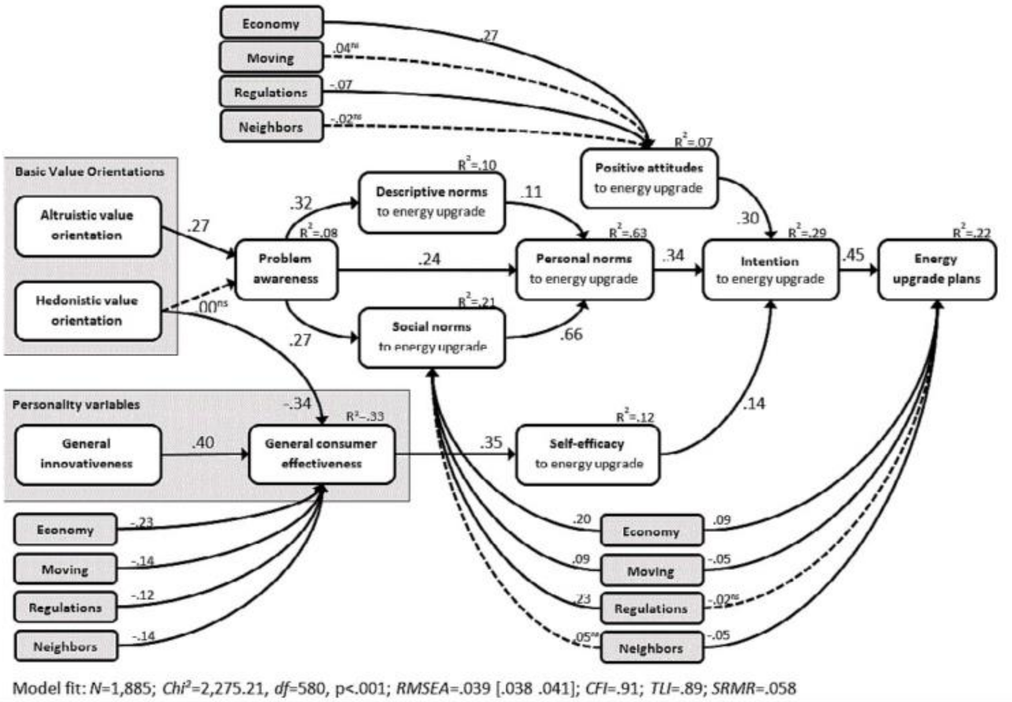

Figure 1. Behavioral model used by [11] based on the TPB framework.

While the TPB framework is well-established in explaining long-term deliberative behavior such as investment in energy-saving renovations, descriptive models such as that proposed by[11] tend to be more suitable for theoretical enquiry and investigative research, rather than translation into a quantitative modelling framework. Recently, agent-based modelling has emerged as a tool for translating individual behavior, such as that described in the TPB framework, to quantitative models and simulation environments. Agent-based modelling is a type of computational modelling which simulates the actions and relationships of autonomous agents (individual or collective). The purpose of ABMs is to determine the effects which the actions of agents have on the system which they are embedded in. In the case of the diffusion of new technologies, or innovations, agent-based modelling has been extensively used to simulate the complex emergence phenomena relevant to this research area. Agents are assumed to behave within a model of bounded rationality, using basic heuristic rules to increase their utility. However, they can change their behavior in response to a shift in the properties of the system, and they interact with each other through social networks or access of social resources[12].

Agent-based modelling overcomes some of the challenges faced by traditional aggregate models, when attempting to simulate the uptake of innovations by human actors. Looking

[12] Elmar Kiesling et al., "Agent-Based Simulation of Innovation Diffusion: A Review," *Central European Journal of Operations Research* 20, no. 2 (June 2012): 183–230, doi:10.1007/s10100-011-0210-y.

towards the domestic energy research field, ABMs have been used mostly to simulate energy consumption in buildings, both commercial and residential. [13] use agent-based modelling to simulate the behavior and energy consumption of multiple users in commercial buildings. [14] also focus on occupant behavior in commercial buildings. [15] dock an ABM to an equational model, in order to model national-scale domestic energy consumption and carbon emissions in the UK. Researchers in the UK's ongoing ENLITEN project are developing a building occupant model, using data from qualitative surveys[16].

ABMs have also been used, more specifically, for projecting the diffusion of household energy technologies and energy renovation habits. [17] propose an ABM to predict the uptake of highly efficient lighting in the residential sector. [18] present an ABM focused on the adoption of solar PV installations in households. In a related study, the same authors develop four variations of the adoption ABM, finding that high-resolution (agent-level) data on attitudes and social networks is necessary to predict patterns of residential solar PV adoption. [19] apply an ABM to heating feedback devices, to assess the diffusion of this technology and related behavior change between households. In a similar study, the same authors assess the impact and diffusion potential of "CO_2 meters" in Germany [20]. Another ABM was presented by the same authors in [21], to simulate the uptake of feedback technologies under different simulated marketing strategies. They identified an important role of socially influential individuals and information, in addition to eliminating initial costs for the first few devices.

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[13] Yoon Soo Lee and Ali M Malkawi, "Simulating Multiple Occupant Behaviors in Buildings: An Agent-Based Modeling Approach," *Energy & Buildings* 69 (2014): 407–16, doi:10.1016/j.enbuild.2013.11.020.

[14] Elie Azar and Cc Menassa, "Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings," *Journal of Computing in Civil Engineering* 26, no. August (2011): 506–18, doi:10.1061/(ASCE)CP.1943-5487.0000158.

[15] Sukumar Natarajan, Julian Padget, and Liam Elliott, "Modelling UK Domestic Energy and Carbon Emissions: An Agent-Based Approach," *Energy and Buildings* 43, no. 10 (2011): 2602–12, doi:10.1016/j.enbuild.2011.05.013.

[16] Tom Lovett et al., "'Just Enough' Sensing to ENLITEN A Preliminary Demonstration of Sensing Strategy for the 'ENergy LIteracy Through an Intelligent Home ENergy Advisor' (ENLITEN) Project," *'E-Energy "13: Proceedings of the Fourth International Conference on Future Energy Systems,"* 2013, doi:10.1145/2487166.2487206.

[17] Jinjian Cao, Chul Hun Choi, and Fu Zhao, "Agent-Based Modeling of the Adoption of High-Efficiency Lighting in the Residential Sector," *Sustainable Energy Technologies and Assessments* 19 (February 1, 2017): 70–78, doi:10.1016/J.SETA.2016.12.003.

[18] Scott A Robinson and Varun Rai, "Determinants of Spatio-Temporal Patterns of Energy Technology Adoption: An Agent-Based Modeling Approach," *Applied Energy* 151 (2015): 273–84, doi:10.1016/j.apenergy.2015.04.071.

[19] Thorben Jensen, Georg Holtz, and Émile J.L. Chappin, "Agent-Based Assessment Framework for Behavior-Changing Feedback Devices: Spreading of Devices and Heating Behavior," *Technological Forecasting and Social Change* 98 (September 1, 2015): 105–19, doi:10.1016/J.TECHFORE.2015.06.006.

[20] Thorben Jensen et al., "Energy-Efficiency Impacts of an Air-Quality Feedback Device in Residential Buildings: An Agent-Based Modeling Assessment," *Energy and Buildings* 116 (March 15, 2016): 151–63, doi:10.1016/J.ENBUILD.2015.11.067.

[21] Thorben Jensen and Émile J.L. Chappin, "Reducing Domestic Heating Demand: Managing the Impact of Behavior-Changing Feedback Devices via Marketing," *Journal of Environmental Management* 197 (July 15, 2017): 642–55, doi:10.1016/J.JENVMAN.2017.04.036.

Several studies apply the TPB framework as a conceptual foundation for developing ABMs. For example, [22] propose an ABM based on the TPB framework, for predicting the adoption of residential solar PV in Austin, Texas. They define the attitude of their agents as a weighted average of financial, environmental and social beliefs of individuals, subjective norms as the average number of contact with adopters of residential solar PV, and perceived behavioral control as the minimum tolerable payback time for the technology. Of relevance to our research was the method used to simulate agent social networks, which the authors did on the basis of income similarity between agents, with some added stochasticity to simulate random connections within an agent's social network. The evolution of agent attitudes over time was simulated based on these interactions within an agent's network, using the Relative Agreement algorithm in a small-world social network.

There is agreement within most research that energy-saving renovation behavior has a highly deliberative decision-making processes, within which a number of stages must be distinguished and analyzed. The complexity of the decision-making process is further enhanced by the effects of agent-agent interaction, as demonstrated in the application of ABMs to renovation problems. However, agent-based modelling provides a useful framework for the simulation of behavior and interaction in multi-actor complex systems. Although not without its challenges, it offers multiple opportunities in the modelling of systems described in socio-technical terms, the simulation of social networks and informal information flows such as word-of-mouth, and the differentiation of agents based on their aversion to innovation. This last opportunity is highly important in the provision of robust policy recommendations for variable targeting of households. Furthermore, agent-based modelling can be docked against other models to form integrated frameworks (e.g. [23]), such as network models, cellular automata structures and fuzzy logic, to provide an even more comprehensive picture of the complex behavior of residential retrofit actors.

Methodological proposal

The purpose of this research is to model the probability of adoption of different energy technologies by agents in the UK retrofit sector, and integrate this model into the MUSE ® modelling framework. The framework for definition of the agents and their decision-making process should be designed to be flexible enough for any other retrofit measures to be included as inputs to the model, provided the techno-economic characteristics are available and accurate. The following sections outline the methodological proposal for characterizing and initializing the agents, and simulating their decision-making processes based on the TPB framework.

Agent characterization

In the first step of developing the ABM, agents must be characterized according to a number of attributes. In this ABM, the agents are defined as households, as opposed to dwellings (physical properties), which avoids the complications of updating agent

[22] Varun Rai and Scott A. Robinson, "Agent-Based Modeling of Energy Technology Adoption: Empirical Integration of Social, Behavioral, Economic, and Environmental Factors," *Environmental Modelling & Software* 70 (August 2015): 163–77, doi:10.1016/j.envsoft.2015.04.014.

[23] Natarajan, Padget, and Elliott, "Modelling UK Domestic Energy and Carbon Emissions: An Agent-Based Approach."

attributes when a property is demolished. The personal characteristics of the agent are the attributes of one household member, considered to be the main decision-maker with regards to property upgrades. The selected agent attributes are listed in Table 1.

Table 1. Preliminary agent attributes for characterization.

Household characteristics	**Personal characteristics**	**National characteristics**
Property type	Education level	Individualism
Floor area	Age bracket	Uncertainty avoidance
Number of residents	Environmental attitude	Power distance
Age of property	Social network attitude	Masculinity
Tenure of property	Perceived behavioral control	
Length of tenure	Exposure to technology	
Combined income	Technology attitude	
Annual energy consumption	Exposure to sector agents	
	Attitude towards cost/importance of wealth	
	Attitude towards comfort/hedonism	
	Attitude towards convenience	

The “national characteristics” attributed to populations of agents national to the same country are derived from Hofstede’s national cultures framework Geert Hofstede, “The Cultural Relativity of Organizational Practices and Theories,” *Journal of International Business Studies* 14, no. 2 (June 1, 1983): 75–89, doi:10.1057/palgrave.jibs.8490867.. The purpose of including these characteristics is to derive useful agent attributes from national-level characteristics:

1. Individualism (defined as the extent to which individuals are integrated into “strong, cohesive in-groups”) is used to derive the level of interaction between an agent and their peers;
2. Uncertainty avoidance (defined as the extent to which individuals are fearful of uncertain or unknown situations) is used to derive the general level of innovativeness of an agent
3. Power distance (defined as a measure of individual sensitivity to status differences and motivation to conform to a status group) is used to derive the attitude towards social network influencers and as a precursor to the exposure to sector agents
4. Masculinity (defined as a measure of the distinctiveness between gender roles, with masculine cultures emphasizing material success, wealth and achievement) is used to derive the relative weighting.

Out of the personal characteristics of the agent, the “technology attitude” is one of the most important, as it allows disaggregation of the agent’s attitude towards technology and innovation, which is usually treated broadly, using concepts such as general innovativeness (or “uncertainty avoidance”) to place agents in populations according to the theory of diffusion of innovation[24]. This theory states that agents can be grouped into

[24] Ismail Sahin, “Detailed Review of Roger’s Diffusion of Innovation Theory and Educational Technology-Related Studies Based on Roger’s Theory,” *The Turkish Online Journal of Educational*

different populations, or categories, according to their relative propensity to adopt new products or technologies. However, the tendency of behavioral models to characterize agents based on general “innovativeness”, or propensity to adopt new products in general, risks ignoring the fact that attitudes of agents towards new technologies can be differentiated according to various agent characteristics: for example, an agent may have a higher propensity to adopt a new technology if its cost is lower, its demonstrability is higher, it directly addresses a high priority of the agent, or a number of other motives. By introducing the “technology attitude” characteristic, we aim to construct a simple model, which could predict the likelihood of adoption of a technology by an agent, based on the combination of technology and agent characteristics.

Based on personal and household characteristics, agents can be grouped into different representative categories for simulating investment decision-making processes. Grouping agents into these categories reduces the need for simulating individual agents with pre-assigned characteristics, but rather allows to simulate a pre-defined number of agents with the same characteristics, which are allowed to vary randomly within a certain range, to simulate uncertainty. This grouping of agents should be done based on robust statistical techniques, such as cluster analysis, a technique which forms natural groupings based on similarities in data on certain pre-assigned variables, such as the above-mentioned personal and household characteristics.

Technology characterization

A number of household energy technologies (production, management and consumption) are prescribed for inclusion into the ABM. The list of these technologies should be flexible according to the geographical area within which the agents are being simulated, as this may introduce constraints as to which technologies are available. The technologies are characterized by capital cost, operating cost, lifetime and annual CO_2 emissions.

When agents are characterized as households, the main heating, hot water, lighting and cooling technologies of the property are also assigned to the agent. Replacement of one of these technologies would thus result in a change in operating cost, lifetime and annual CO_2 emissions of the technology; and thus a change in the annual energy consumption and CO_2 emissions of the agent (the household).

Agent initialization

The second step of developing the ABM is to set a procedure for “initializing” the agents; i.e. assigning a trigger for agents to begin considering the option of implementing the behavior of investing in an energy-saving technology. Researchers have proposed a variety of triggers for initializing energy-saving renovation behavior, ranging from a building component reaching its end of life[25] to complicated changes in so-called

Technology – TOJET April 5, no. 2 (2006): 14–23, https://pdfs.semanticscholar.org/8fd5/7ff59979753a03f3fac0ed241d3eaace8db2.pdf.

[25] Energy Saving Trust, “Trigger Points: A Convenient Truth” (London, 2010), http://www.energysavingtrust.org.uk/sites/default/files/reports/EST_Trigger_Points_report.pdf.

Conditions of Domestic Life, including tensions between household member priorities and needs[26].

We propose to initialize agents based on a number of possible conditions:

1. A technology reaching the end of its life
2. A technology becoming affordable to household of a certain income
3. A short tenure length combined with an advanced property age
4. Change of tenure from tenant to owner
5. Change of property, with the agent owning the new property
6. Change in adoption of the technology within the agent's social network
7. Change in household composition, e.g. childbirth
8. Retirement of the principal decision-maker
9. External intervention, such as an information campaign or government legislation

Each condition, or combination of conditions, will trigger agents to begin the decision-making process; however, not all agents will be triggered in the same way, and as such the ABM needs to know which agent category is triggered by which conditions, whether there is need for repetition of a condition before triggering occurs, and which conditions change over time (e.g. whether susceptibility to external intervention decreases with advancing age of the agent).

Decision-making process

Once the agents have been characterized and initialized, they initiate their decision-making process. As we propose to apply the TPB to the agent decision-making process, the agent attributes outlined in the "Agent characterization" section will be used to derive the 3 main constructs which make up the pre-disposition of agents to undertaking retrofit investment. If this pre-disposition is positive towards retrofit behavior, the agent moves to the "intention" stage, in which the agent must analyze the different constraints on performing the behavior. If these constraints can be removed, the agent can move to the implementation of the behavior (Figure 2).

[26] C Wilson, H Pettifor, and G Chryssochoidis, "Quantitative Modelling of Why and How Homeowners Decide to Renovate Energy Efficiently," *Applied Energy* 212, no. November 2017 (2018): 1333–44, doi:https://doi.org/10.1016/j.apenergy.2017.11.099.

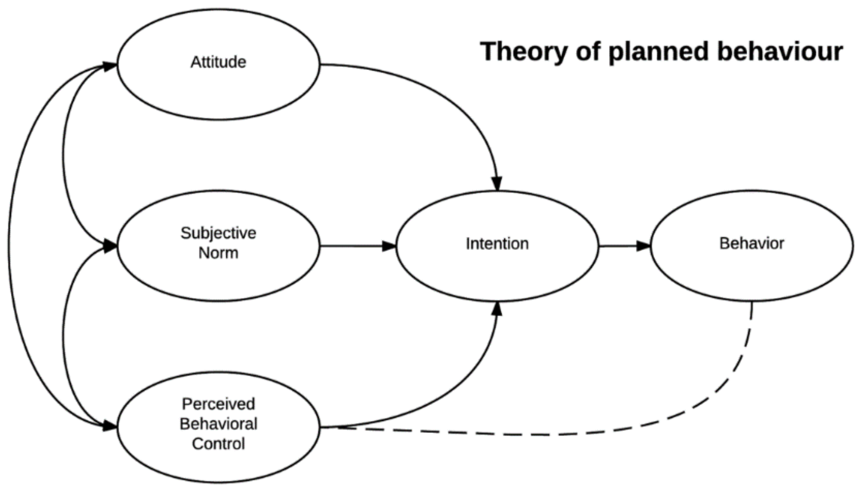

Figure 2. Overview of the Theory of Planned Behavior (TPB) framework.

Agent pre-disposition

The 3 constructs of agent pre-disposition are:

1. Attitude of agent (derived from behavioral beliefs):

The attitude component of the framework is composed of the agent's attitude towards the technology in question and towards their objectives (cost minimization, comfort and convenience maximization, emissions minimization).

Attitude towards technologies. This component is expressed as a weighted product of the strength and age of the linkage between the agent and the technology, separated into "positive" or "negative" through a threshold which needs to be confirmed.

The strength of the linkage is defined as the level of interaction between an agent and a technology, expressed through a Likert scale (Table 1).

Table 2. Description of linkage strengths and associated Likert scaling.

Strength of linkage	Description	Likert scaling
Very strong	Has used in the past (positive outcome)	7
Strong	Is aware and high likelihood that social network contains adopters	6
Neutral-strong	Is aware but low likelihood that social network contains adopters	5
Neutral	Is not aware but high likelihood that social network contains adopters	4
Neutral-weak	Is not aware	3
Weak	Is not aware and low likelihood that social network contains adopters	2
Very weak	Has used in the past (negative outcome)	1

The age of the linkage is defined as the time since the technology has been available to the agent on the market; defined as time since average price (minus subsidies available) was within income of agent likely to be allocated to property improvements. If the average price is not within this bracket, the value is 0.

The age of the linkage is meant to act as an indicator of exposure to the technology. It will play a less important role than the strength of the linkage in deriving the attitude of the agent towards a technology.

This proposed definition is in line with the general view that attitudes are determined by how much an agent values an object or behavior (the strength of the link) and how accessible that object or behavior is to their memory (the age of the link).

<u>Attitude towards objective functions.</u> This component is expressed through the importance (weight) which an agent assigns to the following objectives, and thus how much the different technology characteristics will move them to an intention-formulation stage.

Cost minimization, with the associated goals: capital cost of renovation not exceeding an income threshold; household energy costs falling below a pre-defined threshold expressed as percentage of household income.

Comfort maximization, with the associated goal: thermal comfort to become neutral for 80% of household occupants.

Convenience maximization, with the associated goals: number of hours spent on operation and maintenance of heating and lighting systems to decrease; number of system failures (e.g. boiler issues) to decrease.

Climate impact minimization, with the associated goals: total amount of CO_2 generated by energy consumption of household to decrease.

Overall, the strength of an agent-technology link will contribute to the strength of the intention to perform a particular retrofit behavior. It does not directly affect the individual's payoff from performing the behavior, but it plays an important role in the progression of the investment decision-making process of the agent, which will be detailed in a different paper. The constraints and weights of the agent's objectives will dictate the individual payoff gained from investing in a certain technology: if the agent is cost-driven (thereby assigning a significant weight to the "cost" objective) and the technology consumes less energy than that which it is replacing, the individual payoff will be higher than for a technology which consumes more energy, but increases thermal comfort.

2. Subjective norm

This construct defines, on the one hand, how normative the behavior that the agent is contemplating is, and how likely the agent is to conform to norms. It is related to the agent's exposure to, and perceived importance of, *wider societal pressure* (e.g. mass media and advertising, simulated in the original Bass model of innovation diffusion by a "p" parameter) and *social network pressure* (e.g. relational or positional pressure from within their social network, simulated in the original Bass model of innovation diffusion by a "q" parameter). The value of these parameters will dictate the value of the network externality (the social payoff) gained from undertaking the relevant behavior (adoption of technology).

Exposure to *wider societal pressure* (mass-media and advertising) is difficult to quantify with global data. However, assumptions about between-country and between-age-range variation in the “p” parameter could be made based on the availability of information on retrofit technologies (exposure) and on social studies on the impact of media and advertising on agent groups (perceived importance).

When considering the “q” parameter, the *social network* of an agent must be defined. If it proposed that this definition be carried out using social network diffusion theory and the social contagion model demonstrated in[27]. This model is a “contagion model”, where the probability of adoption is a product of “exposure” to adopting agents and the “importance” of the relationship to those agents.

a. Exposure can be defined as the number of links to adopting agents at time t. We can presume that the social networks of agents are small-world networks and that most agents have a very small number of connections.
b. The perceived importance of each link can be defined as a weight w_{ij}, which will be based on a number of factors. The most prominent ones are:
   i. Geographical proximity (spatial distance between agents);
   ii. Demographic similarity (difference in age/difference in income between linked agents);

In addition, the weight w_{ij} will be affected by value of Hofstede’s national culture dimensions for a particular agent. [28] conducted a meta-analysis of 293 studies to test their hypotheses on these four dimensions are related to the Bass q/p ratio and thus the relative weight of social network pressure on an agent. The results they obtain are as follows:

a. The shape of the diffusion (q/p ratio) is negatively related to the individualism of a culture and positively related to its masculinity and power distance.
b. The q/p ratio is positively related to the uncertainty aversion of a culture, but only when a product has competing standards.

Estimating values for the p and q parameters will allow the estimation of the network externality of performing a retrofit behavior, i.e. the social payoff of that behavior. This can be done by weighting each link locally with a q parameter (taking into account variation between “normal” agents and “central agents”, in developing countries where diffusion centrality is high) and globally with a p parameter.

Overall, the payoff of conducting the behavior would be of the form:

$$Ui(x) = \sum w(ij)u\big(x(i), x(j)\big) + v(i)(x(i))$$

[27] H Peyton Young, “Innovation Diffusion in Heterogeneous Populations: Contagion, Social Influence and Social Learning,” *American Economic Review* 99, no. 5 (2009), doi:10.1257/aer.99.5.1899.
[28] Christophe Van Den Bulte and Stefan Stremersch, “Social Contagion and Income Heterogeneity in New Product Diffusion: A Meta-Analytic Test,” *Marketing Science* 23, no. 4 (2004): 530–44, doi:10.1287/mksc.1040.0054.

Where x is the state of agent i, $U_i(x)$ is the payoff of agent x in state I, v_i is the individual component of the payoff and $u(x_i, x_j)$ is the network externality that agent i would get from interacting with agent j.

This payoff is then added to the individual payoff described in the previous section, forming a total payoff of conducting the behavior, as perceived by the agent.

3. Perceived Behavioral Control

The last construct of the TPB is perceived behavioral control, a pre-disposition construct which is unique in its effect on intention and behavior alike. It affects the strength of intention to perform a behavior, and thus the state of the agent at the start of the investment thought process. It will also introduce variation in the final behavior, which must be defined and validated at a later stage. It will not affect the individual or social payoffs of the agent, but rather it globally affects the relationship between the total payoff and the threshold for moving to the “intention” stage. If an agent’s total payoff is high, and above the threshold for moving to the “intention” stage, but their perceived ability to conduct the behavior and its outcome (and resulting payoff) is low, they may not move to the “intention” stage at all, or from the “intention” to the “implementation” stage. The PBC thus acts as a constraint, increasing the threshold for moving to ultimate stages of the decision-making process.

Intention formulation and behavior implementation

Agents triggered to engage in the decision-making process, will only move to the intention formulation stage if their attitude, subjective norm and PBC level are above a certain threshold. These thresholds, as well as the weighting of the different components, will be different between groups of agents and must be set based on empirical evidence. Thereby, an agent with a positive attitude towards a technology, which in turn exhibits technical characteristics which fulfil the agents’ objectives, embedded in a social network that is important to them, and which contains a number of adopters of the technology, and finally with enough PBC over installing this energy technology, will formulate an intention to install said technology.

Once an intention is formulated, the agents will move to the behavioral implementation stage only if certain constraints are overcome. Two main constraints are designed for this model: the cost of the technology must be within the income boundaries of the agent, the payback time must be less than the estimated remaining tenure length and there must be adequate supply of the technology and installation services. This last constraint has yet to be defined and simulated in the ABM, as an external condition dependent on the geographical area and the rurality of residence.

Conclusion and future work

In the research field of residential energy efficiency, there is a need for behavioral models based on robust decision-making frameworks, which can be translated into quantitative modelling environments and integrated into wider energy systems simulation tools. In this study, we outline a methodological proposal for simulating investment in residential energy technologies, which would allow the projection of future uptake of energy efficiency measures or alternative energy technologies. We use the TPB framework as the conceptual foundation for decision-making processes undertaken by individuals occupying households in different geographical areas or environments. These individuals are simulated as agents with household, personal and national characteristics, who have a pre-existing attitude towards pre-defined energy technologies and towards their objectives of cost and emissions minimization, and comfort and convenience maximization. Agents are grouped into different categories, initialized according to certain conditions acting as triggers for decision-making, and then move through the intention formulation and behavior implementation stage.

Future research based on this study will comprise the collection of data on household and personal characteristics, via large-scale surveys among tenants and homeowners, in order to characterize the agents and their groupings. In order to calibrate the TPB framework, data also needs to be collected on the intention to install technologies, as well as the actual installation of these technologies. The data collection process must be conducted consistently and robustly, acknowledging the risk of self-reporting in qualitative data collection on fairly abstract terms such as agent-technology linkage strength. In order to avoid misleading information, randomness should be introduced in the conceptual model and ABM alike, to simulate the uncertainty surrounding agent personal and household characteristics and the relationship between them and .

Comprehensive data analysis based on robust statistical methods will be conducted to determine the relationship between components of the TPB framework and develop a model with sufficient predictive power to forecast the intention to invest in a technology, and the actual investment in that technology, of an agent characterized by the attitudinal components, household and personal characteristics outlined above. Once the conceptual model has been developed, it will then be translated into the ABM, including initialization and decision-making processes based on previously gathered data. This ABM must then be linked to the wider MUSE ® model, ensuring that the outputs of the model (household-level investments in energy technologies and the resulting changes in energy consumption and related CO_2 emissions) feed into other modules of the modelling framework.

We hope that our proposed methodological framework provides an avenue for connective theoretical behavioural models with quantitative energy systems modelling framework, with enough flexibility to allow for implementation across different technology databases and agent populations. Our forthcoming research will aim to validate the proposed methodology for developing, and to calibrate and implement a quantitative behavioural model for agent investment in energy technologies. In the long-term, we aim to refine and validate our ABM against a number of policy scenarios, and offer it as a decision support tool for policy-makers and stakeholders within the retrofit sector to assess the projected investment in energy technologies, under different policies and programmes. We hope that this will support future policy design and decision-making, but also create avenues for future research to investigate the use of other conceptual and quantitative behavioural models for projecting investment in energy technologies, and thus the contribution of consumer decisions to reducing energy-related emissions in the long term.