Exploring Investment Decisions in Energy Retrofitting with a Multi-Stage Algorithm: An Agent-Based Model

Ivan Digel[1], Sascha Holzhauer[1] , Friedrich Krebs[1,2]

[1] University Kassel, Wilhelmshöher Allee 71-73, 34121 Kassel, Germany
[2]Fraunhofer Institute for Energy Economics and Energy System Technology, Joseph-Beuys-Straße 8, 34117 Kassel, Germany

Abstract. The challenge of climate change demands active political interventions. Private building energy retrofitting is one of the main fields such interventions focus on, as in the European Union households consume around a quarter of total produced energy. Finding an efficient way to propose and evaluate policies aiming to stimulate private energy retrofitting is a promising direction approached from different methodical perspectives, among which agent-based modelling is a yet an underdeveloped one. This paper aims to introduce a psychologically grounded multi-stage algorithm to simulate houseowners' decision-making related to heating system replacements. Preliminary model runs with this algorithm show that it is able to produce complex dynamics with different agents being at different decision-making stages at the same time.

Keywords: Decision-making Process, Energy Retrofitting, Policy Assessment, Agent-based Modelling

1. Introduction and literature review

Sustainable development aims to satisfy the current generation's needs while ensuring that future generations can fulfil their own needs, as stated by the United Nations [1]. The reduction of global energy consumption is crucial in achieving this objective. According to Eurostat, in the European Union private households consumed 27% of final energy consumption in 2020, with heating taking 62.8% from it [2]. Energy retrofitting is widely regarded as the most effective method of reducing household energy consumption [3]. There are several large-scale research projects, such as the European Renovation Wave [4] or A European Green Deal [5], and governmental policies in place, such as those implemented by the Federal Office for the Environment in 2018, to increase the rate of household retrofitting.

The problem of private energy retrofitting is addressed from many points of view, among which social simulation is one of the promising. Social simulations offer a powerful tool for understanding the complex social, environmental and economic factors influencing energy consumption, and can help identify effective interventions before they are implemented [6]. Agent-based models (ABMs) have been developed to support policymaking on private household energy retrofitting.

Most existing ABMs about human decision-making related to energy consumption are one-step algorithms in terms that whenever an agent starts the decision process, (s)he has to move forward from the beginning to the end. This usually takes only one model time step for the whole process from being triggered to engage in decision-making to the execution of a resulting behaviour. Many articles present different kinds of one-step algorithms using different methods to calculate final decisions, from which utility models are the most popular (see [7], [8], [9], [10]). Some rare ones present approaches like multi-criteria analysis [11]. It does not mean that the decision-making is simple - on the contrary, these articles might employ sophisticated mathematics or many different factors and variables (e.g. [12]), allow agents to choose between different modes of the decision-making (e.g. [13]), or investigate different groups of agents with their own goals, methods and decision-making processes (e.g. [14]).

The main advantage of such representations is using conventional assumptions of human behaviour, including perfect information and rationality, as well as unlimited cognitive capacity to ease the algorithmic implementation. However, such assumptions are proven to be at least imprecise when it comes to the behaviour of real people having numerous predictable biases like “retain the status quo”, “satisficing”, “loss aversion”, “sunk cost effect”, “temporal and spatial discounting”, “conform to social norms”, “availability bias” etc. [15]. The time needed to gather data and make a choice, as well as the intensity of effort to do so are important. Thus, human decision-making is a more complex, time and context depended process, that could be separated into several steps to take a closer look at.

Several papers introduce multi-stage decision-making for their agents, meaning that an agent not necessarily moves through the decision-making during one time step of a simulation or (s)he does not have to move from the beginning to the end of the decision-making due to being stuck at a certain step or quitting it completely. Such algorithms usually strive to simulate processes of human cognition to increase validity of model results. They often make use of psychological theories of decision-making to derive number and content of decision-making steps, transition rules to move between them, and possible outcomes.

One of the most popular psychological theories used for multi-stage algorithms is the Theory of Planned Behaviour (TPB) [16]. For example, Caprioli et al. [17], Pagani et al. [18] or Egner & Klöckner [19] presented different multi-stage decision-making algorithms based on the TPB. These algorithms include three steps, with different names derived from the TPB, but all including initial evaluation of the object of investment, calculation of intentions (not) to perform an investment and performing the investment if feasible.

Some other ABM modellers do not explicitly justify stages of their decision-making algorithms by a certain theory, but still make them multi-stage. Friege [20] introduced three stages – thinking, planning and executing. Liang [21] gives three stages – operation (zero stage), incentive (negotiations between agents) and realization (implementing decisions).

Egner & Klöckner [19] presented a model of energy-related retrofits to analyse dynamics of change in energy standard of Norwegian buildings based on Bamberg's scheme of decision-making ([22], [23]). In their model, agents move between three stages of decision-making with a certain probability determined by a set of psychological variables. These are different for different agents and create heterogeneity in a synthetic population. Agents might move back and forth between stages, and if the last stage is successfully passed, then agents check whether they can afford the retrofit, and perform it accordingly.

This paper proposes a new decision-making algorithm as a part of an agent-based model to analyse investments of individual building owners in residential heating technology. The model is close to the paper of Egner & Klöckner [19] but presents a four-stage decision-making algorithm allowing agents not only to move back and forth between stages, but to interact with each other being in different stages of decision-making, as well as to quit the decision-making completely if certain conditions are (not) met. The concepts of bounded rationality [24], imperfect information [25], cognitive biases [26] that affect the real decision-making of humans are reflected by the algorithm. The proposed model has the objective to enhance policymaking with specific suggestions of interventions for every stage of the decision-making, by analysing its complex and detailed nature.

Two main competitors for TPB to be used in agent-based modelling are the alphabet theory [27] and the goal-framing theory [28]. The particular reason to use TPB and Bamberg's stage model is the interest in modelling of interventions, for which it has the simplest and the clearest stage division with certain assumptions about possible interventions. The alphabet theory lacks such a convenient stage implementation, while the goal-framing theory is too focused on factors of decision-making, which are not in the focus of the model. However, it is possible to supplement Bamberg's model and TPB with the abovementioned theories, if it suits the purpose of research [29].

The paper consists of five parts. The following section presents the algorithm used to model the decision-making of agents regarding new heating system installation and describes it in detail. Section 3 illustrates preliminary results of the model run using this algorithm. Section 4 highlights possible advantages and future prospects of the approach. Section 5 concludes by outlining the paper's most important findings in short.

2. Scheme of the decision-making process

Bamberg's model of decision-making consists of four stages with three breakpoints connecting them. The main idea of the model is that under certain conditions an individual might decide to change something in his/her behaviour and has to pass through the four stages to do it, with transitions between phases tied to achieving certain breakpoints, be it having a specific goal, an image of desired behavioural change or an idea of how to implement it [22].

The stages are (see **Fig. 1**) – predecisional, preactional, actional and postactional with goal intention breakpoint linking predecisional and preactional stages, behavioural intention connecting preactional and actional and implementation intention coupling actional and postactional. This scheme was adopted as a decision-making algorithm of agents regarding new heating system installation in the following way.

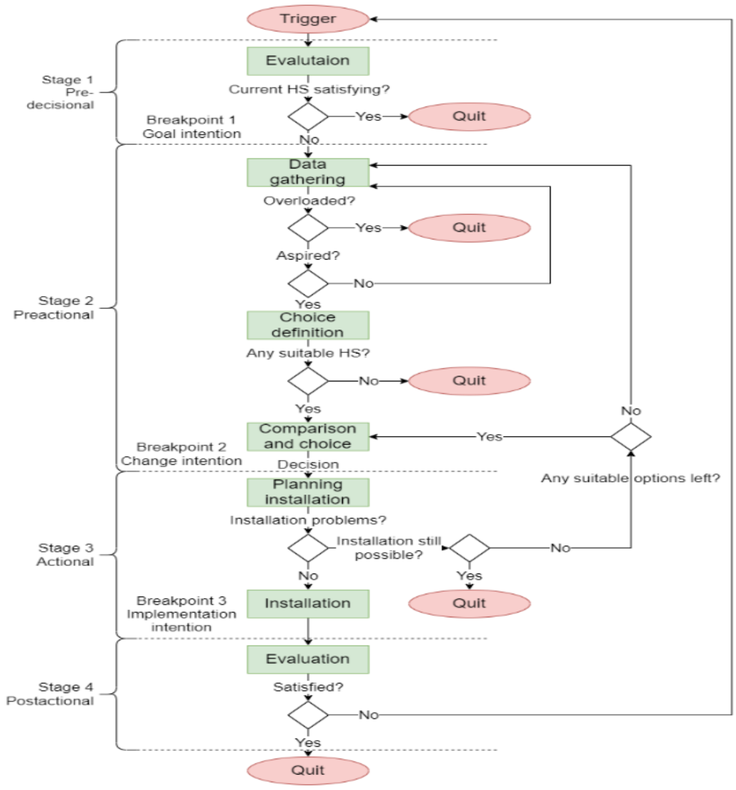

Fig. 1. The investment decision-making algorithm

Agents enter the decision-making only if they encounter a trigger that forces them to consider changing their heating system. Otherwise, they will perform other activities related to energy refurbishment. For example, they can meet other agents, which might cause some information and opinion exchange. There are several trigger types that might be either fully exogenous to the model, e.g. as a part of a scenario, or model endogenous, caused by the change in the environment of an agent, such as a certain share of neighbours installing new heating systems of a particular type.

The aim of agents during predecisional stage is to check whether they still consider their current heating systems as appropriate. The stage involves evaluation of the current heating system with regard to an agent's preferences and thresholds, be them fuel or installation price ceiling, volume of emissions, effort needed to install and operate a system etc. If an agent finds his/her current heating system appropriate, then (s)he quits the decision-making completely and will re-enter it only if a new trigger occurs. Whenever an agent decides that his/her current heating system does not match his preference thresholds anymore, (s)he achieves the first breakpoint – “goal intention”, meaning that this agent now wants to change his/her heating system. The “goal intention” breakpoint marks the starting point for an agent to enter the decision-making, should (s)he quit it later. Then the agent proceeds to the next stage.

Preactional stage is dedicated to the information search and evaluation of newly found heating system options to determine those suitable for installation. Agents get access to the data sources available in the environment, such as neighbours, specialists, media and the like. Agents invest cognitive effort into information gathering and are prone to different cognitive biases such that the perceived values of heating system parameters deviate from their “true”, objective values. Therefore, agents form subjective expectations regarding the attributes of heating systems instead of perfect knowledge. An agent would gather data until (s)he feels sufficiently informed or overwhelmed by the amount of information. In case of information overwhelming, an agent quits the decision-making and will re-enter it only if a new trigger occurs, with data gathering as a starting point.

If an agent feels sufficiently informed, (s)he proceeds to the “choice definition” and evaluates every known option using the same individual thresholds as during the predecisional stage. If there is at least one acceptable option, (s)he proceeds to “comparison and choice” and chooses whatever of the suitable heating systems fits her/his preferences best. With no suitable option at hand, (s)he quits the decision-making again, waiting for a new trigger, and starts data gathering anew. With a heating system chosen to be installed, an agent reaches the second breakpoint of “behavioural intention”, which replaces the “goal intention” as a checkpoint, and proceeds to the actional stage.

In the actional stage the agent plans and performs the installation. This step represents the phase during which the building owner contacts professionals (plumbers and the like) in order to collect information on the overall feasibility, timeframe, and effort scale of the chosen heating system. In the model, the estimation is performed through a simple random process and aims to represent the possibility that a certain heating system might not suit the dwelling of an agent, thus introducing a dummy for technological and knowledge barriers for installation. Should this happen, the agent might try to choose another suitable heating system to install, gather more information to get more options, or put off the installation entirely. If the installation is feasible, then the agent gets the chosen heating system installed, changes its breakpoint to “implementation intention” and proceeds to the last stage of the decision-making process.

The postactional stage is about evaluating the new heating system with regards to the expectations formed during data gathering. Agents now have to compare the “true” values of the parameters of his/her new heating system with the “expected” ones and decide whether (s)he feels satisfied or not with his/her new accomplishment. Whenever the new heating system appears to be worse than it was expected, the agent feels dissatisfied. This would have two impacts on his/her behaviour. First, this might be a trigger to start the decision-making anew from the first stage. Since the agent evaluates satisfaction during stage 4 using comparison of “true” and “expected” values, even if the “true” values are worse than expected, they might still comply with the internal standard of the agent. Thus, (s)he will eventually be satisfied with his new heating system. Second, the agent will complain about its new heating system to other agents met, thus influencing their opinion about this system.

3. Model setup and initial results

The model is in a prototype stage, having generated placeholders instead of the real-world data. It is planned to parametrize the model using a series of surveys which will happen in the city of Kiel located in Northern Germany as a part of "WAERMER" project devoted to analysis of household investments in heating systems. The main parameters of agents to be calibrated in that way are listed in Table 1.

Table 1. Parameters of agents in the model

Parameter	**Description**	**Dimension**	**Main source**
Preferences	Set of personal preferences linked to heating systems. These include importance of costs, considerations of social peers, perceived behavioural control, importance of effort needed to install and operate a heating system, environmental considerations, and importance of subsidies.	Normalized socio-demographic, economic and psychological variables	Bamberg [22], and the survey
Standard	A number used by an agent to compare evaluations of heating systems with. Represents internal standard with which any heating system must comply in order to satisfy an agent.	Varying from 0 to 1	Survey
Cognitive resource	Representation of available resources of agents to find data, make decisions, and evaluate options.	Hours of cognitive effort per unit of time	Survey
Perception	Represents personal features to form expectations when agents encounter information. E.g. if perception is 0.1 then all parameters of the heating system investigated by this agent will fluctuate by ±10% to imitate imperfect perception of information.	Decimals	Survey
Aspiration	Threshold defining agents' satisfaction with data gathered before they proceed with decision-making.	Abstract value	Survey
Budget	Amount of money to spend on replacement of a heating system.	EUR	Survey

Satisfaction	Agents' satisfaction with their current heating systems.	Binary – "Satisfied"/ "Dissatisfied"	Survey

Several test runs were performed with the model using plausible parameters for the purpose of verification. Parameters of agents and heating systems were set to be drawn from a uniform distribution within certain borders to simulate heterogeneity. The agents had two sources with different, yet overlapping, sets of information. The agents start with heating systems of the same type. Each agent might perceive a triggering event. **Fig. 2** shows that such a model set-up is able to distribute agents between different stages of decision-making. With the current state of the model the majority of agents quickly decide that they want to change their heating systems, find suitable alternatives, but have to wait for their plumbers to come and do the installation (big yellow zone of waiting during the stage 3).

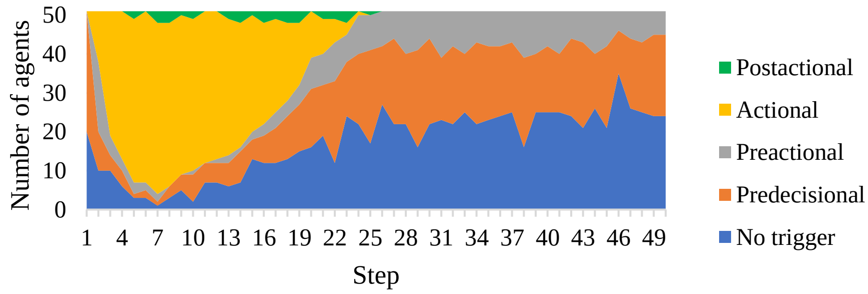

Fig. 2. Distribution of agents between the stages of decision-making

It is possible to draw individual agents from the population and look closely at their individual dynamics. **Fig. 3** shows two exemplar agents passing through the decision-making. Agent 1 was activated by a trigger during the 1st step of the model and quickly decided that his/her current heating system suits him/her no more. During the 2nd step the agent performed data search and found a suitable alternative. During step 3 the agent called a plumber and ordered an installation. (S)he was lucky to be one of the first clients of the plumber and having a feasible option, so the 4th step ended up with the new heating system installed, and the agent spent the 5th step to evaluate his/her satisfaction with the new heating system. Every next time Agent 1 was activated by a trigger he/she evaluated his/her current heating system and remained satisfied with no further steps taken. Agent 2 was triggered a couple of steps later. Though it was easy for him/her to find a suitable alternative, waiting for a plumber took much more time. However, the plumber only notified the agent that the heating system of choice is not feasible. The agent tried to find an alternative (step 24 of the model, falling back to preactional stage), but had no success and spent the rest of the run searching for a heating system good enough to install.

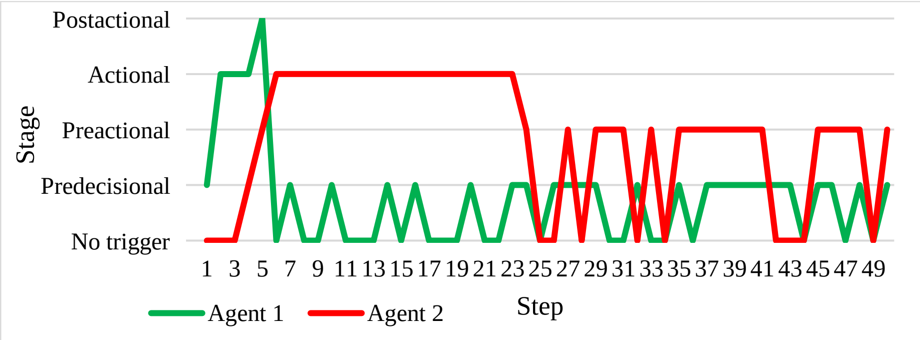

Fig. 3. An example of agents passing through the decision-making

As a result of the model run the dynamics of the distribution of heating systems in the population of agents can be observed. The names of heating systems here are only tags to distinguish between them and cannot be used to draw conclusions about the real world.

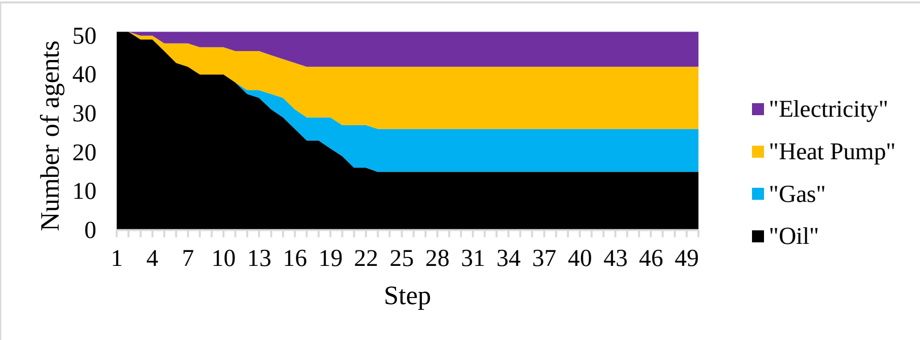

Fig. 4. Distribution of different heating systems among agents over time

As for now, the model parameters are set so that agents are very unlikely to replace their heating systems again once they have done it, but this might change as soon as the model is parametrized with the real-world data.

4. Discussion

There are several advantages of using the proposed algorithm to model houseowners' decision-making. Breaking investment decisions into multiple stages can more accurately reflect their complex, iterative nature. For example, explicitly representing the information gathering process enables explorations about the impact of different data sources, their reliability and accessibility, as well as effort needed to gather and process necessary information. The installation step might reveal agents encountering lack of specialists to perform installation, waiting lists of them being too long or even the technological impossibility to install chosen heating. Bamberg's approach is very useful here, because it proposes stages with these considerations in mind and already has developments in that direction [22]. The main assumption made about this particular implementation of the scheme is the possibility to translate the scheme of behavioural change to model consumer investment decision, that is usually made only several times over a lifetime. All this is supplemented with psychological biases to further limit agents so that they might become disappointed of their choice or feel the pressure of their peers regarding some heating options. Each agent might need different amounts of time to pass through the decision-making process, and the interaction might impact this temporal effort. The presented model is capable of creating complex social dynamics due to interactions between agents being on different stages of decision-making, influencing its outcomes.

The algorithm allows to develop specific policies for each decision-making step. For example, policies like banning certain heating technologies might serve as triggers to nudge consumer towards thinking about changing their heating systems, while information campaigns would influence those who are busy with data gathering, or support to installers might enhance those planning to install their chosen option. In addition, such an algorithm enhances model power to identify barriers for each decision-making step, be it insufficient or "too-late-to-come" trigger, lack of trustworthy information sources, information overwhelming, deficit of specialists etc. This can help policymakers to develop targeted interventions or policies to address these barriers and improve the overall effectiveness of the investment process. Moreover, separating the decision-making into stages allows to investigate possible windows of opportunity, i.e. moments of time, in which it is more successful to incentivise heating system replacement for groups of people. An interesting research question might be whether certain triggers have the power to align individual decision-making processes for different groups, thus making them susceptible for specific interventions.

The algorithm introduces importance of time for the analysis of decision-making. As the climate change sets unforgiving deadlines for climate policy to be successful in the long term, the time needed to increase the share of "clean" heating systems is extremely important. Thus, introducing algorithms that take the time needed to make decisions into account looks as a necessary addition to existing research.

The main direction of the development of the model is validation. Saturating it with empirical data and parametrization are natural steps to make in the future. The data needed can be separated in several groups. First, information about how long it takes for an individual to pass through all the stages. There is some survey-based evidence discussing the duration of each decision-making step, that looks promising [30]. In addition, it could be useful to have an impression about the percentage of people being at different stages of decision-making. Second, it would be good to supplement the previous data with an image of how long it takes to install certain heating systems in practice. Such knowledge could be obtained from surveys of specialists. Third, time-series data about the mix of heating systems present in population of interest. This would allow to perform historic validation of the model to show that it reproduces known dynamics of the share of heating systems. The sources could be surveys as well as statistical data, for example, MikroZensus survey performed by Federal Statistical Office of Germany [31]. Fourth, macro-level data about annual rate of energy refurbishment might be helpful, as it would give general system dynamics to converge the model to. März et al. give an annual energy refurbishment rate for Germany at 1% level [32].

It is easy to come up with ideas to deepen aspects of the model. First, trust might be introduced to represent agents' preferences among data sources. Some agents might value opinions of their neighbours, while others would prefer to address energy advisers or plumbers with their issues. Second, difficulties with decision-making might be introduced to show that, given options that are similar or have too many attributes, people are not able to choose quickly between them [33]. Third, installation feasibility could be enhanced so that specialist agents consider parameters of the houses of their clients to draw conclusions instead of "tossing a coin". Such an addition could help investigate problems of plumber undereducation and introduce importance of house parameters to the model. The latter could be supplemented with some kind of deterioration of heating systems as the time passes. Fourth, "government" could be introduced as a special type of agent to make interventions endogenous, not only the part of scenarios made by modellers.

5. Conclusion

This paper presents a multi-stage decision-making algorithm to be used in agent-based models related to investment decisions. The algorithm adopts a well-established psychological scheme of human decision-making created by Bamberg along with other psychological concepts to improve decision-making representation in agent-based models.

Agents may move between the stages of the algorithm, as well as quit and (re)enter it under certain circumstances, interacting with each other in the process. The agents themselves are subject to various cognitive biases and have limited cognitive resource to perform decision-making. They do not have instant access to all the information existing in the environment. They might not feel themselves capable of performing the whole process. They form expectations instead of getting perfect knowledge and use these expectations afterwards to evaluate newly installed heating systems. The multi-stage nature of the algorithm supported by psychologically-grounded features of agents create complex dynamics of the decisions made by socially-embedded agents.

Preliminary results of the model built to simulate houseowners' investment decisions in heating systems show that the model is able to simulate complex behaviour. Agents are distributed between different stages of decision-making and interacting, while the share of different heating systems change over time as they make their decisions.

Further developments of the model consist of parametrization with real-world data, adding more external and internal triggers, introducing houses and their properties to enrich the installation part of the model, allowing plumbers to learn to be able to consult agents about new heating system options and install them.

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