Simulating Bounded Rationality in Decision-Making: An Agent-Based Choice Modelling of Vehicle Purchasing

Khoa Nguyen[1], Valentino Piana[1], and René Schumann[1]

HES-SO Valais Wallis, SILab, Rue de Technpôle 3, 3960 Sierre, Switzerland
{khoa.nguyen,valentino.piana,rene.schumann}@hevs.ch
http://silab.hevs.ch

Abstract. This paper investigates the possibility of simulating bounded rationality effects in an agent's decision-making scheme by limiting its capability of perceiving information and utilising a decision-making framework of Triandis' Theory of Interpersonal Behaviour. Based on previous work on an agent-based platform, BedDeM, we propose how to capture the effects of sequential, emotional, habitual and multi-criteria decision-making. The Perception component in the agent is further extended to take into account confirmation bias and the bandwagon effect. We demonstrate the functionality of this model in the context of purchasing vehicles in Switzerland's households.

Keywords: Agent-based simulation · Bounded rationality · Choice modelling · Behavioural theory.

1 Introduction

The number of agent-based models (ABM) used to represent human decision making are increasing. Agent designs with notion of perfectly rational maximise expected utility but crucially ignore the resource costs incurred. Researches in bounded rationality (BR) offer an alternative to how to model behaviours in an uncertain environment with limited available cognitive resources. However, the ABMs utilised in these researches often focus only on simulating one particular type of BR (see surveys such as [6, 15] and Section 2). This study looks at an universal approach of developing an agent-based platform that can investigate the impact of multiple BRs on decision-making.

Discussing the term *bounded rationality* equals walking on a tightrope due to different interpretations across and even within disciplines. In this study, we follow the definition provided by Carley et al. [5] regarding two types of bounds in agents - limits to capabilities and limits to knowledge. Capabilities are related to the agent's physical, cognitive and computational architecture. Knowledge is the ability to learn and construct intellectual history. This paper attempts to take advantage of active perception to limit the agent's capability to observe relevant information. Through this data filtering capacity, BR is an extension of the model of the perfectly informed, optimised individuals to account for restricted knowledge and resources, i.e. a form of *bounded optimality* [22][p. 1050]. Coupling this definition with the notions of bounded rationality coined by Simon [23] and the heuristics and biases advanced by other researchers, several phenomena can be targeted in this study:

- *Sequential decision-making* refers to algorithms that consider the dynamics of the world, thus delaying parts of the problem until they must be solved [8, p. 337].
- *Emotional decisions* happen when the people's emotional state influences the depth of information processing related to decision-making [24].
- *Habit formation* is the process by which a behaviour becomes automatic when it is repeated with a routine [24].
- *Multiple criteria* other than cost can be considered, depending on the decision-making context [22][p. 622-628].
- *Confirmation bias* is the tendency of people to select the information that supports their views, ignore contrary information, or when interpret ambiguous evidence as supporting their existing beliefs or values [18].
- *Bandwagon effect* is a psychological phenomenon in which an idea or belief is being followed because everyone seems to be doing so [14].

We acknowledge that this list is limited and only covers the general ideas of each BR. However, it represents topics that are often mentioned in ABM research (see surveys such as [6, 15]) and provides a starting point for what can be considered in our study.

Previously, we have developed an agent-based model, and integrated tooling - BedDeM - based on Triandis' Theory of Interpersonal Behaviour (TIB) [16, 17]. The decision-making modules in this model can be used to implement different mechanisms representing items from the list above. In particular, it currently factor in the effects of *sequential*, *emotional*, *habitual* and *multiple criteria* decision-making (see Section 3.4). We modify the *Perception* component to take into account *confirmation bias* and *bandwagon effect.*

Purchasing new vehicles is an essential field for Switzerland's energy strategy, especially when it provides an understanding of the need of individual consumers and requirements for future infrastructure [4]. It is also an area where BRs are particularly pervasive, as decisions are made on the level of deeply heterogeneous individuals and households. Due to the significant number of individual decision-makers involved and alternatives offered in vehicle purchasing, ABMs are often utilised for the assessment of BRs effects in the lab as well as in the field (e.g. [10, 13]. Therefore, it is chosen as a suitable context to implement and test the functionality of the new bounded *Perception* component.

The paper is organised as follows: After considering some of the related ABM architectures in Section 2, we present the structure of our agent-based model and explain how the mentioned BRs are specified in Section 3. Next, a case study is provided to evaluate the result of applying this bounded Perception in Section 4. Finally, we conclude and suggest further development in Section 5.

2 Related works

This section provides the state-of-the-art in terms of ABM that addressed the BRs mentioned, i.e. sequential, emotional, habitual, multi-criteria decision-making, confirmation bias, and the bandwagon effect. Our agent decision-making architecture, which also covers several different types of BRs, will be discussed in Section 3.

In terms of sequential decision-making, researchers in ABM often take the approach of multiple steps/stages in decision-making before the final output. The most famous architecture of this category is Belief-Desires-Intention (BDI) model [9]. It is centred around three mental attitudes, namely beliefs (the informational state of the agent), desires (the objectives or situations that the agent would like to accomplish or bring about) and, especially, intentions (the deliberative state of the agent - what the agent has chosen to do). Other extensions of BDI, cognitive and normative architectures that have a perception-deliberation-action cycle also belong to this category. A good summary of them can be found in [2].

There is a body of work focussing on emotions in BDI agent reasoning (see [2]). However, only a few agent architectures considered emotions explicitly in literature. These include PECS [27], Emotional BDI (eBDI) [19] and BRIDGE [7]. The first of these is an extension of the BDI architecture that incorporates emotions as one decision criterion into the agent's decision-making process. PECS aims to enable integrative modelling of physical, emotional, cognitive and social influences within a component-oriented agent architecture. BRIDGE represents emotions by using the *Ego* component to specify different emotional responses to various stimuli. According to [2] and the best of our knowledge, these architectures are used as reference models, so few specifics can be found about their actual implementations in practice.

To represent the habitual patterns in human behaviour, hybrid approaches that allow for heuristics, as well as deliberation and reactive production rules, are often utilised in ABM. Two examples of this category are Consumat [12] and BRIDGE [7]. Consumat allowed for modelling habitual behaviour by introducing five heuristics based on uncertainty and cognitive effort that can be utilised instead of complete deliberation. BRIDGE, similar to Consumat, introduces the idea of the basic needs of the agent, which can overrule any deliberate decision-making process via a response component to ensure that agents can react when needed.

Multi-criteria decision-making is usually addressed by applying *multi-attribute utility theory*, which is used to represent the preferences of an agent over bundles of goods either under conditions of certainty about the results of any potential choice or under conditions of uncertainty [22][p. 622-628]. To consider the attribute that is not mutually utility independent, Thiriot et al. also propose a multi-objective multi-agent system (MOMAS) to explicitly consider the possible trade-offs between conflicting objective functions [26]. The criteria are often context-dependent, i.e. the modeller has to define them based on statistics or previous empirical studies.

Confirmation bias considers how various sources of information are filtered due to personal cognitive biases. For example, eBDI filters information from all perceptions and other sensor stimuli using semantic association rules derived from its internal beliefs. BRIDGE architecture has a *Ego* component that contains different filters and ordering preferences. They are utilised to interpret the input stream of information to form the beliefs in the agent. Confirmation bias is also considered under the opinion dynamics modelling frameworks. Sobkowicz introduced a quasi-Bayesian belief updating framework, where the incoming information is filtered by the cognitive biases or predispositions of the agent (e.g. memory priming/availability, simplicity/attention and emotional filters) [25]. Rollwage et al. suggest implementing confirmation bias via metacognition (accuracy of belief formation) of agents, allowing them to down weight contradictory information when correct but still able to seek new information when they realise they are wrong [21].

The bandwagon effect can be associated with the ability to consider social learning in agent design, which is often found in normative models. Several architectures can be listed in this category, including BRIDGE, EMIL-A [1] and Consumat. BRIDGE accounts for some social concepts, including a social interaction consideration, the social concept of culture, and a notion of self-awareness (and resulting differentiation of one-self and other agents). In EMIL-A, social norms instead play a central role. It models the process of agents learning about norms in a society, the internalisation of norms and the use of these norms in the agents' decision making. On the social level, Consumat has some idea of sociality in terms of agents being able to reason about the success of their actions in relation to the success resulting from the actions of their peers. If the agent does perform as well, it simply imitates (i.e. copies) the action(s) of others.

Although some account for multiple aspects of behaviour, the agent architectures and implementations surveyed above do not comprehensively cover all BRs effects mentioned in Section 1. Therefore, in this study, we create an agent model capable of considering these effects in its decision-making scheme.

3 Simulating bounded rationalities in agent's decision-making

Several effects of BRs can already be covered using our previous work on an agent framework based on TIB [17], including sequential, emotional, habitual and multi-criteria decision-making. We further extend the *Perception* component to cover the confirmation bias and the bandwagon effect. In the first subsection, we provide an overview of the agent's decision-making cycle. The following subsections describe the two main components related to this study: *Perception* and *Decision-making*. We then summarise how each BP type has been captured in our agent architecture.

3.1 Agent's decision-making cycle

The main components of our agent's decision-making cycle are illustrated in Fig. 1. First, it uses the *Perception* component to observe information about the available options. Using the agent's reference, it then filters, sorts, and creates a shortlist of options. If the agent's internal state or these options satisfy specific criteria, the *Decision-making* component gets triggered. It follows the procedure of the TIB framework to evaluate the list of options in terms of a utility value (detailed below). Finally, an option is selected based on the provided utility, either by choosing the best (deterministic agent) or using a probability (probabilistic agent). The *Communication* component then outputs this action to the environment and updates the *Memory* component of the agent.

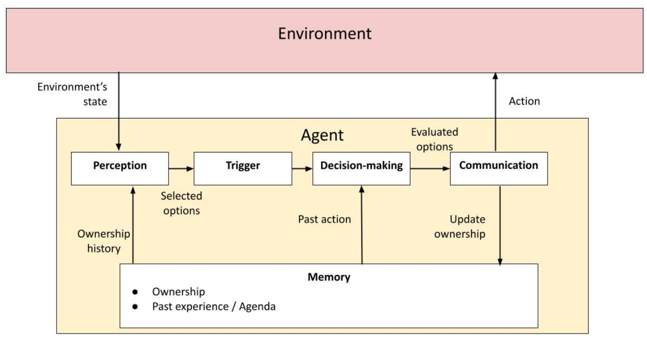


Fig. 1: Overview of agent's components

3.2 Perception component

The *Perception* component (see Fig. 2) first gather information about the available option from the environment, including its neighbour's opinion. It then options into several lists, each satisfying certain criteria. These lists are then sorted, multiplied with certain weights and merged to form a list of selected options for decision-making. The criteria and their weights are based on the agent's personal preferences about the option's properties, which can be calibrated with the empirical data.

The mechanism can be explained clearer in the context of car purchasing: a consumer often starts by filtering out models that have a certain type of engine, price, energy labels and neighbour review. As human mental accounting mechanisms are limited [11], s/he has to sort the options to get the best one of each category and combine them to make a final list of available models for the final decision-making step.

Using this structure, the confirmation bias can be represented with the filtering process with only relevant options being considered. The bandwagon effect is

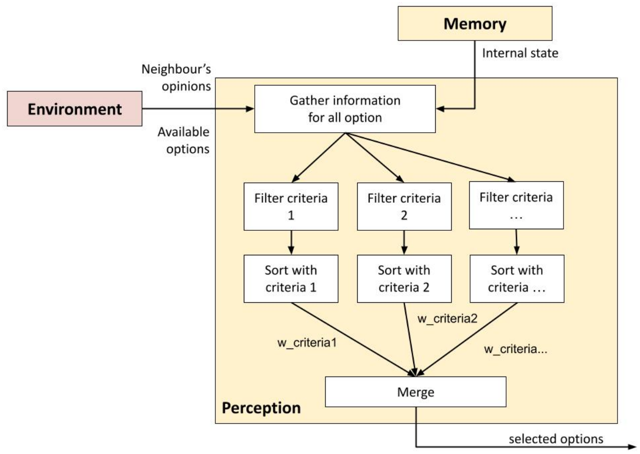


Fig. 2: Perception component

highlighted with the inclusion of neighbour opinion as one of the criteria. Using an associated weight, the agent can decide on the influence of this effect on its final list of selected options.

3.3 Decision-making component

A full decision-making component with the TIB framework is illustrated in Fig. 3. For all determinants (d), each option (opt) is given a utility value which comes from comparing its property with other's ($U_d(opt)$). In the first level, this value can be in the form of a real numerical system (for determinants such as price or time) or ranking function (for determinants such as emotion). Either of which can be calculated from empirical data (e.g. census, survey) or calibrated with expert's knowledge and stakeholders' assessment. The results for these determinants are then normalized and multiplied with an associated weight (called w_d); the sum of which becomes the referenced value for the option in the next level. This process is captured in the following equation:

$$EU_d(opt) = \sum_{a=1}^{A}(EU_a(opt) * w_a/(\sum_{o=1}^{O} EU_a(o)) \tag{1}$$

where EU_d(opt) is the utility value of an option (opt) at determinant d. A is the set of all ancestors of d (i.e. determinants connects with d in the previous level). O is the set of all available options. $w(a)$ is the weight of ancestor a. In this case, the weight represents the importance of a decision-making determinant compare to others at the same level and emphasizes on the heterogeneity of individuals. It also allows the modeller to cut determinants (i.e. setting their values to 0) that are not relevant to a context. The combination process then continues until it reaches the behaviour output list; the utility value of which

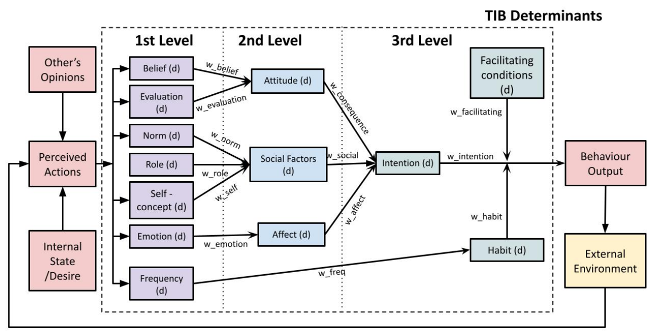


Fig. 3: Decision-making component with TIB framework

can be translated to the probabilities that an agent will choose that option. If the agent is assumed to be deterministic, it picks the option that is correlated to the highest or lowest utility depending on modeller's assumptions.

3.4 Summary of the simulated bounded rationality effects

With the two components above, we can summarise how the BRs can be simulated:

– **Sequential decision-making**: A decision-making cycle includes several steps, one after another. This procedure starts with the agent gathering information about the alternatives. Then, using its references, it filters, sorts, and cuts this list to a selected few. If triggered, these selected options are evaluated in the decision-making component. Finally, the highest/lowest evaluated alternative is selected and communicated to the environment. Using a procedural approach, this process follows the description of sequential decision-making in Section 1, i.e. the current step waits for the result of the previous step.
– **Emotional decision-making**: It is captured in the determinant *Affect* in the 2nd level of the *Decision-making* component (see Fig. 3). Its evaluation is dependent on the context of decision-making. For example, our purchasing agent can rank how much comfort/pleasure it can have from a model compared to others. The *Affect* determinant is associated with a weight (w_{affect}). By increasing this weight and lowering the weights of other related determinants, we can highlight the contribution of emotion to the overall behavioural output.
– **Habits**: Similar to emotion, the agent also accounts for past behaviour in its 3rd level of the TIB framework (see Fig. 3). Its weight can be adjusted to mark its influence on the final choice.
– **Multiple criteria**: The TIB framework in the *Decision-making* component allows users to capture different factors in decision-making, i.e. attitude(e.g. cost, time), norms, role, self-concept, emotion, habit, and past behaviour.

A mapping with empirical data can be provided better to interpret these factors in a decision-making context. Function 1 provides a mean to combine them in the form of a utility value. Using associated weights, the agent can also decide which one has a larger/lower impact on the final choice. This concept also allows the agent to express its preferences on certain criteria of decision-making.

- **Confirmation bias**: In the *Perception* component, an agent filters the information received from the environment to form different short lists of options. This process represents the idea that the agent selects the information that supports its preference. The associated weights of each criterion mark the contribution of this bias to the final list. For example, in the car purchasing context, the user can generate an agent who only wants to receive information about electric cars by first setting the filter to only allow electric engine cars and zeroing all weights except for the engine's weight.
- **Bandwagon effect**: In its perception phrase, the agent starts with observing its environment, including the patterns of its neighbour. It also accumulates the neighbours' opinions. This information is then used as a filter for in Perception component (Fig. 2) and be fed into the Social factors determinant in the Decision-making component (Fig. 3). Each of them is associated with a weight to provide a way to compare its effects to other factors in the decision-making.

4 Case study

This study focuses on observing the effect of bounded perception in an agent's decision-making. In the first subsection 4.1, we first calibrate our model with empirical data. The next subsection describes an experiment to demonstrate the function of the extended *Perception* component.

4.1 Data mapping and calibration

The environment in this study includes two main entities: *Market* and *Opinion Platform*. The *Market* consists of the details of the currently available car models, which are extracted from a Swiss car catalogue [20]. The given information include engine type, energy label, market price, brand and years of availability. The *Opinion Platform* provides reviews (value from 0-1) from the neighbourhood, dealer and media. Their weights are created based on the network from the SHEDS panel data [28].

An agent in our model represents a household in Switzerland, which is generated using the process in [3]. There are currently 3080 agent profiles available. Each of them is associated with a weight to represent a portion of Switzerland's population. The behaviour outputs are multiplied with these weights to scale up to the national level.

In *Decision-making* component, the following properties can be mapped to determinants of the first TIB level (see Fig. 3): Price - *Evaluation*, Review of dealer/media - *Role*, Review of neighbours - *Norm*, Brand of vehicle - *Self-concept*, Comfortability - *Emotion*, Available of charging - *Facilitating condition* and Past usage of the same model - *Habit*.

To calibrate this purchasing model, two different sets of parameters corresponding to different components - *Perception* and *Decision-making* - are selected. In the Perception component, there are two main categories: thresholds for filters and weights (see Fig. 2). The thresholds include: 1) preferred engine (Gasoline, Diesel, Electric, Hybrid, other), 2) energy label (A, B, C, D, E, F and below), 3) price, 4) brand (1-8), recommendation level (value 0-1). In addition, each is associated with a weight, which also needs to be calibrated. In terms of the Decision-making component, we calibrate the following determinants' weights: price, energy label, recommendation, social status, brand, emotion, habit, attitude, social factor, intention and facilitating condition (charging infrastructure). At this stage of development, all weights will take a value in the set (0, 0.25, 0.5, 0.75, 1).

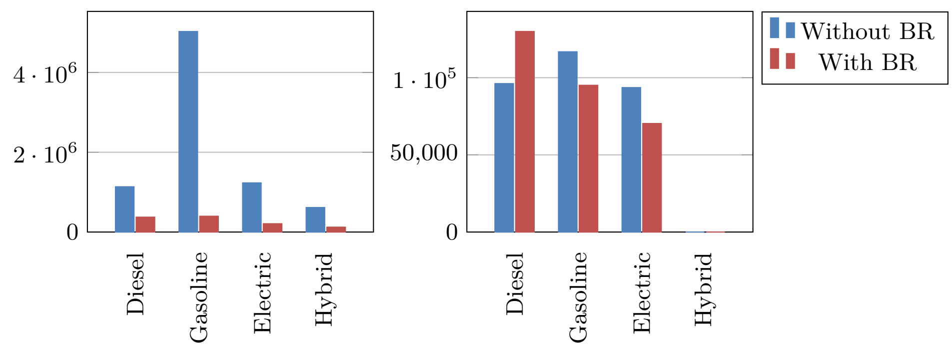
The number of parameters is significantly large, increasing the combined number of test runs exponentially. Therefore, we choose to perform a sensitive test for all parameters. The less critical parameters are assigned only two steps (0-1) in data calibration. From our tests, energy label, brand, and social status belongs to this group. All parameters are then further grouped to create eight different agent purchasing profiles. Each agent is then assigned a random group for each of its parameters. This process ensures the heterogeneity in our agent population.

Our main objective is to minimise the error calculated by the total differences between the final number of vehicles purchased and real sales, multiplied by the weights (representing the adjusted importance) of the following criteria: 1) the total unit sales, 2) sum of sales of gasoline, diesel, electric and hybrid models and 3) the total sales different clusters of models of different brands.

We calibrated with the data from 2015 to 2019. The more recent years, 2020 - 2021, are separated due to the effect of the pandemic COVID-19. Therefore, its car stock is adapted directly from correspondences in SHEDS panel data. We repeat this procedure for all agent's profiles set at deterministic (i.e. choosing the best option) to find the smallest error. After a period of two weeks, the best setting satisfies the 1,2,3 condition with the yearly average errors after multiplied with weights equal to 305'485.

4.2 Evaluation of bounded perception

As the sequential, emotional, habitual, multi-criteria decision-making mechanisms are mainly implemented in the formerly developed *Decision-making* component, their effects on behaviour can be by changing associated weights, similar to what was done previously in [16]. In this section, we focus on testing the functionality of the bounded *Perception* component in our agents. The number of vehicles (considered and purchased) calibrated for the final year (2019) is used as ground truth. We perform the experiment by turning the filtering, shorting and cutting functions off and evaluating the results against this ground truth. Fig. 4a shows the results as the number of models being considered among the agent's population after the perception process. Fig. 4b presents the final sales after the decision-making process. The figures are categorised by different engines, including diesel, gasoline, electric and hybrid vehicles.



(a) Total models being considered (b) Total sales

Fig. 4: Simulation results in term of total number of vehicles per engine type

The number of the models considered is much higher in the ground truth case (without BR), especially for gasoline models (considered nearly 12 times). When we apply filters with bounded perception, the distribution between different engine types is more balanced though it is proportioned to the case. In the total sales of ground truth, the highest number is gasoline with 1.1 million vehicles. Even though electric vehicles are considered more, they have fewer sales. With the bounded perception applied, there are significant increases in the number of diesel cars sold. The gasoline and electric figures drop to 95'071 and 70'327 respectively. It is mainly due to betters models of diesel and fewer models from gasoline/electric type being selected after the perception phase. Overall, we can clearly observe the difference in the number of models being considered (individual perception level) can lead to the difference in the percentage of car types sold (macro level).

5 Conclusion

In this study, we adopt our simulation platform - BedDeM - to simulate the impacts of different types of BRs. With the framework developed in [16,17], sequential, emotional, habitual and multiple criteria decision-making can be considered in the agent's architecture. In addition, the Perception component is extended to cover the confirmation bias and bandwagon effect. This paper describes the agent's architecture design and provides an experiment to demonstrate the impact of bounded perception in the context of car purchasing in Switzerland. Similar experiments can be done to highlight the effect of single or combined BR on an agent's decision-making and output.

The current model is still, however, missing some features, including variability of mapping between the first level determinants with SHEDS and MTMC data (see Fig.3). This process can be accomplished by collaborating with a collaborator from economic or social science to derive a more accurate description of TIB's elements and generate more agent profiles in the current population.

There are also some promising research directions for our mobility platform. With the innovation in technology and increased environmental awareness, it has become more common for people to access electric or hydrogen vehicles. The model can provide a good indication of the roles of determinants in future scenarios (such as new infrastructures or government policies). Coupling with other models from different sectors can also provide a consumer's perspective where bounded rationalities can play a significant role in the agent's decision-making. As the topics provided in Section 1 and their implementation in BedDeM are limited and simplified, one can implement more elaborate decision-making mechanisms in their modules to reflect the complexity of these topics.

Acknowledgement

This project is part of the Research Program Energy-Economy-Society (EWG), which is financially supported by the Swiss Federal Office of Energy (SFOE).

References

1. Andrighetto, G., Conte, R., Turrini, P., Paolucci, M.: Emergence in the loop: Simulating the two way dynamics of norm innovation. In: Dagstuhl Seminar Proceedings. Schloss Dagstuhl-Leibniz-Zentrum für Informatik (2007)
2. Balke, T., Gilbert, N.: How do agents make decisions? A survey. Journal of Artificial Societies and Social Simulation **17**(4), 13 (2014)
3. Bektas, A., Schumann, R.: How to optimize gower distance weights for the k-medoids clustering algorithm to obtain mobility profiles of the swiss population. In: 2019 6th Swiss Conference on Data Science (SDS). pp. 51–56. IEEE (2019)
4. Boulouchos, K., Bach, C., Bauer, C., Bucher, D., Cerruti, D., Dehdarian, A., Filippini, M., Held, M., Hirschberg, S., Kannan, R., et al.: Pathways to a net zero co2 swiss mobility system: Sccer mobility whitepaper. Tech. rep., ETH Zurich (2021)
5. Carley, K.M., Gasser, L.: Computational organization theory. Multiagent systems: A modern approach to distributed artificial intelligence pp. 299–330 (1999)
6. Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T., Savin, I., van den Bergh, J.: A review of agent-based modeling of climate-energy policy. Wiley Interdisciplinary Reviews: Climate Change **11**(4), e647 (2020)
7. Dignum, F., Dignum, V., Jonker, C.M.: Towards agents for policy making. In: International Workshop on Multi-Agent Systems and Agent-Based Simulation. pp. 141–153. Springer (2008)
8. Frankish, K., Ramsey, W.M.: The Cambridge handbook of artificial intelligence. Cambridge University Press (2014)
9. Georgeff, M., Pell, B., Pollack, M., Tambe, M., Wooldridge, M.: The belief-desire-intention model of agency. In: International workshop on agent theories, architectures, and languages. pp. 1–10. Springer (1998)

10. de Haan, P., Mueller, M.G., Scholz, R.W.: How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new carsPart II: Forecasting effects of feebates based on energy-efficiency. Energy Policy **37**(3), 1083–1094 (2009)
11. Hahnel, U.J., Chatelain, G., Conte, B., Piana, V., Brosch, T.: Mental accounting mechanisms in energy decision-making and behaviour. Nature Energy **5**(12), 952–958 (2020)
12. Jager, W., Janssen, M.: The need for and development of behaviourally realistic agents. In: International Workshop on Multi-Agent Systems and Agent-Based Simulation. pp. 36–49. Springer (2002)
13. Kim, S., Lee, K., Cho, J.K., Kim, C.O.: Agent-based diffusion model for an automobile market with fuzzy topsis-based product adoption process. Expert Systems with Applications **38**(6), 7270–7276 (2011)
14. Kiss, Á., Simonovits, G.: Identifying the bandwagon effect in two-round elections. Public Choice **160**(3), 327–344 (2014)
15. Kremmydas, D., Athanasiadis, I.N., Rozakis, S.: A review of agent based modeling for agricultural policy evaluation. Agricultural systems **164**, 95–106 (2018)
16. Nguyen, K., Schumann, R.: An exploratory comparison of behavioural determinants in mobility modal choices. In: Conference of the European Social Simulation Association. pp. 569–581. Springer (2019)
17. Nguyen, K., Schumann, R.: On developing a more comprehensive decision-making architecture for empirical social research: Agent-based simulation of mobility demands in switzerland. In: International Workshop on Multi-Agent Systems and Agent-Based Simulation. pp. 39–54. Springer (2019)
18. Nickerson, R.S.: Confirmation bias: A ubiquitous phenomenon in many guises. Review of general psychology **2**(2), 175–220 (1998)
19. Pereira, D., Oliveira, E., Moreira, N., Sarmento, L.: Towards an architecture for emotional bdi agents. In: 2005 portuguese conference on artificial intelligence. pp. 40–46. IEEE (2005)
20. Revue Automobile Catalogue. https://revueautomobile.ch/, [Last accessed 28-April-2022]
21. Rollwage, M., Fleming, S.M.: Confirmation bias is adaptive when coupled with efficient metacognition. Philosophical Transactions of the Royal Society B **376**(1822), 20200131 (2021)
22. Russell, S., Norvig, P.: Artificial Intelligence: A Modern Approach. Prentice Hall Press, USA, 3rd edn. (2010)
23. Simon, H.A.: Rationality as process and as product of thought. The American economic review **68**(2), 1–16 (1978)
24. Simon, H.A.: Making management decisions: The role of intuition and emotion. Academy of Management Perspectives **1**(1), 57–64 (1987)
25. Sobkowicz, P.: Opinion dynamics model based on cognitive biases of complex agents. Journal of Artificial Societies and Social Simulation **21**(4) (2018)
26. Thiriot, S., Kant, J.D.: A multi-agent cognitive framework to model human decision making under bounded rationality. In: IAREPSABE 06 (International Conference on Behavioural Economics and Economic Psychology), Paris (2006)
27. Urban, C.: Pecs: A reference model for the simulation of multi-agent systems. In: Tools and techniques for social science simulation, pp. 83–114. Springer (2000)
28. Weber, S., Burger, P., Farsi, M., Martinez-Cruz, A.L., Puntiroli, M., Schubert, I., Volland, B.: Swiss household energy demand survey (SHEDS): Objectives, design, and implementation. Tech. rep., IRENE Working Paper (2017)