PANDORA - an Agent-Based-Model to analyze acceptability of (energy) policies, applied to the German heating sector

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Abstract. Simulation or optimization models that project developments given specific policy scenarios are important tools to assess the efficacy of policy instruments. Those models typically assume a certain policy be implemented, and examine its effectiveness regarding the behavioural change achieved in the targeted population and the resulting impacts on the development of economic and environmental indicators. However, the adoption of a desired behaviour in a population is to a significant extent moderated by the collective acceptance of the policy measures put into effect. An integration of the process of public policy acceptance would not only improve the accuracy and stability of techno-economic model outputs, but also help to identify policy properties corresponding with societal preferences and guide improved policy design. Still, the formation of public policy acceptance is complex in nature because it is driven by heterogeneity in the target population of the policy measure and governed by social dynamics.

In this paper, we present the agent-based model PANDORA (Policy AcceptaNce, Diffusion of Opinions and Relations among Actors) that represents the process of acceptance among a network of actors in face of an introduced policy measure in the heating sector. The transition of the heating sector is particularly challenging because its success critically depends on coordinated investments of heterogeneous building owners in heating technologies and insulation. Therefore, a comparative assessment of the acceptance of policy measures aiming to stimulate the decentralised investment flow is an important building block of policy formation. The presented model draws on theory on policy acceptance, theory on opinion dynamics and on empirical data obtained from a survey in Germany.

Keywords: agent-based modelling, socio-political acceptance, attitude formation, opinion dynamics, heating sector

1 Introduction

In order to effectively achieve the 2030 climate change target without overburdening citizens and businesses, it is necessary to further develop and optimize policy instruments, in particular to transform the heating sector.

As citizens are the primary target group for policy measures in the domestic buildings sector and are expected to change their behaviour or adopt new technologies to achieve policy objectives, their response to policy instruments (e.g. acceptance or opposition) is crucial for their successful implementation. If the public does not support a significant change through a policy that promotes a transition from a conventional to a renewable heating system, it will not be viable.

Public opposition in democratic countries and the associated reluctance on the part of elected representatives can hinder the successful implementation of any long-term oriented energy or climate policy program [1–5]. The policy measure deemed most effective in promoting energy transition may not be considered the most equitable or just by the public. Processes of opinion dynamics may contribute to form, amplify and reveal public attitudes which can manifest themselves in social movements [6, 7]. Immediate impacts occur, for example, when decision-makers reverse or modify a policy or practice.

Public reaction to the introduction of carbon taxation has been the focus of many empirical research studies [8–13, 2]. Among other policy measures, carbon tax appears to be the least favored option [13]. Despite the potential effectiveness of carbon taxes in mitigating carbon emissions, their implementation has faced opposition from the public in several countries. For instance, the 'Yellow Vest' protests in France in 2018 opposed the implementation of a fuel tax with a carbon component [14, 15]. The movement was able to secure a number of concessions from the government, including the cancellation of the proposed taxation measure. Other examples include the repeal of carbon pricing in Australia in 2014 [16], or the dismissal of a carbon tax initiative in Washington State by public referendum [17]. In comparison, fewer research is available on public acceptability of policy measures other than carbon taxation [18].

The favorable or unfavorable attitude towards a policy before it is implemented can be referred to as 'acceptability' [19]. It is defined as the extent to which individuals or groups accept that a particular policy is legitimate and valid. The degree of acceptability of a policy is influenced by the attitudes prevailing in a particular social group or society towards the policy's objectives, potential outcomes, and the approaches used to achieve them. In contrast, public acceptability for climate policy measures is primarily expressed through non-activist public behaviour, such as the willingness to bear the financial or behavioural costs associated with climate policies [20]. This is distinct from more active forms of environmental citizenship, such as signing petitions, joining environmental organizations, or participating in demonstrations. For the design of PANDORA, we only consider non-activist behaviour.

The focus of our study is on the impact of opinion formation and diffusion on public policy when a new policy measure is to be introduced. Political discourse plays a substantial role in shaping an individual's opinions and attitudes towards policies [21, 22]. Moreover, the formation of a political opinion is governed by a continuous process of inter-individual exchange which in turn is influenced by the structure of the social network to which the individual belongs [23–25].

However, it can be difficult to identify which specific determinants are most influential in a given context. Attitudes can be influenced by socio-demographics, social norms and personal experiences, as well as by time and environment. Research studies in the field of climate and energy policy suggest that policy acceptability is particularly linked to belief-specific determinants such as environmental attitudes and political ideology, or the perceived impact of the policy [26, 18, 27]. In general, the determinants of climate policy acceptability can be divided into three distinct groups: (1) socio-psychological factors, (2) the perception of climate policy and its design, and (3) contextual factors [26]. We use these categories to build a research framework for the design of the agent-based model [28].

The category 'socio-psychological factors' comprises determinants that describe more general individual preferences, values, general beliefs, etc. The category 'perception of climate policy and its design' lists factors that are relevant to understanding how attitudes are affected by the characteristics of policy instruments. We make an explicit distinction between the objective characteristics of a policy measure, and the perceived characteristics of a policy measure. Objective policy characteristics relate to the type of policy, which can include economic incentives, regulations or information campaigns. Empirical studies highlight that the most relevant elements relate to the level of coercion [3, 29], the use of resulting revenues (e.g. from carbon taxation) [1, 30], and the personal or financial burden on those affected [31]. On the other hand, individuals may perceive the objective policy characteristics differently. From the literature review, we identify the perceived personal burden, fairness, and efficiency of a policy measure as the most relevant characteristics that matter for policy perception.

To assess the effects of potential climate or energy policies it has become common practice to use techno-economic modelling tools to estimate the economic, environmental, and social impacts. Developing successful strategies to address climate change requires a comprehensive understanding of the behaviour and interactions of different entities. Whereas techno-economic models have a strong focus on quantitative analysis and insights from socio-psychology often appear to be ambiguous and the representation of socio-political aspects remains implicit within the model design. The integration of socio-political aspects in energy-system models (EMS), integrated assessment models (IAM), or computable general equilibrium models (CGE) is mainly done by integrating exogenous assumptions or by discussing of model outputs [32, 33]. Furthermore, such models often lack the ability to map small-scale actor structures due to their focus on macroscopic phenomena or large model size. Techno-economic models that focus on a specific segment of the energy system are, in principle, able to map such actor structures. However, the level of detail of the technologies considered in these models is often already very high. Therefore, the additional consideration of different groups and sub-groups of actors and their interactions reaches practical limits in terms of the acceptable level of model complexity and the resulting computational time. Nevertheless, in cases where the research focus is on the development of techno-economic systems, socio-political aspects must not be neglected. The development and coupling of actor models that allow the analysis of socio-political aspects could enable techno-economic models to provide resilient strategies and recommendations for political practitioners.

The use of ABMs can provide a bridge between policy analysis at the systemic level and behavioural studies by incorporating relevant aspects of human behaviour such as deviations from rationality, social influence in social networks and the heterogeneity of agents. ABMs can also be used to combine the results of different empirical analyses, behavioural rules of bounded rationality, or social psychological theories to simulate the complexity of the social system.

ABMs are a valuable tool for studying opinion dynamics, capturing the interplay between individual opinions, social interactions, and the information flows within a society. In general, opinions are conceptualized as a generic construct capable of representing beliefs, behaviours or attitudes [34]. Opinion dynamics models aim to describe the mechanisms behind opinion formation and diffusion. Different opinion dynamics models have been proposed to capture various aspects of opinion formation and evolution through distinctive sets of rules. Some models assume that individuals seek to align their opinions with those of their neighbours, resulting in convergence of opinions over time [35–37]. Other models incorporate the role of stubbornness or contrarian behaviour, where individuals resist changing their opinions [38, 39].

ABMs are also widely used to analyse the impact of policies on the diffusion of technologies, including the impact of social aspects. Many studies have used ABMs to depict the role of social acceptance of different renewable technologies or schemes in policy evaluation [13]. In the context of domestic heating, the ABM approach has been used to model the role of consumer choice in the diffusion of heating technologies [40–42]. These studies have focused on the technological characteristics of innovative heating technologies and consumer choice in order to understand the adoption potential of new technologies.

However, less attention has been paid to the acceptability of policy measures that would promote the deployment of renewable technologies. Furthermore, few ABMs include the dimension of policy acceptability in the climate and energy nexus [43].

In this paper, we present the framework for the agent-based model PANDORA (Policy AcceptaNce, Diffusion of Opinions and Relations among Actors). Furthermore, we explore how the overall process of public acceptability of policies can be formalized and translated into an ABM. Accordingly, we present different dimensions of the acceptability process in a network of agents in the face of a newly introduced policy measure: the attitude formation of the individual agent, and communication within the social network by exchanging opinions on the policy perception. Furthermore, we outline how empirical data are integrated in the agent-based model.

The model is used as an example to explore the dynamics of the policy acceptability process in a policy scenarios targeting the heating sector. The policy scenarios vary in their level of coercion, i.e. that they could either support low-carbon heating technologies by introducing different levels of carbon tax, or use bans on fossil fuel technologies. The PANDORA output could be combined with techno-economic models to integrate uncertainty with regard to public policy acceptability.

2 Model description

PANDORA assesses the acceptability of policies to promote low-carbon heating technologies in the building sector. Our approach combines theoretical and empirical elements, using an agent-based approach. For the purposes of this paper, we focus only on the effect of opinion dynamics within a social network has on an attitude, in our case the change in policy acceptability by different societal groups. Opinions and attitudes are often used interchangeably to refer to mental constructs that can be influenced and persuaded through social interactions. However, an important distinction between opinions and attitudes was made by Allport - while attitudes refer to evaluations, opinions are more specific and situational expressions of preferences about particular issues [44].

On the one hand, we hypothesize that individual perceptual factors, such as the perceptions of fairness, effectiveness, and financial burden, are essential in shaping the of individuals' attitude formation towards a policy. On the other hand, we assume that the same perceptual factors are also relevant for opinion formation, communication and political discourse.

The core of the model form individual agents representing the statistical distribution of individuals in German society based on the results of an empirical survey. The aim of the model is not to imitate any empirically observable data, but rather to uncover possible paths that society's acceptability of a newly introduced policy measure might take, when the effects of a public political discourse are factored in. Future iterations of the model will also include the impact of media and sector relevant institutional actors. Furthermore, the model allows for the testing of different policy scenarios in the heating sector.

The model doesn't consider local effects or spatial units. Each individual agent is a representation of a discrete individual with a set of attributes, attitude formation capability, and communication behavior. Agents interact within the model environment, which connects agents through a network graph, and stores state variables. Based on their exchange of opinions with regard to their perceptual factors with other agents in the network, they have the ability to change their attitude towards the policy. Assuming that members of each social group display a similar initial attitude towards a policy scenario, interactions in the social network lead to changes in the attitudes of individual agents, as the model progresses.

Table 1: State variables of agents

Entity	Name	Description	States
Agent	Identity number	Unique identifier	1,…,N
Agent	Group identity number	Identifier for groups of agents with similar policy perception and evaluation values at initialization	1,…,N
Agent	*Uncertainty range*	Agent's uncertainty range, where they would consider the opinion of other agents (according to the Relative Agreement model, (see section	[0..1]

		2.4)	
Agent	*Effectiveness/ Burden/ Fairness*	Agent's subjective perception of the effectiveness, personal burden, and fairness of a policy measure	[-1..1]
Agent	*Evaluation_Effectivenss/ Evaluation_Burden/ Evaluation_Fairness*	Agent's subjective evaluation of effectiveness, personal, burden, and fairness	[-1..1]
Agent	*Attitude*	Agents' calculated attitude towards the policy measure at each Step	[-1..1]

2.1 Input data

After reviewing the relevant literature, we identified key determinants of climate and energy policy acceptability. We then conducted an empirical factorial survey (vignette experiment) to investigate the influence of these determinants on the acceptability and perception of a policy measure in the heating sector. The collected data we serve as a basis for the parametrization of the PANDORA model.

The study was conducted in 2020 (n = 2048) and was designed as an online factorial survey (vignette experiment). The study focused on the perception and acceptability of a potential policy measure in the heating sector by German households. The survey consisted of three different sections and aimed to collect comprehensive data from the participants. The first section was designed to collect demographic information required for quota allocation, as well as additional details on demographic characteristics. In the second section, the respondents rated vignettes representing a policy targeting a heating sector. The data collected in this section allows to evaluate different policy scenarios. The dimensions of a potential scenario include: (1) a variation in the financial burden imposed on households by the carbon tax, (2) use of carbon tax revenues, (3) bans on oil and gas heating systems and replacement requirements, (4) penalties for heating system installers or manufacturers, (5) criticism from various associations. In total of 4.500 unique combinations of the policy attributes are possible. Respondents were presented with eight variations of the policy. They were asked to rate each variation using a 6-point Likert scale for four dependent variables: (1) acceptability of the policy, (2) perceived fairness, (3) perceived effectiveness, and (4) perceived financial burden. The design of this section made it possible to test the dependence of policy acceptability on the perception factors (fairness, effectiveness and financial burden) and to derive the regression coefficients which are used to initialize the attitude formation process (see section 2.3). Finally, the third section was devoted to gathering information on attitudinal and personality constructs, such as political ideology, environmental attitudes, and technophily.

2.2 Process Overview and Scheduling:

Communication between two agents within the social network occurs randomly at each step of the model. Agents interact and potentially change their attitudes based on the opinions of their neighbors. Our assumption is that when individuals are engaged in a face-to-face exchange, they tend to articulate the reasons for their acceptance or rejection of a policy measure, rather than simply stating their overall attitude towards the policy measure. In PANDORA, each agent communicates their opinion on the policy measure, which consists of their policy perception attributes 'Effectiveness', 'Fairness' and 'Personal Burden' (continuous values between -1 and 1), and compares their policy perception attributes with those of their counterparts. These agent-agent interactions are governed by the RA model. A similar approach has been used in a model of opinion dynamics by Stefanelli and Seidl [45]. Consequently, value adjustments and influence may occur for one attribute due to the overlap of uncertainty ranges, while other attributes remain unaffected. This means that, agents may be influenced by one policy perception attribute, but not by another. Finally, as a result of the interaction, each agent's policy acceptance value is recalculated in accordance with the EV theory formula.

2.3 Attitude formation process:

We hypothesize that individuals' policy acceptance in the heating sector is mediated by policy perception attributes. To establish a link between these policy perception attributes and attitude formation, we use the Expectancy-Value (EV) theory [46]. The EV theory is a widely used psychological explanatory model of how individuals form attitudes toward an object. According to the theory, attitudes are a function of beliefs about the attitude object and the evaluative aspect of those beliefs:

$$(1) \quad A_0 = \sum_{i=1}^{n} b_i e_i$$

Where A_0 is the attitude towards the object (policy measure), b_i is the belief that the object has the attribute i , e_i is the evaluation of attribute i, and n is the number of beliefs. The EV theory suggests that beliefs can be assessed through a series of questions that inquire about an individual's perception of the attributes of an object, such as its effectiveness and perceived cost in the case of the policy measure. It also suggests that attitudes are not static, but rather are subject to change. This change can occur by exposure to new information, by changing the individual's beliefs about the object, or by changing the importance the individual places on certain attributes. For each individual in PANDORA, an overall attitude toward the policy measure (object) is calculated based on their beliefs and evaluation of the policy perception attributes. While the beliefs vary for each individual in the model, the evaluation of the beliefs remains unchanged.

2.4 Communication process:

Different rules govern how individuals' opinions can impact each other, which is reflected in the variety of opinion dynamic models that describe social influence [34]. One option to describe interaction and social influence within a social network is the Relative Agreement (RA) model [47]. The RA model attempts to simulate opinion formation and convergence in a network of individuals with different opinions. As in many models of social influence, the opinion change mechanism is consistent with key principles from psychological literature on conformity [48, 49], cognitive consistency [48, 50], and persuasion [51, 52]. In addition, the model distinguishes between strongly committed individuals (‘extremists’, or stubborn agents) and individuals who are susceptible to opinion change [53–55].

The RA model assumes that agents are only receptive to influences that are consistent with their pre-existing beliefs, and thus their susceptibility to influence is limited by their uncertainty range. Two values determine the interaction: the agent’s opinion and the respective uncertainty range. In the RA model, agents are randomly paired for interaction. In each interaction, both agents share and revise their opinions based on the other's opinion. During each interaction, a predetermined uncertainty range is used as a threshold, and if the difference between the opinions of two interacting individuals is less than or equal to the threshold, they will move closer together, resulting in convergence of their opinions. Conversely, if the difference between the individuals' opinions is greater than the threshold, there is no change in opinion. After each interaction, individuals move on to interact with other members of the social network.

As the results of the empirical study indicated, respondents with strong opinions were present either strongly supporting or opposing the presented policy measures. Respondents with a strong opinion were more likely to provide an explanation of their position after completing the vignette section. This finding makes the application of the RA model in PANDORA a suitable fit, as it allows the introduction of ‘extremists’, agents with a strong opinion and a narrow uncertainty range.

2.5 Model initialization:

First, the policy scenario is defined by selecting a policy attribute for each policy dimension. Subsequently, we configure the critical parameters for the model, such as the number of agents, simulation steps, network-specific features, and communication model parameters.

Each individual agent belongs to a social group that determines the initial values of the policy perception attributes and group-specific weights (beliefs) to calculate the agent’s attitude. We hereby assume that members of the same social group with the same socio-demographic data would exhibit similar attitude formation towards a policy. Social group properties are derived from a prior analysis of empirical data using regression coefficients and distributions. Within each group, there are three types of uncertainty ranges by which an agent can be defined: narrow, medium, and wide. These categories reflect the results of the survey, with a narrow range indicating a more defined or 'extreme' viewpoint (the proportion of individuals who responded on the positive or negative end of the Likert scale), and medium and wide ranges indicating more 'moderate' evaluations. The distributions of these three types of agents per group are determined from the empirical data and used as probabilities to define the individual agents.

The N number of agents are connected by a social network. The formation of social networks and their inherent structure are significantly influenced by a principle known as homophily, a social selection effect that predicts the development of social ties on the basis of shared socio-demographic characteristics [56]. Homophily is present in political discussion networks and political conversations often occur within networks where individuals with similar political values tend to associate to reinforce shared beliefs [57]. Furthermore, political discussions are more likely to take place among actors who share strong ties, such as friends and family [58, 59]. However, interactions and political discourse occur between people regardless of their political similarities [60]. In fact, individuals with similar political orientations may find themselves in dissimilar social and political environments, which can lead to a more diverse range of perspectives [61].

To account for homophily in political discussion networks, we apply a (heterogeneous) Watts-Strogatz small-world network. First, the network is initialized using the Watts-Strogatz small-world model, where each agent is connected to its k nearest neighbors on a ring lattice structure. Second, we use the Social Distance Attachment (SDA) model [62] to rewire the Watts-Strogatz network. The SDA is a theoretical framework that explains how individuals form and maintain relationships based on their social distance. Social distance refers to the degree of closeness or familiarity that individuals feel towards each other, based on various socio-demographic factors. It is a measure of the perceived psychological or emotional distance between individuals or groups, and can influence how people interact and communicate with each other. Social distance attachment refers to the tendency of individuals to form relationships with others who are closer to them in the social network, while avoiding or having fewer connections with those who are more distant [63, 62]. We formalize the SDA model by applying the Euclidean distance metric and deriving a probability distribution for the connection of nodes. This approach ensures that nodes are more likely to connect to others with similar socio-demographic factors, while preserving the small-world properties of the network during the rewiring process. Finally, the network structure is adjusted according to the selected demographic variables of age, education, income, and political ideology. The network structure remains fixed for a model run and is not changed by social opinion dynamics.

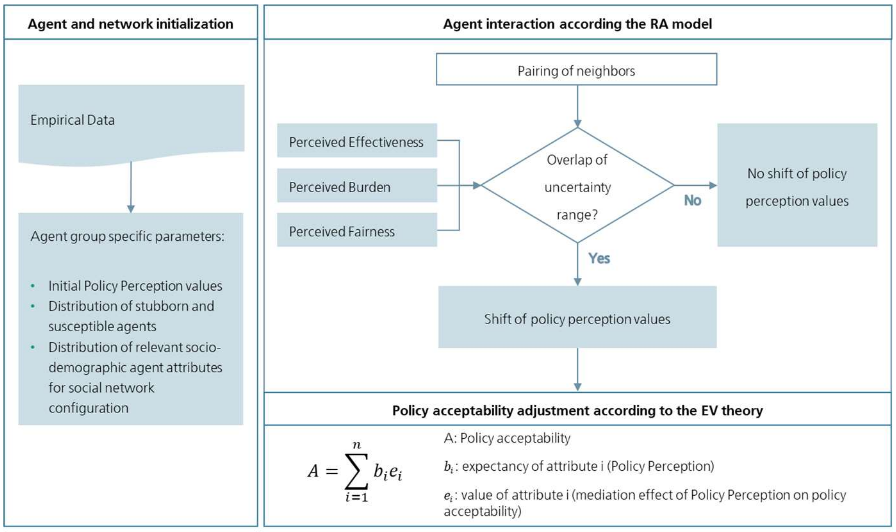


Fig. 1 : PANDORA model overview

3 Preliminary Results – Proof of Concept

3.1 Agent Parameters

In this chapter, we provide a proof of concept for our agent-based model, demonstrating its ability to effectively simulate the effects that opinion dynamics within a social network might have on the acceptability of different policy measures in the heating sector. For the scenario runs presented here, the simplified assumption is that policy acceptability is only influenced by the political ideology of individuals. The importance of political ideology for the acceptability of climate policies has been shown in previous studies [64, 65]. As the results of our empirical analysis show, political ideology is a significant, but not the only relevant determinant of policy acceptability. Future research will include model runs for clusters of distinctive groups based on a latent class analysis. **Table 2** shows the distribution of survey respondents by political ideology, which is used to initialize the agents for each model run.

Table 2: Distribution of political ideology derived from empirical data

	left								right
Political ideology group ID	0	1	2	3	4	5	6	7	8
Fraction of total population	0.05	0.07	0.12	0.13	0.41	0.11	0.07	0.03	0.02

3.2 Network parameters

For each model run the parameters of the network generator are fixed. We select a network configuration according to the results of Holzhauer (2017) [66]. The number of nearest neighbors is set to k = 6, the rewiring probability is set to p = 0.05, and the homophily factor is set to alpha = 5. **Fig. 2** shows an exemplary network generated for a model run with N=100 agents. The resulting average clustering coefficient is approximately 0.4. This means that the nodes in the network are highly connected to their neighbours. The model generates networks that are highly clustered and tend to form tightly connected groups. The degree distribution shows that the majority of nodes have 6 connections. The network is relatively sparse, consisting of isolated clusters of nodes with similar degrees.

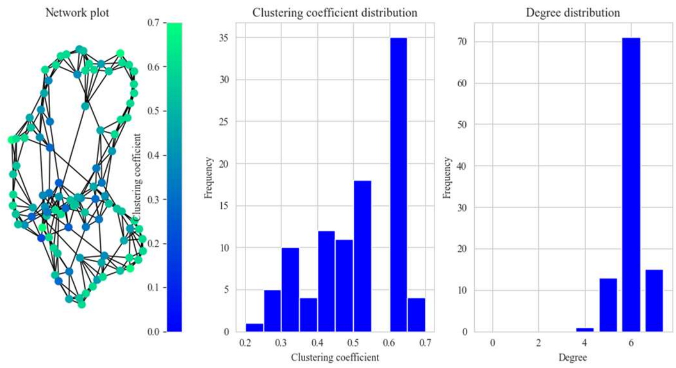


Fig. 2: Description of an exemplary generated network with set parameters: network plot, clustering coefficient distribution, and degree distribution of the social network

3.3 Exemplary scenario runs

Baseline Scenario: The baseline scenario assumes the lowest value for the expected burden of carbon taxation for households of 150 EUR/year. No use of carbon tax revenues or further regulations are included. A number of N=500 agents (or higher) produces stable results. **Fig. 3** shows the development of the policy perception attributes 'Burden', 'Fairness', and 'Effectiveness' and the respective resulting policy acceptability after 150 model ticks. Some of the political groups are already very close in their opinion on the policy perception attributes at the beginning of the model run. Since in these cases the uncertainty ranges of the agents overlap, the values converge. However, the network effects and influence of the opinion of the agent's neighbors are also visible, as some of the opinions of the political groups diverge and tend to lean towards the values of other groups. Besides the social network effects, the agents' width of the uncertainty range is the driving determinant for the system dynamics. Furthermore, the fraction of 'extremists' within each political group defines how much the range of the opinion space for each political group increases until all values converge. Opinions on the policy perception attributes tend to converge more closely to the values of the majority opinion, which in turn, is influenced by the groups with the highest proportions in the artificial society. The results for the policy perception attributes show the expected behavior of the RA model.

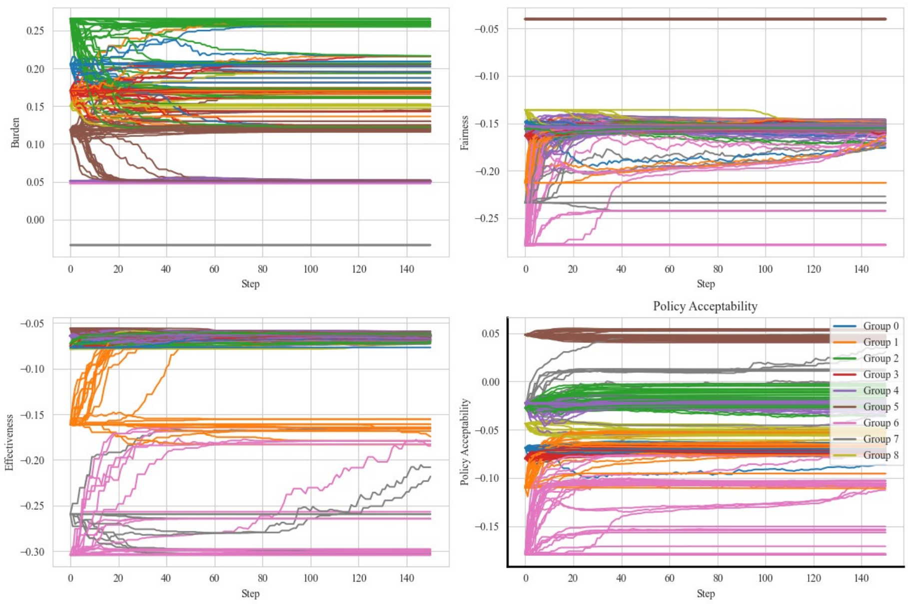


Fig. 3: Development of the policy perception attributes 'Burden', 'Fairness' and 'Effectiveness, as well as the resulting 'Policy Acceptability' for individual agents of each political group (group 0 to 8). Exemplary run for the baseline scenario for N=500 agents and 150 ticks.

The 'Policy Acceptability' value shows the combined result after the attitude adjustment according to the EV theory. The figure shows, that there are variations of attitudes within each of the groups at the end of the model run. However, the range of opinions on the 'Attitude' scale for the political groups as a whole is rather narrow [-0.18, 0.05]. As **Fig. 4** shows, the majority of agents change their attitude only slightly, as the deviation of 'Policy Acceptability' between step 0 and step 150 is dense around the value 0.

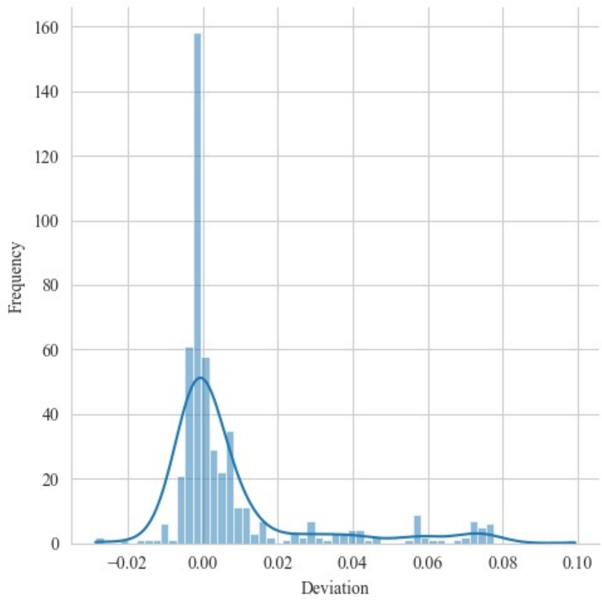


Fig. 4: Distribution of the deviation of attitude between tick 0 and tick 150 for all agents for the baseline scenario.

Comparing two different policy scenarios: The more interesting question is, how policy acceptability changes for different policy scenarios. Therefore, we compare two policy scenarios:

- In Policy Scenario 1 (PS1), the carbon tax burden on households is increased to 1,400 EUR/year. Carbon tax revenues are used for compensation measures for low-income households. The other policy features remain the same as in the baseline.
- In Policy Scenario 2 (PS2), the carbon tax burden is 650 EUR/year. The use of carbon tax revenues is not specified. In addition, the policy includes a ban on oil and gas technologies after 2025 and an obligation to replace inefficient heating systems.

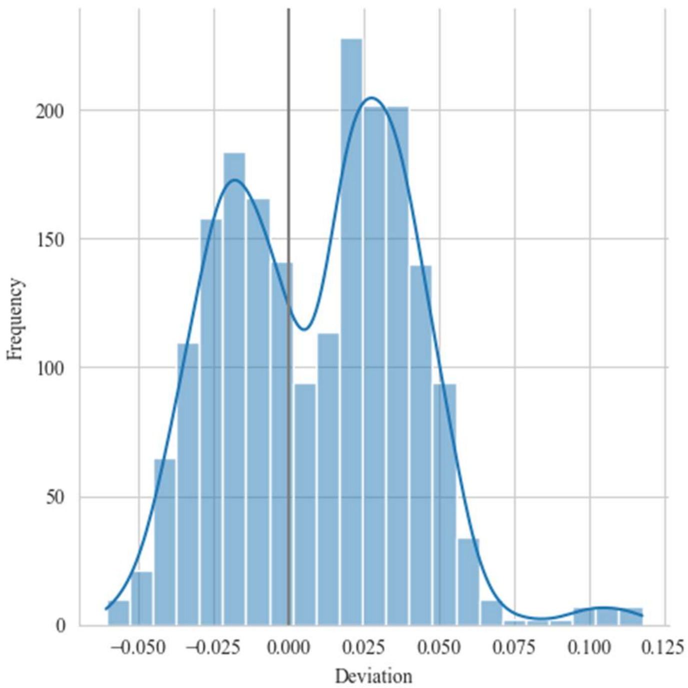
Table 3 shows the policy acceptability for each of the political ideology groups at model initialization for both policy scenarios. PS1 has a lower policy acceptability across all groups. This is mainly explained by the generally negative effect carbon taxation on policy perceptions. Bans and replacement obligations of heating technologies with a low energy efficiency heating technologies are not perceived as controversial according to results of the empirical results.

Table 3: Policy acceptability for PS1 and PS2 by political ideology after initial attitude calculation according to EV, using the regression coefficients derived from empirical data.

	left								right
Political ideology group ID	0	1	2	3	4	5	6	7	8
Policy Acceptability at Step 0:									
Policy Scenario 1 (PS1)	-0.25	-0.26	-0.19	-0.29	-0.27	-0.24	-0.36	-0.20	-0.28
Policy Scenario 2 (PS2)	-0.14	-0.23	-0.08	-0.23	-0.12	-0.09	-0.11	-0.06	-0.18

After running the model, the policy acceptability value shifts due to the exchange of opinions among the agents. **Fig. 5** shows the differences in the distribution of the policy acceptability deviation between the two policy scenarios. In PS1, the attitude shifts more negatively for a part of the agents and more positively for another part, resulting in two peaks. In comparison, the majority of agents in PS2 do not deviate from their initial policy acceptability, although the width of the distribution is similar. However, the deviation from the initial policy acceptability value per agent is rather low in both cases.

PS1



PS2

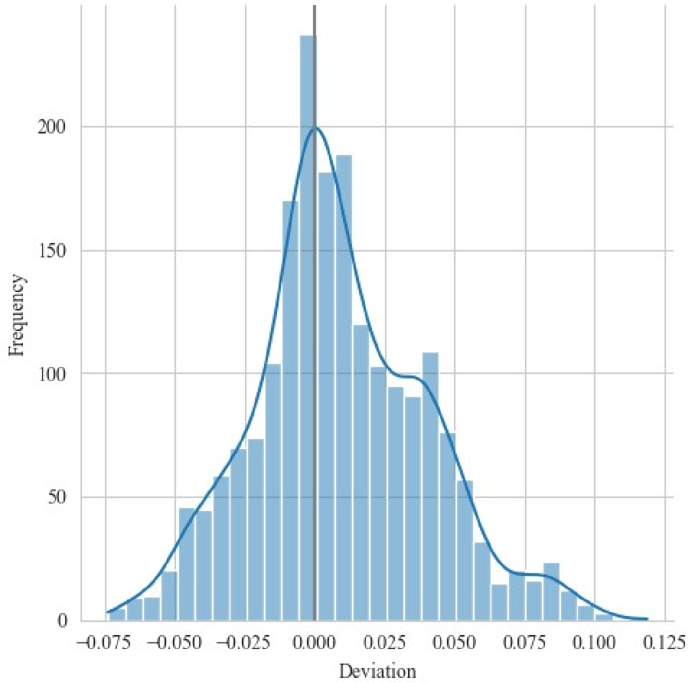


Fig. 5: Distribution of the policy acceptability deviation between tick 0 and tick 150 for PS1 and PS2 for all agents. Example run for N=2.000 Agents and 150 ticks.

A more interesting comparison of the two scenarios is the policy acceptability deviations are analyzed within political ideology groups **(Fig. 6)**. Within the groups the opinion space for policy acceptability widens. Whether the change from the initial opinion is positive or negative differs. Opposing evaluations of PS1 compared to PS2 occur for groups 1, 4, 6, and 7. Political ideology group 7 has the most positive evaluation of the policy measure at model initialization. In PS1, opinion dynamics processes and network effects lead to an even higher evaluation. And while political ideology groups 7 and 2 also have a comparatively high assessment of PS2, the deviation of political acceptance after the model run goes in both directions. However, the typical averaging effects resulting from the use of a bounded confidence approach are evident. Those groups that had rather negative initial policy acceptability values have a positive shift, and vice versa.

PS1

PS2

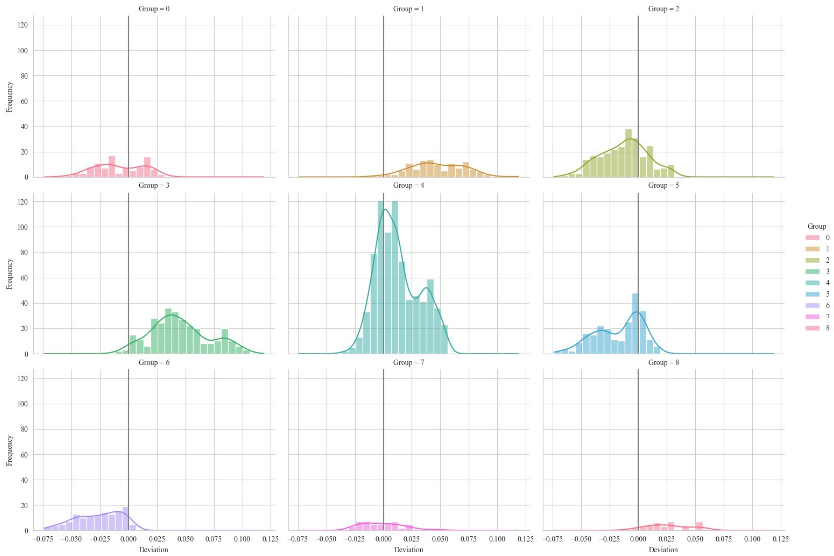


Fig. 6*:* Distribution of the policy acceptability deviation between tick 0 and tick 150 for PS1 and PS2 by political ideology group. Example run for N=2.000 agents and 150 ticks.

4 Discussion and Outlook

In order to explore the potential of simulating acceptability processes, we employ a novel modelling framework that integrates empirical data, established theories from socio-psychology, and opinion dynamics with agent-based modelling. In doing so, we not only contribute to existing research in the field of opinion dynamics, but also to literature on the policy acceptability of energy policies. Our approach may provide guidance for combining of empirical data analysis and agent based modelling.

For the formalization of acceptability processes we emphasize that the individual's subjective perception of policies is crucial for attitude formation. Based on the EV theory, the underlying assumption of PANDORA is that an individual's attitude towards a policy measure is determined by a summative policy perception index. Thereby, attitude is a function of pre-existing beliefs about an object and the subjective value an individual attaches to them. Both, beliefs and values differ across socio-demographic groups. We integrate the empirical evidence that climate or energy policy measures are evaluated based on subjective perceptions of their effectiveness, burden, or fairness into the process of attitude formation and opinion dynamics. A change in policy acceptability in a favorable direction requires an increase in the summed policy perception products, while a change it in an unfavorable direction requires a decrease in the summed products.

Furthermore, agents do not directly influence the final policy acceptability value. Instead, the agents exchange and compare their policy perception values, which serve as indicators to explain their reasons for supporting or opposing a policy measure. The degree of influence occurs in agent interactions also depends on characteristics of the population. The degree of influence during interactions is influenced by the dissimilarity between the identified social groups and the proportions of 'extremist', and 'susceptible' agents within those social groups.

With preliminary model results for different policy scenarios, we provide a proof of concept for the model framework. The model results demonstrate how social network structure and social influence may affect initial policy acceptability. The model allows the testing of different policy scenarios. The analysis could lead to recommendations for policy design that take into account the perspectives of different social groups.

The variation of policy scenarios compared to the baseline leads to different evaluations for the agent groups. Consistent with expectations, the bounded rationality approach of the RA model results in the convergence of policy perception attributes. This, in turn, results in changes in policy acceptability evaluations.

The network structure affects the attitude formation process because it allows agents to interact with members of groups other than their own who have different perceptions of the policy. Opinions on burden, fairness, and effectiveness tend to align more closely with the values of the majority opinion, which in turn, is influenced by the group with the highest proportion in the artificial society. However, the dynamics within a group are dependent on the proportion of 'extremists' present in each group. The effects of the policy perception attributes are visible in the resulting policy acceptability. The final value is adjusted depending on which policy perception attribute is prioritized by a group. The results also show that communication within the network increases the opinion space for each group.

However, at this stage the model has several limitations. First, under bounded confidence, opinions are mathematically averaged. This means that a population with a high tolerance for a policy measure would lead to conformity, while the results for a population with a low tolerance would show polarization.

Second, while the bounded confidence model can illustrate how diverse opinions can converge to some degree of agreement, it may not accurately capture the dynamics of the persistence of extreme opinions within a population. In real-world situations, extreme opinions may not be easily moderated by interactions, and polarisation may persist over time. Therefore, this limitation of the Deffuant model should be taken into account, as it may not fully represent the complexity of opinion formation.

Third, another important limitation is the random assignment of communication frequency between agents, which can lead to inflated values. The random model may not take into account real-world constraints and limitations that affect communication frequency, such as time, resources or physical distance. Additionally, the lack of contextual considerations means that important social dynamics and underlying context that drive communication patterns may be overlooked. Future iterations of the model will include some constraints on communication frequency based on the literature and available data to make the results more realistic.

In its final state, PANDORA should be able to project the public acceptability of different policy scenarios in the heating sector, taking into account and assessing a variety of influencing factors. In future iterations of PANDORA, we plan to extend the model to include the media as an important entity affecting the transmission of policy measures to individual agents. Since individuals typically receive policy information that is already framed, including media bias, it is important to consider the impact of the media on subjective policy perception. This extension will allow us to better understand how the media may shape attitudes toward policies, to examine the mutual influence of public opinion and the media, and to explore how institutional actors indirectly compete in the framing of policies in public discourse.

Another key area for model development is the coupling with a techno-economic model of the building-stock. First, this approach allows for a comprehensive understanding of the interplay between policy stringency and societal response as the agent-based model offers insights into how various policies might be accepted or rejected by different segments of society. Second, the techno-economic model evaluates key indicators such as total energy demand, fuel mix, carbon emission reductions and space heating costs. This provides a detailed understanding of the technical and economic implications of different policy scenarios. As the techno-economic model updates indicators based on policy changes, the agent-based model can in turn reassess policy acceptability in light of these changes. The process of continuous updating and adjustment in both models provides a dynamic and evolving representation of possible policy impacts. Incorporating policy acceptability would allow not only efficient but also feasible policy trajectories to be identified.

5 Conclusion

Empirical surveys capture a snapshot of a particular phenomenon at a specific time and place, potentially limiting the broader applicability of the findings. In a survey study, each participant forms their opinion independently and in isolation. However, these opinions may be subject to change when individuals engage in interactions with others or are exposed to new information. However, agent-based models offer a powerful alternative for exploring potential developments stemming from such analyses. By simulating the interactions between individual agents within a dynamic system, this would allow to investigate the effects of varying conditions and parameters on the system's behaviour. This flexibility not only enables the exploration of alternative scenarios but also facilitates the identification of underlying mechanisms and patterns that may not be immediately evident in a single empirical snapshot. The PANDORA model is specifically designed to address these questions with a focus on the attitude towards a policy in the heating sector. In our research approach we explore how the process of policy attitude formation could be formalized, relying on available empirical data and established models of attitude formation and opinion dynamics. Given that the model depends on simplifying assumptions, we recognize that all conclusions are provisional and require further testing and sensitivity analysis. Additionally, there remains potential for further model developments in various aspects. However, we hope that the model framework which combines empirical observations with agent-based modelling will prove useful for other research studies.

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