Network dynamics of solar PV adoption

Reconsidering flat tax-credits and influencer seeding for inclusive renewable energy access in Albany county, New York

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DOI
10.1016/j.erss.2024.103518

Publication date
2024

Document Version
Final published version

Published in
Energy Research and Social Science

Energy Research & Social Science 112 (2024) 103518

Contents lists available at ScienceDirect

Energy Research & Social Science

journal homepage: www.elsevier.com/locate/erss

Original research article

Network dynamics of solar PV adoption: Reconsidering flat tax-credits and influencer seeding for inclusive renewable energy access in Albany county, New York

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A R T I C L E I N F O

Keywords:
Energy transition
Agent-based modeling
Justice
Social influence
Just transition

A B S T R A C T

Governments often use price-based policies such as tax-subsidies and rebates to encourage households to shift to renewable energy sources like rooftop solar photovoltaics (PV). These policies, however, have primarily benefited high-income homeowners, leaving others behind. This paper proposes leveraging social networks' influence on attitudes and perceptions to design more equitable solar PV adoption programs. Using data from Albany county (New York State, USA) we develop an Agent-based model, integrating a novel implementation of circles of influence into the theory of planned behavior. We test two policy categories (generic and targeted) under two network scenarios (integrated and segregated). Resulting solar PV adoption rates are evaluated using egalitarian, utilitarian and cost metrics to analyze policy impact on different income groups. Our findings indicate that network structure significantly influences adoption rates within income groups. Low-income groups in segregated networks can experience higher adoption driven by positive attitudes towards solar PV, while high-income groups in segregated networks may face poor policy performance despite higher affordability. Seeding policies and information dissemination through influential network members may not necessarily improve adoption rates, as trust can a more important role. The study underscores the importance of trusted information sources in influencing adoption decisions. The insights gained from this research can guide policy design for tailored interventions to improve access to renewable energy for all income groups.

1. Introduction

The residential sector is responsible for the largest share of greenhouse gas emissions in the built environment [1]. Given the large energy use and greenhouse gas emissions associated with the construction and operation of buildings [2], decarbonizing this sector is one of the most effective ways to mitigate the impacts of climate change [3]. Reducing these emissions requires a twofold approach: (1) decarbonizing/reducing energy demand for operational uses and (2) decarbonizing/reducing embodied emissions resulting from the lifecycle of buildings (production of materials, construction etc.). Hertwich et al. [4] illustrate how to reduce residential emissions through the adoption of low-carbon technologies at the household level. Governments facilitate this transition by financially supporting the renovation of buildings as well as the adoption of renewable energy sources and energy-efficient appliances [5]. Among the various low carbon technologies available, solar photovoltaics (solar PV) are poised to have the largest installed capacity expansion by 2050 [6,7], with governments actively designing incentives for the adoption of rooftop solar PV at the household level. Investments in solar PV – leading towards economies of scale – have reduced its costs rapidly, making it an attractive energy choice for households [8]. This has been complemented by policy support in the form of tax credits and subsidies [9].

Despite attractive prices and government incentives, the adoption of solar PV is an inequitable process, with high-income households more likely to adopt solar PV than low and middle-income households [7,10]. This results in unequal impact of transitions with low-income households paying disproportionately higher in energy costs and missing out on benefits via extra revenue streams from selling excess electricity back to the grid. Inequity in solar adoption follows other deeply-entrenched social divisions: in a recent study in the United States of America (USA), racial disparities were observed in solar deployment, with households in black-majority census-tracts installing 69% less solar PV on their roofs as opposed to non-black majority census-tracts [11]. Addressing the inequity in solar adoption can also

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https://doi.org/10.1016/j.erss.2024.103518
Received 28 March 2023; Received in revised form 30 November 2023; Accepted 13 March 2024
Available online 20 March 2024

translate to environmental benefits: in countries such as the USA, low and middle-income households constitute 42% of rooftop space suited for solar PV deployment which, if adequately utilized, can accelerate realization of clean energy goals [10].

There is a general perception that installing rooftop PV is expensive and cumbersome to maintain, adding more costs to the consumer [12, 13]. By focusing on improving the economic value of solar PV, factors that have been shown to be more predictive of adoption such as risk perception and influence of social networks, are ignored, thus translating policies and their subsequent benefits into disproportionate adoption rates and outcomes among social groups. Qualitative and quantitative studies in new technology adoption argue that risk perception, attitude towards new technology, and information procured through social networks play a more decisive role in a household decision to adopt than merely financial concerns [14–16]. The adoption of new technology is a complex socio-technical process [13] that is highly behavior-driven [17]. The difference in adoption behavior between income groups is highlighted by several studies. For example, a study of PV poverty alleviation programs note that adoption behavior in reaction to generic policies like rebates or mass information campaigns is different in low-income and high-income households [18]. Another study of solar PV adoption in Bangladesh, corroborates this finding by showing that local community organizations play a significant role in increasing solar PV adoption rates in low-income households; this is not the case for high-income households [19]. Further, scholarly work illustrates that the structure of the underlying social network in which the households interact influences the overall adoption rates across social groups [20]. For example, a policy that performs well in an integrated network (where inter-group interaction is as likely as intra-group interaction) may reduce adoption by lower income groups if deployed in a segregated network (in which there is more interactions within a group than between two different social groups) [13,21].

To improve equitable adoption across social groups, policy-support tools like modeling and simulation studies need to incorporate additional elements such as social dynamics and network effects [13]. Firstly, households have to be considered in the complex environments of their social networks [14]. Secondly, household adoption decision-making has to be rooted in socio-psychological theories that consider the role of *perception, trust and uncertainty* in the face of new technologies [22]. Finally, evaluation of policy performance should include dis-aggregated metrics that consider their impact on different income groups, thereby moving beyond a focus on simply boosting overall adoption rates [13,18,19].

One way to incorporate social dynamics and network effects into policy modeling approaches is by using Agent-based Modeling (ABM) [7,23–25]. However, studies that consider both social dynamics and equitable adoption [13,15,26] do not address two key aspects for an equitable adoption of solar PV. First, these are conceptual models whose insights may not reflect reality and therefore cannot be used to inform tailored policy needs. Secondly, these studies focus only on generic price-based policies like tax rebates and subsidies, which are applied universally without regard for economic or social factors. They do not take into account targeted policies designed for specific income groups and the underlying social network structure, which can harness peer effects to address adoption barriers unrelated to finances.

Building on these gaps, this paper investigates the influence of social dynamics and network effects on an equitable adoption of solar PV at the household level. We present and demonstrate a modeling approach to design solar PV policies that aim at equitable adoption across social groups. For this, we use open-source data sets to build a data-driven agent-based model (ABM) grounded in the Theory of Planned Behavior (TPB). We apply our model to the case-study of Albany county (New York State, USA) where adequate datasets are available for various components of our model. The proposed model has several features that address important gaps in existing approaches in the following ways:

- **Contextualizing** the model in a data-driven case-study incorporating social dynamics. In addition to financial considerations, household decision-making incorporates risk-perception, and social influence that shapes their attitude towards solar PV.
- **Testing** both generic and tailored policies on two different social network structures that households are embedded in: integrated and segregated networks.
- **Evaluating** the policy performance using an aggregated as well as a dis-aggregated metric to examine equity impacts of a policy on adoption by different income groups such as low, medium and high-income households. We use *overall adoption rates* as the aggregated metric, based on the distributive justice principle of utilitarianism, which focuses on maximizing distribution of benefits to as many households as possible [27]. We use a dis-aggregated metric, *adoption rates across low, medium and high income groups*, to examine how the same policy is received differently based on income. This metric aligns with the egalitarian concept of equalizing the distribution of impacts among all involved parties, drawing inspiration from Rawls' difference principle [28–30]. Finally, to comment on the cost of resources required to execute these adoption policies by the government, we use a third metric: *policy cost*.

Explicit inclusion of energy justice considerations into low-carbon transition studies is becoming increasingly important. Many conceptual frameworks of energy justice exist within literature such as the Ten Principles of Energy Justice introduced by Sovacool et al. [31] which considers the issue through dimensions like affordability, availability, due-process, inter-and intra-generational equity, among others. Discussions of energy justice also use the Three-Tenets of Energy Justice Framework as introduced by McCauley et al. [32] where energy justice can be seen as procedural, distributive and recognition justice. More recently, restorative justice is also entering the discourse, in the context of compensation for the historically disadvantaged. The subject of this study – equitable adoption of solar PV – exemplifies several of these justice issues as outlined earlier: income disparities, gender-bias, racial and ethnic inequalities in affordability of solar PV and access to information or participatory processes. Gender, racial and ethnic issues are also intersectional in nature, offering a lot of opportunities to expand existing methods to provide policy support that can examine these considerations [31]. Additionally, the conceptualization of energy justice via evaluation of policy effectiveness can be expanded to include environmental impacts; for instance, by calculating emissions saved by the solar PV adoption rates resulting from the policy [33].

Within this study, we take a first step in including dis-aggregated metrics to analyze policy performance while also incorporating social dynamics and network effects in a data-driven model setting. This also limits our scope of addressing energy justice to studying the distributive fairness from an income point of view primarily. Our modeling methodology brings together theories from different disciplines such as energy justice, social-psychology and social science in a data-driven approach within the case-study of Albany. The results presented in this paper show how the model can support the design of equitable solar adoption programs, by providing insights on adoption rates across different income groups. Policy-makers should consider targeted policy programs that can accommodate differential requirements, ensuring that no one is left behind in the energy transition process.

2. Material and methods

Overview of the methodology. To study the role of social networks in promoting equitable adoption policies for solar energy, we developed a spatial data-driven Agent-based Model to simulate adoption dynamics. Decision-making process of the households behind adopting solar PV (or not) is rooted in the Theory of Planned Behavior (TPB). As a case study, the spatial context from Albany County is leveraged

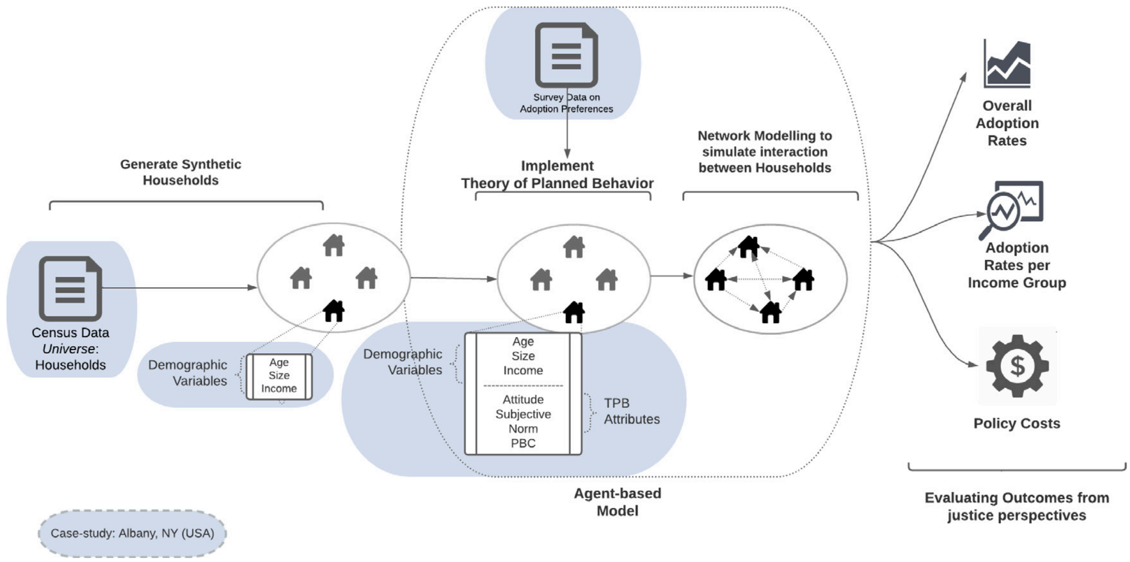


Fig. 1. Methodology to study equity outcomes of adoption policies for rooftop solar PV The overarching methodology diagram shows how a data-driven agent-based model (ABM) is constructed using theory of planned behavior (TPB) and network modeling. Spatially explicit synthetic households are generated from census data. The ABM has two components: (1) implementation of TPB using survey data, that models household-level decision-making concerning solar PV adoption and (2) modeling of realistic household social networks through which they interact. Households' attitudes perceptions towards solar PV evolve as a result of these interactions. The outcomes of the ABM (adoption rates) are tested under two social network structure scenarios and evaluated according to equity metrics.

to generate synthetic households to serve as agents in the Agent-based Model. TPB requires each household agent in the model to be initialized with TPB attributes. However because it is not possible to get data on households' attitudes towards solar PV for all households in Albany county (about 80,000 households), it is necessary that data from the available adoption survey which contains attitude information of a smaller population subset, is used to initialize the TPB attributes of all synthetic households within Albany county. The ABM models households' interaction over time leading to evolution of these attitudes towards solar PV, which can lead to a household deciding to adopt solar PV. Using network modeling and a novel implementation of the Dunbar's number, called the Circles of Influence Theory, realistic multi-level social networks between agents are generated to simulate the interactions between households, which in turn influence adoption behavior of households. Two types of household social networks are studied: integrated (likelihood of inter-group and intra-group interaction is similar) and segregated (limited interaction between groups, but more interaction within a group). This is done to evaluate the role of household social networks in influencing adoption decisions of households. In order to understand the implications of two kinds of policies (generic and targeted) on the equitable adoption of rooftop solar PV, the resulting adoption rates are evaluated from two different distributive justice perspectives of utilitarianism and egalitarianism. Economic costs associated with deployment of each policy are studied as a third metric to evaluate the economic feasibility of just adoption policies. A conceptual overview of the methodology is illustrated in Fig. 1.

Modeling steps. Households are modeled as agents, using openly available US Household Census data (an overview of census datasets used is provided in Table 1). The datasets refer to the year of 2015, the year from which solar adoption data is available for Albany county. The development and application of the model follows a four-stage process.

Initializing agents. In the first step, about 80,000 households are synthetically generated. To these synthetic households, demographic and behavioral attributes are assigned from open-source adoption attitude surveys [34] and census datasets.

Conceptualizing household interactions. In the second step, the resulting household agents are embedded in realistic multi-level social networks that facilitate the evolution of attitudes via the *Relative Agreement Theory* introduced by Deffuant et al. [35], with different degrees of influence modeled through the *Circles of Influence* Theory adapted from Dunbar [36].

Modeling rooftop solar PV adoption by households. In the third step, the initialized model containing households and their social networks is calibrated to historical adoption curves of Albany county. The spatial data-driven ABM is then used to test policy scenarios of two categories (i.e. generic and targeted) under two different network structures (i.e. integrated and segregated).

Evaluating policy outcomes using justice perspectives. In the final step, the policy outcomes are evaluated based on equity and cost metrics: (a) overall adoption (utilitarian principle), (b) adoption across low, middle and high-income groups (egalitarian principle) and, (c) the cost of policy implementation.

The code behind the model can be accessed via github here.

2.1. Initializing agents

2.1.1. Generating synthetic households

A synthetic population of owner-occupied single-family households were modeled using the population of the Albany county, for the year of 2015. Each household generated is characterized by 3 demographic variables: Age, Household Size and Household Income (see Supplementary Information for a discussion on the choice of demographic variables, in Section 2). For each of these demographic attributes, data was obtained from the US Census for owner-occupied single-family households at block-level resolution for the year of 2015. Where the data was not available at a block-level resolution (for example, household income) the data was dis-aggregated using the naive method of using marginal probability distributions to breakdown the data to a higher resolution (for details on how this is done, see Supplementary Information section 3.1). The choice to only include owner-occupied, single-family households is driven by three reasons: (1) to enable a comparative study of generic policies versus policies targeted towards specific income groups, it was required that a single family live in the house so that an agent in the model can be attributed with a single income group and age of the head of household; (2) to keep calculations

Table 1
US Census Datasets used to Generate Synthetic Households for Albany County (New York State, USA.

Variable	Year	Dataset	Aggregation
Tenure by Household Income in Owner Occupied Households	2015	ACS-5yrs, B25118	Census Tract Level
Tenure by Age of Householder in Owner Occupied Households	2015	ACS-5yrs, B25007	Block Group Level
Tenure by Household Size in Owner Occupied Households	2015	ACS-5yrs, B25009	Block Group Level
Average Electricity Consumption by Area Median Income (AMI) and Building Type	2011–2015	SEEDS-II REPLICA Project & LEAD Dataset	County Level

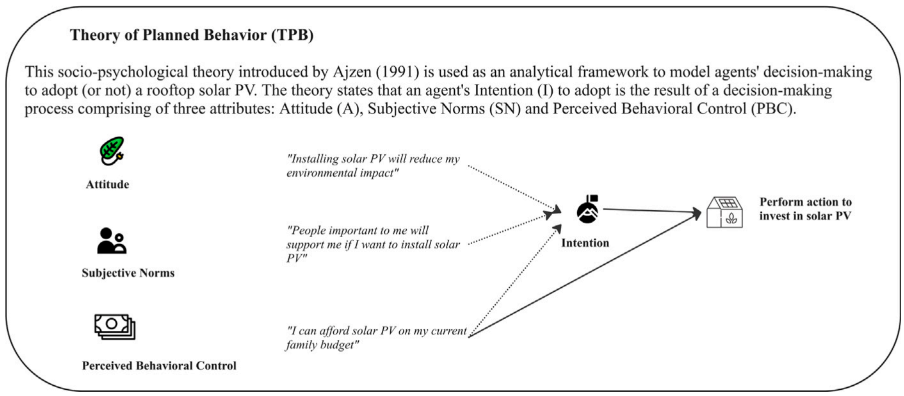


Fig. 2. A brief summary of the Theory of Planned Behavior.

of tax-rebates and estimation of payback period simpler per household, we excluded other installation options such as solar PV leasing, shared ownership via solar PV on building roofs or community solar; (3) there was no data availability on income levels of owners who owned houses currently occupied by tenants. In the lack of such a data, it was not possible to keep the household characteristics such as electricity usage, its location and therefore interaction with neighbors, directly related to the demographic characteristics. These methodological and data limitations have implications on the analysis of energy justice considerations, which we address in Section 4.

2.1.2. Allocating behavioral attributes to households

As established in Section 1, decision-making involved in new technology adoption is a complex socio-technical process, that in addition to financial considerations also involves behavioral factors such as risk-perception and social influence. To include these social dynamics in the model, household agents in the ABM make decisions grounded in TPB. TPB is a useful socio-psychological analytical framework that has been applied widely to model new technology adoption in the context of pro-environmental behaviors [37]. TPB states that an agent's *intention* to perform an action (adopting solar PV in this case) is the result of a combination of three attributes: Attitude (A), Subjective Norms (SN) and Perceived Behavioral Control (PBC) [38]. Attitude encapsulates the agent's opinion/predisposition towards performing that action. Subjective Norms capture the agent's perceived social pressure to perform the action in the presence of peer influence. Finally, PBC quantifies the perception of the agent's ability to perform that action. For example, even if a household is positively predisposed to the idea of adopting solar PV and has social connections that are also positive about adopting, if the household does not have the financial means to buy and install a solar PV system, the household will still not adopt. TPB is a useful tool because the three attributes (henceforth referred to as TPB attributes) can be empirically derived from adoption surveys and used as inputs in ABM models (see Fig. 2).

To initialize the synthetically generated households with behavioral attributes in addition to the demographic attributes, we use publicly available attitude survey datasets published by USA's National Renewable Energy Laboratory (NREL) titled "Understanding the solution of customer motivations and adoption barriers in residential photovoltaic markets" of the SEEDS Project [39]. The surveys include household respondents from four US states (New York State, New Jersey, California and Arizona) for the year of 2015 [39]. Data collected includes households' opinions on benefits of solar PV, their general attitude towards climate change, the importance of reducing emissions, risk perception, etc. These responses are used to estimate the three TPB attributes (A, SN and PBC) for each of the 4000 household respondents in the attitude surveys. To maximize datapoints available to initialize TPB attributes for the approximately 80,000 synthetic households in Albany county, we first test if the adoption survey data is associated with the differences in states (the location of the household such as New York or New Jersey, for example). Through linear regression, we confirm that the State variable does not significantly explain TPB attributes. Three demographic variables that most explain the household's TPB attributes are chosen: household size, age of the head of household (as described in the dataset) and household income (refer to Section 4.3.1 in Supplementary Information). Using regression, the weights for the three TPB attributes (w^a, w^s, w^p) are derived from the adoption survey dataset to calculate the Intention (I_i) for every household i in the survey dataset (see (1) below). To now allocate TPB variables for all 80,000 households, we employ a method that uses the Gower's Distance to match a representative household from the synthetically generated household data, to a household record in the attitude survey data. Details of the method can be found in Section 4.4 in the Supplementary Information.

Intention. The behavioral intention (I_i) to adopt or non-adopt is a likelihood scored according to Eq. (1), where i is every household agent, a, s, p are attitudes, subjective-norms and PBC respectively are the TPB attributes of each household and w are the weights for each attribute, which are derived from the regression model.

$$I_i = w_a * a_i + w_s * s_i + w_p * p_i. \tag{1}$$

If I_i crosses a threshold known as the Intention Threshold that is empirically derived from the survey dataset, the household's adoption status is set to 1, else it remains 0. At the end of the initialization step, each of the synthetic household agents possess six attributes that factor into their adoption decision-making: three demographic variables (age, household size and household income) and three TPB attributes (A, SN and PBC).

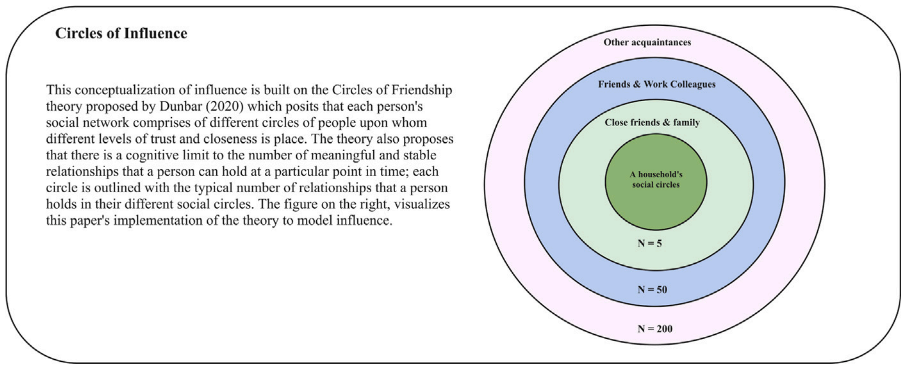


Fig. 3. A brief summary of the Circles of Influence theory.

2.2. Conceptualizing household interactions

In order to model interactions as realistically as possible, two important social science principles are leveraged. First, the principle of homophily states that intra-group social ties are more likely compared to inter-group; these groups can be based on income, socioeconomic status, etc [40,41]. In our model, agents belonging to the same income group are given a higher likelihood of interacting with each other if we are establishing a segregated network, else they interact with the same likelihood with all other agents. Second, studies show that geographically proximate connections are far more likely to interact compared to non-local connections further away [42]. This results in household agents belonging to the same neighborhood (block-level) having greater likelihood of interaction. These two principles form the basis on which agents are made to interact with each other in the ABM process in every time-step.

2.2.1. Circles of influence theory

In reality, not all acquaintances have the same level of influence over our personal opinions. It is likely that each of us have a close-knit group of trusted members of family and friends whose opinions/experiences we value more than an interaction with a random person on the internet or a friend of a friend. Dunbar [36] posits that there is a cognitive limit to the number of meaningful and stable relationships one can hold at any particular point in time. This number, known as Dunbar's number, is on an average between 100 to 250 [43]. In our model implementation of this concept, referred to as the Circles of Influence theory, we assign three social circles to every household. The first and innermost circle contains 5 households with whom very close relationship is maintained. The second outer circle is initialized with 50 other households; they can be friends, workplace colleagues. At every time-step, a household agent interacts with about 15 of them, which is assumed to be a realistic assumption in the context of solar PV adoption. The third and outermost circle is initialized with 200 households who can be acquaintances with whom the household comes into contact less frequently. A household agent interacts with a maximum of 20 of these third-circle households during the modeling time steps (1 step = 1 year). The time-step adopted in this study is one year, within which we assume the household agents would have interacted with other agents within their social networks related to the topic of installing a rooftop solar. Realistically, it is likely that a household does not interact with all members within their social circles about the topic of solar PV every year. However in the absence of any empirical evidence on the frequency of interactions, we assume that both adopters and non-adopters communicate every year. After installation, it is assumed that new adopters will continue to communicate about their experiences (see Fig. 3).

Table 2
Four Income Groups, the corresponding annual household income ranges and labels used henceforth in the study, when defining policy scenarios.

Household income group	Income category	Label
Less than USD 75 k per annum	Low Income	less75k
Between USD 75 k to 100 k per annum	Middle Income	75to100k
Between USD 100 k to 150 k per annum	High Income (1)	100to150k
Greater than USD 150 k per annum	High Income (2)	150kplus

The parameter that determines how influential these interactions can be on the household's decision to adopt is the *Intensity of interaction* from the Relative Agreement (RA) component of the model. This intensity, (μ) is a value between 0 to 1, which decreases in magnitude from the innermost to the outermost circle. This value is determined when the ABM is calibrated to historical adoption curves, details of which can be found in the Supplementary Information (see section 5.1).

2.2.2. Integrated and segregated networks

Two types of social network structures are implemented to operationalize the circles of influence: integrated and segregated networks. In the *integrated* network structure, agents are assigned a higher likelihood of establishing social ties with members of other income groups. While initializing circles of influence, this is reflected in equally-likely sampling of households from any income group. In the *segregated* scenario, agents follow the homophily principle more strictly, by forming ties with higher likelihood within their income groups. This reflects the socioeconomic divide that is often observed in certain areas being labeled rich or poor neighborhoods (see Fig. 4).

The four income groups are used henceforth in this study are summarized in Table 2 below:

Within this study, we will refer to household income groups by their income group labels. Because there are two high income groups (100to150k and 150kplus), any reference to high income groups can be taken to refer to both these income groups.

2.3. Modeling evolution of household adoption behavior

To simulate realistic adoption behaviors in households, the behavioral attributes are modeled to change based on interaction with other agents, thereby ensuring that a household's likelihood to adopt rooftop solar PV is based not just on financial considerations (such as changes in the unit price of rooftop solar PV) but also due to peer influences (such as information received from a close-friend or family who has recently adopted solar PV, or seeing a neighbor installing it on their rooftops). To accomplish this in the spatial data-driven ABM, the behavioral TPB attributes (A, SN and PBC) assigned to the household agents at the initialization stage are modeled to evolve over time as these households interact with others within their networks.

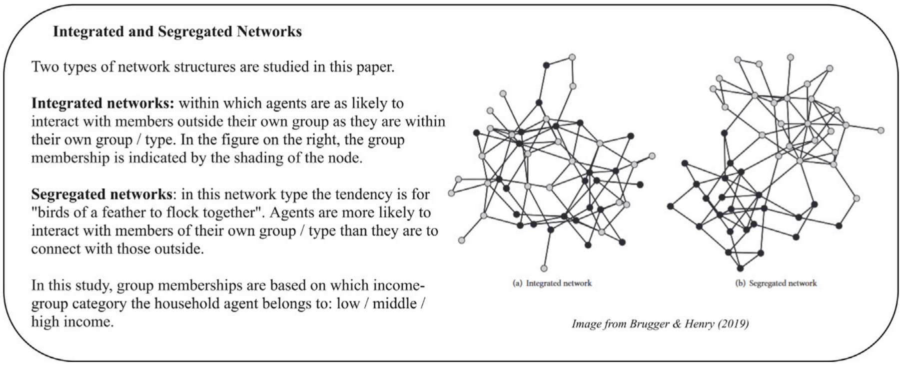


Fig. 4. A brief summary of the two network structures explored within this study: Integrated and Segregated Networks.

2.3.1. Evolution of behavioral attributes

The agents' intention (I) to adopt is recalculated after every time-step. An overview of how all the separate processes come together to influence an adoption decision is presented in Fig. 5.

Evolution of Attitudes: Attitudes change based on our opinions and interactions with others. Among several opinion dynamics models available, the Relative Agreement (RA) Model developed by Deffuant et al. [35] is the most widely used model integrated with ABMs. The key advantages of an RA Model are that (1) agents possess different levels of confidence (uncertainty) on their opinions, (2) more confident agents are more persuasive, having more influence over the less confident agent, and (3) agents are more likely to be influenced by those agents within their opinion range; For example, a person who denies climate change is less likely to influence a person who acknowledges climate change, while a person who does not have a strong opinion about the subject has a higher likelihood of resonating with a more confident person. Not all agents have an equal likelihood of interacting with each other and not all acquaintances have the same level of influence over each other's opinions. To reflect this realistic behavior, we combine the existing approach of Deffuant's Relative Agreement Theory with the Circles of Influence model. As the model runs, the agents' attitude variable evolves through the RA framework through interaction with other agents. The attitude (A) attribute of a given household towards solar PV adoption can change upon interaction with other households, each of which may have either a positive or negative experience with installing solar PV (reflected by their attitude value). The strength of this influence depends on whether the adopter or non-adopter belongs to the household agent's innermost trusted circle or is just a passing acquaintance (in an outer circle). This results in agents (1) being less influenced by extreme opinions of the opposite spectrum, giving more weight to opinions closer to their range of opinions while (2) giving more importance to the opinions of agents in their immediate friend/family circles (see Supplementary Information sections 5 and 6 for more details on how this is calculated).

Evolution of Subjective Norms: The larger the presence of solar PV adopters within the circles of influence of an agent, the higher is the likelihood that this agent will consider solar adoption seriously. It has been shown that an increase in the number of solar PV in a zipcode area increases the likelihood that another household in the area will adopt as well — this phenomenon is called 'observability bias' of adoption [44]. Implementing the observability bias requires increasing the value of subjective-norms as the share of adopters in an agent's neighborhood increases.

Evolution of Perceived Behavioral Control: Research shows that the perception of affordability is the most cited barrier to adoption [7]; financial considerations therefore include not just income considerations, but also the agent's perceived ability to make the adoption decision. These include the household's concerns on being able to afford, payback period (time taken to break-even on investment costs) that can be tolerated by them and cost of solar PV. At every time-step (1 year period), the agent (a) checks their attitude and subjective-norm levels, (b) checks their own household's electricity consumption that year, and (c) estimate an actual payback period (see Eq. (4)) to check if it is within their tolerable limit. This process is encapsulated in Eqs. (2)–(4).[1]

$$NetSolarCost = \frac{(MonthlyElectricityUse * 12 * AvgPrice/Watt * TaxCredit)}{SolarProductionRatio}. \tag{2}$$

$$AnnualSavings = AnnualElectricityCost - (AnnualSolarProduction * FeedinTariff). \tag{3}$$

$$ActualPaybackPeriod = \frac{NetSolarCost}{AnnualSavings}. \tag{4}$$

The flowchart in Fig. 6 illustrates how the initial PBC is used to estimate the tolerated payback period for the household (see details of this estimation process in Supplementary Information Section 5.2). Unlike the other two attributes of Attitude and Subjective Norms, PBC of the agent does not change at every time step, but rather it is used to determine the tolerable payback period for the household which is then compared to the actual payback period they would achieve if they invested in solar that month (at the current prices, tax credits and other incentives). If the actual payback period of the solar system is within their tolerated limit, their PBC switches to 1, which implies they are (financially) ready to adopt, but will only adopt if their behavioral intention (I) also crosses threshold limits. Average monthly electricity consumption data for different income group levels at census tract levels is derived from the Low-Income Energy Affordability (LEAD) Tool developed by the U.S. Department of Energy and made public under the SEEDS-II REPLICA Project (available at: https://data.nrel.gov/submissions/81). As per the documentation of the REPLICA Project, "the residential energy expenditures dataset provides estimates of average monthly electricity expenditures, at the County level, per Area Median Income (AMI) group (0%–30% AMI, 30%–50% AMI, 50%–80% AMI, 80%–120% AMI, greater than 120% AMI), building type (multi-family or single-family), and tenure (renter or owner)" [34]. For this project, we specifically focus on single-family, owner-occupied households and map the energy consumption data of households within a particular county, based on their AMI.

[1] Solar Production Ratio is defined as the estimated number of kWh a set of solar panels will produce in a year, divided by the wattage of the panels.

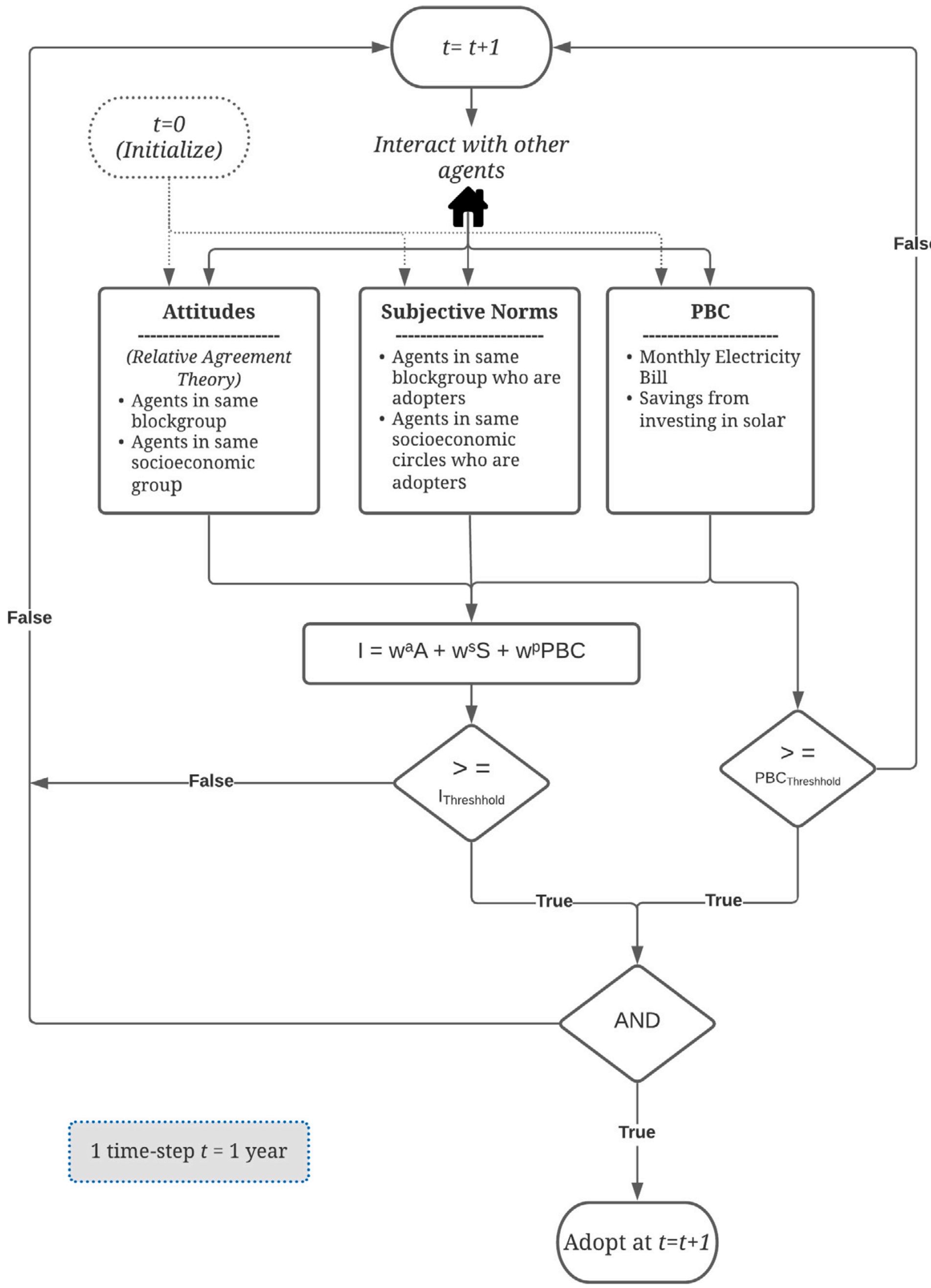


Fig. 5. Overview of the ABM modeling process over time. The three TPB attributes evolve over time as a result of agents interacting with each other via their social networks and this eventually influences their adoption decision. At every time-step of a year, each agent's adoption Intention (I) is recalculated. If it crosses the intention threshold while at the same time satisfying the condition that the agent's perceived behavioral control is also strong enough to perform the action, then the agent adopts solar PV at the end of the time-step.

2.3.2. Calibration, verification and validation of model

ABMs built for use in policy-support are expected to be empirically grounded [45]. The reliability of such ABMs is associated with their ability to realistically replicate, represent and predict the behavior of the target phenomenon being modeled (in this case, solar PV adoption dynamics in Albany county). Therefore, the initialized model from the previous step is calibrated to reproduce historical adoption curves of Albany county between the years of 2015 to 2021. To investigate the sensitivity of the outputs to changes in the parameter values, a sensitivity analysis is carried out using the One-Factor-At-A-Time (OFAT) approach. OFAT approach involves running the baseline model by varying one parameter at a time while all other variables are held constant. The parameters and respective baseline and variation range used for the model verification, are found in the Supplementary Information.

2.3.3. Policy and network scenarios

We consider two broad schemes: (1) tax credit schemes, whereby a specific percentage of the cost of a solar PV is reimbursed by the State and Federal government in terms of tax-credits that can be claimed by the household purchasing and installing the solar PV on their rooftops, and (2) seeding schemes, whereby a household is provided with a solar

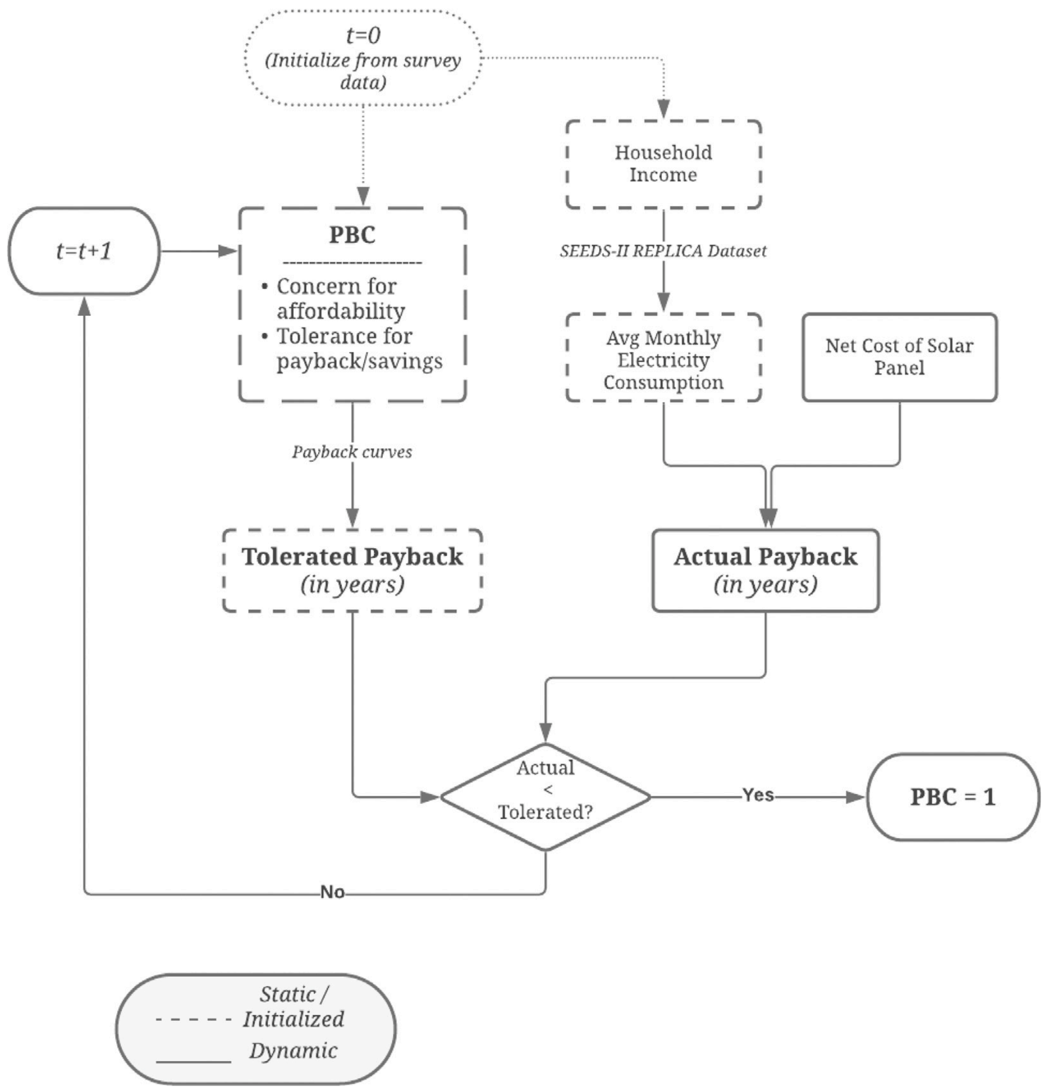


Fig. 6. Evolution of Perceived Behavioral Control (PBC). At every time-step the agent evaluates how much would be the payback period if they would have bought a solar PV system at the current price of one unit and retail electricity rates. They also factor in their annual electricity consumption to assess the benefits. If the payback time is below their maximum tolerable period, their perceived behavior control value (PBC) becomes 1. If not, despite their attitudes and peer influence positively disposed towards solar PV adoption, they remain non-adopters.

PV. Policy scenarios are created based on these two schemes and are grouped into two categories: targeted and generic policy scenarios.

Targeted policies. these include policy scenarios that are tailored to the underlying network structure: flat-tax credit schemes, tax credits tailored to income groups, random seeding policies, and seeding policies tailored to low-income groups.

Generic policies. the second category refers to generic policies not tailored to the network structure, including seeding influencers randomly and seeding influencers within specific income groups.

Influencers are identified according the network type considered. For integrated networks, ***degree centrality*** is used as the measure of an agent's influence, while in segregated networks, ***betweenness centrality*** is adopted [46]. The policies are tested under two network scenarios each: integrated and segregated networks. A total of 10 policy scenarios simulated for the period between 2015 and 2021. For a summary of the policy scenarios and their categories, refer to Table 3.

2.4. Policy evaluation

Two equity metrics are used to provide insights into how benefits of policy outcomes are distributed. The utilitarian metric in this study is equal to the overall adoption rate (of the entire Albany county), regardless of income group. The egalitarian metric likewise, reflects the egalitarian philosophy which asserts that a policy should strive to maximize overall welfare, subject to the constraint that all individual members equally benefit from it. The egalitarian metric is therefore designed as: adoption numbers per income group. We make explicit our assumption here that a household *benefits* by adopting rooftop solar PV. The third metric is the policy cost, used to evaluate policy scenarios on their financial viability. In the case of policies providing tax-credits, the policy cost is calculated by summing up the costs that are reimbursed by the government as tax-incentives to adopters. This involves calculating the size of the solar system and the respective year's price-per-watt of solar and retail electricity rates. In policies that involve

Table 3
Experimental Setup: Ten policy scenarios belonging to two categories of Generic or Targeted Policies are defined.

Policy scenario	Category	Description	Parameters
1	Generic	Tax credits of 46%	Panel Cost = 54% of Net Panel Cost
2	Generic	[Baseline] tax credits of 51%	Panel Cost = 49% of Net Panel Cost
3	Generic	Tax credits of 56%	Panel Cost = 44% of Net Panel Cost
4	Targeted	Tax credits based on Income-Group	less75k (low income): tax credits = 56%, 75to100k (middle income): tax credits = 51%, 100to150k (high income): tax credits = 46%, 150k+ (very high income): tax credits = 46%,
5	Targeted	Seeding Low Income Groups	[0.1%, 1%, 2%] of households in the Income-Group less75k
6	Targeted	Seeding Low and Middle Income Group	[0.1%, 1%, 2%] of households in the Income-Groups less75k and 75to100k
7	Targeted	Seeding Random Influencers	[0.1%, 1%, 2%] of top influencers in network
8	Targeted	Seeding Low Income Group Influencers	[0.1%, 1%, 2%] of top influencers low income group network
9	Targeted	Seeding Low & Middle Income Group Influencers	[0.1%, 1%, 2%] of top influencers low and middle income group network
10	Generic	Seeding Random Households	[0.1%, 1%, 2%] of all households in network

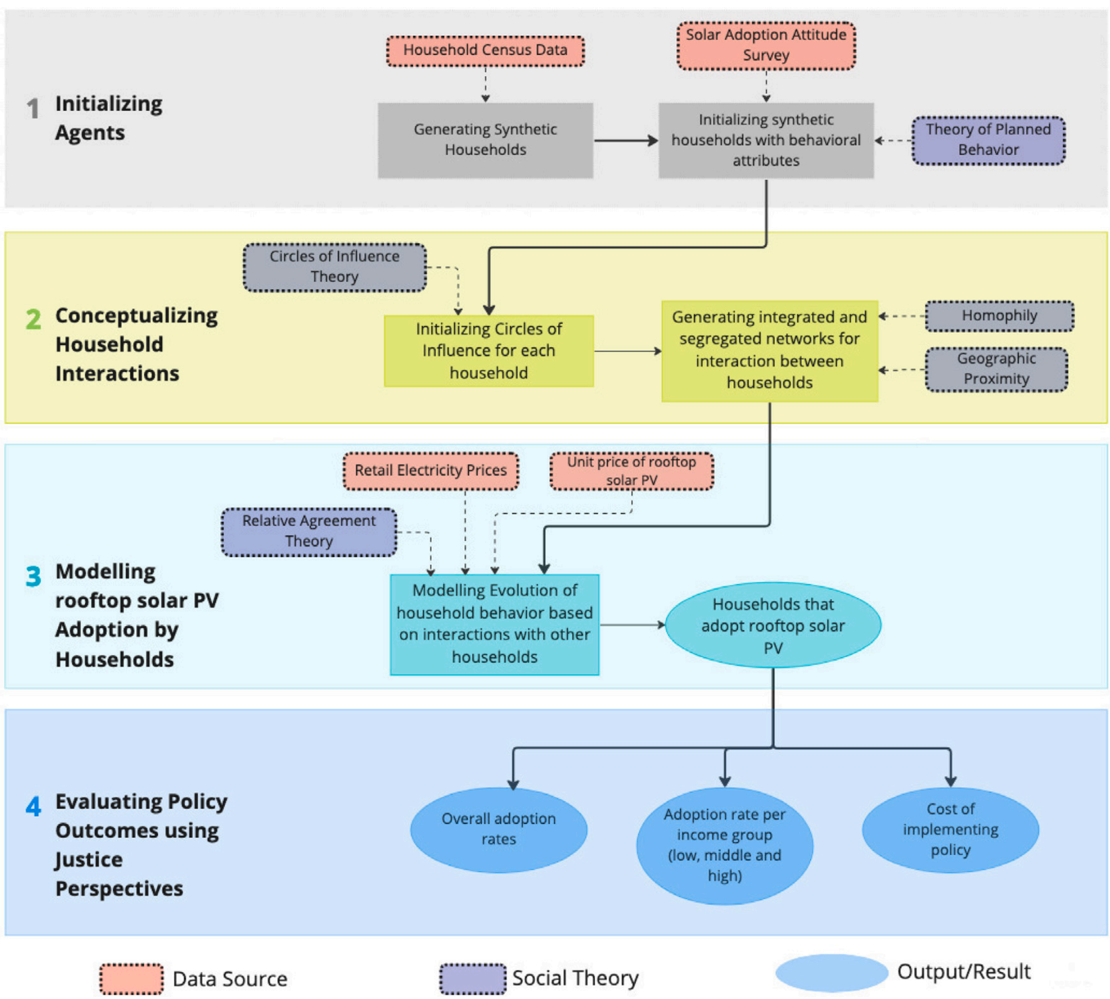


Fig. 7. **Four step modeling process.** Key steps implemented in each stage of the modeling process, namely (1). Initializing agents, (2)Conceptualizing household interaction, (3) Agent-based modeling, and (4) Evaluations of policy outcomes in light of justice concerns.

seeding strategies (either specific income groups or influencers), the full net cost of the panel is included. By seeding, the household is provided with a solar panel at no cost to the beneficiary (a member of an income group or an influencer). Furthermore, in the case of seeding an influencer's household, it is assumed that the influencers are paid no additional cost for volunteering to install a panel on their roof; only the cost of panel is considered.

The overall modeling process is visually summarized in Fig. 7.

3. Results

3.1. Generic policies

Two types of generic policies were simulated: flat-tax credit schemes and random seeding of solar PV to households. The latter is considered

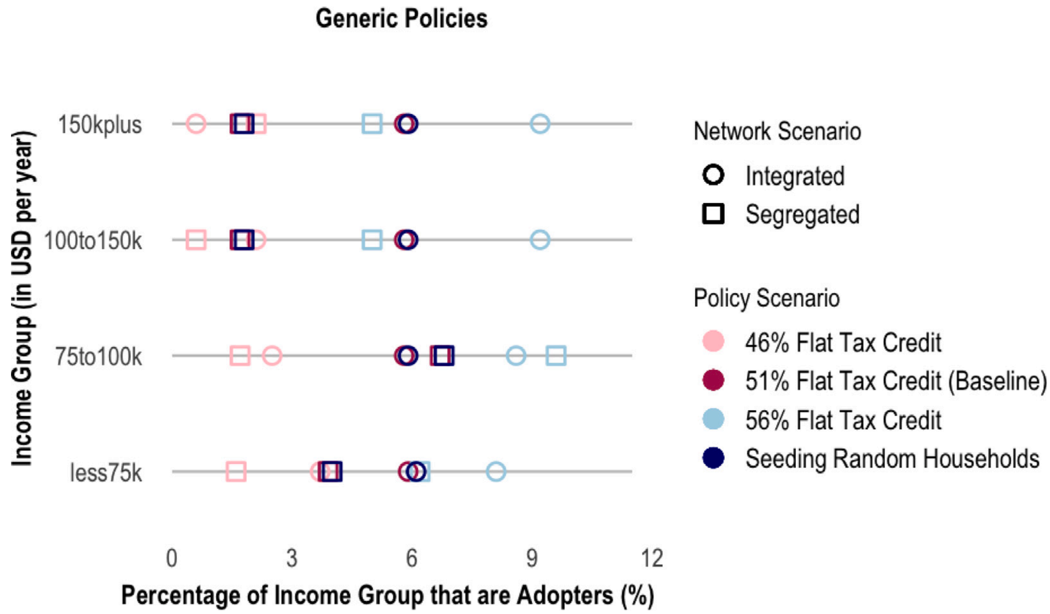


Fig. 8. Generic Policy Scenarios [Scenario 1, 2,3]: Integrated vs. segregated network — Adoption rates for across income categories for a flat tax credits of 46%, 51% (Baseline value) and 56% respectively. [Scenario 10] Adoption rates for policy where households are randomly seeded with a solar PV. Tabular format of these results can be found in Section 8 of Supplementary Information.

generic because beneficiary households are not targeted based on any socioeconomic or demographic indicators, with households belonging to any income-group equally likely to be seeded with a solar PV system at no cost to them. Adoption percentages per income group for all four generic policies simulated are presented in Fig. 8.

We start analyzing the results of the baseline scenario (Scenario 2 in Table 3), in which a tax credit of 51% is applied to all households, regardless of their income level. In this case, integrated networks perform better for all income levels except for the income range between 75to100k, for which the segregated network performs slightly better (Fig. 8). In addition, integrated networks also lead to uniform adoption across the population, as the adoption rates are roughly the same for all income levels. This is not the case for segregated networks, in which the middle-income group performs significantly better than the others, followed by the lower income level of less than USD 75 k per annum. This pattern repeats for the cases in which the tax credits are increased to 56%. In addition, when the tax credits increase to 56% making the cost of the panel more affordable, a significant increase in adoption rates is observed in the middle-income groups (USD 75to100k) in the segregated network scenario. This pattern of increasing adoption rates with increasing tax credits in a segregated network is not observed in the other income groups, indicating that just affordability of solar PV alone is not the driver of adoption rates. In the case of Albany county, the middle-income group is larger than the others, suggesting the role of network size in increasing the diversity of communication sources (within the same income group in the case of segregated) and thus driving adoption numbers. Here, larger network size does not mean possibilities of more connections per household, because the implementation of Circles of Influence limits the size of social circles for each household to similar values. Larger network size however can lead to higher likelihood of a household interacting with those whose attitudes differ from their own (i.e., diversity in attitudes), thereby resulting in changes in attitude. We posit that this is one of the drivers of adoption for middle-income groups in the segregated scenario where interactions are mostly within the income group; in smaller groups, changes in attitude due to interactions stagnate over time, because of lower diversity in attitudes. However, it must be noted that this can also work in the other direction: leading to lower adoption rates, if more members of the income group are more negatively predisposed to solar PV and the negative perceptions proliferate through the group via interactions. While this has not been done in this study yet, further steps can be taken in the future to investigate the relationship between attitudes and adoption numbers within income groups.

In the low tax-credit case of 46%, when a higher cost of the panel is borne by the consumer, integrated networks perform better for all income levels, except for the higher income category of 150kplus. The exception in the latter case suggests two things: (a) attitudinal factors are more influential than economic feasibility, in driving adoption amongst high income households; they appears to give more weight to opinions and experiences of their acquaintances and (b) high-income group households appear to function in more homogeneous tightly-knit social circles.

This analysis shows that integrated networks generally lead to higher adoption percentages compared to segregated networks, except for the middle-income group of USD 75to100k where the policy performs better in segregated networks in most flat-tax scenarios. The generally improved performance of policies in integrated networks suggests that attitude-driven adoptions arising due to information exchange between trusted sources (close friends and family belonging to the first circle of influence) and diverse communication channels (intergroup interaction) that are provided by the integrated network scenario improves the likelihood of adoption.

Next, we look at the generic seeding policy of Scenario 10, in which 0.1% of the households in the network are randomly seeded with a solar PV system (where 100% of the cost of buying and installing a panel is fully reimbursed by the government). Compared to the baseline case, Scenario 10 shows no significant difference in performance (adoption percentages across income groups. Given no difference in performance from the perspective of the egalitarian metric (adoption percentages within income groups), the merit of a random seeding policy can be assessed using the other two KPIs of the cost of implementing the policy or the overall adoption rates achieved. This is explored in the following sections.

Lastly, an important observation is that high-income groups of 100to150k and 150kplus show similar adoption rates across all policy and network scenarios in Fig. 8. This result can be attributed to similar TPB attributes within the two high-income group populations; given the lack of any policy targeting these two groups and similar initial agent attitudes and random seeds, their evolution across time steps follow the same pattern. As shown in Figure 20 in the Supplementary Information, the results are robust since the model runs are stable under different random seeds.

3.2. Targeted policies

3.2.1. Targeting based on income

Targeting based on income is simulated in two ways: by tailoring flat-tax credits according to income group or by seeding households of a particular income group. The three scenarios are considered:

- Scenario 4: Targeting income groups with different flat-tax credits (tax credits decrease with increasing income)
- Scenario 5: Targeting households belonging to the low-income group (less than USD 75 k per annum) by seeding solar PV systems randomly within this group.
- Scenario 6: Targeting households belonging to both low-income (less than USD 75 k per annum) and middle-income category (between USD 75 k to 100 k per annum) by seeding solar PV systems randomly within these groups.

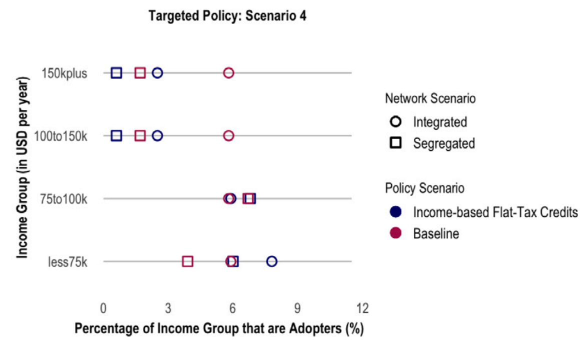
Scenario 4: Flat-tax credits tailored to income groups

Adoption percentages per income group for this scenario are presented in (Fig. 9(a)). In this case, all income groups receive tax credits, but the tax credit decreases with increasing income level (for the exact values, refer to Scenario 4 in Table 3). Compared to the baseline case of 51% flat-tax credits, this policy strategy benefits the low-income group the most (less than 75 k), as this group receives the largest tax credit, increasing affordability. Fig. 9(a) shows that the adoption rates for low-income group (less than 75 k) increases from about 4 to 6% in the segregated network case and from about 6 and 8% in the integrated one. In contrast, the higher-income groups experience the largest drop compared to the baseline (Fig. 8), from about 6 to 2% in the integrated network and from about 1 to less than 0.5% in the segregated network (note again that 100 to 150 k and 150 k plus groups have similar adoption rates). This shows that the underlying network plays a key role in improving adoption numbers. Yet, the adoption numbers for high-income groups in the integrated network case remain higher than in the segregated case. This suggests the importance of diverse information sources that the integrated network offers, which contribute to increased attitude-driven adoption even if tax incentives are lower.

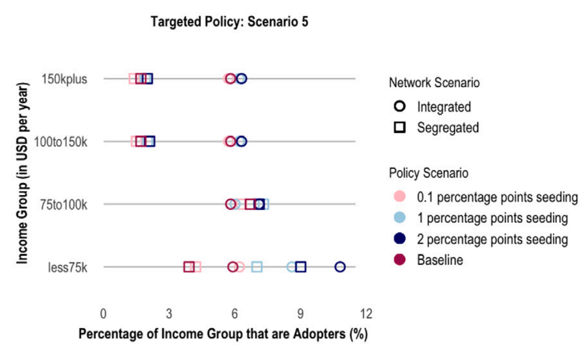
Scenarios 5 and 6: Seeding households based on income group

In the second type of income-based targeting policies, we look at policies that promote (seed) adoption of solar energy at the household level by fully reimbursing the cost of installing a solar PV system. We implement this policy by changing the proportion of initial adopters (i.e., sampling percentages). We consider three sampling percentages 0.1%, 1% and 2%, which represent the percentage of the population or the income group that is 'seeded' with a solar system at the beginning of the simulation period (see Table 3).

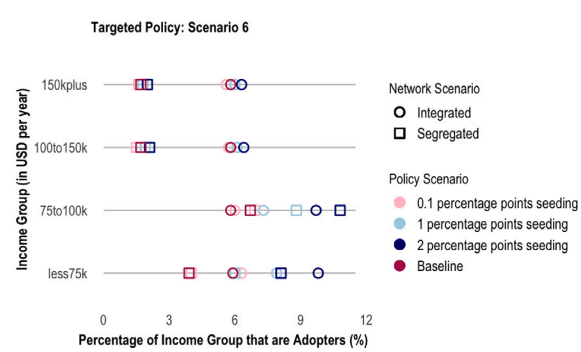
The income group targeted by the policy benefits the most across both sampling percentages and type of network (integrated or segregated) (Scenario 5 and 6 in Figs. 9(b) and 9(c)). Policies that seed random households within low or middle income groups, while benefiting the adoption percentages of respective groups significantly, appears to come at the cost of numbers from the high-income groups as the total adoption numbers remain similar across the two scenarios in both segregated as well as integrated network case; we see this later in the next section when comparing the policy scenarios across all three output metrics in Fig. 12. These output metrics are also referred to as Key Performance Indicators (KPIs), as they are used to evaluate the policy performance. This suggests the importance of looking at adoption rates not just via the overall numbers, but by breaking down results by income groups (and other demographic indicators) to get a more nuanced understanding of the policy's impact on different groups and, consequently, the justice implications of different policies. From a utilitarian point of view, it can be observed that seeding policies do not necessarily help increase overall adoption numbers but rather are egalitarian in nature, by redistributing numbers within income groups depending on which group is targeted.



(a) Flat-tax credit rates tailored to income-group of the household. For percentages, refer to Table 3



(b) Seeding Households belonging to the Low Income Group (with annual household income less than USD 75k)



(c) Seeding Households belonging to the Low and Middle Income Group (with annual household income of less than USD 75k and within range USD 75k to 100k)

Fig. 9. Income-based targeted policies: While Scenario 4 is tax-based, scenario 5 and 6 involves seeding households belonging to the targeted income-group. Tabular format of these results can be found in Section 8 of Supplementary Information.

3.2.2. Targeting influencers: Seeding influencers within income groups

Another targeting strategy tested in this study is introducing “influencers” into the networks to improve word-of-mouth based dispersion of information. Influencers are agents socially well-connected either by having a high number of connections (degree-centrality as network measure) or by acting as information bridges by connecting disparate groups together (high betweenness-centrality as network measure). Similar to the strategy of seeding initial adopters, we also introduce targeted and random influencers (Scenarios 7–9 in Table 3). The goal is to understand whether seeding information agents within the network results in improved adoption rates for the same seeding percentages compared to randomly seeding households, through the process of faster information spread. The results are presented in Fig. 10.

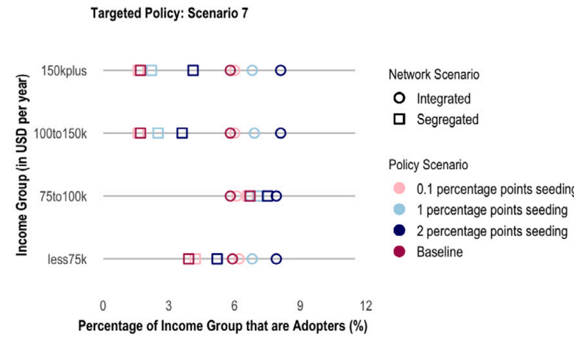
In the case of random influencer seeding (Fig. 10(a)), adoption patterns across income levels for the lower seeding percentages are similar to the baseline case. As seeding percentages increase, the policy performs consistently better in integrated networks across income groups, compared to the segregated network case. The larger middle-income group (75to100k group) remains the exception, with the policy performing better in segregated networks than in integrated networks (except in the case of 2% seeding, in which segregated and integrated networks show similar adoption rate).

Comparing adoption numbers of the income-based seeding policies (Scenarios 5, 6, 10 in Fig. 9) with influencer seeding policies (Scenarios 7, 8, 9 in Fig. 10) show similar results across income groups in the case of overall adoption numbers, maximum group adoption rates achieved, and network scenarios. These results suggest that “influencers” are not necessarily more effective in transferring information across different groups or dispersing information within a group. This hints at the role of trust being an important reason why influencers are not as effective as they are intended to be. This result however cannot be extended to the type of influencers more prevalent in real world, such as digital influencers on social media, where they are mass communicators who often do not have a two-way interaction with their followers. While it is plausible that due to psychological phenomena that include parasocial relationships, certain influencers can be very influential despite having no two-way interactions with their followers, research shows that interpersonal communication is far more effective in influencing individuals’ attitudes than mass communication [47,48]. Within this model, we explicitly focus on seeding initiatives that target “household” influencers: those who are opinion leaders or individuals with plenty of social connections, who engage in two-way communication on their experience of installing solar PV. They convey contextual information that is relevant to the neighborhood they live in and their own socio-economic situation.

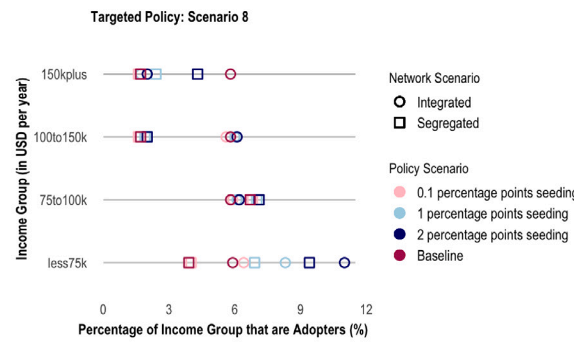
3.3. Overall policy evaluation

The policy cost is calculated for all the scenarios and presented in Fig. 11 together with the overall adoption rates and the adoption rate per income level (utilitarian and egalitarian metrics). The figure shows that as the number of adopters increases, the policy costs increase accordingly, making policies deployed in integrated networks more expensive compared to segregated networks.

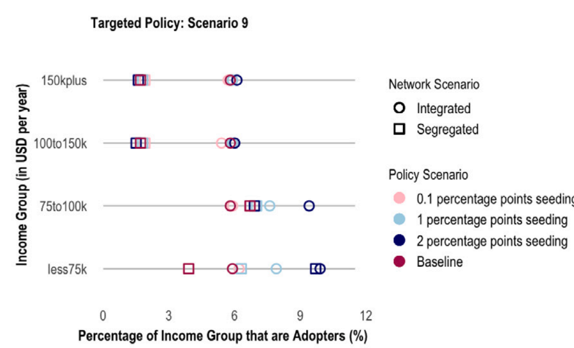
The overall adoption rates are also consistently higher for policies deployed in integrated networks, except for the cases where tax credits were high. For example, Scenario 7 (seeding random influencers) does not perform better than Scenario 5 (seeding random individuals who are not necessarily influencers), but when we look at the policy costs (see Fig. 12), we observe that Scenario 5 costs US$ 67 million to the tax-payers while achieving similar overall rates and group-adoption rates as that of Scenario 7 that costs the taxpayer US$ 68 million. Therefore, if decision-makers were to consider trade-offs between a cost-effective strategy that maximizes both overall adoption rates while also improving low-income adoption rates in their segregated network, tailoring tax credits per income group can be considered.



(a) Seeding Influencer Households randomly.



(b) Seeding Influencer Households belonging to Low Income Group (of annual household income less than USD 75k)



(c) Seeding Influencer Households belonging to Low and Middle Income Groups (where annual household income is less USD 75k and within range of USD 75k and 100k)

Fig. 10. Influencer-based Targeted Policies: Seeding Influencer Households with a solar PV. Tabular format of these results can be found in Section 8 of Supplementary Information.

4. Discussion

This section discusses the outcomes and limitations of the study. Starting with three main insights for discussion, as follows:

1. The structure of the underlying network and attitude factors play key role in driving adoption: The structure of the underlying network, as a measure of being an integrated or segregated network, consistently influences the overall as well as group adoption rates. This is revealed in scenarios where flat-tax incentives across income

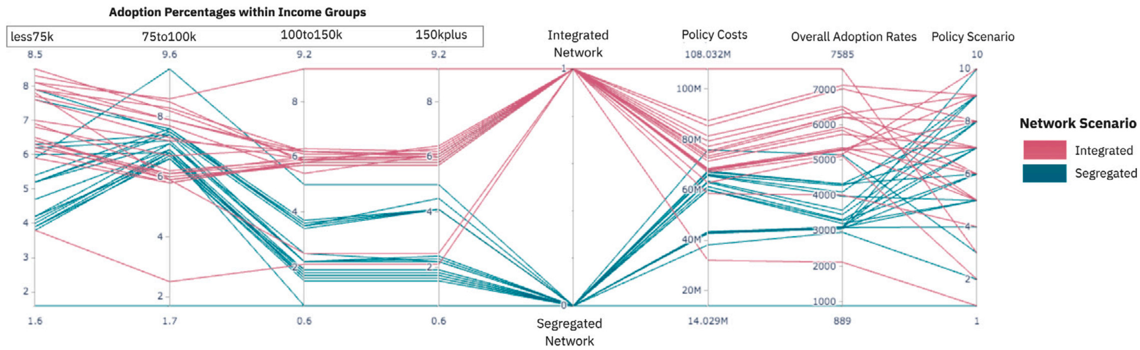


Fig. 11. Comparing Policy trade-offs across all three Key Performance Indicators (KPIs) or output metrics: Utilitarian metric of Overall Adoption Rates, Egalitarian Metric of Adoption Percentages across income groups and finally the Cost Metric of Policy Cost.

groups are applied (Scenarios 1, 2 and 3): despite higher upfront costs that have to be borne by the household, low-income groups in segregated networks show higher adoption rates because of attitude-driven adoptions. When the financial component remains constant, attitudes are the only component of the decision-making structure that evolves over time. Information is exchanged between acquaintances and when these acquaintances are adopters who also share an intimate relationship with the adopter, the change in attitude that positively impacts adoption is greater. This is especially revealed when integrated and segregated scenarios are compared: high-income groups which are smaller in size/population see policies perform poorly in their group as the segregated network causes information to circulate only within this group and, therefore, attitude stagnates over time (group is small and segregated) and adoption numbers are low (since all other factors remaining constant). This result, whereby attitude-related factors are a more influential driver of adoption numbers, is similar to observations by adoption modeling studies in other fields such as Plug-in hybrid vehicles [49] and in Electric Vehicle adoption [50]. Eppstein et al. [49] find that people's perception of risk and attitude towards the technology can override the benefits of tax-credit programs.

Another key aspect of the network structure that plays a role is the number of group members. This is reflected in the fact that all policies perform consistently well in the middle-income group of 75to100k which is similar in population size to the low-income group. The reason is that when the tax incentives are low for this group, the attitude-driven adoption sustains performance, and when tax-incentives are also in favor, the adoption rate of this group far exceeds all the other three. This once again highlights the importance of inducing attitude-driven adoptions by planting credible sources of information in personal networks.

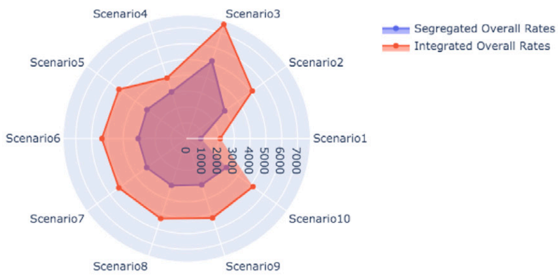
2. Importance of diverse communication channels: In segregated networks, information circulates primarily within the group, which can result in stagnation of adoptions within the group in two cases: (1) absence of tax incentives or (2) a low number of group members and lack of adopters in known circles. This can be avoided by seeding income-group members at a block-level (a smaller geographic unit) as opposed to at a census-tract level, possibly increasing the chances of increasing adopters in people's known-circles because of an increase in observability of the solar PV within the neighborhood [44]. Efforts such as 'solar parties' can be encouraged where adopters host members of the neighborhood to share their experience of installing a solar PV system to address the inequities that result from a lack of access to information [51].

3. Role of Trust: Scenarios 7, 8, 9 reveal the importance of credible sources of information. The results show that influencers (either who are bridges or highly-connected individuals) are not necessarily effective in disseminating information. If influencers are mass-communicators dealing mainly with one-sided communication and belong mostly to the agents' third circles (outer-most circle in the circles of influence model, with no intimate relationship with the agent), their influence is far lesser compared to the influence that people within the first circle have over agent's attitudes. This result is in line with Abrahamse et al. [52] and Valente [14] that stress the importance of policy-makers to ensure tailored information campaigns that increase number of credible sources of information. This can be done by redefining the role of influencers (high number of connections) or information agents (bridges between networks) from that of popular online social networks) to personal networks at a more local level (in a municipality or block level). Observations by Moglia et al. [25] show that there can be other factors that can also influence the effectiveness of influencer-seeding programs apart from trust: delivering information to a household at the right place and time. For example, in the case of adoption of solar water-heating systems, a plumber talking to the household when their existing system breaks down for example, can be more effective than seeding a random influencer.

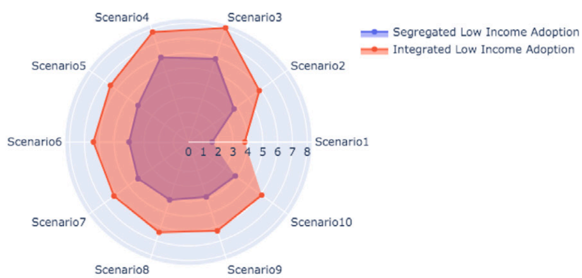
The findings presented in this study result from a model initialized using data specific to Albany County, limiting our ability to generalize outcomes. Beyond the geographical specificity, it is important to recognize limitations inherent to model construction. These constraints arise from assumptions made due to data availability constraints and parameter uncertainties. Structural uncertainties are introduced through the implementation of the circles of influence theory, where the evolution of household attitudes is influenced more by interactions with close friends than with casual acquaintances, thereby impacting our interpretation of the role of trust. More importantly, the robustness of these results is dependent on the verification and validation process used (refer to Supplementary Information). Due to computational resource constraints, the model was run through only 20 random-seed run tests and a limited range of uncertain parameters. This approach can have repercussions for scenarios where differences in policy outcomes among income groups were marginal. Specifically, in the policy scenario involving randomly seeding influencers, the subtle variation in adoption rates within integrated and segregated networks could be influenced by the variability in random seed runs. However, given the absence of such a trend in other policy scenarios, where distinctions in policy performance across network scenarios and income groups are more evident, a decision was made to acknowledge and accept this limitation while factoring it in during formulation of conclusions. The following limitations should be taken into account when interpreting results pertaining to the overall effectiveness of the policy.

4.1. Limitations

Replication of historical adoption curves. In this study, we developed a model that realistically simulates interactions between households and the influence of these interactions on the household's decision to adopt rooftop solar PV. The goal of the developing this model was to investigate the influence of underlying social networks on equity outcomes of two groups of policy interventions that are tested: generic policies and targeted policies that are tailored to underlying networks.



(a) **Utilitarian Metric: Overall Adoption Rates**: Exploring performance of all network and policy scenarios based on the overall adoption rates achieved.



(b) **Egalitarian Metric: Adoption Rates per Income Group**: Exploring performance of all network and policy scenarios based on percentage of adopters in the low-income group, in this particular figure.

(c) **Cost Metric**: Exploring the economic feasibility of policies in both integrated and segregated network scenarios.

Fig. 12. Exploring performance of policies in integrated and segregated network scenarios, based on the three KPIs: Utilitarian, Egalitarian and Cost metrics.

Because the relationship studied is one between social networks and equity outcomes of tested policy interventions, it mainly involves relative comparisons of policy performances: for example, does a targeted policy lead to better adoption rates for low-income groups in the integrated network scenario, compared to a generic policy intervention? The interpretation of these comparative results focusing on policy performance, is not dependent on how accurately the model replicates the actual historical adoption curves of Albany county. Therefore, given the aim and the computational and time-intensive model runs, a decision was made to (a) achieve a similarity in overall trend and (b) give more importance to stability of model runs across random seeds.

Static TPB weights. Although the use of TPB as the base to further model adoption behavior of households is a definite improvement over equation-based Bass Models and decision models that are based purely on economic considerations, TPB itself is limited its scope to include the impact of people's responses to unconscious biases and subliminal messaging such as political advertisement on their decision-making [53]. Another caveat is TPB's limited predictive validity: not everyone who crosses a certain threshold will actually perform the behavior. The TPB attribute weights are initialized at the start of the model for the year of 2015 and not updated later. While the attributes evolve dynamically in this model, the weights attached to each do not change over time. In an attempt to limit the number of moving parts of the model, it was assumed that characteristics such as household income, electricity consumption and social circles do not change over the simulation time period. In real-life perception of affordability can change due an increase in income, increasing electricity prices or decreasing price of solar PV units.

Focus on single-family, owner-occupied households. Sigrin and Mooney [54] find that majority of the rooftop solar potential lies amongst single-family owner-occupied households. This paper tests policies that are designed for this dwelling type, which ensures that the findings can be used to reasonably improve understanding of the impact of policy and network type combinations on different income groups belonging to this category. However, this choice has distributive justice implications when looking at the bigger picture: solar policies of today have primarily benefitted the wealthy [55]. A significant proportion of lower and middle-income households consisting of renters and multi-family homes are left out of studies because of not considering policies that explicitly address perception of split-incentives. Tenants, with lower disposable incomes and information asymmetry, form a disadvantaged group requiring different targeting policies [56]. Policies that reduce upfront costs of solar PV units for owners or provide attractive tax credits to incentivize installation in renter-occupied households can be studied. For a holistic engagement with the distributive justice impacts of policies, the scope can be extended to explore the potential of affordable participatory shared-risk forms of ownership such as community solar.

Application of energy justice concepts. The focus of distributive justice in this paper is still restricted to the financial component; although wealth gap is one of the prominent concerns in solar PV adoption today, it is important to acknowledge the intersectional nature of these vulnerabilities and include gender-based, racial and ethnic considerations when designing and evaluating policies. This can be done by extending the current model to include more demographic indicators that represent these non-income considerations when dis-aggregating adoption rates and test policies that explicitly improve access to these groups.

5. Conclusion

The goal of this study is to develop a data-driven agent-based model which can investigate the influence of household social networks on the equity outcomes of policy interventions that are designed to improve adoption rates of rooftop solar PV. We simulate the adoption dynamics of rooftop solar PV at a household level, by allowing non-economic factors such as social influence, information exchange, perception of green technology etc., to be influenced by the households' interactions with others within their network. This study improves upon existing ways of modeling the influence of social network interactions on household-level decision-making, through a novel implementation of the Circles of Influence Theory to realistically simulate the fact that people trust or act upon information differently, depending on whether the information source belongs to their inner-most circles, their 'friends-of-friends' circle, or their acquaintance circle. In using Deffuant's Relative Agreement Theory in combination with the TPB implementation and Circles of Influence, the model also allows for agents to be more influenced by people with similar opinion than a strongly opinionated agent who is on the other extreme of the opinion spectrum. By grounding all the agents and their demographic and behavioral attributes on open-source datasets and the realistic case-study of Albany County (New York State, United States of America) this study contributes to studies that aim to understand how realistically modeling social networks can produce decision-support tools that can better represent the impact of energy transition policies on different income groups.

In this study, a just transition is conceptualized as equitable adoption of rooftop solar PV, by using distributive justice principles of utilitarianism and egalitarianism. They are operationalized as overall adoption rates and improved adoption rates across income-groups respectively. Our results indicate that the underlying network structure significantly influences adoption rates. Low-income groups in segregated networks can experience higher adoption driven by positive attitudes towards solar PV, whereas high-income groups in segregated networks can experience poor policy performance despite being able to afford solar PV more easily. Seeding policies and information dissemination through influential network members may not necessarily improve adoption rates, indicating that trusted sources can play a more effective important role in influencing adoption decisions. Instead of targeting mass-communicators as influencers, seeding programs can focus on planting credible sources of information within personal networks through more grass-root initiatives like neighborhood-level solar parties. From an equity perspective, flat-tax credits work well if the metric used is that of improving overall adoption rates. On the other hand, they perform poorly in segregated networks, if egalitarian measures of policy evaluation are employed. Seeding policies that are tailored to income groups and segregated networks, perform better on the egalitarian metrics.

Results of this work encourage expanding the use of the concept of circles of influence to model adoption dynamics and design effective policy interventions. Given the influence of trusted information sources on encouraging attitude-driven adoption, future work can include additional indicators such as, influence of number of adopters in each social circle on the household's likelihood to adopt and frequency of these interactions. This will deepen the understanding of the role of trust and influence on adoption decisions at the individual household level. Future work can also use techniques such as spatial autocorrelation to quantify the influence of observability in increasing local adoption rates e.g., how the introduction of seeded agents within a locality influence the likelihood of adoption of other residents in the area. Spatial influence of the local and non-local social ties can also be explored. While multi-level social networks that have been modeled are primarily real-life networks and physical networks, it is undeniable that online social networks have an equally important role to play in dissemination of information (positive or negative), specially in informing the agent of a product's quality. Future work can also explore the role of social networks via multi-level network modeling, for example, by inferring real-life social networks from existing datasets, such as call data records and Twitter networks.

CRediT authorship contribution statement

Aarthi Sundaram: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Juliana Gonçalves:** Conceptualization, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Amineh Ghorbani:** Methodology, Supervision, Validation, Writing – review & editing. **Trivik Verma:** Conceptualization, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All datasets used in this work are open-source. The sources are cited accordingly.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.erss.2024.103518.

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