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Weatherization Adoption in A Multilayer Social Network: An Agent-based Approach

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ABSTRACT

Energy conservation in residential buildings has been a topic of interest in recent years because of their high levels of energy consumption. Weatherization is set of approaches that can be used to make buildings more energy-efficient, thereby helping residents lower their energy bills and improving environmental sustainability. However, there are two significant challenges associated with weatherization adoption: high upfront investment costs with a long payback period, and minimal awareness of weatherization and its benefits. This paper proposes an agent-based model that will allow researchers to explore residents' socially-motivated energy conservation decisions by providing a realistic social context via a multilayer social network and incorporating opinion dynamics based on the Susceptible-Exposed-Infected-Recovered epidemic model. Several experimental scenarios are run to demonstrate the model's potential to help policymakers determine how to encourage residential weatherization adoption.

KEYWORDS

Weatherization, Agent-based Model, Building Energy Simulation, Multilayer Social Network, Theory of Planned Behavior, Epidemic Model

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1 INTRODUCTION

The promotion of energy-saving innovations in residential buildings has been an area of significant interest in recent years [7, 21, 27, 39, 50]. Residential buildings are responsible for nearly 27% of all energy consumption [2] and 36.5% of electricity use [1] in the U.S., and are therefore a major contributor to climate change. Low-income households tend to be more heavily burdened with energy costs, typically spending 16.3% of their total annual income on energy, compared with 3.5% for other households [40].

Weatherization is the practice of improving the energy efficiency of existing residential buildings through a variety of approaches, such as installing insulation in walls, upgrading inefficient refrigerators, and reducing air leakage. This yields many benefits for residents, including reduced energy costs and improved health and safety, as well as benefits for society through job creation and a reduction in greenhouse gas emissions [16]. Despite these benefits, adoption rates remain low, with high upfront investment costs and long payback periods, as well as a general lack of awareness about weatherization techniques and benefits, serving as barriers [29]. The government has tried to overcome these barriers through various campaigns aimed at raising awareness of the energy cost savings from weatherization, as well as providing financial assistance to low-income residents to help them weatherize their homes [26]. However, these efforts have had limited success.

Rather than only relying on financial incentives to convince residents to weatherize, research suggests that policymakers should instead leverage the power of social influence. Peer interactions have proved to be an important factor in residents' decisions to adopt energy-related behaviors [21, 27, 29, 32, 39, 47], and the influence of social networks on energy-efficiency innovation diffusion has been demonstrated [33]. In particular, social interaction regarding energy tips and information is a predictor of weatherization behavior [50].

The importance of social interactions in determining residents' energy-related decisions suggests that agent-based modeling would be an appropriate method for modeling a network of residents. Agent-based models (ABMs) allow researchers to model individual decision makers as autonomous agents that are capable of social behaviors and interactions (e.g., information sharing) with other agents. Over time, the effects of these repeated interactions and feedbacks on individuals' decisions (i.e., at the micro level) may yield system-wide changes that are unexpected and difficult to predict without the use of computational modeling [52]. ABM is a promising methodology for capturing consumer behavior in general and energy technology adoption in particular [14, 19, 31, 36–38, 55]. ABM facilitates the modeling of opinion dynamics in a social system, which is useful in representing residents' socially-motivated decisions to weatherize their homes [11, 47, 50].

However, when modeling energy-related behaviors, adequate consideration must be given to the agents' social network structure and properties [8]. To this end, some modelers have made efforts to incorporate realistic social networks into ABMs [6, 20, 23, 46]. In particular, small-world networks, which have a structure that is an interpolation between regular and random networks, are often used to represent social networks to explore social behavior. Small-world networks have been integrated into ABMs to model the diffusion of solar photovoltaic adoption [44, 47], the diffusion of organic farming practices [28], and the diffusion of water-saving innovations [49]. The networks in these models are used to represent interactions that occur in a physical space, such as a neighborhood. However, in reality, interactions between individuals are often multidimensional, occurring in both physical and virtual environments (e.g., via online social networks). Additionally, in these existing models the agents typically interact in the same way with all of their neighbors [25, 29], or they randomly select pairs of agents to interact [34, 47]. By contrast, Azar and Menassa developed an ABM of energy adoption in which they assumed that only adopters were capable of spreading information to non-adopters, since only adopters would have realistic and reliable assessments [11]. The agents in this model have specific attitudes toward information sharing; for example, some agents may have no interest in the information and are therefore immune to it, which means their existing information will not be affected by social interactions. However, we are unaware of any existing models of socially-motivated energy conservation decisions that incorporate the agents' intention to spread and receive information.

This paper describes a conceptual ABM that is embedded in a multilayer social network to model weatherization adoption among residential households, with a specific focus on low-income residents. The model is based on the Capitol East Neighborhood in Des Moines, Iowa, which is a low-income neighborhood that has a strong neighborhood association and a goal of improving sustainability. The multilayer approach allows the agents to interact via both a physical social network (i.e., their neighborhood) and a virtual social network (i.e., online). Small-world networks are used to describe the physical social networks (PSNs), while scale-free networks are used to represent the online social networks (OSNs), since the primary characteristic of many OSNs (e.g., Flicker, YouTube) is the scale-free property [3, 12, 35]. To incorporate agents' intention to spread information, a Susceptible-Exposed-Infected-Recovered (SEIR) epidemic model [9, 17, 30] is used. The SEIR model allows agents to be in different states, depending on how informed they are, and it provides a framework by which rules can be defined to determine which kinds of agents can have interactions and be influenced. The agents' decisions about adopting weatherization are characterized by emotional and economic factors and are based on the theory of planned behavior (TPB) [4], a widely-used theory in studies on energy-related behaviors [5, 24, 47]. The model is used to perform several experiments, in which the influence of randomness in the physical social network, the number of media agents that can spread weatherization information, and the efficiency of the Weatherization Assistance Program are explored. The results of these experiments demonstrate the potential of this modeling framework to inform policymakers' decisions regarding programs for increasing weatherization.

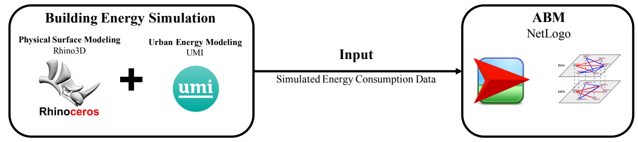


Figure 1: Implementation Details.

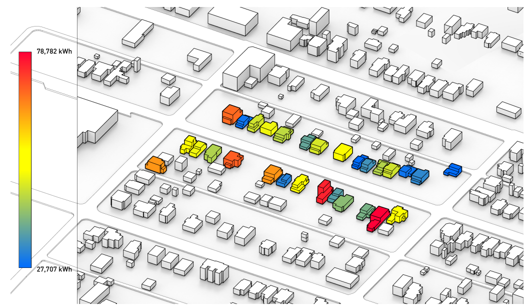


Figure 2: A visualization of energy consumptions for residential buildings in the Capitol East Neighborhood.

2 CONCEPTUAL MODEL

Figure 1 provides an overview of the weatherization model, which consists of two different simulation models: a building energy model and an ABM. The building energy model is a digital model of the Capitol East Neighborhood in Des Moines that was built using Rhinoceros 3D and the Urban Modeling Interface (UMI) plugin from MIT's Sustainable Design Lab [48]. This model was used to create a dataset consisting of the monthly energy consumption values of residential buildings in the neighborhood under pre- and post-weatherization conditions [26]. The Rhino-UMI model uses geographic information system (GIS) data obtained from the City of Des Moines to model the physical geometry of the Capitol East Neighborhood. Information available in the Polk County Assessor's database [10] is then used to refine the Rhino model at the building scale. This database provides detailed information on the each building in the neighborhood, including the parcel number, date of construction, construction materials, number of stories, and number of separate residences contained within. Because regional climate strongly influences residential energy consumption patterns, regional weather data was also included in the simulation. We use typical meteorological year weather data (TMY3) obtained from the Department of Energy [54] and the future typical meteorological year weather data (FTMY) [45] weather datasets to incorporate the climatic impact on energy consumption in residential buildings. TMY3 provides a reasonably sized annual dataset consisting of hourly meteorological values that are intended to typify conditions at a specific location over a longer period of time. Aforementioned data about building footprint, building forms, construction materials and weather conditions served as a basis for the Rhino model. Additional details about the model are available in [26]). Figure 2 shows a visualization of building energy consumption generated by the Rhino-UMI model, where different colors indicate different energy consumption values.

The ABM is used to represent each household in the Capitol East Neighborhood as an autonomous agent that is capable of communicating with other agents via its social networks and making decisions about weatherizing its home. The ABM is implemented in NetLogo 5.3.1. The following sections describe the agents and the sub-models of the ABM in detail. A description of the ABM using the ODD (Overview, Design concepts, Details) protocol [22] is included in Appendix.

2.1 Agents

The ABM contains two types of agents: household agents and media agents.

2.1.1 Household Agents. Households agents have the ability to adopt weatherization and share weatherization information with other household agents. Each agent represents an entire household, rather than an individual resident, because weatherization decisions are assumed to occur at the household level. Only single-family residential buildings were included since the energy consumption values for multi-family buildings (e.g., apartments) are difficult to capture with the Rhino-UMI model. The model has 1548 household agents, among which 548 household agents are in the Capitol East Neighborhood and 1000 household agents are outside the Capitol East Neighborhood. Each household agent is characterized by seven key parameters:

- *ID:* Each household agent is assigned a unique identification number.
- *Income level (L):* A household agent's income level is binary and determines its eligibility for financial assistance. An agent with an income level of 1 has a total household income that is at or below 200% of the federal poverty level [41]. This means that the agent is eligible for the Weatherization Assistance Program (WAP), which is a federal grant program that provides financial assistance to help low-income residents to weatherize their homes [42]. A household agent with an annual income level of 0 is not eligible for WAP (i.e., its total household income is too high).
- *Monthly energy consumption (E):* In each month m, each household agent is assigned two values that represent its monthly energy consumption (in kWh) before and after weatherization (NWE_m and WE_m, respectively). These values are outputs of the Rhino-UMI simulation.
- *Estimated payback period (P):* Each household agent is capable of estimating the breakeven point at which the upfront investment in weatherization pays for itself through subsequent energy cost savings. The upfront investment (U_t) in year t is initialized as \$4,695 (U_0) [40] and increases over time due to inflation,

$$\mathrm{U}_t = \mathrm{U}_0(1+\mathrm{R}_1)(1+\mathrm{R}_2)\ldots(1+\mathrm{R}_t)(1-\mathrm{F}_t), \tag{1}$$

where R_t denotes the inflation rate in year t, and F_t refers to the federal income tax credits for energy efficiency, which is assumed to be 30% [51]. By weatherizing, single-family homes saved an average of \$283, annually on energy costs [40]. Therefore, each agent's annual household energy cost savings in the year in which it decides to weatherize (S_0) is set to \$283. If an agent weatherizes in year t, its total savings over n years (TS_{t+n}) is calculated as:

$$\begin{aligned}\mathrm{TS}_{t+n} &= \mathrm{S}_t + \mathrm{S}_{t+1} + \ldots + \mathrm{S}_{t+n}\\ &= \mathrm{S}_0((1+\mathrm{R}_t) + (1+\mathrm{R}_t)(1+\mathrm{R}_{t+1})\\ &\quad + \ldots + (1+\mathrm{R}_t)\ldots(1+\mathrm{R}_{t+n})).\end{aligned} \tag{2}$$

An agent's estimated payback period P is the value of n (in years) for which $\mathrm{U}_t = \mathrm{TS}_{t+n}$.
- *Budget:* The maximum amount of money (in dollars) that an agent is able to spend on weatherization. Household agents with an income level of 0 must pay U_t for weatherization out of pocket. Their budgets for weatherization are drawn randomly from a uniform distribution between \$500 and \$5,000.
- *Distance from others (D):* GIS data obtained from City of Des Moines provides 548 residential buildings' spatial information in the Capitol East Neighborhood, which is used to calculate geographical distances (in meters) between each building. Each agent in the Capitol East Neighborhood therefore has a vector that stores its distance from all other 547 agents in the Capitol East Neighborhood.
- *Influence coefficient (IC_{ab}):* The influence coefficient defines agent a's influence on agent b, which is assumed to be symmetrical (i.e., $\mathrm{IC}_{\mathrm{ab}} = \mathrm{IC}_{\mathrm{ba}}$). Each household agent has a set of influence coefficients, with a value assigned to each of its connections. It is assumed that an agent's influence on another agent is directly proportional to their geographical proximity, based on the idea that short physical distances bring people together, increase information sharing, and stimulate the exchange of knowledge [15]. The influence coefficient values of the 1000 household agents outside the Capitol East Neighborhood (for which there are no spatial data) are drawn from a uniform distribution between 0 and 1. Otherwise, the influence coefficient between two agents a and b is defined as follows:

$$\mathrm{IC}_{\mathrm{ab}} = \mathrm{IC}_{\mathrm{ba}} = \frac{D_{\max} - D_{\mathrm{ab}}}{D_{\max} - D_{\min}}, \tag{3}$$

where D_{ab} denotes the distance from agent a to agent b, and $D_{\min}, D_{\max}$ refer to the minimum and maximum distance between all household agents in the Capitol East Neighborhood, respectively.

Each household agent also has 10 state variables and that may be updated in each monthly time-step:

- *Weatherization status (WS):* This binary variable represents the agent's state of weatherization adoption, where a value of 1 indicates that the agent has weatherized its home, and a value of 0 indicates that it has not yet weatherized. An agent can only transition from a status of 0 to a status of 1, based on the assumption that weatherization is irreversible.
- *WAP status:* This binary variable represents the agent's state of receiving weatherization assistance, where a value of 1 indicates that it has successfully received assistance, and a value of 0 indicates that it hasn't been served by the WAP. It is assumed that an agent with a WAP status of 1 cannot return to a status of 0.
- *Current energy consumption (C):* Based on its weatherization status and the current time-step (i.e., month), a household agent's current monthly energy consumption (in kWh) is obtained from the outputs of the Rhino-UMI model (i.e., the agent's NWE_m and WE_m).
- *Monthly savings (M_m):* The money that a weatherized household agent saves in month m is based on the difference between its energy consumption before and after weatherization (NWE_m and WE_m, respectively). This difference is multiplied by the energy cost per kWh, which includes the current residential electricity rate E, a rate equalization factor REF, an energy adjustment clause EAC, a transmission cost adjustment TCA, and a 1.00% sales tax, according to the electricity bill calculation provided by MidAmerican Energy Company [18],

$$\mathrm{M}_m = (\mathrm{NWE}_m - \mathrm{WE}_m)(E + \mathrm{REF} + \mathrm{EAC} + \mathrm{TCA})(1 + \mathrm{TAX}). \quad (4)$$

- *Current average saving (AS):* This variable, which is calculated for household agents that have weatherized, is determined by dividing the agent's total savings by the number of months since it weatherized.
- *Information status (IS):* This variable is defined based on the epidemic SEIR epidemic model [9]. A household agent can take on one of four different IS values in each time-step,
  - S (Susceptible): An agent that has not received weatherization-related information from another agent but is ready to receive it.
  - E (Exposed): An agent that has received information but is not yet infectious (i.e., cannot transmit information to others).
  - I (Infected): An agent that can spread weatherization-related information to others.
  - R (Recovered): An agent that is immune to weatherization-related information (i.e., it neither receives nor transmits information).

  An agent's status towards spreading known information can potentially be different in it its PSN and OSN; however, its status with respect to weatherization awareness must be the same in both networks. In other words, an agent could be in status E in its PSN and status I in its OSN, but if it is in status S in one network and has a non-S status in the other, its information status will be reconciled to the non-S value in both PSN and OSN after the current time-step.
- *Intention level (IL):* This variable, which takes values between 0 and 1, denotes a non-weatherized agent's intention to adopt weatherization.
- *Intention:* This binary variable may change from 0 to 1 with a probability of IL in each monthly time-step. A value of 1 indicates the agent wants to adopt weatherization.
- *Assessment level (AL):* This variable takes a value between 0 and 1 and represents is the degree to which a weatherized agent is satisfied with its weatherization adoption. An agent's *AL* value is based on its assessment of the perceived value of its weatherization decision and will be influenced by social interactions.
- *Ability:* This binary variable takes on a value of 1 for an agent if it has the ability to weatherize and a value of 0 if it does not. Ability can be achieved in two ways:
  - The agent has received assistance through WAP.
  - The agent's budget exceeds the upfront investment required for self-weatherization.

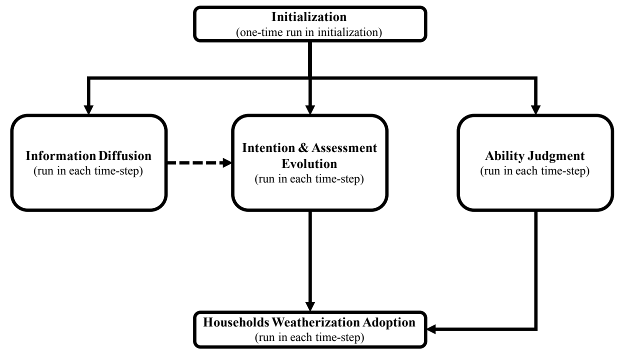
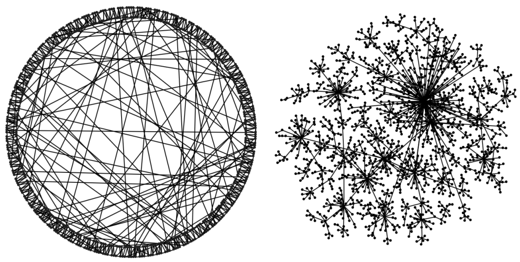


Figure 3: Sub-models.

2.1.2 Media Agents. The media is a means by which the government can share weatherization-related information to residents. In this model, media agents seek to spread weatherization information to household agents. Each media agent has three parameters, which take on values that remain unchanged throughout the simulation run:

- *Information status (IS):* All media agents are assumed to have an information status of I, since they play the role of information providers.
- *Assessment level (AL):* This value is assumed to be 1 for media agents, since it is assumed that the media is supportive of weatherization adoption.
- *Impact factor:* This variable, which takes values between 0 and 1, defines the probability of household agents having access to a media agent.



(a) PSN (b) OSN

Figure 4: Multilayer Social Networks.

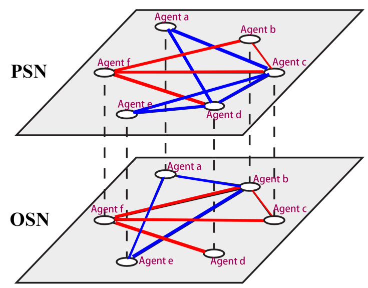


Figure 5: Overlaps and differences in a multilayer social network.

2.2 Sub-models

The ABM contains five sub-models: *Initialization, Information Diffusion, Intention & Assessment Level Evolution, Ability Judgment,* and *Household Weatherization Adoption*. First, the multilayer social network is generated, and the agents' parameter values are initialized. Then, in each monthly time-step, agents will have interactions via the multilayer social network, where information diffusion will take place. Based on these interactions, agents' intention and assessment values will evolve, which will inform their judgments regarding their weatherization abilities. Finally, at the end of each time-step, each non-weatherized household agent will decide whether to adopt weatherization, based on its intention and ability values. An overview of the model is shown in Figure 3.

Initialization: Before the first time-step, a multilayer social network is created to allow the agents to interact through both a physical social network (PSN) and an online social network (OSN). There are 548 single-family household agents in the Capitol East Neighborhood. Each node in the PSN (Figure 4a) represents one of these agents, and each edge represents a connection between the nodes it connects. The PSN is a small-world network that was built using the Watts-Strogatz algorithm [53]. This algorithm starts with a regular network and "rewires" the edges of this network randomly, based on a probability P_{rewire}. In other words, the small-world network is an interpolation between regular and random networks, and the greater the value of P_{rewire}, the more random the network will be.

The Barabási-Albert (BA) algorithm [13] was used to generate a scale-free network for the agents' OSN (shown in Figure 4b). The

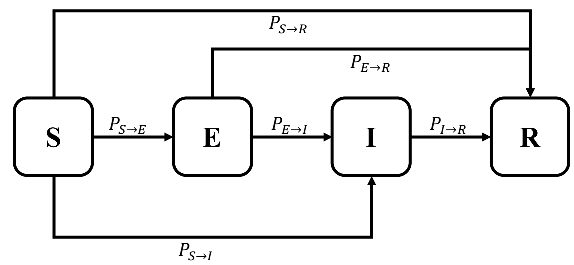


Figure 6: A schematic diagram for SEIR model.

OSN consists of the 548 household agents in the Capitol East Neighborhood, additional 1000 household agents that exist outside the Capitol East Neighborhood, and an experimentally-varied number of media agents. Thus the 548 agents that represent households in the Capitol East Neighborhood exist both in the PSN and the OSN, while the 1000 household agents outside the neighborhood only have virtual connections via the OSN. If no media agents are included, the number of nodes in the OSN is therefore 1548, and the total number of nodes in the multilayer social network (MSN) is 2096. As with individuals in the real world, there are overlaps and differences between the 548 household agents' connections in the PSN and the OSN. Figure 5 demonstrates this phenomenon, with red edges indicating overlapping connections and blue edges representing differences.

The PSN and OSN are initialized as follows: 1) there are 20 household agents have weatherized among the 548 agents in the Capitol East Neighborhood, 2) there are 100 weatherized houses outside this neighborhood. In other words, initially, there are 20 weatherized agents in PSN while 120 weatherized agents in OSN. The information status (*IS*) for all non-weatherized agents is initialized to 'S' and for weatherized agents it is initialized to 'I'. The intention level (*IL*) of each non-weatherized household agent is initialized to 0. Based on upfront investment U and estimated payback period P, the estimated monthly savings $\frac{\mathrm{U}}{12\mathrm{P}}$ represents the estimated savings which can pay off U over $12P$ months. The assessment level (*AL*) of each weatherized household agent is based on actual average savings (*AS*) and estimated monthly savings $\frac{\mathrm{U}}{12\mathrm{P}}$ due to weatherization using a sigmoid function:

$$\mathrm{AL}_0 = \frac{1}{1 + e^{-(\mathrm{AS} - \frac{\mathrm{U}}{12\mathrm{P}})}}. \tag{5}$$

Information Diffusion: In this sub-model, the agents interact and then update their weatherization-related information status (*IS*) values accordingly. At the beginning of each time-step, the *IS* value for each agent will have one of four possible values (S/E/I/R). Only infected agents (*IS* = I) can be information senders, while only susceptible, exposed, and infected agents (*IS* = S, E, or I) can be information receivers. In each time-step, all infected agents will expose their neighbors with S/E/I status to weatherization-related information. Figure 6 shows the transition probabilities associated with changes in an agent's *IS* value. As an example, if an agent with information status I is exposed to information, it will transition to

Agent i	Agent j	Rules
I/W	S/N | E/N	$\mathrm{AL}_i = \mathrm{AL}_i$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{ij}(\mathrm{AL}_i - \mathrm{IL}_j)$
I/W	I/N	$\mathrm{AL}_i = \mathrm{AL}_i + \mathrm{IC}_{ij}(\mathrm{IL}_j - \mathrm{AL}_i)$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{ij}(\mathrm{AL}_i - \mathrm{IL}_j)$
I/W	E/W	$\mathrm{AL}_i = \mathrm{AL}_i$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{ij}(\mathrm{AL}_i - \mathrm{AL}_j)$
I/W	I/W	$\mathrm{AL}_i = \mathrm{AL}_i + \mathrm{IC}_{ij}(\mathrm{AL}_j - \mathrm{AL}_i)$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{ij}(\mathrm{AL}_i - \mathrm{AL}_j)$
I/N	S/N | E/N	$\mathrm{IL}_i = \mathrm{IL}_i$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{ij}(\mathrm{IL}_i - \mathrm{IL}_j)$
I/N	I/N	$\mathrm{IL}_i = \mathrm{IL}_i + \mathrm{IC}_{ij}(\mathrm{IL}_j - \mathrm{IL}_i)$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{ij}(\mathrm{IL}_i - \mathrm{IL}_j)$
I/N	E/W	$\mathrm{IL}_i = \mathrm{IL}_i$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{ij}(\mathrm{IL}_i - \mathrm{AL}_j)$
I/N	I/W	$\mathrm{IL}_i = \mathrm{IL}_i + \mathrm{IC}_{ij}(\mathrm{AL}_j - \mathrm{IL}_i)$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{ij}(\mathrm{IL}_i - \mathrm{AL}_j)$

Table 1: IL & AL Evolution Rules (Agent $i \rightarrow$ Agent j).

status R with probability $P_{I \rightarrow R}$. As discussed previously, an agent's information status value in its PSN and OSN will not always be synchronized to be the same after each time-step.

Intention & Assessment Level Evolution: A household agent's intention level (*IL*) is only activated if the agent is in a non-weatherized state, while its assessment level (*AL*) is only activated if it has weatherized. The values of both *IL* and *AL* evolve with interactions.

In each time-step, all agents with IS = I will interact with their connected agents that have IS = S/E/I, which will influence the agents' *IL* or *AL* values. Table 1 summarizes the rules and outcomes when agent i exposes agent j to information. Based on its information status and weatherization status, each agent falls into a certain category (e.g., I/W). The first letter refers to the agent's IS value , and the second letter represents its WS value, which can be W (WS = 1) or N (WS = 0). At the beginning of each time-step, the values of *IL*/*A*L for the 548 household agents in the Capitol East Neighborhood will be the same in their PSN and OSN. However, over the course of a time-step, the *IL*/*AL* values in their PSN and OSN may become different, as a result of the different interactions that may occur in different layers of the social network. The *IL*/*AL* of these 548 agents is reconciled to the arithmetic mean of the values in the agent's PSN and OSN at the end of each time-step, thereby ensuring that their *IL*/*AL* will have the same value in both layers at the beginning of the next time-step. Each non-weatherized household agent has a probability of *IL* to change its intention value from 0 to 1. For weatherized agents, the value of *AL* at the beginning of each time-step t following weatherization will be the arithmetic mean of its *AL* value at the end of time-step $t-1$ and initialized value $\mathrm{AL}_{t(I)}$:

$$\mathrm{AL}_t = \frac{\mathrm{AL}_{t-1} + \mathrm{AL}_{t(I)}}{2}. \tag{6}$$

Since each agent's actual savings (*AS*) is updated at the beginning of each time-step, and agents' AL will be affected by *AS*, it will have an initialized value $\mathrm{AL}_{t(I)} = \frac{1}{1+e^{-(\mathrm{AS}-\frac{\mathrm{U}}{12\mathrm{P}})}}$.

Parameter name	Value	Parameter name	Value
$P_{\mathrm{S}\rightarrow\mathrm{E}}$	0.20	$P_{\mathrm{S}\rightarrow\mathrm{I}}$	0.70
$P_{\mathrm{S}\rightarrow\mathrm{R}}$	0.10	$P_{\mathrm{E}\rightarrow\mathrm{I}}$	0.80
$P_{\mathrm{E}\rightarrow\mathrm{R}}$	0.10	$P_{\mathrm{I}\rightarrow\mathrm{R}}$	0.10

Table 2: Fixed Experimental Parameters.

Experimental scenario	P_{rewire}	P_{wap}	# Media
Baseline scenario	0.10	2.5%	0
Scenario 1	0	2.5%	0
Scenario 2	0.50	2.5%	0
Scenario 3	1.00	2.5%	0
Scenario 4	0.10	5.0%	0
Scenario 5	0.10	7.5%	0
Scenario 6	0.10	10%	0
Scenario 7	0.10	50%	0
Scenario 8	0.10	100%	0
Scenario 9	0.10	2.5%	1
Scenario 10	0.10	2.5%	2
Scenario 11	0.10	2.5%	3
Scenario 12	0.10	2.5%	4
Scenario 13	0.10	2.5%	5
Scenario 14	0.10	2.5%	10
Scenario 15	0.10	2.5%	50

Table 3: Experimental Scenarios.

Ability Judgment: As shown in Figure 8, an agent has the ability to weatherize if its WAP status is equal to 1, or if it has a budget that is sufficient to pay for weatherization out of pocket. Only household agents with an income level of 1 qualify for weatherization assistance. In reality, there are many eligible applicants for WAP; however, very few of them receive assistance each year because of limited funding and inefficiencies. For examole, in Iowa, 80,000 WAP applicants are approved each year, but only approximately 2,000 applicants can be served [43]. Therefore, the probability P_{wap} that eligible agents receive assistance from WAP in each time-step is assumed to be 2.5%.

Households Weatherization Adoption: The household agents' weatherization behavior is based on the Theory of Planned Behavior (TPB) [4]. TPB is a static model which states that intention and perceived behavioral control can result in the actual human behavior. However, this theory does not consider the evolution of these variables with time and interactions [47]. In this model, the agents' intention and ability components are used to represent the intention and perceived behavioral control elements of TPB. Each agent's intention component is dynamic and evolves in the Information Diffusion and Intention and Assessment Level Evolution sub-models in each time-step, and its ability component evolves with the value of the inflation rate in the payback period calculation. In the final decision-making stage, a household agent will weatherize its house if and only if its intention and ability levels are both equal to 1.

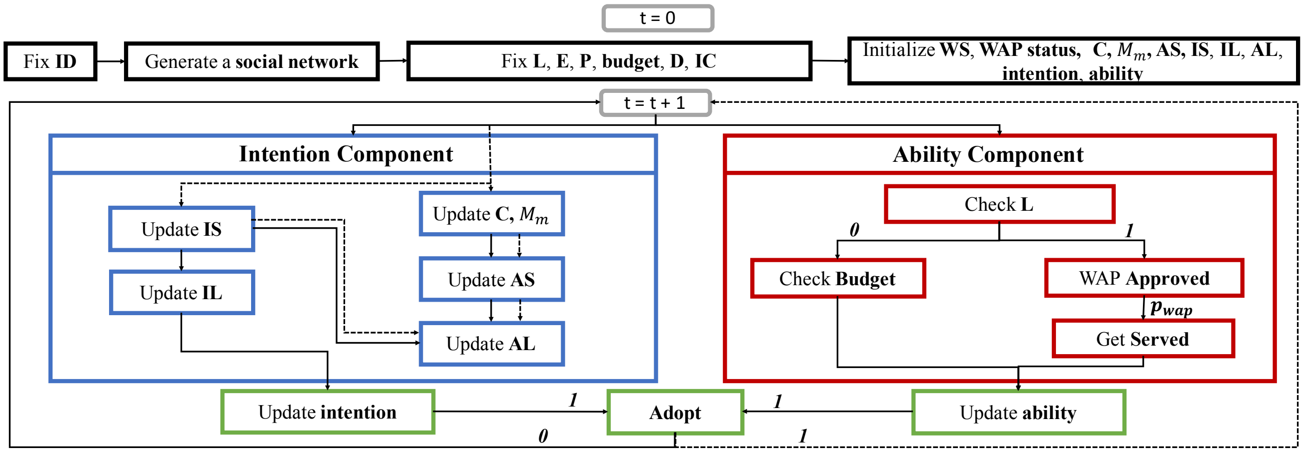


Figure 7: Flowchart describing the logic for updating household agent state variables. Agents that adopt weatherization will follow the dashed line to update their *IS* and *AL* values.

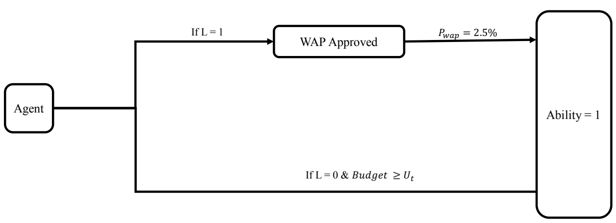


Figure 8: Ability Judgment.

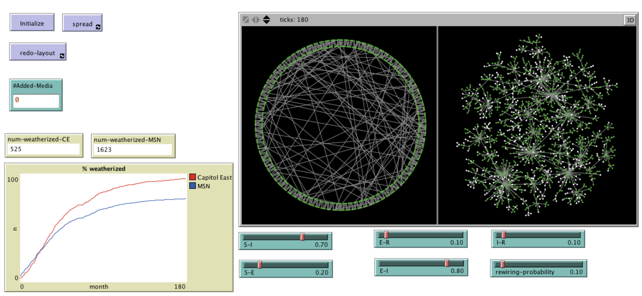


Figure 9: NetLogo Interface.

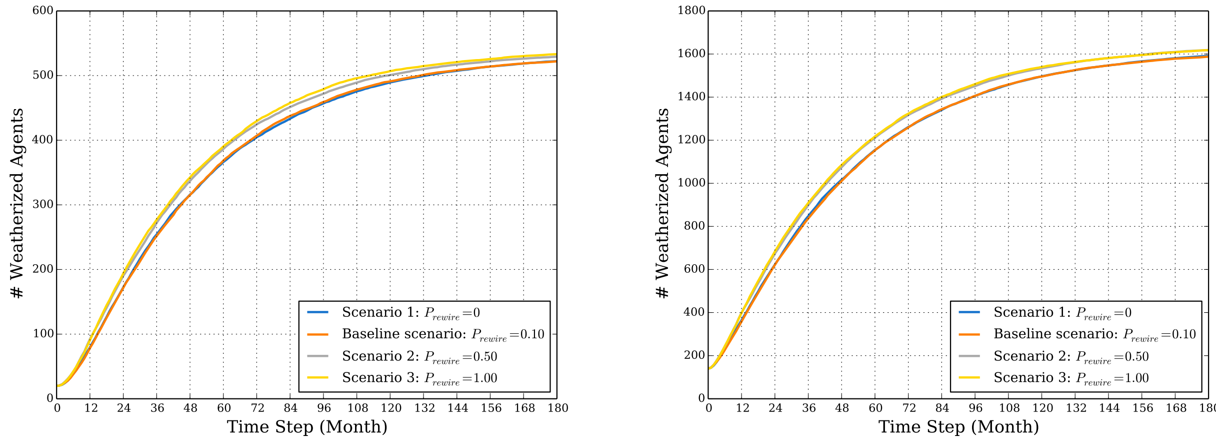
3 EXPERIMENTS AND RESULTS

A user-friendly interface was developed for the weatherization ABM in NetLogo 5.3.1 (shown in Figure 9), which allows for the control of multiple experimental variables and provides a visualization of the dynamic social network generation process (left: PSN, right: OSN). To gain a better understanding of how certain factors might influence weatherization adoption, and to provide some potentially useful recommendations to government actors with the City of Des Moines to encourage residents to weatherize, a set of 16 experimental scenarios was developed and run over 180-month replications, which allowed long-run system behavior to be observed. For each scenario, twenty 180-month replications were run. In each replication, the total number of weatherized houses in each monthly time-step was captured. Table 2 shows the values of six parameters that are fixed and constant throughout all experiments, and Table 3 provides the experimental variable values for all 16 scenarios.

First, a baseline scenario was run. Next, the value of P_{rewire} was experimentally varied to determine how the physical network structure, especially the randomness of the physical network, would affect household agents’ decisions to adopt weatherization (Scenarios 1-3). Then, the probability of an approved applicant being served by WAP (P_{wap}) was experimentally varied (Scenarios 4-8). The current real-life value of P_{wap} is quite low (2.5%), and it was hypothesized that increased investment by the government could yield greater weatherization adoption rates. Finally, in order to understand the role of the media in increasing weatherization adoption, the number of media agents that were included in the model was experimentally varied (Scenarios 9-15). All media agents are assigned the same impact factor of 0.1, which means that each household agent has a 10% chance of being exposed to the weatherization information provided by each media agent in each time-step.

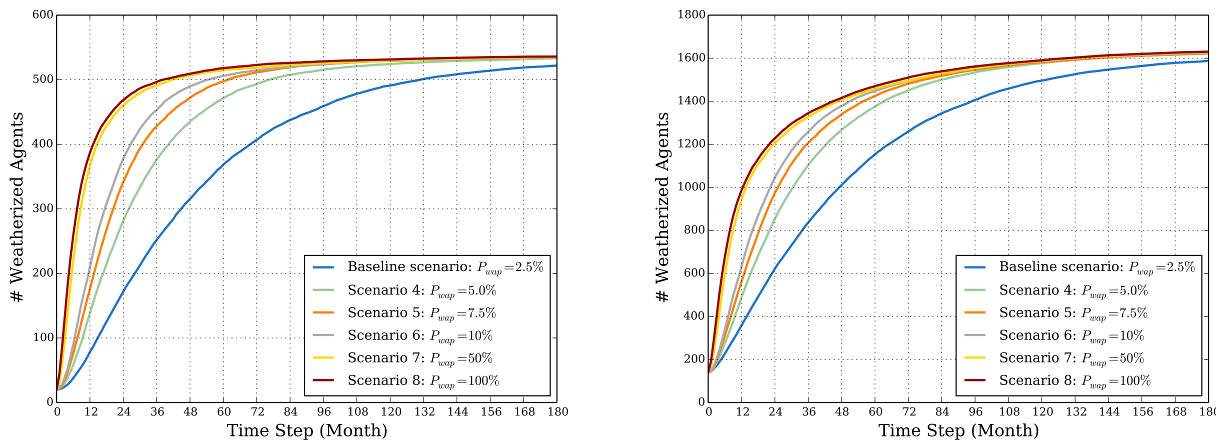
Figures 10a and 10b indicate that the weatherization adoption rate is slightly higher in a more random PSN but that it is generally insensitive to changes in P_{rewire}. By contrast, weatherization adoption exhibits noticeable increases with the increases in P_{wap}, as shown in Figures 11a and 11b. Furthermore, higher values of P_{wap} tend to encourage more households to choose to weatherize in an earlier time-step. While increasing P_{wap} from 2.5% to 5.0% yields dramatic increases in adoption, there are diminishing returns from increasing P_{wap} from 50% to 100%. Similar adoption trends are apparent in PSN and MSN.

As Figures 12a and 12b show, adding more media agents to spread weatherization information can promote greater weatherization adoption, even when their impact factor (0.1) is quite low. Interestingly, however, increasing the number of media agents does not increase adoption proportionally. For example, the increase in adoption that occurs by increasing the number of media agents from 0 to 50 is only about twice as much as that which is gained by



(a) @ PSN **(b) @ MSN**

Figure 10: Effects of PSN randomness on weatherization adoption.



(a) @ PSN **(b) @ MSN**

Figure 11: Effects of increased WAP service probability on weatherization adoption.

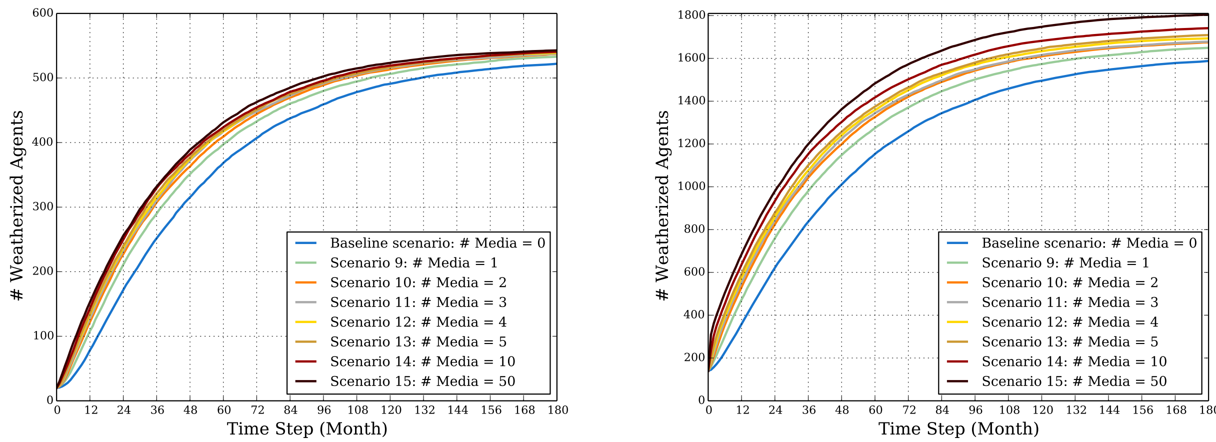
increasing the number of media agents from 0 to 1 in the PSN (four times in the MSN).

Figure 13 shows the average month in which non-weatherized household agents adopt weatherization in each experimental scenario during the 180-month simulation run. These results suggest that increasing randomness, P_{wap}, or the number of media agents tends to increase the rate of the household agents' weatherization adoption. Among them, increasing P_{wap} has the largest impact.

4 CONCLUSION

The agent-based model described in this paper incorporates a multi-layer social network to explore the effects of information diffusion through different types of social interactions (i.e., physical and online) on households' decisions about adopting weatherization. The Theory of Planned Behavior provides the basis for the household agents' decision process, in which the agents' intention levels are influenced by social interactions with neighbors and media agents, and their ability to weatherize depends on both their available budget for weatherization and their WAP eligibility. The agents' social influence is determined by their information statuses, which are updated using logic that is based on the SEIR epidemical model. The model was used to explore the effects of increased randomness in the physical social network, increased WAP eligibility, and increased media exposure on households' weatherization adoption over time.

Future work will include the development of a dynamic social network which considers the possibility of population migration in certain areas. Empirical data must be collected to enable model



(a) @ PSN **(b) @ MSN**

Figure 12: Effects of increased number of media agents on weatherization adoption.

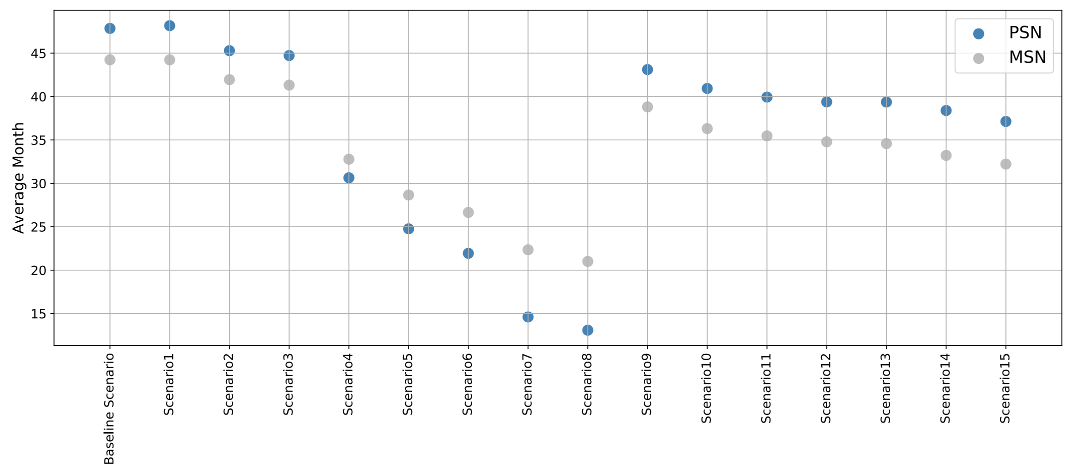


Figure 13: Average weatherization adoption month.

validation, including: 1) the number of houses in the Capitol East neighborhood that actually weatherize in each month, 2) real-time cost of electricity, 3) behavioral data to inform the media agents' impact on households (e.g., how often they read certain newspapers or listen to certain radio stations), 4) households' budgets for weatherization and their income levels, and 5) households' evaluations of the extent to which information from physical and online social networks influence their attitude toward weatherization adoption. An empirically-validated version of the conceptual model described in this paper has the potential to serve as a useful decision support tool for the City of Des Moines to assist them in their efforts to promote residential weatherization adoption, thereby reducing energy consumption.

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The ODD Protocol for Weatherization Adoption in A Multilayer Social Network: An Agent-based Approach

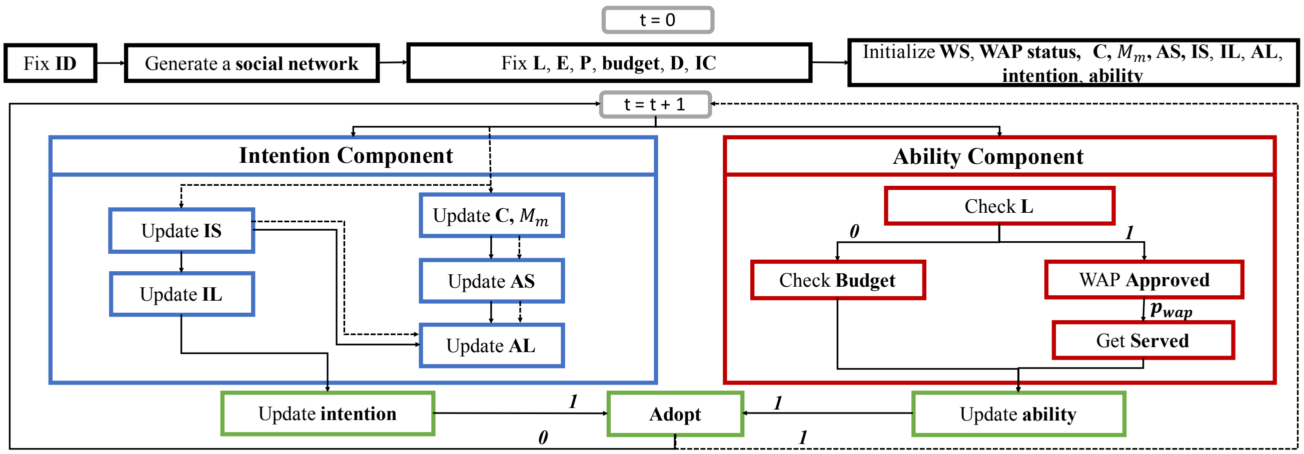

Figure 1: Flowchart describing the logic for updating household agent state variables.

1 OVERVIEW

1.1 Purpose

Our model is intended to model residents' weatherization adoption at the household level in a more realistic context. It can also be used to evaluate different interventions that government and other policy makers could adopt in an effort to promote weatherization adoption in residential buildings.

1.2 Entities, state variables, and scales

Our model consists of two main entities: 1) household agents, 2) media agents. We focus on household agents' adoption of weatherization. Media is a common information carrier for people to learn information and news. It also offers government an access to spread more weatherization information to common people. We add media agents to our model to explore their influence on weatherization adoption. Table. 1 shows the 17 state variables of each household agent. The first seven state variables are key parameters to identify each agent and remain constant. The remaining 10 state variables will be updated in each time-step. For *P*, *IC*, M_m, mathematical definitions are provided as follows. Table. 2 summaries the three state variables of each media agent and we assume they will remain constant all the time.

- *Estimated payback period (P):* Each household agent is capable of estimating the breakeven point at which the upfront investment in weatherization pays for itself through subsequent energy cost savings. The upfront investment (U_t) in year t is initialized as \$4,695 (U_0) [9] and increases over time due to inflation,

$$U_t = U_0(1 + R_1)(1 + R_2)...(1 + R_t)(1 - F_t), \tag{1}$$

where R_t denotes the inflation rate in year t, and F_t refers to the federal income tax credits for energy efficiency, which is assumed to be 30% [13]. By weatherizing, single-family homes saved an average of \$283, annually on energy costs [9]. Therefore, each agent's annual household energy cost savings in the year in which it decides to weatherize (S_0) is set to \$283. If an agent weatherizes in year t, its total savings over n years (TS_{t+n}) is calculated as:

$$\begin{aligned} TS_{t+n} &= S_t + S_{t+1} + ... + S_{t+n} \\ &= S_0((1 + R_t) + (1 + R_t)(1 + R_{t+1}) \\ &\quad + ... + (1 + R_t)...(1 + R_{t+n})). \end{aligned} \tag{2}$$

An agent's estimated payback period P is the value of n (in years) for which $U_t = TS_{t+n}$.

- *Influence coefficient (IC_{ab}):* The influence coefficient defines agent a's influence on agent b, which is assumed to be symmetrical (i.e., $IC_{ab} = IC_{ba}$). Each household agent has a set of influence coefficients, with a value assigned to each of its connections. It is assumed that an agent's influence on another agent is directly proportional to their geographical

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Variable name	Brief description	Scales
ID	A unique identification number for each agent.	An integer in range [1, 2096]
Income level (L)	A household agent's income level is binary and determines its eligibility for financial assistance.	1 (If at or below 200%) 0 (Others)
Monthly energy consumption (E)	Each agent is assigned 24 energy consumption values (kWh) that are specific to its own house that were generated by the Rhino-UMI energy use model. The first 12 values refer to the monthly energy consumption for the agent's house without any weatherization. The last 12 values represent the monthly energy consumption with weatherization applied to its home.	A positive number (kWh)
Estimated payback period (P)	An estimation about how long it will take when the upfront investment (U) can be paid off by total savings (TS).	A positive integer (Year)
Budget	The maximum amount of money ($) that an agent is able to spend on weatherization.	A positive number ($)
Distance from others (D)	For agents in the Capitol East Neighborhood, each one has a vector including spatial distances from all other 547 agents in the neighborhood.	A positive number (meter)
Influence coefficient ($\mathrm{IC}_{\mathrm{ab}}$)	It defines the influence from an agent a to agent b.	A number in range [0, 1]
Weatherization status (WS)	A binary state for representing adoption and non-adoption. An agent can only transition from a status of 0 to a status of 1, based on the assumption that weatherization is irreversible.	1 (Adoption) 0 (Non-adoption)
WAP Status	A binary variable representing the agent's state of receiving weatherization assistance.	1 (Successful) 0 (Others)
Current energy consumption (C)	Based on its weatherization status and the current time-step (i.e., month), a household agent's current monthly energy consumption (in kWh) is obtained from the outputs of the Rhino-UMI model (i.e., the agent's E values).	A positive number (kWh)
Monthly savings (M_m)	The money that an agent saves in month m.	A positive number ($)
Current average saving (AS)	For weatherized household agents, its AS is determined by dividing the agent's total savings by the number of months since it weatherized.	A positive number ($)
Information status (IS)	Each agent has specific attitude toward spreading and receiving certain information. A household agent can take on one of four different IS values, including Susceptible (S), Exposed (E), Infected (I), Recovered (R), in each time-step.	S: An agent who doesn't know the information but is ready to receive it. E: An agent who know the information but don't share it with others. I: An information sender. R: Neither receive nor spread information.
Intention Level (IL)	Intention to adopt weatherization of agents who haven't weatherized their houses.	A number in range [0, 1]
Intention	Each non-weatherized agent have the probability of IL to change its intention from 0 to 1.	1 (Want) 0 (Don't want)
Assessment Level (AL)	An agent will make an assessment for its previous weatherization decision based on its assessment of the perceived value of its weatherization decision and will be influenced by social interactions.	A number in range [0, 1]
Ability	Whether an agent has the ability to weatherize or not.	1 (Have the ability) 0 (Others)

Table 1: State Variables for Household Agents.

Variable name	Brief description	Scales
Information Status (*IS*)	All media agents are assumed to be in status I since we assume they always play the role of information senders.	Infected (I)
Assessment level (*AL*)	We assume each media agent will always spread very positive information to residents about weatherzation and have the $AL = 1$ all the time.	1
Impact Factor	An indicator showing the probability that household agents can have access to the media agent.	A number in range [0, 1]

Table 2: State Variables for Media Agents.

proximity, based on the idea that short physical distances bring people together, increase information sharing, and stimulate the exchange of knowledge [4]. The influence coefficient values of the 1000 household agents outside the Capitol East Neighborhood (for which there are no spatial data) are drawn from a uniform distribution between 0 and 1. Otherwise, the influence coefficient between two agents a and b is defined as follows:

$$\mathrm{IC_{ab}} = \mathrm{IC_{ba}} = \frac{D_{\max} - D_{\mathrm{ab}}}{D_{\max} - D_{\min}}, \tag{3}$$

where D_{ab} denotes the distance from agent a to agent b, and $D_{\min}, D_{\max}$ refer to the minimum and maximum distance between all household agents in the Capitol East Neighborhood, respectively.

- *Monthly savings (M_m):* The money that a weatherized household agent saves in month m is based on the difference between its energy consumption before and after weatherization (NWE_m and WE_m, respectively). This difference is multiplied by the energy cost per kWh, which includes the current residential electricity rate E, a rate equalization factor REF, an energy adjustment clause EAC, a transmission cost adjustment TCA, and a 1.00% sales tax, according to the electricity bill calculation provided by MidAmerican Energy Company [5],

$$\mathrm{M}_m = (\mathrm{NWE}_m - \mathrm{WE}_m)(E + \mathrm{REF} + \mathrm{EAC} + \mathrm{TCA})(1 + \mathrm{TAX}). \tag{4}$$

1.3 Process overview and scheduling

Figure 1 displays the process that how a household agent evolves with time. We take one month as one time-step in our simulation since the energy consumption we got is monthly one. First, a multilayer social network is built and we assume it is a static network. A household agent is initialized with its seven fixed state variables. Its WS, WAP status, C, M_m, AS, IL, AL, intention and ability are all assigned 0, and we set its IS as 'S' at first. Then, in each time-step, household agents with $IS = I$ will spread weatherization information with their neighbors. During the interactions, agents' IS will change based on Information Diffusion Model (it will be explained in details in Sub-modelss section). Their IL or AL and neighbors' IL or AL will also evolve because of the energy conservation. For non-weatherized household agents, at the end of each time-step, they will check their ability and intention to decide whether to adopt weatherization or not. For weatherized household agents, who will follow the dash line in Figure 1, they will have social interactions and update AL based on interactions and financial calculations in each time-step.

2 DESIGN CONCEPTS

2.1 Basic principles

In order to build a more realistic and mechanistically richer model, we take the following basic principles into account. Small-world [15] network and scale-free [3] network are used to generate a multilayer social network to reveal the multidimensionality of people's social networks in reality. We adopt the Susceptible-Exposed-Infected-Recovered epidemic model [6, 8, 14] to describe households' statuses during information propagation and social interactions. Our paper also improves Theory of Planned Behavior [1] as our basic principle of the weatherization behavior through adding dynamic components.

2.2 Emergence

Household agents' decisions to adopt weatherization will influence other Household agents' decisions because of social interactions. Also, media agents can spread positive weatherization information to household agents and also impact their adoption decisions.

2.3 Objectives

Each household agent wants to use weatherization to lower energy bill. Since weatherization also requires upfront investment, households will consider the estimated saving due to weatherization, the big upfront investment or applying WAP to pay less on energy consumption.

2.4 Sensing

Household agents consider their intention and ability when they make decisions on weatherization.

2.5 Interaction

There are three kinds of interactions: 1) interactions between household agents and their neighbors in physical social network through face-to-face talks, 2) interactions between household agents and their neighbors in online social network via online conservations, 3) interactions between household agents and media agents.

2.6 Observation

The number of adopters of weatherization in PSN and MSN are both captured at each time-step.

3 DETAILS

3.1 Initialization

There are 548 household agents in physical social network and 1548 household agents in online social network, among which there are 548 agents exist both in PSN and OSN. All household agents have seven state variables which will remain constant as Table. 1 shows. 20 household agents in PSN are initialized to be adopters at the beginning of the simulation run and their WAP are initialized to be 1. 120 household agents in OSN are initialized to be adopters at the beginning, and their WAP are based on their income level. For those adopters, their IL have the value 'I'. At time t = 0 of a simulation run, for all other household agents, they are initialized to be non-adopters and their WAP statuses are assigned 0. The initial values of their IL, AL, intention and ability are 0 while their IL are 'S'.

3.2 Input data

Considering social and economic composition, the Capitol East Neighborhood in Des Monies was selected as a pilot case for the study. In order to show the potential energy saving when a building is weatherized, an energy model of a single residential block in the Capitol East Neighborhood was proposed [7]. 548 residential buildings compose this neighborhood. We use Rhinoceros 3D and the Urban Modelling Interface (UMI) plugin from MIT's Sustainable Design Lab [12] to build a digital model of this neighborhood and simulate each building's energy consumption. UMI enable us to assemble each building's material and test different influence taken by various weatherization practices. Based on this energy model, a dataset composed of pre- and post-weatherization conditions and corresponding energy consumption can be collected. First, the physical geometry of the neighborhood is modeled by Rhinoceros 3D. We use spatial information, extracted from GIS maps that are maintained by the City of Des Moines, to model building footprints, sidewalks, streets and lot boundaries. Rough floor plans are used to refine the extent of the heights of each building. Then, we extract building-related data, which is needed by UMI model building, from the Polk County assessor data [2]. It consists of each building's address, parcel number, date of construction, number of building stories and separate residences. Each building is identified through the parcel number of lot and the identification approach enables cross-reference information between the Rhino-UMI model and the Assessor's data. The 3D building model prepared in Rhino from GIS and assessor's data is fed into UMI. And each house is assigned a building template which reflects the construction type and detailed condition of the house. 548 buildings' energy consumption under pre- and post-weatherization conditions can be simulated, which would serve as the inputs to the agent-based model to show the energy savings due to weatherization.

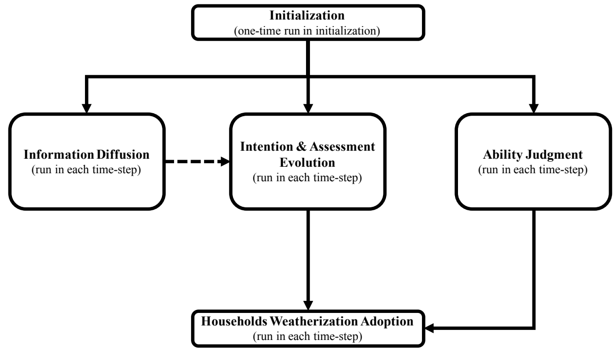
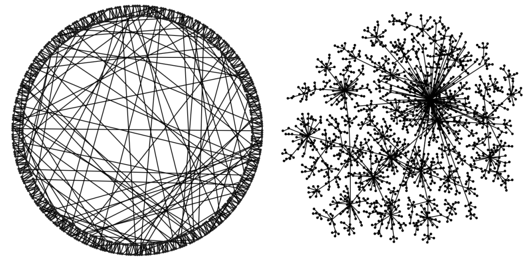


Figure 2: Sub-modelss.



(a) PSN **(b) OSN**

Figure 3: Multilayer Social Networks.

3.3 Sub-modelss

The ABM contains five sub-models: *Initialization, Information Diffusion, Intention & Assessment Level Evolution, Ability Judgment,* and *Household Weatherization Adoption*. First, the multilayer social network is generated, and the agents' parameter values are initialized. Then, in each monthly time-step, agents will have interactions via the multilayer social network, where information diffusion will take place. Based on these interactions, agents' intention and assessment values will evolve, which will inform their judgments regarding their weatherization abilities. Finally, at the end of each time-step, each non-weatherized household agent will decide whether to adopt weatherization, based on its intention and ability values. An overview of the model is shown in Figure 2.

Initialization: Before the first time-step, a multilayer social network is created to allow the agents to interact through both a physical social network (PSN) and an online social network (OSN). There are 548 single-family household agents in the Capitol East Neighborhood. Each node in the PSN (Figure 3a) represents one of these agents, and each edge represents a connection between the nodes it connects. The PSN is a small-world network that was built using the Watts-Strogatz algorithm [15]. This algorithm starts with a regular network and "rewires" the edges of this network randomly, based on a probability P_{rewire}. In other words, the small-world network is an interpolation between regular and random networks, and the greater the value of P_{rewire}, the more random the network will be.

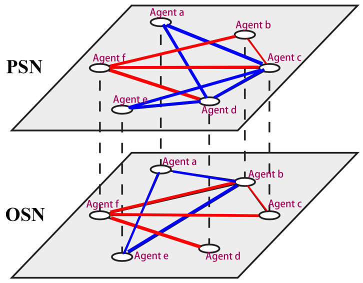
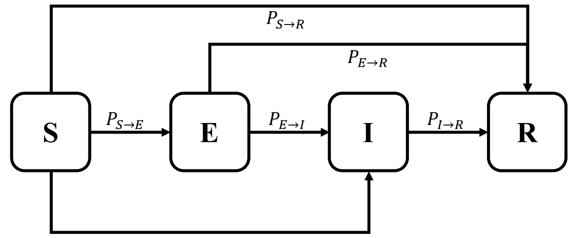


Figure 4: Overlaps and differences in a multilayer social network.



$P_{S\to R}$ $P_{E\to R}$ $P_{S\to E}$ $P_{E\to I}$ $P_{I\to R}$ $P_{S\to I}$

Figure 5: A schematic diagram for SEIR model.

The Barabási-Albert (BA) algorithm [3] was used to generate a scale-free network for the agents' OSN (shown in Figure 3b). The OSN consists of the 548 household agents in the Capitol East Neighborhood, additional 1000 household agents that exist outside the Capitol East Neighborhood, and an experimentally-varied number of media agents. Thus the 548 agents that represent households in the Capitol East Neighborhood exist both in the PSN and the OSN, while the 1000 household agents outside the neighborhood only have virtual connections via the OSN. If no media agents are included, the number of nodes in the OSN is therefore 1548, and the total number of nodes in the multilayer social network (MSN) is 2096. As with individuals in the real world, there are overlaps and differences between the 548 household agents' connections in the PSN and the OSN. Figure 4 demonstrates this phenomenon, with red edges indicating overlapping connections and blue edges representing differences.

The PSN and OSN are initialized as follows: 1) there are 20 household agents have weatherized among the 548 agents in the Capitol East Neighborhood, 2) there are 100 weatherized houses outside this neighborhood. In other words, initially, there are 20 weatherized agents in PSN while 120 weatherized agents in OSN. The information status (*IS*) for all non-weatherized agents is initialized to 'S' and for weatherized agents it is initialized to 'I'. The intention level (*IL*) of each non-weatherized household agent is initialized to 0. Based on upfront investment U and estimated payback period P, the estimated monthly savings $\frac{\mathrm{U}}{12\mathrm{P}}$ represents the estimated savings which can pay off U over $12P$ months. The assessment level (*AL*) of each weatherized household agent is based on actual average savings (*AS*) and estimated monthly savings $\frac{\mathrm{U}}{12\mathrm{P}}$ due to weatherization using a sigmoid function:

$$\mathrm{AL}_0 = \frac{1}{1 + e^{-(\mathrm{AS}-\frac{\mathrm{U}}{12\mathrm{P}})}}. \tag{5}$$

Information Diffusion: In this submodel, the agents interact and then update their weatherization-related information status (*IS*) values accordingly. At the beginning of each time-step, the *IS* value for each agent will have one of four possible values (S/E/I/R). Only infected agents (*IS* = I) can be information senders, while only susceptible, exposed, and infected agents (*IS* = S, E, or I) can be information receivers. In each time-step, all infected agents will expose their neighbors with S/E/I status to weatherization-related information. Figure 5 shows the transition probabilities associated with changes in an agent's *IS* value. As an example, if an agent with information status I is exposed to information, it will transition to status R with probability $P_{I\to R}$. As discussed previously, an agent's information status value in its PSN and OSN will not always be synchronized to be the same after each time-step.

Agent i	Agent j	Rules
I/W	S/N | E/N	$\mathrm{AL}_i = \mathrm{AL}_i$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{AL}_i - \mathrm{IL}_j)$
I/W	I/N	$\mathrm{AL}_i = \mathrm{AL}_i + \mathrm{IC}_{\mathrm{ij}}(\mathrm{IL}_j - \mathrm{AL}_i)$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{AL}_i - \mathrm{IL}_j)$
I/W	E/W	$\mathrm{AL}_i = \mathrm{AL}_i$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{AL}_i - \mathrm{AL}_j)$
I/W	I/W	$\mathrm{AL}_i = \mathrm{AL}_i + \mathrm{IC}_{\mathrm{ij}}(\mathrm{AL}_j - \mathrm{AL}_i)$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{AL}_i - \mathrm{AL}_j)$
I/N	S/N | E/N	$\mathrm{IL}_i = \mathrm{IL}_i$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{IL}_i - \mathrm{IL}_j)$
I/N	I/N	$\mathrm{IL}_i = \mathrm{IL}_i + \mathrm{IC}_{\mathrm{ij}}(\mathrm{IL}_j - \mathrm{IL}_i)$ $\mathrm{IL}_j = \mathrm{IL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{IL}_i - \mathrm{IL}_j)$
I/N	E/W	$\mathrm{IL}_i = \mathrm{IL}_i$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{IL}_i - \mathrm{AL}_j)$
I/N	I/W	$\mathrm{IL}_i = \mathrm{IL}_i + \mathrm{IC}_{\mathrm{ij}}(\mathrm{AL}_j - \mathrm{IL}_i)$ $\mathrm{AL}_j = \mathrm{AL}_j + \mathrm{IC}_{\mathrm{ij}}(\mathrm{IL}_i - \mathrm{AL}_j)$

Table 3: IL & AL Evolution Rules (Agent $i \to$ Agent j).

Intention & Assessment Level Evolution: A household agent's intention level (*IL*) is only activated if the agent is in a non-weatherized state, while its assessment level (*AL*) is only activated if it has weatherized. The values of both *IL* and *AL* evolve with interactions.

In each time-step, all agents with *IS* = I will interact with their connected agents that have *IS* = S/E/I, which will influence the agents' *IL* or *AL* values. Table 1 summarizes the rules and outcomes when agent i exposes agent j to information. Based on its information status and weatherization status, each agent falls into a certain category (e.g., I/W). The first letter refers to the agent's *IS* value , and the second letter represents its *WS* value, which can be W (WS = 1) or N (WS = 0). At the beginning of each time-step, the values of *IL*/*A*L for the 548 household agents in the Capitol East Neighborhood will be the same in their PSN and OSN. However, over the course of a time-step, the *IL*/*AL* values in their PSN and

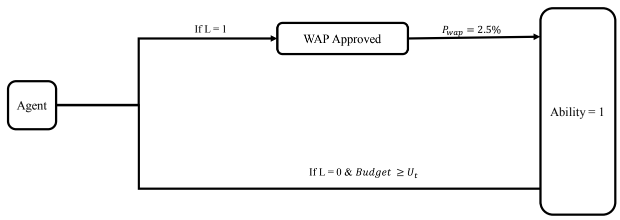


Figure 6: Ability Judgment.

OSN may become different, as a result of the different interactions that may occur in different layers of the social network. The IL/AL of these 548 agents is reconciled to the arithmetic mean of the values in the agent's PSN and OSN at the end of each time-step, thereby ensuring that their IL/AL will have the same value in both layers at the beginning of the next time-step. Each non-weatherized household agent has a probability of IL to change its intention value from 0 to 1. For weatherized agents, the value of AL at the beginning of each time-step t following weatherization will be the arithmetic mean of its AL value at the end of time-step $t-1$ and initialized value $\mathrm{AL}_{t(I)}$:

$$\mathrm{AL}_t = \frac{\mathrm{AL}_{t-1} + \mathrm{AL}_{t(I)}}{2}. \tag{6}$$

Since each agent's actual savings (AS) is updated at the beginning of each time-step, and agents' AL will be affected by AS, it will have an initialized value $\mathrm{AL}_{t(I)} = \frac{1}{1+e^{-(\mathrm{AS}-\frac{\mathrm{U}}{12\mathrm{P}})}}$.

Ability Judgment: As shown in Figure 6, an agent has the ability to weatherize if its WAP status is equal to 1, or if it has a budget that is sufficient to pay for weatherization out of pocket. Only household agents with an income level of 1 qualify for weatherization assistance. In reality, there are many eligible applicants for WAP; however, very few of them receive assistance each year because of limited funding and inefficiencies. For examole, in Iowa, 80,000 WAP applicants are approved each year, but only approximately 2,000 applicants can be served [10]. Therefore, the probability P_{wap} that eligible agents receive assistance from WAP in each time-step is assumed to be 2.5%.

Households Weatherization Adoption: The household agents' weatherization behavior is based on the Theory of Planned Behavior (TPB) [1]. TPB is a static model which states that intention and perceived behavioral control can result in the actual human behavior. However, this theory does not consider the evolution of these variables with time and interactions [11]. In this model, the agents' intention and ability components are used to represent the intention and perceived behavioral control elements of TPB. Each agent's intention component is dynamic and evolves in the Information Diffusion and Intention and Assessment Level Evolution sub-models in each time-step, and its ability component evolves with the value of the inflation rate in the payback period calculation. In the final decision-making stage, a household agent will weatherize its house if and only if its intention and ability levels are both equal to 1.

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