

# How Information Propagation in Hybrid Spaces Affects Decision-Making: Using ABM to Simulate Covid-19 Vaccine Uptake

## Overview, Design Concepts, and Details Protocol (ODD)

## 1 Overview

The description of the model will be given based on the Overview, Design C concepts, and Details (ODD) protocol by [Grimm et al. \(2010\)](#) for the purpose of model reproducibility and extension if so desired by the reader. However, full implementation details including source code, raw data, model file and results are available at CoMSES Net <https://www.comses.net/codebase-release/8967d4ca-9199-4ca8-be49-cab6d14db12c/>.

### 1.1 Purpose

During a global pandemic such as Covid-19, vaccines provide an effective way to protect people against disease and have the potential to save lives ([Polack et al., 2020](#)). However, the decision-making process that governs how individuals decide to vaccinate or not remains elusive (e.g., [Kerr et al. 2021](#)). While studies have explored the reasons behind vaccination decision-making from a non-modeling perspective (e.g., [Cotfas et al. 2021](#); [Yin et al. 2022](#); [Murphy et al. 2021](#); [Dror et al. 2020](#)). There are only a few studies that attempt to model the vaccination decision-making process at the individual level. For example, [Ancona et al. \(2022\)](#) built a mathematical model to explain how vaccine hesitancy can diffuse across social networks. Coinciding with the lack of studies on individuals' decision-making mechanism is that of studies on how the rise of hybrid spaces (i.e., the physical, relational, and cyber spaces according to [Shaw & Sui \(2020\)](#)'s *Spatial* framework) can affect the information propagation about vaccines. To fill these gaps, using the Covid-19 pandemic as a case study, our research attempts to simulate the diffusion of pro-vaccine, anti-vaccine and neutral opinions in physical, relational and cyber space networks, and modeled individuals' decision-making process on taking Covid-19 vaccines or not.

### 1.2 Entities, state variables, and scales

The entities in this model represent individuals. Each individual has a state variable that describes their vaccination status and also distinguishes their behavior rules. Their vaccination status (i.e., vaccinated, or unvaccinated) is the key variable that our model aims to predict. For unvaccinated people, our model updates their opinions and vaccination status at every time step. However, for vaccinated people, our model assumes their positive opinions toward vaccines will last for the entire simulation period. In the model, people's opinion dynamics towards COVID-19 vaccines are defined based on the social influence network theory ([Friedkin & Johnsen, 1990](#)) and coded using Eq. 1 which is explained in Section 1.3. Specifically, people's opinions at every time step are updated based on the social level factors including interpersonal influences, and cognitive level factors such as intrinsic belief and susceptibility scores (see Section 3). In addition to the factors that can affect their opinion dynamics, people also have other variables to describe their demographic attributes (e.g., age, gender, living in urban or rural areas), their home locations in the form of coordinates (e.g., longitude and latitude) and their social ties (e.g., numbers of neighbors in family, work, school, and social media networks). Section 3.1 and 3.2 explains the functions and input data that are used to create these variables.

The other component of the model is the environment which consists of a geographic space of the study area and three network layers. Turning to our study area, Chautauqua County, is located in the southwest of New York State. People are placed in a geographic space based on their home location. People from the same households or group quarters (e.g., nursing homes) live on the same residential parcel. The three layers of networks, including the physical, relational and cyber space networks, constitute the hybrid spaces through which vaccine-related opinions can spread. Figure 1 demonstrates the hybrid spaces and their components. The physical space includes family and group quarter networks. These two networks are defined based on physical distance, for example, a family is a group of people who live under the same roof. Relational space includes school and work networks that are formed based on social relationships (e.g., coworkers or classmates). Cyber space consists of a social media network that allows people to exchange information in a more flexible and timely manner (Yu & Shaw, 2008). Once a person has access to the cyber space, they can communicate almost with everyone from anywhere (e.g., Saud et al. 2020). The networks in the hybrid spaces are stylized based on literature and Table 1 shows the properties of these networks. Family networks are parameterized based on U.S. Census data and will be explained in detail in Section 3.2.

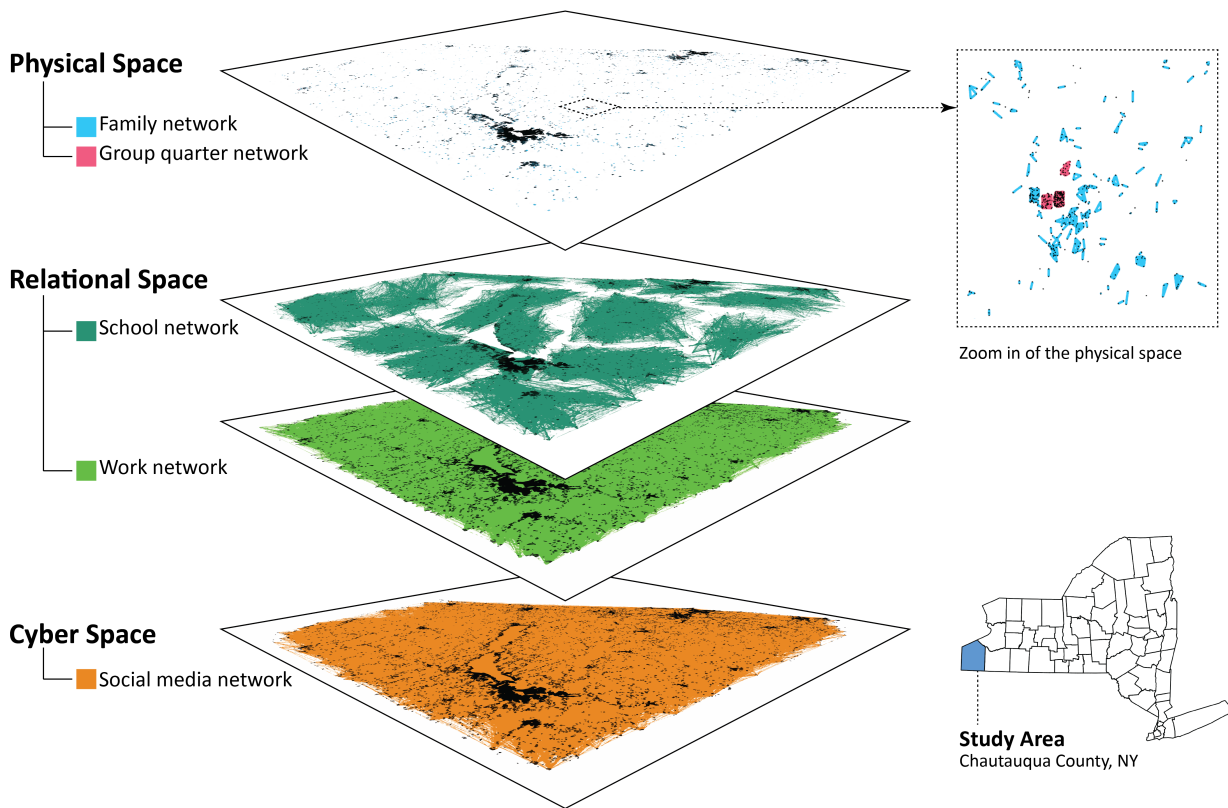


Figure 1: Schematic representation of hybrid spaces: physical, relational and cyber space networks

The model runs at a discrete time step. While people’s opinion changes are often difficult to capture, recent studies found that opinion changes can happen as quickly as one week or as slowly as a year (e.g., Laurin 2018; Bialik 2018). In considering the fierce discussions about Covid-19 vaccines during the pandemic, our study assumes that people can update their opinions relatively frequently. Therefore, our model sets the temporal resolution as one week assuming that people update their opinions towards Covid-19 vaccines every week. The simulation lasts for 500 days from January 1, 2021, until May 15, 2022. This period is selected because it captures the main phases of New York State’s vaccination administration plan for people 5 years old and above (e.g., NYS 2021a,b), and also catches the upsurge in vaccine debates on social media (e.g., Chen & Crooks 2022). Since this model is grounded in an empirical setting, people in the model need to follow a realistic vaccination administration plan. Specifically, except for essential workers who are

Table 1: Properties of stylized networks used in hybrid spaces

Network type	Parameter	Values	Source
Family/group quarter	Num. nodes	110198	US Census Bureau (2020b)
	Num. edges	145734	-
	Avg. degree	2.64	-
School	Num. nodes	21613	-
	Num. edges	64539	-
	Avg. degree	5.97	Sijtsema et al. (2010); Huang et al. (2014)
Work	Num. nodes	49119	-
	Num. edges	246367	-
	Avg. degree	10.03	Feeley et al. (2008)
Social media	Num. nodes	74302	Auxier & Anderson (2021); Vogels et al. (2022)
	Num. edges	1856900	-
	Avg. degree	49.98	Ugander et al. (2011); Bailey et al. (2020)

eligible to vaccinate since the beginning of the simulation, people in the model need to wait for the date until they are eligible. Table 2 shows the official vaccination administration plan for different age groups and the corresponding time step in the model.

Table 2: New York State’s vaccination administration plan and the corresponding time step in the model

Date	Time step	Eligible age group
January 1, 2021	0	Essential workers
January 11, 2021	2	Individuals 75 and older
January 23, 2021	4	Individuals 65 and older
March 10, 2021	10	Individuals 60 and older
March 22, 2021	12	Individuals 50 and older
March 30, 2021	13	Individuals 30 and older
April 6, 2021	14	Individuals 16 and older
May 19, 2021	20	Individuals 12 and older
December 1, 2021	48	Individuals 5 and older

### 1.3 Process overview and scheduling

Figure 2 shows the flowchart of the modeling process. The notations in this figure are explained in detail in Table 4. After model initialization and setup (Section 3.1 and Section 3.2), agents will be activated in a random order to perform the following actions. First, each person checks if they have already been vaccinated or not. We assume that vaccinated agents demonstrate positive opinions toward Covid-19 vaccines and will remain pro-vaccine during the entire simulation. However, unvaccinated agents will update their vaccination status at each time step based on their opinions. The opinion updating mechanism of those unvaccinated follows the social influence network theory as introduced in Section 1.2. This theory combines both cognitive and social structural factors to predict individuals’ opinion changes. Among many classical social influence network models, we chose the Friedkin & Johnsen (1990) model because it can engender a diversity of opinion patterns ranging from assimilation to polarization (e.g., Flache et al. 2017; Anderson & Ye 2019). Meanwhile, it has been extensively verified in various settings such as cultural reception, consensus reaching and political opinions (e.g., Childress & Friedkin 2012; Urena et al. 2019). The Friedkin & Johnsen (1990)’s model assumes that an individual’s opinion toward a particular issue is not only affected by their intrinsic belief but also affected by other people’s attitudes through interpersonal influence. Hence, adapted from the Friedkin & Johnsen (1990) model, we used the recursive Eq. (1) to model the opinion of the  $i$ -th person among  $N$  actors at time step  $t$ :

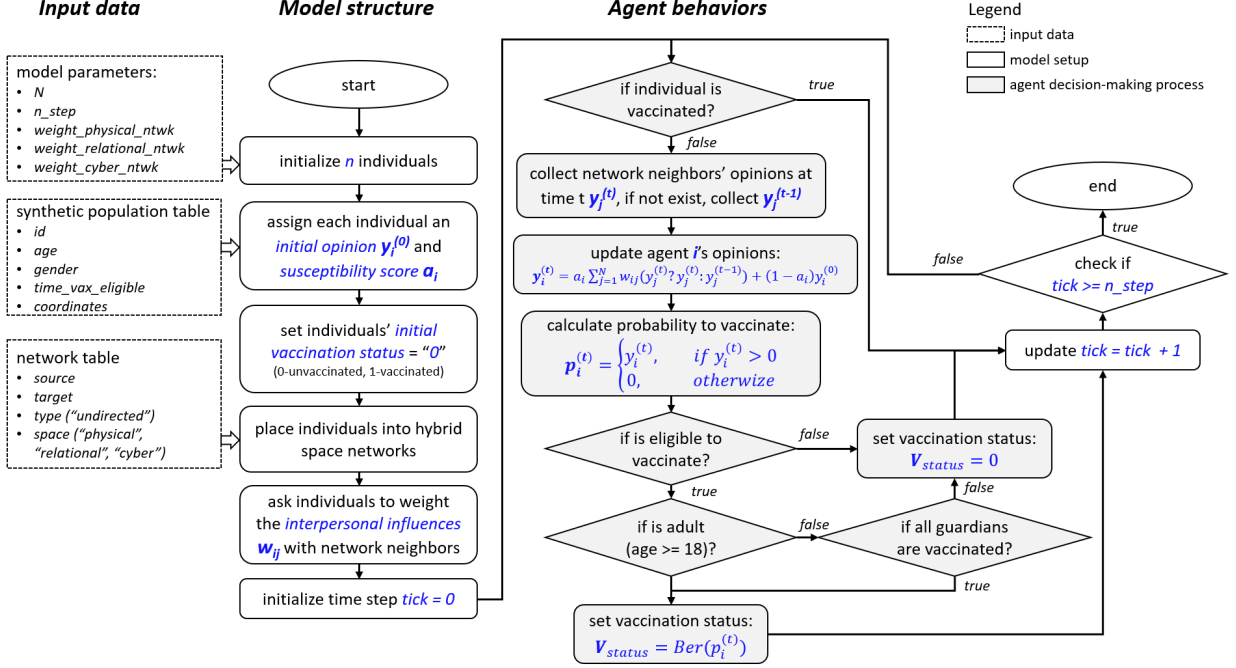


Figure 2: Flowchart of the modeling process

$$y_i^{(t)} = a_i \sum_{j=1}^N w_{ij} (y_j^{(t)} \cdot y_j^{(t-1)} : y_j^{(t-1)}) + (1 - a_i) y_i^{(0)} \quad (1)$$

for  $t = 1, 2, 3, \dots$ , where  $w_{ij}$  describes the weight of interpersonal influence between people  $i$  and  $j$  ( $0 < w_{ij} < 1, \sum_j w_{ij} = 1$ ), and  $a_i$  is  $i$ -th person's susceptibility to interpersonal influence ( $0 < a_i < 1$ ), and  $y_i^{(0)}$  is the  $i$ -th person's initial opinion towards Covid-19 vaccines. At the time step  $t$ , the people  $i$  will collect their network neighbor  $j$ 's opinion at the same time step  $y_j^{(t)}$ , if not exist, then collect their opinion at the previous time step  $y_j^{(t-1)}$ . The first term of Eq. (1) captures the structural level factors (e.g., averaging weighted opinions through interpersonal influence), and the second term represents the cognitive level factors (e.g., intrinsic belief toward Covid-19 vaccines).

After people have updated their opinions towards Covid-19 vaccines, they will check the time step to see if they are eligible for vaccination or not according to Table 2. If they are eligible, they will make a binary decision of vaccination based on a Bernoulli random variable (e.g., Ancona et al. 2022) whose parameter is derived from  $y_i^{(t)}$  (see Eq. 2, 3 in Section 3.3). Additionally, our model imposed more strict decision-making rules for minors due to potential parental vaccine hesitancy (Gowda & Dempsey, 2013; Dror et al., 2020). Specifically, all the adults in their family network must have been vaccinated before minors are vaccinated. Once a person has been vaccinated, they will automatically change their opinions to pro-vaccine.

## 2 Design concepts

### 2.1 Basic principles

The design principles of our model, specifically the opinion dynamics of agents (or people), are based on the social influence network theory as explained in Section 1.3. While this theory has been widely applied to study opinion dynamics under different scenarios from assimilation to zealotry effects (e.g., Childress & Friedkin 2012; Bindel et al. 2015; Urena et al. 2019), rarely have studies applied this theory to investigate



health-related issues such as vaccine uptake. Among a few studies, [Ancona et al. \(2022\)](#) made a crucial step to bridge the abstract theory with concrete and pressing health issues such as vaccine hesitancy. However, these studies often took a mathematical instead of an agent-based modeling approach, therefore they are criticized for ignoring the autonomy and interaction between agents ([Crooks et al., 2018](#)). Meanwhile, with the development of information and communication technologies, information propagation is no longer limited to physical and relational spaces, and can also take place in cyber space. Therefore, there is an urgent need to update our understanding of opinion dynamics in considering the coexistence of hybrid space networks ([Croitoru et al., 2015](#)). To fill these gaps, our study combined social influence network theory with an agent-based model to investigate the information diffusion mechanism across hybrid space networks (i.e., physical, relational and cyber space networks) through the case study of Covid-19 vaccine uptake.

## 2.2 Emergence

The model’s primary outputs are vaccination rates for different age groups: all ages, ages 65 and older, ages 18-64, ages 12-17, and ages 5-11. These outputs emerge from individual vaccination decisions that are determined by the structure of hybrid space networks and the social influence network function (i.e., [Friedkin & Johnsen 1990](#) model).

## 2.3 Adaptation

The key individual decision is whether to vaccinate or not (Section 1.2). At each time step, agents will check their vaccination status and update their opinions based on Eq. (1). After updating their opinions, individuals then check if they can satisfy the prerequisites for vaccination or not (Figure 2). First, they check their vaccine eligibility according to the vaccination administration plan (Table 2). Next, minors need to have all their guardians vaccinated before they can vaccinate. Once all the prerequisites have been met, the vaccination decision is a stochastic function (i.e., Bernoulli random variable introduced in Section 1.3) of (a) the averaging weighted opinions of their neighbors in hybrid space networks, and (b) their initial opinions towards Covid-19 vaccines. Section 3.3 explains this stochastic process in detail. Consequently, people adapt their vaccination decisions to compromise between the external social pressure of vaccination and their intrinsic belief towards Covid-19 vaccines. However, people do not adapt their social networks in any way.

## 2.4 Objectives, fitness

Conformity with individuals’ intrinsic beliefs and the vaccination status of their network neighbors is an implicit fitness measure. The adaptive behavior acts to give people a vaccination status more (dis)similar to that of their network neighbors based on their susceptibility to interpersonal influence.

## 2.5 Learning and prediction

People’s adaptive traits are not based on estimating the future consequences of decisions. No learning or prediction is represented in this model.

## 2.6 Sensing

First, people can read some environmental state variables such as the current time step, the corresponding date in the real world, and the time step when they are eligible for vaccination. Next, people can identify their network neighbors in the hybrid space networks (i.e., physical, relational and cyber spaces) and they also know the vaccination status and opinion scores of their network neighbors at current and previous time steps.

## 2.7 Interaction

Direct interaction involving communication occurs between people and their network neighbors. For example, if a person changes their opinions towards Covid-19 vaccines, this person will communicate their updated

opinions to all network neighbors in all three spaces: physical, relational and cyber. Unlike what happens in reality, our model does not consider the competition among people for vaccines. Individuals who are eligible and want to vaccinate can get vaccines.

## 2.8 Stochasticity

Stochasticity can be seen in several processes within the model. First, stochastic functions are used to initialize people’s initial opinions towards Covid-19 vaccines  $y_i^{(0)}$ , susceptibility score to interpersonal influence  $a_i$  and to identify essential workers among people. Essential workers are eligible to receive the vaccines from the start of the simulation due to their critical roles during the pandemic (NYSDOL, 2021). Meanwhile, the order in which people execute actions (i.e., update opinions) at each time step is also stochastic. Such stochasticity in execution order, by adding complexity to the decision-making process, makes our model less predictable but more realistic than the other mathematical models that often take a deterministic approach (e.g., Ancona et al. 2022).

## 2.9 Collectives

Collectives are not represented. Each individual has hybrid space networks including a physical space network with family or group quarter members, a relational space network with coworkers or schoolmates, and a cyber space network with social media friends. While these hybrid space networks can have different weights in people’s decision-making process (see  $w_{ij}$  in Eq. 1), these networks have no behaviors of their own.

## 2.10 Observation

The visualization window of the model portrays the spatial distribution of vaccinated and unvaccinated individuals. We also monitor the process of vaccination rates for different age groups: all ages, ages 65 and older, ages 18-64, ages 12-17, and ages 5-1, which will be compared against the ground truth vaccination data at the county level (CDC, 2023). We also collect the vaccination status of each individual at the end of the simulation for further analysis.

# 3 Details

## 3.1 Initialization

The initialization of the model and the agents relies on the demographic and geographic data of the study area. We calibrate parameter values based on relevant literature and all the default parameter values are summarized in Table 3. This model gives the flexibility for users to run experiments using different parameters. For example, users can give the hybrid space networks different weights, or define people’s susceptibility scores using other functions such as a normal distribution (e.g., Yuan & Crooks 2017).

## 3.2 Input data

This model required synthetic population data and hybrid space network data to create agents and define their connections in hybrid spaces (i.e., cyber, relational and physical). Table 4 explains the variables in the synthetic population data and the hybrid space network data. Both the population synthesis and hybrid space network data can be generated from publicly available data sources (i.e., US Census or literature). Table 4 explains the input data in detail and presents the sources for calibration. Population synthesis, a key stage in spatial micro-simulation techniques, has long been used in social science to overcome data limitation problems while protecting individual privacy (Lovell & Dumont, 2017). Population synthesis allows researchers to create population and individual households that are representative of the study area based on the aggregated outputs from census or survey results. The aggregated outputs consist of a set of marginal distributions for characteristics of the true population of interest (Barthelemy & Toint, 2013). In agent-based models, population synthesis has been widely used for different research purposes (Wheaton et al., 2009), such as transportation planning, disaster response and disease control (Wise, 2014; Fournier et al.,

Table 3: Input parameter values

Parameters	Default values	References
<b>Model</b>		
Number of agents	127,584	US Census Bureau (2020b)
Time step (opinion updating frequency)	1 week	Laurin (2018)
Duration	500 days (Jan. 1, 2021 - May 15, 2022)	NYS (2021a,b)
Proportion of essential workers	18.2% of working individuals with ages 18 and over	NYSDOL (2021)
Weights of hybrid space networks [physical, relational, cyber]	[1, 1, 1], [3, 1, 1], [1, 3, 1], [1, 1, 3] weights will be normalized to sum to 1	Authors' estimation
<b>Agent <math>i</math></b>		
Initial vaccination status	0 - unvaccinated	CDC (2023)
Initial opinion $y_i^{(0)}$	Uniform distribution [-1, 1]; positive values represent pro-vaccine opinions and vice versa	Dong et al. (2017)
Susceptibility scores $a_i$	Uniform distribution [0, 1]	Authors' estimation
Opinion updating function $y_i^{(t)}$	Eq. 1 based on social influence network theory	Friedkin & Johnsen (1990)
Probability of vaccination $p_i^{(t)}$	Eq. 2	Ancona et al. (2022)
Vaccination decision $V_{decision}$	Eq. 3. 0 - unvaccinated; 1 - vaccinated	Ancona et al. (2022)
Time step of eligibility	Table 2	NYS (2021a,b)

2018), Recently, scholars proposed a novel method to incorporate social networks with synthetic population that allows modelers to study complex social interactions between agents (Jiang et al., 2022). Based on the method used in other studies (e.g., Wise 2014; Jiang et al. 2022; Barthelemy & Toint 2013, we create the synthetic population data for agents and their hybrid space networks. For interested readers, we provided the R scripts of population synthesis and network generation at CoMSES Net <https://www.comses.net/codebase-release/8967d4ca-9199-4ca8-be49-cab6d14db12c/>.

### 3.3 Submodels

As explained in Section 1.3 Process overview and scheduling, after model setup and initialization, agents are activated in random order to update their opinions and make vaccination decisions. While agents' decision-making process is often considered complicated (Balke & Gilbert, 2014), our model allows researchers to represent people's vaccination decision-making process into several simple but meaningful submodels, which are highlighted in Figure 2. The submodels include one that examines the social structural impacts on vaccination decisions (Section 3.3.1), one that represents the cognitive reasoning behind it (Section 3.3.2), and the other one that explains the additional constraints on vaccine update (Section 3.3.3). Meanwhile, by applying social influence network theory (Friedkin & Johnsen, 1990) in a hybrid space setting (Shaw & Sui, 2020), our model allows researchers to investigate how information propagation in hybrid spaces (i.e., physical, relational and cyber spaces) affects people's vaccination decisions. As shown in the model flowchart Figure 2, people determine their activity based on their current vaccination status. If an individual is already vaccinated, they are assumed to have a stable pro-vaccine stance during the entire simulation. Otherwise, they will update their opinions towards Covid-19 vaccines at each time step based on their social and cognitive level.

#### 3.3.1 Social level submodel

Deciding an individual's social level starts with identifying their network neighbors in physical (i.e., family or group quarter networks), relational (i.e., work or school networks) and cyber (i.e., social media networks)

Table 4: Variables in input data

Variables	Details	Sources/census table id
<b>Synthetic population data</b>		
Individual id	Unique identifier of agents	-
Household id	Identifier of agents' household	-
GEOID	Identifier of census block groups where agents live	-
Gender	-	US Census Bureau (2020b)
Age	-	US Census Bureau (2020b)
Household role	Agents' role in households such as "mom", "dad", "child under 18"	US Census Bureau (2020d,e,f,g,h,j)
Urban or rural	If agents live in urban or rural areas	US Census Bureau (2020a)
If work	If agents work or not	US Census Bureau (2020l)
Work place	If agents work in the county or out-of-county	US Census Bureau (2020c)
Work company	Identifier of agents' work company if they work in county	US Census Bureau (2020i)
If school	If agents attend school (i.e., K-12) or not	US Census Bureau (2020k)
School district code	Identifier of the school district of agents	NYS GIS Clearinghouse (2020)
School id	Identifier of agents' school if they study in school	
If social media (adult)	If adult agents use social media or not	Auxier & Anderson (2021)
If social media (teen)	If teen agents use social media or not	Vogels et al. (2022)
Parcel id	Identifier of residential parcels of agents' household	NYS GIS Clearinghouse (2021)
Coordinates	Agents' geographic location in the form of latitude and longitude based on parcel data	-
<b>Hybrid space network data</b>		
Source	Nodes of an edge based on individual id	-
Target	Nodes of an edge based on individual id	-
Type	Undirected	-
Relation	Relationships of edges including "family", "group quarter", "work", "school", "social media adult", and "social media teen"	-

spaces, saving their network neighbors as a list, and recording the number of neighbors in each space. Next, individuals will weigh the interpersonal influences of hybrid spaces. The weights are calculated based on the global weights that modelers have manually assigned, and also on individuals' network structure. Figure 3 explains the calculation process using examples. Since individuals' social structures are fixed during the simulation, they only need to identify their network neighbors and weights at the start of the model.

After identifying network neighbors and calculating weights, individuals will calculate the average opinions of their neighbors in hybrid spaces. Individuals calculate their neighbors' average opinions at each time step and in random order. If a neighbor of an individual does not have their opinions yet at time  $t$ , this neighbor will report their opinions at the previous time  $t-1$ . The results generated from this social level submodel including the network weights and the neighbors' average opinions will feed into the cognitive level submodel.

### 3.3.2 Cognitive level submodel

The submodel at the cognitive level represents the reasoning process that agents use to develop their own opinions based on external stimuli (i.e., interpersonal influences) and internal psychological traits (i.e., intrinsic belief and susceptibility level) (Balke & Gilbert, 2014). According to Friedkin & Johnsen (1990)'s model, individuals in our model calculate their opinions towards Covid-19 vaccines  $y_i^{(t)}$  using Eq. 1. Then, individuals further derived the probability of vaccination using Eq. 2 (e.g., Ancona et al. 2022). Based on the

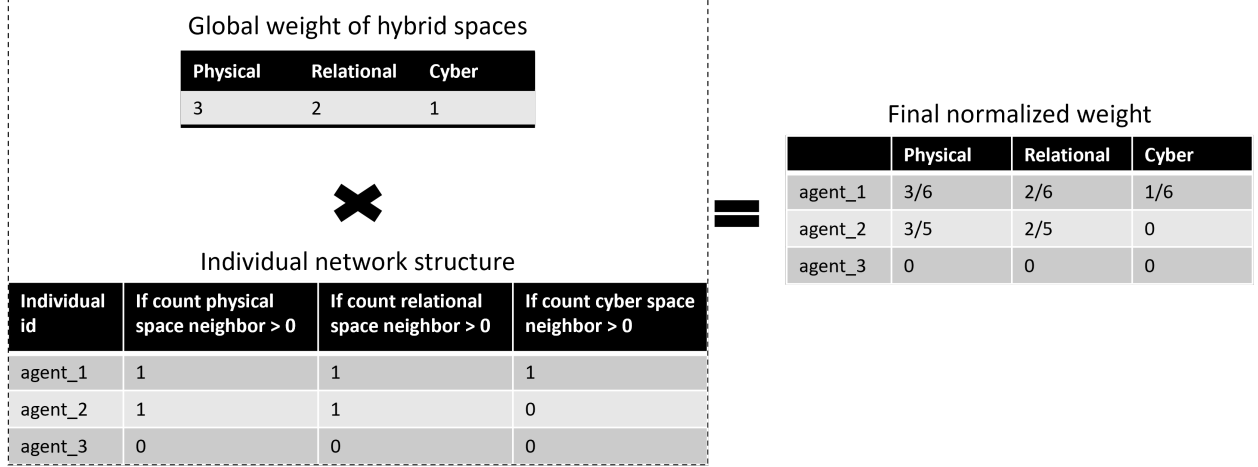


Figure 3: Calculating the weights of interpersonal influences in hybrid spaces

probability  $p_i^{(t)}$ , an individual's binary decision of vaccination or not becomes a Bernoulli random variable as shown in Eq. 3.

$$p_i^{(t)} = \begin{cases} y_i^{(t)}, & \text{if } y_i^{(t)} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$V_{status} \sim Ber(p_i^{(t)}) \quad (3)$$

### 3.3.3 Other constraints on vaccination

In addition to their own vaccination decisions, individuals' vaccination status is also constrained by official vaccination administration plans (NYS, 2021a,b). People need to wait until they are eligible for vaccines (see Table 2). Furthermore, more strict decision-making rules are applied for minors (ages less than 18) due to parental vaccine hesitancy (Gowda & Dempsey, 2013; Dror et al., 2020). Parents' trust and permission in vaccines are required before minors can vaccinate. Translating these requirements into modeling languages, minor agents need to have all their guardians of the family network vaccinated already before they can take vaccines.

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