Teaching through Simulation: Epidemic Dynamics and Public Health Policies

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A growing number of epidemiologists are now working to refine computer simulation methods for diseases as a strategy for helping public policy decision-makers assess the potential efficacies of tactics in response to newly emerging epidemics. These efforts spiked after the SARS outbreak of 2002–2003. Here we describe our attempt to help novice researchers understand epidemic dynamics with the help of the cellular automata with social mirror identity model (CASMIM), a small-world epidemiological simulation system created by Huang et al. in 2004. Using the SARS scenario as a teaching example, we designed three sets of instructional experiments to test our assumptions regarding (i) simulating epidemic transmission dynamics and associated public health policies, (ii) assisting with understanding the properties and efficacies of various public health policies, (iii) constructing an effective, low-cost (in social and financial terms) and executable suite of epidemic prevention strategies, and (iv) reducing the difficulties and costs associated with learning epidemiological concepts. With the aid of the proposed simulation tool, novice researchers can create various scenarios for discovering epidemic dynamics and for exploring applicable combinations of prevention or suppression strategies. Results from an evaluative test indicate a significant improvement in the ability of a group of college students with little experience in epidemiology to understand epidemiological concepts.

Keywords: Learning through simulation, epidemiological model, public health policy, small-world network

1. Introduction

Complex network science and agent-based social simulation techniques [1–3] have intensified interest in using computer-based social simulations to analyze social phenomena and processes. Motivations for using computer-based social simulations include the following: (i) the shortcomings of traditional social science research methods for investigating the dynamics of social systems, as social phenomena cannot be adequately represented by static relations and simple interaction rules [4]; (ii) the ability to alter computer simulation parameters, which allows researchers with any level of technological skill to create "what-if" experiments for examining factors that might affect social issue outcomes [5]; (iii) computer-based social simulations allow for faster construction of new social models [6]; (iv) computer-based social simulations make it easier to create reports and to import information from CD-ROMs or the Internet [7].

Epidemiologists favor computer-based social simulations for at least four reasons, as follows [3].

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1. Observation and visualization: Computer-based social simulations allow for slowing down or speeding up epidemic simulations to observe complete or partial spreading within a proper time-scale.
2. Operational training: Computer-based social simulations reduce the dangers and costs associated with gathering and manipulating data on actual epidemics.
3. Modeling: Computer-based social simulations allow new learners to construct epidemic models to explore emerging epidemic factors and to analyze simulation processes and experimental results.
4. Understanding: Computer-based social simulations let learners observe the effects of various transmission routes and modes on epidemic transmission dynamics and test various combinations of prevention or suppression strategies [8].

Parallel processes, nonlinearity, and actor heterogeneity are significant challenges for designers of mathematical and other forms of analytical models [2]. Thus, until recently the literature in this area tended toward model simplification rather than attempting to reflect real-world complexities in simulations [9].

Constructed social networks based on interpersonal relationships and simple daily human contact can exert significant impacts on epidemic transmission dynamics [10–16]. For instance, interactions among individuals and contact routes are known to affect outbreaks of short-distance contagious diseases, such as SARS and other enteroviruses. Because of the potential complexity of human interactions, epidemiologists and public health specialists require computer simulations that can incorporate multiple social networks to analyze and control wide ranges of possible transmission behaviors and epidemic characteristics. Furthermore, epidemic transmission speed and scope are affected by daily human activities, including the entrenched habits of modern lifestyles. For instance, the majority of adults in developed countries use identical transportation modes for daily short- and long-distance travel. The limited diversity of transportation options to regularly visited sites (e.g., workplaces and schools) creates environments for rapid disease transmission.

Because it is difficult to control human movement in terms of method, timing, direction, and distance, researchers are repeatedly challenged by the task of simulating individual movement within a society—an issue referred to in the literature as the “mobile individual problem” [17–20]. After the SARS outbreak of 2003, Huang et al. [21, 22] proposed a small-world epidemiological model for simulating epidemic transmission dynamics and public health policies; they called this the cellular automata with social mirror identity model, or CASMIM (Figure 1). They established the social mirror identity for integrating long-distance movement and geographic mobility into their model, simulating the transmission dynamics of contagious diseases, and investigating the effectiveness of various combinations of public health policies and epidemic prevention strategies [21–23].

Results from experimental simulations indicate that CASMIM is a robust and extensible epidemiological simulation system suitable for multiple applications, including classroom demonstrations of many types of epidemics and detailed numerical experiments involving specific epidemic diseases and public health policy suites. It can therefore serve as a good starting point for teaching and training novice researchers and epidemiology students. In addition, it should be noted that CASMIM’s value is not just for demonstrations, but also for performing interactive simulations. Novice researchers can use CASMIM to simulate and confront real-world problems. Through comparisons and discussions of simulation results with peers [24], individual understanding of epidemic dynamics can be enriched and different hypotheses may be evaluated in terms of their rationalities.

In this paper we describe three sets of instructional experiments for teaching social science researchers and inexperienced epidemiologists how to use the CASMIM system to simulate epidemic dynamics and create strategies to address real-world issues. Our primary teaching goals are as follows: (i) to simulate epidemic transmission dynamics and public health policies associated with epidemics; (ii) to understand the properties and effectiveness of various public health policies, alone and in combination; (iii) to construct effective, inexpensive (in terms of financial and social costs), and executable suites of epidemic prevention strategies; (iv) to reduce costs associated with learning epidemiological principles.

2. Related Theories and Systems

2.1 Teaching and Learning through Simulation: High-Level Intellectual Effort

Instruction-based education is often criticized for only providing information, without teaching practical skills that learners can use to solve real-world problems [25]. Until very recently, science education has emphasized hastily taught concepts while neglecting the importance of exploring problems from a learner’s own experiences. Consequently, learners tend to become obsessed with complex procedures described in textbooks. Computer simulations are now employed to support learning or training based on constructivist learning principles [26, 27]. In a report on educational technology prepared for the United States President’s Office, a committee of science advisors presented a list of the most promising constructivist applications of technology; simulations were at the top of that list [28].

Learning through simulation fits well with constructivist principles, as both focus on active learning and knowledge construction based on interactions between

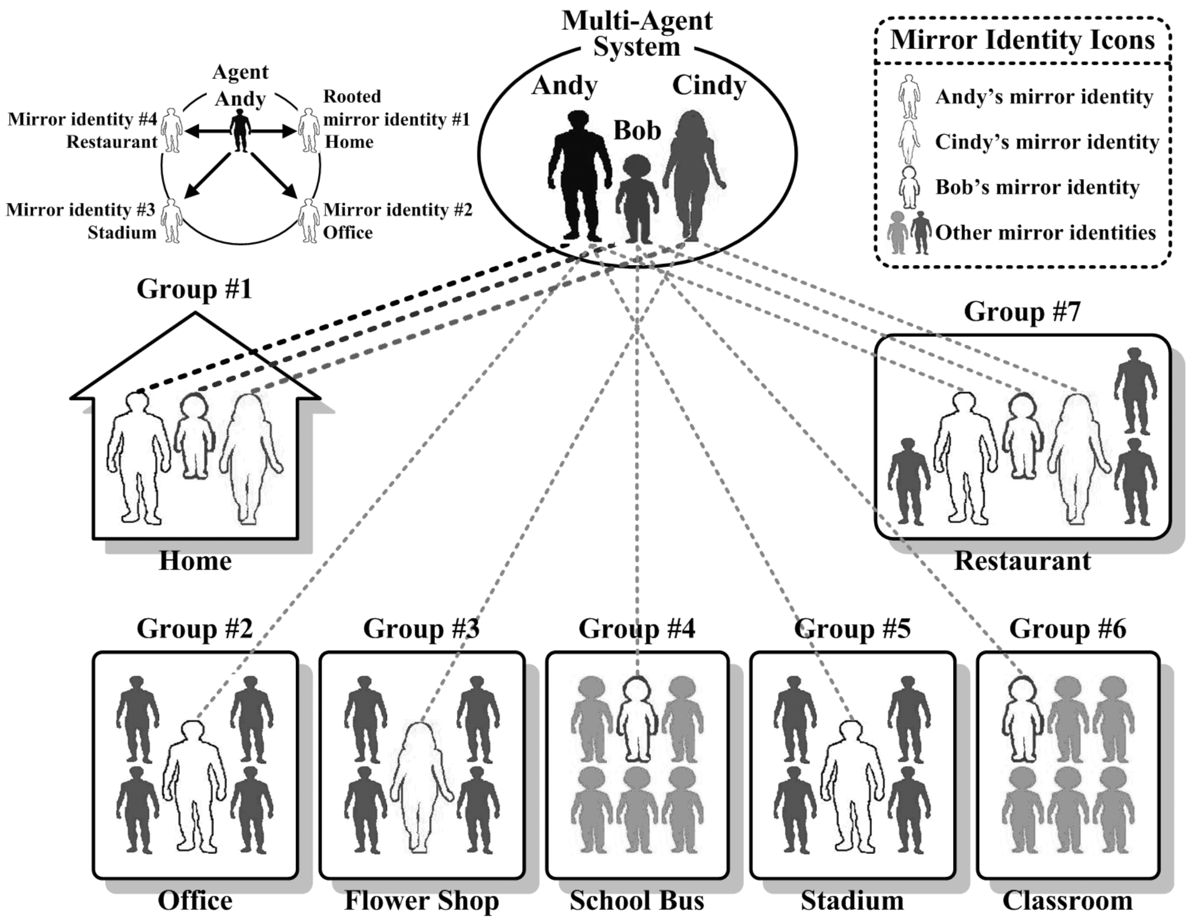

Figure 1. An example of the social mirror identity concept

previous experiences and ongoing events. Aldrich [29] describes simulations as interactive, representational environments that provide experiences that require learners to actively construct knowledge. Constructivists believe that learners draw upon prior knowledge to form new schema for discovery learning [30]. When learners are confronted with a new stimulus, they apply their own knowledge bases to accommodate new information and alter their existing schema [31]. When a constructive learning process is embedded in a simulation tool, learners can "learn by doing", have better opportunities to discover interesting primary and secondary issues, and gain hands-on experience to deal with real-world problems.

Learning through simulation can be viewed as an example of problem-based learning (PBL) in that it confronts learners with authentic problems that serve as contexts for practice. As a general model, PBL was developed for medical education in the early 1970s; since that time, it has been refined and implemented in over 60 medical schools [32]. Two characteristics make PBL compatible with the theoretical foundation of learning/teaching through simulation.

1. Engagement. Learners often request simulations to assist with learning and to gain a sense of engagement with real-world problems. Consequently, related concepts can be introduced to the learning process. There is no "perfect" educational simulation, but simulations support meaningful learning experiences as long as scenario limitations are taken into account [29].

2. Interaction flexibility. Simulation tools can be used with interaction and feedback to show how complex systems work under different circumstances [29]. Simulated problems are usually complex, often with no single "correct" answer. Learners need to model realistic situations via the repeated interactive manipulation of parameters. With sufficient practice, learners or novice researchers can learn how to transfer their new knowledge to real-world issues.

During the simulation process, group discussion provides opportunities for exchanges of alternative views and consensus building on comprehensive and coherent perspectives. It is widely accepted that learners are reluctant to participate in unfocused discussions. A simulation and its results can provide a focus for individuals to discuss a range of observations or strategies for a single epidemic issue [33]. Sharing personal viewpoints within a group context can facilitate follow-up discussions of personal findings or the clarification of rationales behind different opinions. Incorporating group member observations and insights from simulation results can broaden or improve the ability of individuals to understand and learn epidemic concepts.

2.2 Epidemiological Models with Social Networks

The SIR model of Kermack and McKendrick [34] is the foundation on which most contagious disease models are based. The letters represent the three primary states of any individual with respect to a communicable disease: susceptible, meaning that an individual is vulnerable to infection but has not yet been infected; infectious, meaning that an individual can infect others; removed, meaning that an individual has either recovered, died, or otherwise ceased to pose any further threat. During epidemic outbreaks, new infections occur because infected and susceptible individuals come into direct contact with each other. Susceptible individuals consequently become infected according to probabilities associated with a combination of personal and disease characteristics.

The spreading of a contagious disease reflects a close relationship between social networks and individuals who come into contact with each other. The initial version of the SIR model assumed that interactions among S, I and R individuals occur according to a "well-mixed hypothesis" [35, 36] in which they interact without concern for population structure. Though improbable, this hypothesis simplifies contact factors that must be considered when formulating an epidemiological model. A random interaction hypothesis also makes it easier for epidemiologists and public health specialists to construct SIR models that represent ranges of possible transmission dynamics for epidemic outbreaks, infectious origins, and disease parameters based on data collected during previous outbreaks of contagious diseases.

Results from statistical analyses and computer simulations show that the global topological characteristics of social networks exert considerable influence on the behavior of easily spread diseases [15, 21, 35]. These characteristics allow for the detailed study of more subtle aspects of contagious disease transmission that cannot be performed using non-network models such as the original SIR model. Furthermore, the need to identify targeted and more efficient intervention strategies requires accurate model representations of public health policies with geographical properties (e.g., home quarantines and hospital visitation bans). An important disadvantage of the SIR model and its derivatives is that aggregate variables and differential equations can increase very quickly as the number of populations under consideration grows—for instance, healthcare workers, hospital patients, or the family members of individuals under home quarantine [35, 36].

3. Simulation System for Studying Epidemics and Public Health Policies

CASMIM [21, 22] is a small-world computation simulation model. CASMIM conceptualizes individuals as elements and their most frequently visited places as logically abstracted mirror identities—for example, homes, train stations, workplaces, and restaurants. The mirror identity concept utilizes simple social networks (i) to preserve the properties of elements that interact with their neighbors within two-dimensional lattices, and (ii) to reflect such activities as long-distance movement and daily visits to fixed locations. For this reason, the mirror identity concept in CASMIM is suitable for describing epidemics in modern societies. The model has clustering and small-world properties that allow it to simulate epidemic transmission dynamics. By manipulating disease parameters and public health policies, CASMIM can be used to simulate the transmission dynamics of influenza, tuberculosis, and other contagious diseases.

3.1 Cellular Automata with Social Mirror Identity Model (CASMIM)

CASMIM consists of two layers: an upper layer representing a simplified multi-agent system for simulating heterogeneous cohorts and a lower layer that contains two-dimensional $n \times n$ cellular automata (CA) that represent real-world activity spaces (Figure 2). The social mirror identities that connect the two layers establish CASMIM as a small-world network model. In CASMIM, each individual in the upper layer is depicted as a single agent in a multi-agent system; places that any agent visits on a regular basis (e.g., homes, train stations, and workplaces) are defined as that agent's social mirror identities. In a typical cellular automaton, lattices represent abstract agents. In CASMIM, each lower-layer CA lattice represents a social mirror identity.

It is possible for multiple social mirror identities (representing fixed locations that are visited daily or regularly) to be connected to the same agent. The number of social mirror identities for any single agent exhibits a normal distribution. The mirror identity concept utilizes simple social networks to preserve the properties of elements that interact within two-dimensional lattices, thus reflecting such activities as long-distance movement and daily visits to fixed locations. Clusters consisting of a mirror identity and its von Neumann neighbors can represent family members, co-workers, fellow commuters, healthcare workers, relatives in hospitals, or diners in restaurants. Each individual upper-layer agent has a set of attributes that demonstrates

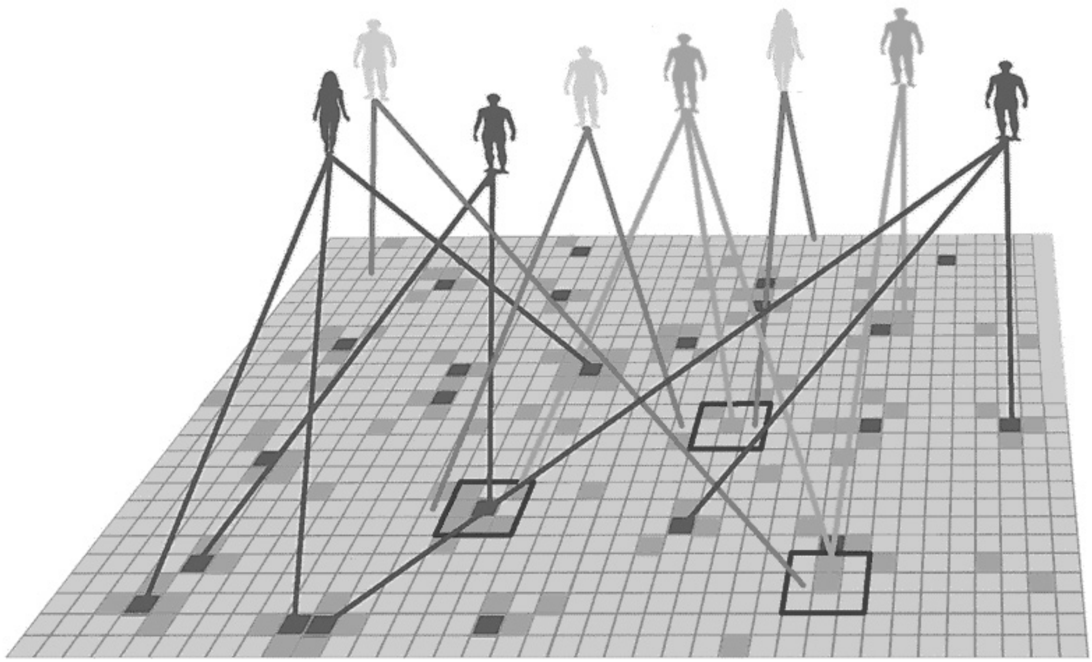

Figure 2. Cellular automata with social mirror identity model (CASMIM)

its epidemiological progress and social mobility status; these attributes are accessible to all of the agent's social mirror identities (Figure 3, Table 1). In addition, each social mirror identity has a group of private attributes that represent its current status, location, and special activity locations such as homes, hospitals, or dormitories (Table 2).

Different epidemics require different simulation time steps. For the SARS example, CASMIM was programmed to define one time step as equivalent to one day in the real world. For diseases with long-term developmental stages (e.g., HIV) one time step may equal one year. Huang et al. incorporated this assumption into their CASMIM design (Figures 4 and 5). The statuses of upper-layer agents change simultaneously with their lower-layer social mirror identity statuses during each time step, reflecting their daily interactions. The attributes of social mirror identities and agents vary according to the following: (i) the attributes of neighboring agents' social mirror identities; (ii) a set of interaction rules; (iii) simulation and epidemic parameters; (iv) public health policy parameters. CASMIM can therefore be considered a small-world epidemiological simulation system having such simple social network attributes as population structure, area clustering, space, heterogeneity, localization, and interaction. It also has the social attributes of long-distance movement, daily visits to fixed locations, multiple activity nodes, and the small-world characteristic of low degree of separation. All of these attributes are required for simulating epidemics.

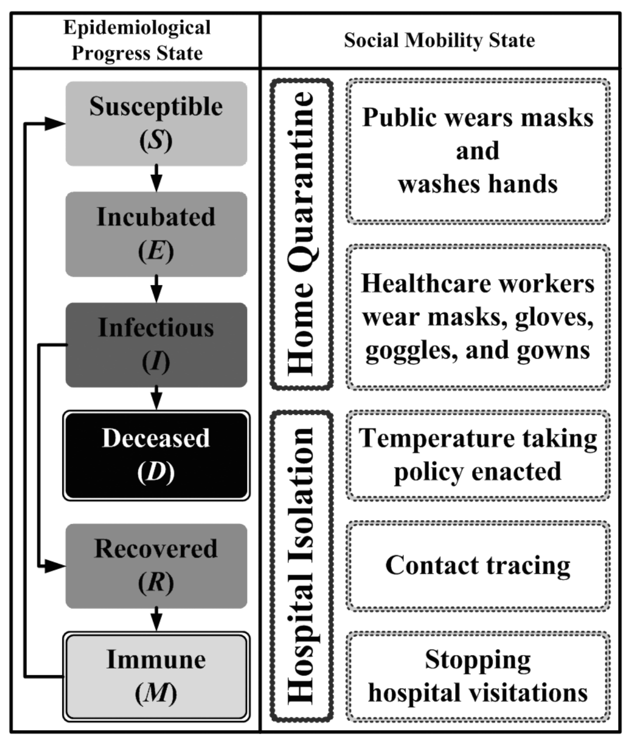

Figure 3. Epidemiological and social mobility states

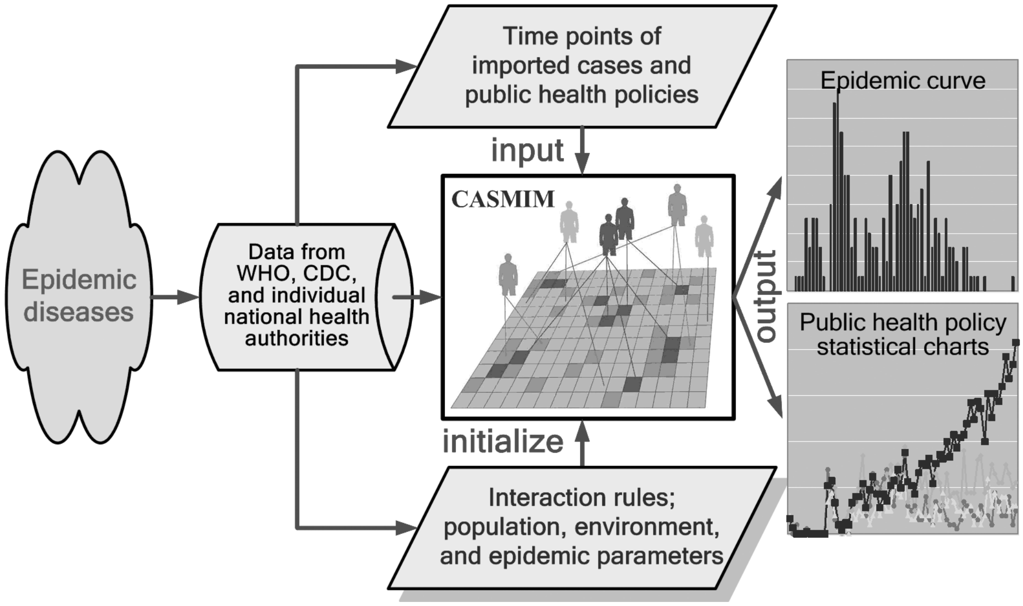

Figure 4. Simulation system framework

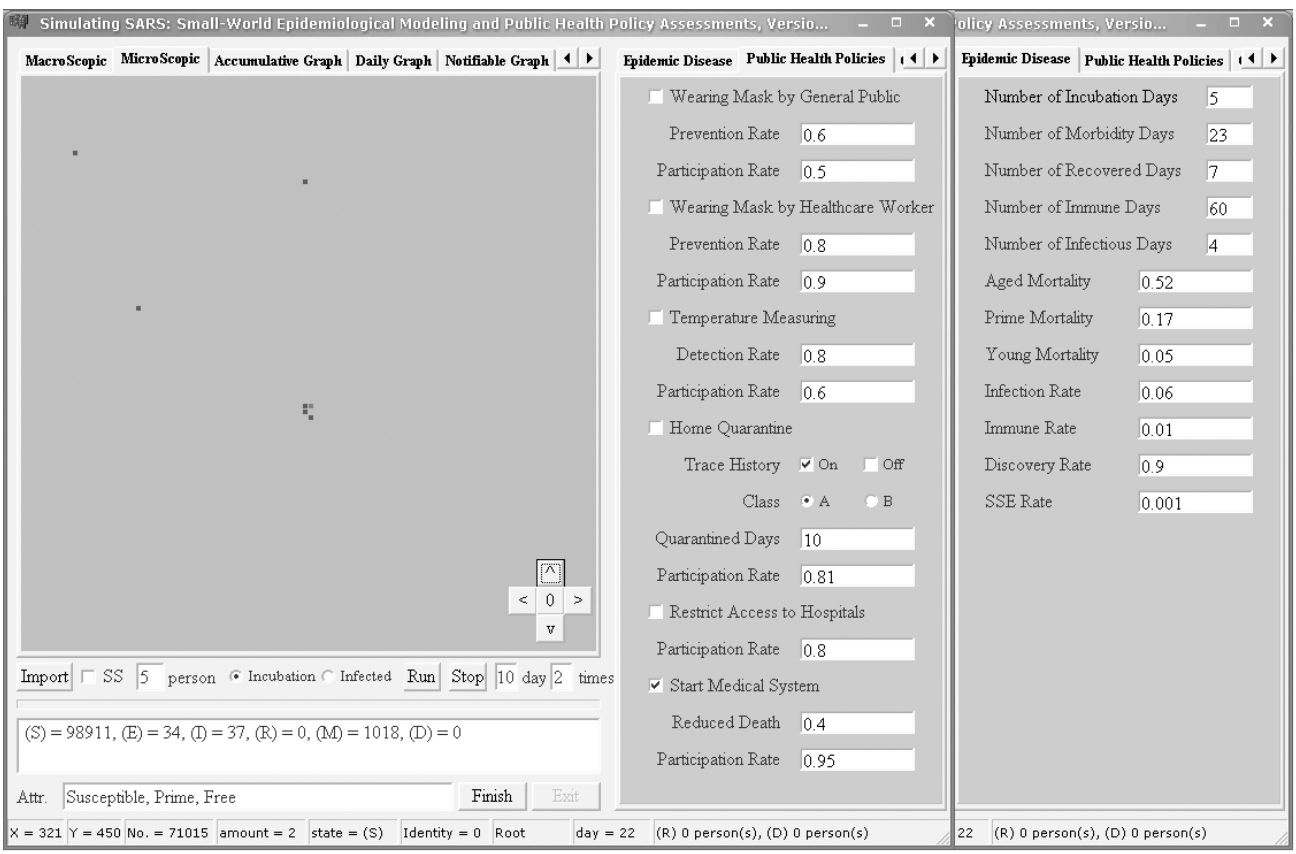

Figure 5. CASMIM simulation system console

Table 1. Agent attributes

Attribute	Description	Default Value
ID	Unique serial number that identifies agent in CASMIM.	1–P
E	$Rate_{ForeverImmune}$ determines proportion of agents classified as M (Immune) in the epidemiological progress attribute E (i.e., the population of permanently immune agents). All other agents are classified as S (Susceptible)—"not yet infected but prone to infection".	Susceptible, Immune
Mobility	Default value is "free"—no restrictions on interacting with the mirror identities of neighboring agents. When an agent is placed under home quarantine or hospital isolation, its *Mobility* status changes to *Quarantined* or *Isolated*, meaning that the agent is restricted to its rooted social mirror identity (home, hospital, or dormitory), and that the activities of all social mirror identities are temporarily suspended.	Free
Count	Records the number of an agent's mirror identities; each agent has a minimum of 1 and a maximum of M. The number of an agent's mirror identities exhibits a normal distribution.	1–M
MirrorIdentity	Data structure for containing mirror identities.	
Age	Agents are categorized as young (1–20), prime (21–60), and old (61 and above). Ages are randomly assigned according to $Rate_{Young}$, $Rate_{Prime}$, and $Rate_{Old}$ parameters.	Young, Prime, Old
Super	Denotes whether an agent is a super-spreader. If yes, set *Super* to "true"; if no, to "false". The $Rate_{Super}$ parameter determines which agents are super-spreaders.	True, False
$Immunity_{Permanent}$	Denotes whether an agent is permanently immune. If yes, set $Immunity_{Permanenty}$ to "true"; if no, to "false". The $Rate_{ForeverImmunity}$ determines which agents are permanently immune.	True, False
Day	Number of days for each of the three epidemiological progress states. If an infected agent has not yet recovered, *Day* is used to indicate the number of infected days. For recovered agents, *Day* is used to indicate the number of days since full recovery. If a recovered agent has temporary antibodies, *Day* is used to indicate the number of immune days.	
$Rate_{Contact}$	Rate of contact with other agents. For all agents, $Rate_{Contact}$ values exhibit a normal distribution.	0–1
WearingMask	Denotes whether an agent wears a mask. If yes, set *WearingMask* to "true"; if no, to "false". Default value is "false". When a mask-wearing policy is enacted (for the general public or for healthcare workers), the $Policy_{WearingMask}.Parameter.Rate_{Participation}$ parameter is used to determine how many agents wear masks.	False
MaskType	Average prevention grade of agent masks. The higher the number (closer to 1), the greater the efficacy.	0–1
$Quarantined_{Day}$	Number of home quarantine days, with a range of 0 to $Policy_{HomeQuarantine}.Parameter.Day_{Quarantined}$.	

3.2 Parameters

In CASMIM, users can manipulate several types of parameter set. For example, parameters H and W in Table 3 control the height and width of two-dimensional CA. A combination of P and M can be used to set up a specific agent population and its mirror identities for a simulation. Detailed examples of simulation parameters are shown in Tables 3–5. Details for environmental and population parameters and their default values are shown in Table 3. The default values allow first-time users to quickly execute simple and understandable demonstrations.

The second set contains three types of epidemic parameters. The first type includes $Period_{Incubation}$, $Period_{Infectious}$, $Period_{Recovered}$, and $Period_{Immune}$ (Table 4). These have strong associations with specified epidemic characteristics and epidemic progress (e.g., SIR or SEIR—susceptible, exposed, infectious, and recovered). The second type consists of individual statuses such as the percentage of super-spreading events and age distribution (e.g., youth, adult, and elderly). The final type consists of $Rate_{ForeverImmunity}$, $Rate_{Infection}$, $Rate_{Death}$, and $Frequency_{Contact}$. These are used to determine epidemic transmission mechanisms among individuals.

The final CASMIM parameter set addresses the efficacy and efficiency of various public health policies (Table 5). Participation rates indicate the percentage of individuals who follow the suggested or required public health policy. Examples of public health policies that affect epidemic prevention rates include wearing masks by the general public or hospital workers, body temperature measurement, and home quarantine for various time periods. Different types of masks—general, activated carbon, disposable surgical, N95—are rated as having the respective efficacies for preventing the transfer of viruses of 25%, 50%, 75%, and

Table 2. Social mirror identity attributes

Attribute	Description	Default Value
Root	Each agent has one mirror identity whose *Root* = true; for all other mirror identities, *Root* = false. The rooted mirror identity is used to mimic special activity locations—for instance, homes, hospitals, and dormitories.	True, False
Suspend	Default value is false for all mirror identities, denoting that they can move about without restriction. Except for rooted mirror identities, *Suspend* = true for all mirror identities of an agent in home quarantine or hospital isolation, representing the idea that the agent cannot interact with other adjacent neighbors outside of its home or hospital until the end of the quarantine or recovery period. If the agent dies, *Suspend* = true for all mirror identities (including rooted mirror identity), representing the idea that the agent can no longer visit any other location.	False
Location	The first number represents the x-axis coordinate and the second the y-axis coordinate for the location of a mirror identity in the two-dimensional CA. Each mirror identity is mapped to a single coordinate location; in other words, each coordinate location contains a single mirror identity of only one agent.	
Neighbor	Represents the coordinate locations of mirror identities of neighboring agents. We adopted the Moore neighborhood definition for our simulation model. Under this neighborhood structure, each mirror identity is defined as having eight neighbors.	

Table 3. Simulation system parameters

Attribute	Description	Default Value
$Population_{Agent}$	Stores total agent population in simulation system	
P	Total number of agents	100,000
M	Upper limit of an agent's mirror identities	5
H	Height of two-dimensional lattice used in CA	500
W	Width of two-dimensional lattice used in CA	500
N	Total number of usable lattices $(H \times W)$ in CA	250,000

Table 4. Epidemic disease parameters

Attribute	Description	Default Value
$Period_{Incubation}$	Number of incubation days	5
$Period_{Infectious}$	Number of infectious days	25
$Period_{Recovered}$	Number of recovered days	7
$Period_{Immune}$	Temporarily immune to the disease	
$Rate_{Super}$	Percentage of super-spreaders in total population	0.0001
$Rate_{Young}$	Percentage of young (0–20 years) agents in total population	0.3
$Rate_{Prime}$	Percentage of prime (21–60 years) agents in total population	0.5
$Rate_{Old}$	Percentage of old (60 years and above) agents in total population	0.2
$Rate_{ForeverImmunity}$	Percentage of permanently immune agents in total population	
$Rate_{Infection}$	Average infection rate	0.045
$Rate_{Death}$	Average death rate	0.204
$Frequency_{Contact}$	Number of contacts between an agent and its neighbors per time step	4

95%. A second example is home quarantine period. During the SARS outbreaks in 2002–2003, the World Health Organization (WHO) suggested that the minimum length of home quarantine should be the twice the viral incubation period. Altering the length of the quarantine period allows students to determine the best combination of length and social costs.

Most data required for establishing epidemic parameters are available from national health authorities or the WHO. This includes data for R_0, $Period_{Incubation}$, $Period_{Infectious}$, $Period_{Recovered}$, and $Period_{Immune}$. Values for $Rate_{ForeverImmunity}$, $Rate_{Death}$, and the average number of mirror identities require input from disease experts and epidemiologists, while novice simulation tool users are ca-

Table 5. Public health policy parameters

Policy	Attribute	Description
WearingMaskInGP	$Rate_{Participation}$	Policy participation rate
	$Rate_{Prevention}$	Infectious disease prevention rate
WearningMaskInHW	$Rate_{Participation}$	Policy participation rate
	$Rate_{Prevention}$	Infectious disease prevention rate
TemperatureMeasuring	$Rate_{Detection}$	Fever detection success rate
	$Rate_{Participation}$	Measurement participation rate
HomeQuarantine	*Class*	A- and B-class quarantines
	$Day_{Quarantined}$	Number of home quarantine days
	$Rate_{Participation}$	Policy participation rate
RestrictedAccessToHospitals	$Rate_{Participation}$	Policy participation rate
ReducedPublicContact	$Rate_{Participation}$	Policy participation rate

pable of manipulating the public health policy parameters listed in Table 5. Some environmental parameters (e.g., $Rate_{Infection}$, $Frequency_{Contact}$) can be derived from R_0 using the following equation: [22]

$$R_0 = \text{(avg. of social mirror identity} \times \text{no. of neighbors} \times R_{contact} \times T_{contact}) \times R_{Infection} \times P_{Infectious}.$$

3.3 Input/Output Function and Simulation Flow

There are two methods for inputting and altering simulation parameters: via console and input files. Additionally, default values for each parameter are automatically loaded whenever the CASMIM simulation system is started without a specified input file. The simulation console consists of a set of modifiable parameters under environment, population, epidemic, and public health policy tabs (Figure 5, Tables 3–5). The parameters are slightly simplified on the simulation console to facilitate variation. Table 6 shows an input data category display consisting of epidemic parameter, imported case, and activated public health policy. In addition, the display console can be used to make changes to the statuses of individual agents on the fly (Tables 1 and 2). Alternatively, simulation parameters can be specified using an input file. Using the input file allows for control over the full set of parameters, including setting data structures for agents and mirror identities.

The left-hand side of Figure 5 shows the geographical location of all individuals using two browser windows. The macroscopic browser window allows users to observe the propagation of an epidemic and the microscopic browser window allows users to observe detailed information on nosocomial infections, home quarantine, individual disease status, and geographic mobility. Users can click on any cluster in the macroscopic graph to view microscopic details. CASMIM also produces daily statistical charts that reflect normal epidemic curves, accumulated epidemic curves, curves of the number of home quarantine individuals, and curves of the number of nosocomially infected individuals. At the end of a simulation, CASMIM creates four log files for further study: user input and interaction processes, initial parameter sets, daily statistics on reported cases, and daily statistics on nosocomial infections. These interaction logs allow students to re-examine and analyze the simulation process.

Students can choose one of three ways to interact with CASMIM's user interface. At the beginning of a simulation, a learner creates parameter sets via the user interface (far right-hand side of Figure 5), including the environmental and epidemic parameters mentioned in an earlier section. Next, the learner uses the button and input fields at the bottom right of Figure 5 to input data on imported cases, to trigger the simulation, and to advance time according to the epidemic outbreak or simulation timeline. Finally, as shown in the mid-section of Figure 5, the user can activate a public health policy according to the timeline and alter any parameter by activating or disabling it while the simulation is running. The simulation dynamic is affected immediately upon parameter modification. CASMIM's simulation flowchart and system architecture are shown in Figures 4 and 6, respectively.

4. Instructional Experiments

After initializing the CASMIM simulation system and setting its parameters according to information distributed by the WHO and national health authorities (Tables 1 and 2), learners can simulate epidemic transmission dynamics in different areas and compare the effectiveness of various public health policies and disease prevention strategies. For example, knowing that SARS originated in China's Guangdong province allows users to view SARS cases in all other countries as imported and to use the number of cases announced by local health authorities to determine transmission source information (e.g., number of infectious individuals entering a country, time steps during which they entered, and whether they entered as incubated or infected individuals). In three sets of instructional experiments we simulated public health policies at certain time steps according to actual announcements made by local health authorities, adjusting our environmental, epidemic, and pub-

Table 6. Input data category for simulating epidemic diseases

Category	Attribute	Description
Imported Cases	*Time Point*	Date when imported case occurred
	Amount	Number of patients
	Phase	Imported during incubation or illness period
	Super-spreader	Determines whether imported patient is a super-spreader
Public Health Policy	*Related Attributes*	
Run	*Day*	Number of execution days

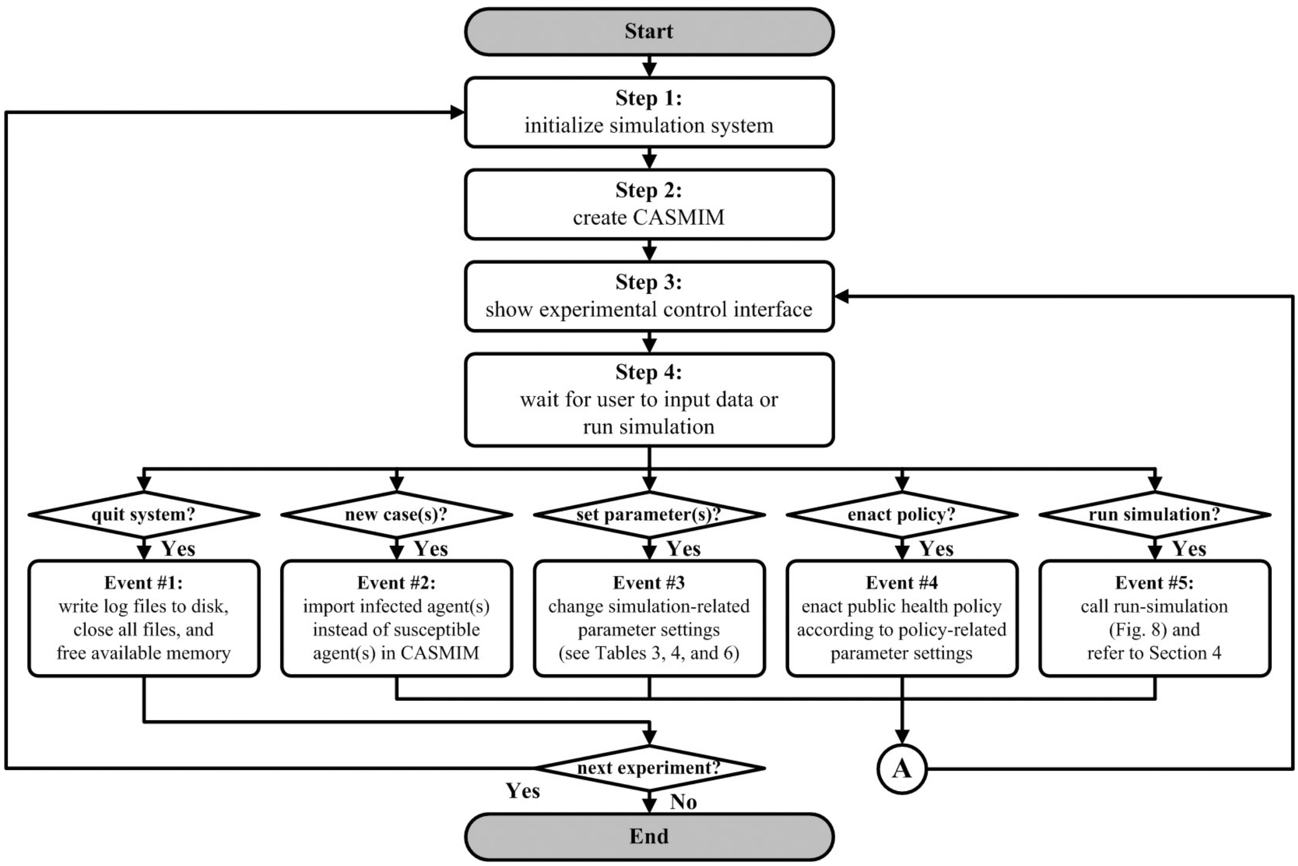

Figure 6. Simulation flowchart

lic health policy parameters according to data reported by the WHO [37] and Kamps and Hoffmann [38].

4.1 Experiment Set 1: Comparing Simulation and Actual Case Results

Experiment Set 1 helps students learn how to simulate the 2002–2003 SARS outbreaks in Singapore, Taiwan, and Toronto. Novices are instructed to follow the command sets shown in Tables 8–10 for running simulations. Learning objectives include: understanding the complexity of epidemic characteristics, learning the advantages of a computer simulation model, and predicting outcomes. A teaching plan based on a constructive approach (e.g., object, goal, problems, methods, activities, and discussions) is presented in Table 7. Before running the simulation, students need to construct a knowledge base of epidemic characteristics and the instructor needs to demonstrate how to reorganize the collected data to form CASMIM-compatible parameter sets. The next step is for learners to input the parameters and perform the instructional commands according to the input and simulation flowchart discussed

Table 7. Constructivist teaching plan for epidemic simulations

Subject	Using CASMIM to simulate the spread of SARS infections in Singapore and Taiwan
Goals	(1) Teach the types of data that need to be collected before running an epidemic simulation. (2) Teach basics of initial epidemic transmission. (3) Show how various health policies influence epidemic propagation.
Introduction	In 2002–2003, imported SARS cases from foreign countries increased early transmission rates via daily social contact networks. The increasing number of cases gained the attention of government authorities, which established control/preventive strategies to abate epidemic spread (e.g., taking body temperature in public areas, stopping hospital visits, asking general public to wear masks and reduce public contact). With the execution of response policies, most countries successfully stopped SARS transmission. This lesson is aimed at teaching novices how to study SARS outbreak factors and to understand the efficacy of various interventions. After running simulations of outbreaks in Singapore and Taiwan, students will understand common characteristics of epidemic outbreaks and learn to prepare essential datasets for creating epidemic simulations.
Practice	(1) Students will gain experience dealing with challenges associated with epidemic dynamics and disease prediction. (2) Students will gain an understanding of the advantages of using a computer model to simulate epidemic outbreaks. (3) Students will gain an understanding of differences between classical compartmental and computer simulation models. (4) Epidemiology students will practice using CASMIM to observe and predict the future development of epidemic situations.
Activities	(1) Problem understanding. (a) Finding epidemic information on the Internet. (b) Understanding epidemic and propagation characteristics. (2) Data search and analysis. (a) Collecting data from Internet or databases provided by each country's government and the WHO. (b) Reorganizing datasets to form CASMIM parameter sets. (c) Consulting epidemiologists to confirm correctness of parameter ranges. (d) Form and input instruction sets to CASMIM. (3) Problem analysis. (a) Determining when and how users should interact with CASMIM. (b) Determining how to set parameters based on previous parameter sets. (4) Executing epidemic simulations. (a) Following instruction sets and using input sets to run simulations step-by-step. (b) Studying epidemic development using CASMIM-based graphical two-dimensional lattice frames and statistical charts. (5) Simulation result analysis. (a) Analyzing graphical two-dimensional lattices to identify significant patterns. (b) Comparing real and simulated epidemic curves. (6) Conclusion and discussion. (a) Do data sets correspond to real epidemic data? (b) Do simulated results fit well with actual epidemic curves? (c) Identifying key reasons/factors for epidemic spreading.
Time	Each student pair collaborates to run the software and discuss results during a 40–50 minute class period. The first of three lessons will require more time to discuss CASMIM, how to build a simulator, and background information on SARS outbreak scenarios.
Equipment and software	Personal computer, CASMIM software, pre-test and post-test.
Software description	CASMIM is a small-world computer simulation model that conceptualizes individual daily contact networks. It is suitable for simulating short-distance contagious epidemic enterovirus diseases such as SARS. The underlying network structure can be modified to simulate other types of disease with different infection routes (e.g., air transmission or sexual contact).
Discussion topics	(1) How can different imported case distributions influence the spread of SARS in different countries? (2) What types of public health policies were executed to control the disease? (3) Can you identify differences in disease trends between countries? (4) What kinds of datasets need to be prepared before running this kind of simulation?
References	Huang, C. Y., C. T. Sun, J. L. Hsieh, and H. Lin. 2004. Simulating SARS: Small-world epidemiological modeling and public health policy assessments. *Journal of Artificial Societies and Social Simulation* 7(4). Available online at http://jasss.soc.surrey.ac.uk/7/4/2. html. Watts, D. J. 2003. *Six Degrees.* New York: W. W. Norton & Company.
Related Material	World Health Organization, http://www.who.int/en/. Taiwan Disease Control Center, http://www.cdc.gov.tw/index1024.htm. Ministry of Health of Singapore, http://www.moh.gov.sg/corp/index.doc.

Table 8. Singapore instructional experiment input data

Time Step	Action	Persons	State	Public Health Policy	Policy Parameter Setting
1	Trigger	1	Infectious		Super-spreader
2	Trigger	2	Infectious		
11	Set			Reduced public contact	Efficacy = 0.9, Participation = 0.5
15	Trigger	1	Incubation	Mask-wearing policy for healthcare workers	Efficacy = 0.9, Participation = 0.9
22	Trigger	2	Incubation		
23	Set			Home quarantine	10 days, Participation = 0.9
				Controlling hospital access	Efficacy = 0.9, Participation = 0.9
				Mask-wearing policy for general public	Efficacy = 0.9, Participation = 0.5
25	Trigger	2	Infectious		
52	Set			Taking body temperature	Efficacy = 0.9, Participation = 0.5

Table 9. Taipei instructional experiment input data

Time Step	Action	Persons	State	Public Health Policy	Policy Parameter Setting
1	Trigger	1	Infectious		
2	Trigger	4	Incubation		
9	Trigger	1	Incubation		
11	Trigger	2	Infectious		
12	Trigger	2	Infectious	Home quarantine	10 days, Participation = 0.9
14	Trigger	1	Infectious		
27	Trigger	1	Infectious	Mask-wearing policy for healthcare workers	Efficacy = 0.9, Participation = 0.9
47	Set			Controlling hospital access	Efficacy = 0.9, Participation = 0.9
53	Set			Home quarantine	14 days, Participation = 0.9
				Mask-wearing policy for general public	Efficacy = 0.9, Participation = 0.5
74	Set			Home quarantine	10 days, Participation = 0.9
88	Set			Taking body temperature	Efficacy = 0.9, Participation = 0.5

Table 10. Toronto instructional experiment input data

Time Step	Action	Persons	State	Public Health Policy	Policy Parameter Setting
1	Trigger	1	Infectious		
6	Trigger	1	Infectious		
19	Trigger	1	Infectious	Mask-wearing policy for healthcare workers	Efficacy = 0.9, Participation = 0.9
				Reduced public contact	Efficacy = 0.9, Participation = 0.5
30	Trigger	1	Infectious		
37	Set			Controlling hospital access	Efficacy = 0.9, Participation = 0.9
				Home quarantine	10 days, Participation = 0.9
38	Trigger	1	Infectious		
68	Close			All public health policies previously opened	
91	Set			Mask-wearing policy for healthcare workers	Efficacy = 0.9, Participation = 0.9
112	Set			All public health policies previously closed	

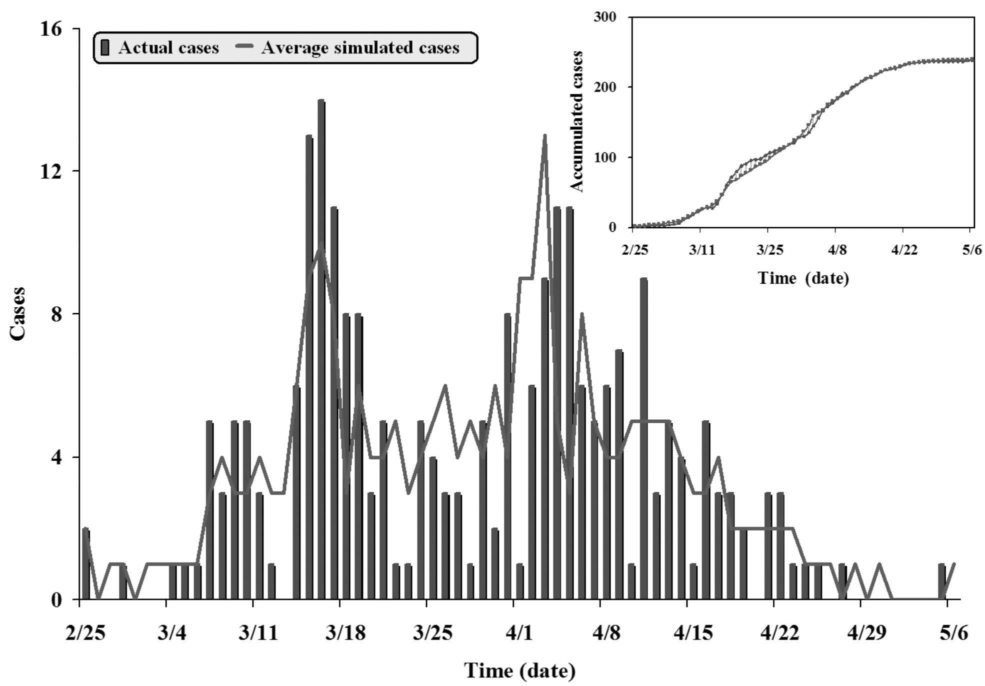

Figure 7. A comparison of actual and simulated epidemic results for the SARS outbreak in Singapore. The bars represent actual reported cases, the line represents an average of results from 20 simulation runs

in Section 3.3. Students also need instruction in reading simulation results, including statistical reports and charts.

4.1.1 Scenario 1: Singapore SARS Outbreak

A comparison of actual and simulated SARS cases in Singapore indicates agreement in terms of two peak outbreaks that occurred between February 25 and May 5, 2003 (Figure 7). Emergency public health policies were not activated following the first outbreak, which was attributed to imported cases. The second outbreak was attributed to the compound effects of secondary infections. Several emergency policies were put into effect on March 24, including a ban on visits to patients in hospitals or under home quarantine. The number of new cases dropped dramatically at the beginning of June; soon afterwards, the WHO announced that the disease was under control.

4.1.2 Scenario 2: Taipei SARS Outbreak

Our Taipei simulation included several public health policies enforced by that city's government, including multiple grades of home quarantine and a mask-wearing requirement for all public bus and train passengers (Table 9). As shown in Figure 8, the simulated results had a close fit with the probable case curve published by the Taiwanese health authority on September 28, 2003—a major spike followed by several smaller outbreaks. The higher concentration in the Taipei curve compared to Singapore's was likely due to late case discoveries, delays in seeking treatment, illness cover-ups, and the large number of cases imported by travelers returning from Hong Kong. In Singapore, all imported cases were reported prior to the first outbreak; the second wave was the result of compound infections. The s-curve for the Taiwan situation is more representative of a typical infection pattern.

4.1.3 Scenario 2: Toronto SARS Outbreak

The SARS scenario in Toronto consisted of two major waves with almost no new cases in between (Figure 9). However, after a re-examination of the August 2003 data, the Canadian authorities acknowledged several additional cases during the lull period. According to our simulation, the second wave would not have been as severe if strict public health policies had been enforced for a longer period following the first wave. In the instructional experiment described below, we relaxed epidemic control measures after the first wave subsided (Table 10). The simulation consequently produced a second spike within a few days of the actual spike reported by Toronto health authorities. Our results support the conclusion by Kamps and Hoffmann [38] that the Toronto government canceled its control measures

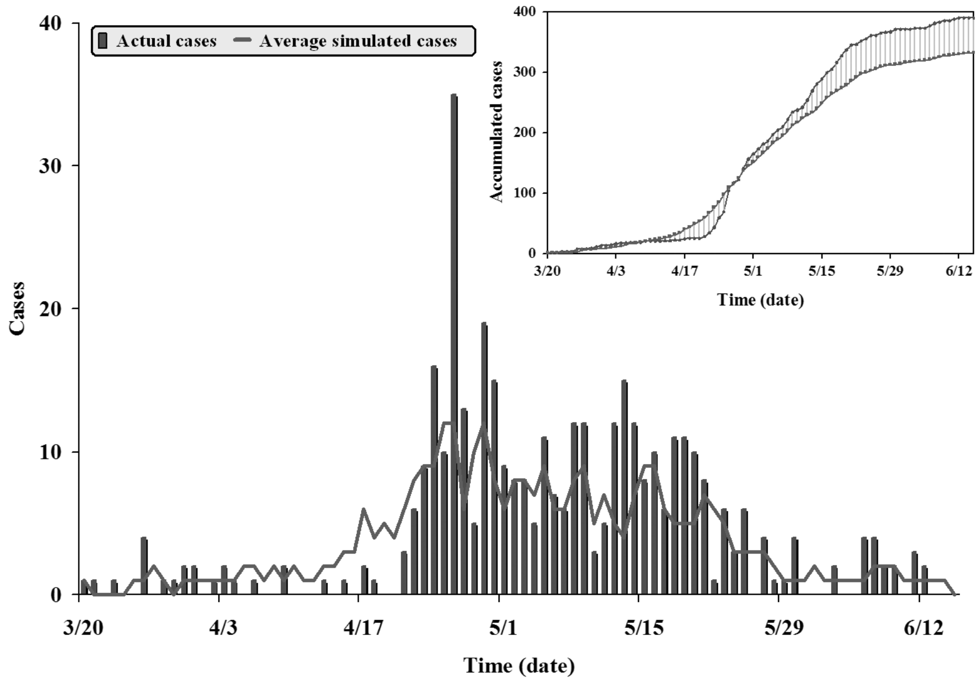

Figure 8. A comparison of actual and simulated epidemic results for the SARS outbreak in Taipei

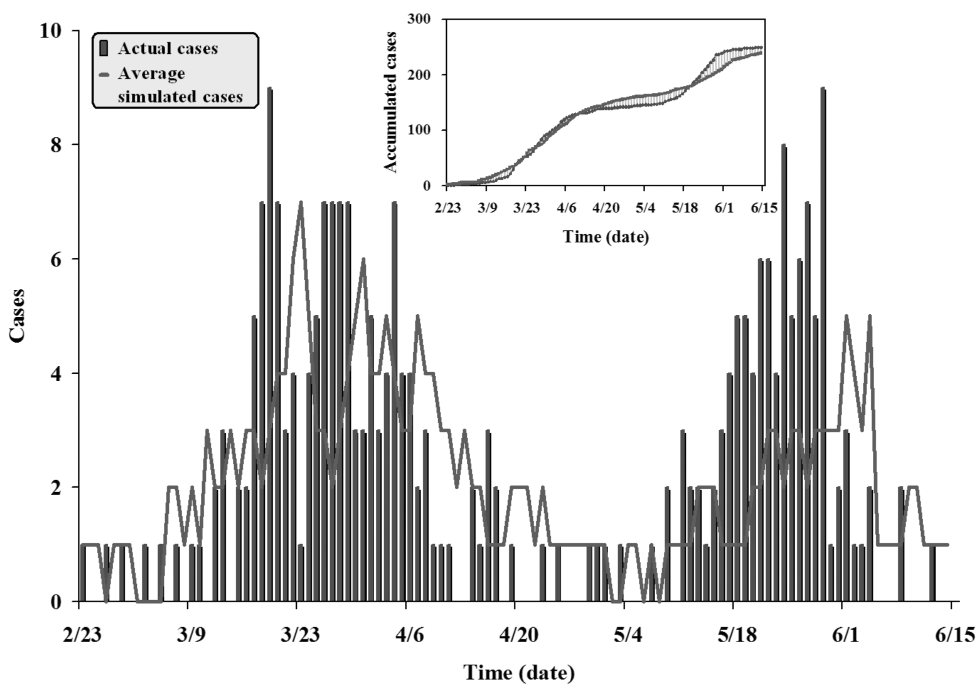

Figure 9. A comparison of actual and simulated epidemic results for the SARS outbreak in Toronto

too quickly. Because of increased contact between patients and visitors and relaxed rules on health care workers wearing masks and/or respirators, Toronto experienced a second wave of nosocomial transmission.

Although most of the epidemic characteristics of these three scenarios were similar or identical, and because all three governments enforced most of the prevention policies suggested by the WHO, there was great variation in simulation results as a result of differences in initial execution dates and participation rates. Instructors can use this variation in data to present information on the effects of underlying social networks on epidemic transmission (e.g., small-world and clustering properties). For example, one important lesson is that distance between individuals (physical or geographical) is no longer the key factor in epidemic outbreaks that it once was, because modern transportation systems allow people to visit several fixed locations on a daily basis or to fly halfway around the world in less than 24 hours [21, 22].

4.2 Experiment Set 2: Analyzing Public Health Policies

In Experiment Set 2, students can analyze the effects of three public health policies executed during the 2003 SARS outbreak (Table 11): taking body temperature, wearing of protective masks by the general public, and wearing of masks by healthcare workers. To build an understanding of the efficacies of these policies, students should practice altering the parameters of the command sets of these three actions. For example, they can manipulate protection rates (e.g., 25%, 50%, 70%, and 95%) to represent the effectiveness of general, carbon-activated, medical, and N95 masks, respectively. Students should also be given statistical charts for comparing the results of the various public health policies. The special statistical chart for nosocomial transmission can be used to analyze the efficacy of banning hospital visits.

4.2.1 Taking Body Temperature

The Singaporean and Taiwanese governments implemented temperature measurement policies during the SARS epidemic, going so far as to launch national campaigns that included installing temperature-monitoring equipment and setting up manual temperature measurement stations at various government buildings, clinics, and public transportation facilities. According to our simulation results, when such policies were both comprehensive and compulsory, they reduced the number of feverish individuals entering public places. However, in the real world this policy is difficult to set up and enforce, because implementation methods tend to vary, oversights are common, and an unknown number of individuals manage to avoid having their temperatures taken. Our results suggest that a participation rate of between 80% and 90% is required for this public health policy to have a positive effect on controlling a SARS-like epidemic (Figure 10); it has little effect at a rate of 65% or lower. The policy also incurs significant social costs that include distributing thermometers, setting up temperature screening stations, and employing workers to take manual temperature measurements at various public facilities and medical clinics.

4.2.2 Wearing Masks with Different Protection Levels: General Public Versus Healthcare Workers

The efforts of the governments of Taiwan and Hong Kong to promote general mask-wearing policies led to hoarding and panic buying. Masks are categorized according to grade: ordinary, surgical, etc. In Taiwan, a serious shortage of professional masks for medical staff occurred following a rush by the general population to purchase masks regardless of grade; this triggered a debate over the necessity of wearing N95 respirator masks outside of hospitals and clinics. According to the results of a simulation that we ran to analyze this policy, ordinary and surgical masks succeeded in controlling the epidemic outbreak as long as they were worn consistently throughout the desired time period (Figure 11). At a prevention efficiency of 65% or more (meaning that the mask covered at least the mouth and nose), the epidemic could be controlled but not eliminated. When wearing ordinary masks, medical staff members still had relatively high infection rates (Figures 11 and 12). These personnel clearly benefited from wearing N95 and other high-resistance masks in hospitals and clinics. According to these simulation results, we suggest that the general public should not be required to wear higher-grade masks, which instead should be reserved for medical staff and healthcare workers.

Students should study the characteristics and properties of individual public health policies before running simulations to ensure reasonable estimates of efficacy and participation rates and proper implementation of each public health policy in the simulation model. For example, in the area of mask-wearing, the Taiwanese and Singaporean governments tried to enforce a requirement that all healthcare workers wear high-protection masks, but only issued advisories for the general public. Accordingly, the degree, range, and target populations for these two public health policies were very different—a point that needs to be emphasized to novice learners. Furthermore, students should study frameworks for analyzing public health policies prior to running simulations [23].

4.2.3 Experiment Set 3: Assessing Public Health Policy Suites

The learning objectives for Experiment Set 3 were showing students how to build combinations of public health policies for assessing efficacy and estimating the social costs of different combinations (Table 12). When faced with a new epidemic outbreak, decision-makers must consider various combinations of public health policies and

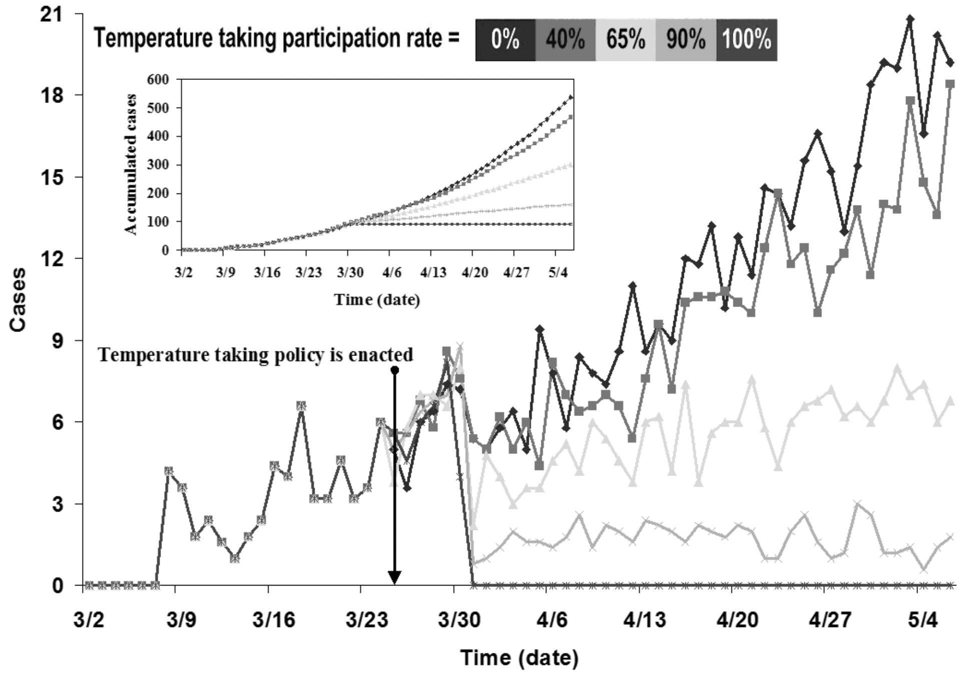

Figure 10. Results from an instructional simulation experiment focused on temperature measurement policy at different participation levels. We used the eight imported cases reported in Singapore to trigger the simulation. In each 66-day simulation run, the policy was activated on day 24

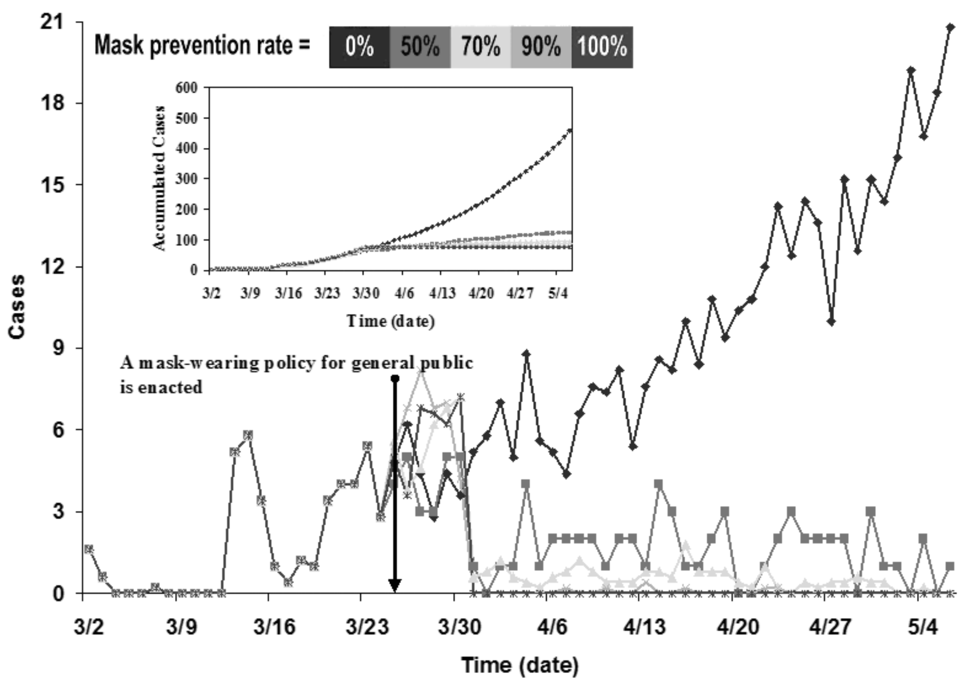

Figure 11. Results from an instructional simulation experiment focused on the impact of mask-wearing by the general public, comparing different mask protection levels

Table 11. Constructivist teaching plan for public health policy assessment using computer simulations

Subject	Using the CASMIM simulator to analyze public health policy efficacy
Goal	To understand the properties of individual health policies, students run simulations at different efficacy levels.
Introduction	Efforts by the Taiwan and Hong Kong governments to promote general mask-wearing led to hoarding and panic buying. In Taiwan, this resulted in a serious shortage of professional-grade masks for medical staff and triggered a debate on the necessity of wearing N95 respirator masks outside of hospitals and clinics. Simulations of general public and healthcare mask-wearing policies at different protection levels are used to teach novices public health policy concepts.
Practice	(1) Students will gain greater understanding of the properties and characteristics of individual health policies. (2) Health authorities and policy makers will gain greater understanding of the degrees to which health policies should be executed, taking into account efficacy and participation rates.
Activities	(1) Problem understanding. (a) Looking up health policy information for specific epidemics on the Internet. (b) Consulting health policy makers to understand how they think and what they need for decision-making. (2) Advance analysis of health policy properties and characteristics. (a) Recognizing how each policy affects individuals with different disease statuses. (b) Transforming health policy facts to parameters that can be input and implemented on CASMIM. (c) Consulting with health policy makers and epidemiologists to verify reasonable parameter value ranges. (3) Executing health policy simulations. (a) Simulating an epidemic without activating any health policy to serve as control. (b) Enabling single health policies according to instruction sets and inputting efficacy and participation rate parameter data. (c) Altering efficacy and participation rates. (d) When using policy suites, disabling all but one policy to determine its effects via steps b and c. (4) Simulation results analysis. (a) Comparing control and experimental group curves. (5) Discussion (a) Comparing emerging experimental and control group trends. (b) Drawing conclusions about simulation results. (c) Identifying relationships between simulation and actual results.
Time	Student pairs collaborate to run the software and discuss results during a 15–20 minute period.
Equipment and software	Personal computer, CASMIM software, pre-test and post-test.
Software description	CASMIM is a small-world computer simulation model that conceptualizes individual daily contact networks. It is suitable for simulating short-distance contagious epidemic enterovirus diseases such as SARS. The underlying network structure can be modified to simulate other types of disease with different infection routes (e.g., air transmission or sexual contact).
Discussion topics	(1) Which mask protection level is sufficient to offer a minimum of protection for the general public? (2) Which mask protection level is sufficient for hospital and clinic healthcare workers? (3) After comparing both mask-wearing policies, decide on a policy for the distribution of masks at difference protection levels to different user populations.
Reference	Hsieh, J. L., C. Y. Huang, C. T. Sun, and Y. M. A. Chen. 2005. Using the CASMIM small-world epidemic model to analyze public health policies. In *Proceedings of the Western Multiconference*, New Orleans, LA, pp. 63–9.
Related material	(1) World Health Organization, http://www.who.int/en/ (2) Taiwan Disease Control Center, http://www.cdc.gov.tw/index1024.htm (3) Ministry of Health of Singapore, http://www.moh.gov.sg/corp/index.doc

decide when to activate them. The compound effects of different combinations can differ a great deal because of the scale, efficacy, and target of each policy. Instructional samples are divided in terms of how individual governments decide to execute public health policies, alone or in combination. Using the suites shown in Figure 13 as an example, an imaginary health authority decides to enforce a policy suite of taking body temperatures, restricting hospital visits, the required wearing of high-efficiency masks by healthcare workers, and an advisory for the general public to wear less efficient masks and to reduce public contact. Social costs clearly vary according to policy combination, allowing for the teaching of the concept of cost-effectiveness. Instructional samples representing four possible public health policy suites executed by the Singaporean health authority are shown in Figure 13. Accord-

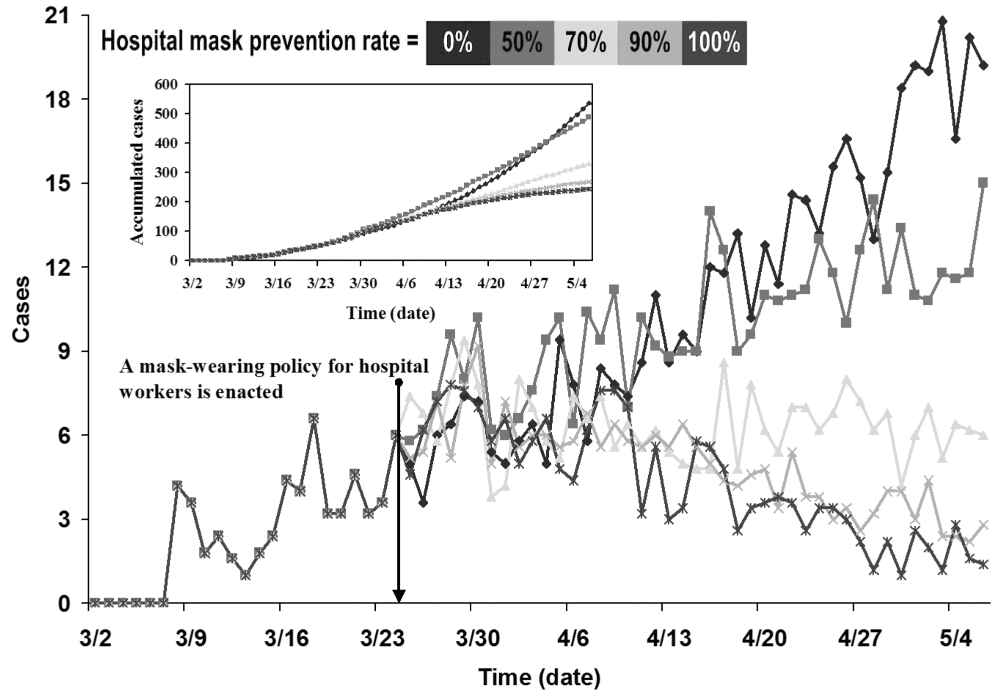

Figure 12. Results from an instructional simulation experiment focused on the impact of mask-wearing by healthcare workers in hospitals, comparing different mask protection levels

ing to the results presented in this figure, a combination of mask-wearing by the general public and reduced contact in public places was best for suppressing the spread of disease. Enforced mask-wearing entails some social and financial costs, but limited public contact does not. Furthermore, masks address epidemics at their source—disease transmission.

Simulation results also suggest that a combination of temperature measurement, restricted hospital visitations, and mask-wearing by healthcare workers should be considered a remedial reaction to a contagious disease outbreak, as these cannot help patients who are in the incubation stage or suffering from minor symptoms. In addition, this policy suite requires substantial amounts of labor and material resources. The combination of home quarantine and reduced contact in public places has high social costs, with results dependent upon how well the isolation guidelines are followed. Numerous instances of intra-family infections were reported during the actual 2002–2003 SARS epidemic—evidence that certain prevention strategies were ineffective in controlling it.

For simultaneously assessing efficacy and social costs, instructors should assist learners in recognizing differences in how governments implement public health policies and in discussing limited resource allocation. Certain resources may be extremely limited or non-existent for an unidentified large-scale epidemic outbreak—for instance, vaccines, hospital beds, healthcare workers, or high-protection masks. Allocating limited resources should be a central learning objective for students of large-scale epidemic simulations.

5. Evaluation

5.1 Participants

Participants were 34 college students recruited from a private university in north Taiwan. They were assigned to working pairs for collaboration and for discussing simulation results.

5.2 Procedure

The 17 participant pairs were given three instructional assignments. For each one, students were given a pre-test to examine their understanding of epidemic dynamics, verbal and written information on simulation goals, tools for using simulation results to answer core questions, and a post-test shown in Appendix A to determine the effects of the CASMIM simulation tool on learning.

Table 12. Constructivist teaching plan for assessing epidemic prevention strategies

Subject	**Use CASMIM to simulate different combinations of public health policies in response to an outbreak of SARS**
Goal	Students test various combinations in order to identify the best for mitigating the epidemic at a reasonable level of social costs.
Introduction	When faced with a new disease outbreak, decision-makers must consider various public health policies and decide when to activate them. The compound effects of different policy suites can differ a great deal according to each policy's scale, efficacy, and targeted goal. Social costs must also be taken into consideration—for example, establishing cooperation between health authorities and enforcement agencies, the cost of a public relations campaign to encourage mask-wearing by the general public, etc.
Practice	Students will practice using a computer simulation model to assess the efficacies and social costs of various health policies.
Activities	(1) Problem understanding. (a) Summarizing characteristics and properties of each health policy from Experiment Set 2. (b) Consulting health policy makers to learn how and why they implement multiple health policies. (2) Analyzing possible health policy combinations. (a) Forming several health policy combinations. (b) Consulting with health policy makers and epidemiologists to gain greater understanding of potential health policy combinations. (c) Using potential health policy combinations to build CASMIM instruction sets. (3) Executing health policy simulations. (a) Simulating an epidemic without activating any health policy to serve as a control. (b) Enabling health policy suites according to instruction sets and inputting parameter data. (4) Simulation results analysis. (a) Comparing control and experimental group curves. (b) Analyzing statistical charts for each health policy's efficacy and efficiency. (5) Discussion. (a) Comparing efficacies of different combinations of health policies. (b) Forming recommendations for health authorities.
Time	Each student pair collaborates to run the software and discuss results during a 10–15 minute period.
Equipment and software	Personal computer, CASMIM software, pre-test and post-test.
Software description	CASMIM is a small-world computer simulation model that conceptualizes individual daily contact networks. It is suitable for simulating short-distance contagious epidemic enterovirus diseases such as SARS. The underlying network structure can be modified to simulate other types of disease with different infection routes (e.g., air transmission or sexual contact).
Discussion topics	(1) Which policy combinations are most effective for abating the spread of SARS? Create a list in order of effectiveness. (2) Which policy combinations have the lowest social costs? List in order. Based on the pre-established data for this lesson, the correct order for most-effective and lowest social costs should be the following. • A-class home quarantine for 10 days and reduced public contact. • Wide-scale taking of body temperatures and hospital visitation restrictions. • Wide-scale taking of body temperatures, hospital visitation restrictions, and mask-wearing by healthcare workers. • Public mask-wearing and reduced public contact.
Reference	Hsieh, J. L., C. Y. Huang, C. T. Sun, and Y. M. A. Chen. 2005. Using the CASMIM small-world epidemic model to analyze public health policies. In *Proceedings of the Western Multiconference*, New Orleans, LA, pp. 63–9.
Related material	World Health Organization, http://www.who.int/en/. Taiwan Disease Control Center, http://www.cdc.gov.tw/index1024.htm. Ministry of Health of Singapore, http://www.moh.gov.sg/corp/index.doc.

5.3 Results

Pre-test/post-test scores were measured on a scale of 0 to 50; scores for individual topics ranged from 0 to 10. Results from a paired-sample t-test indicate statistically significant improvement in overall understanding of epidemic concepts (pre-test: $M = 31.71$, $SD = 3.11$; post-test: $M = 35.15$, $SD = 2.77$; $t = -5.36$, $p < 0.001$). Specifically, the results show a significant difference in experiment sets 1 (comparing simulation and actual case results between outbreaks in Singapore and Taiwan; pre-test: $M = 6.12$, $SD = 1.01$; post-test: $M = 6.91$, $SD = 1.44$; $t = -2.17$, $p < 0.05$) and 3-1 (assessing the efficacies of different combinations of public health policies; pre-test: $M = 6.59$, $SD = 1.37$; post-test: $M = 8.41$, $SD = 0.71$; $t = -5.12$, $p < 0.001$). No significant differences were noted for experiment sets 2-1 (analyzing the effects of the wearing of protective masks by the general public; pre-test: $M = 6.24$, $SD = 1.15$; post-

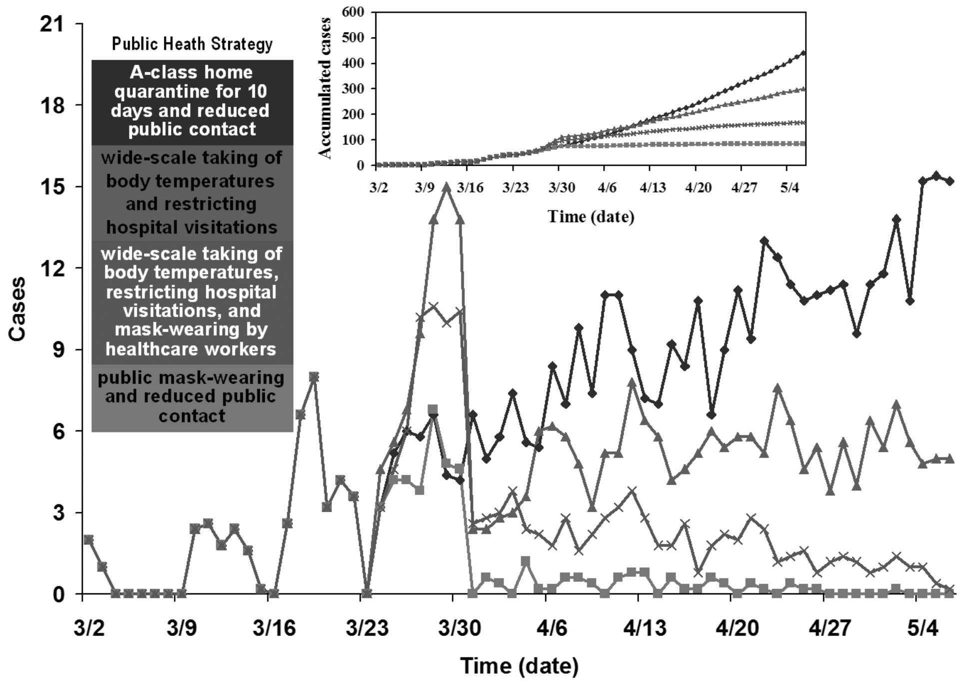

Figure 13. A comparison of various public health policy suites in the third instructional simulation experiment. We used the eight imported cases reported in Singapore to trigger the simulation. Policy suites went into effect on day 24 of our 66-day simulations. Suite 1 (cyan diamonds): A-class home quarantine for 10 days and reduced public contact; suite 2 (red triangles): wide-scale taking of body temperatures and a restriction on hospital visitations; suite 3 (green crosses): wide-scale taking of body temperatures, a restriction on hospital visitations, and mask-wearing by healthcare workers; suite 4 (pink squares): public mask-wearing and reduced public contact

test: $M = 6.53$, $SD = 1.23$; $t = -1.32$, *ns*), 2-2 (analyzing the effects of the wearing of masks by healthcare workers; pre-test: $M = 6.76$, $SD = 1.09$; post-test: $M = 7.06$, $SD = 0.66$; $t = -1.32$, *ns*) or 3-2 (estimating the social costs of different combinations of public health policies; pre-test: $M = 6.00$, $SD = 1.37$; post-test: $M = 6.24$, $SD = 1.15$; $t = -1.00$, *ns*).

5.4 Discussion

As predicted, participants with prior epidemic simulation experience performed better on post-test items addressing epidemic-related concepts. However, detailed analyses of responses for each experiment set indicate insufficient understanding of epidemic transmission dynamics on the part of participants. Possible explanations include the following: (i) fear or misunderstanding of SARS, which may have interfered with the participants' decisions concerning protective equipment; (ii) insufficient time for novices to become familiar with epidemic jargon; or (iii) lack of experience with budgeting social costs. We therefore investigated the results on participant perceptions of simulation issues in an attempt to identify specific reasons for participant choices and misconceptions.

5.4.1 Experiment Set 1: Comparing Simulation and Actual Results for Singapore and Taiwan Outbreaks

The purpose of this set was to guide novices through the simulation process so that they could decide for themselves which data or disease parameters are required for simulation results to resemble actual case results. We gave participants simulation scenarios to picture SARS outbreaks and instructions on manipulating parameters to generate results for follow-up discussion. The pre-test and post-test questionnaires contained items on 13 parameters: seven real (date imported cases occurred, number of imported cases, activated date of public health policies, population size, daily number of suspected infected individuals, daily number of reported infected individuals, and total number of deaths) and six dummy (infected rate for imported cases, location for activating public health policies, public health policy records, total number of infected individuals, daily number of deaths, and human contact history for each infected individual).

Of the seven real parameters, most participants recognized five as important to simulating epidemic transmission dynamics; exceptions were "population size" and "total number of deaths". The results suggest that the participating students were not aware that the relative scale of simulated population size and the number of deaths can serve as determinants for evaluating simulation results. Of the six dummy parameters, four were generally recognized as unnecessary; here the exceptions were "infected rate of imported cases" and "daily number of deaths". A possible explanation is CASMIM's social mirror identity feature, which emphasizes the effect of human contact on epidemic propagation. Accordingly, there is no need to input the infected rate of imported cases (except for super-spreaders) in the simulation process. Some participants gave more weight than necessary to the infected rate while neglecting the significant effect of human contact. Others misunderstood that while the total number of deaths is required for estimating the relative scale between simulation and actual case results, the daily number of deaths is unnecessary for an outbreak simulation.

5.4.2 Experiment Set 2: Analyzing the Effects of Mask-Wearing by the General Public and Healthcare Workers

Participants were instructed to work with masks having different protection levels according to the separate needs of healthcare workers and the general public. The students were encouraged to collaborate on a decision regarding which mask protection level (0%, 10–50%, 60–70%, 80–90%, or 100%) was best for each population to avoid infection; an added factor was a shortage of professional-grade masks. As stated above, no statistically significant improvement between pre- and post-test scores was noted for sets 2-1 or 2-2. A detailed review of set 2-1 test responses revealed the following: (i) almost one-half of the participants (41.2%) chose masks with adequate protection levels in both pre- and post-tests, which may be attributed to the effect of government-sponsored advertisements during the actual SARS outbreak; (ii) about one-fourth (23.5%) of the participants chose masks with lower-protection rates for the general public in their post-test responses (50% versus 60–70%), perhaps due to their recognizing the needs of healthcare workers and the shortage of professional masks; (iii) 11.8% of the participants still favored masks with high protection levels (80–90%) when they learned that such masks could not only control but perhaps eradicate the SARS virus, perhaps because of their personal fears; another 11.8% said they were willing to buy the more costly professional masks to protect themselves. The results for set 2-2 indicate a very small difference between pre- and post-test preferences (100% and 80–90% protection levels). They also indicate that the participants believed that health workers deserved better protection as long as professional masks were available, comfortable to wear while working, and inexpensive.

5.4.3 Experiment Set 3: Assessing the Efficacies and Social Costs of Different Public Health Policy Suites

Participants simulated each public health policy to gather data on efficacy and efficiency. They were taught how to observe the results of activating or disabling individual policies and how to test various combinations. The purpose of this set was to have participants identify which combinations were capable of abating the SARS epidemic within reasonable budget constraints. The set 3-1 results indicate statistically significant improvement regarding participant decisions on the efficacy rates of four public health policy combinations; that is, participants successfully learned the target information as conveyed via the simulation. It appears that follow-up guidance and explanations of simulation results by an instructor are very important for enhancing learning in this area. Test responses show that the participants did not acknowledge the importance of daily human contact on outbreaks of short-distance contagious diseases such as SARS. Pre-test responses show that just under one-half of the students (47%) recognized the combination of "public mask-wearing and reduced public contact" as being the least effective among the four public health policy combinations. A possible explanation is that they were not aware of the dual effects of public mask-wearing: protecting oneself from infection and preventing infected individuals from spreading the disease. Other problems were noted for two policies: "A-class home quarantine for 10 days" and "wide-scale taking of body temperatures". The efficacy of the first may be reduced by difficulties associated with quarantining members of an infected individual's family prior to the individual's infection being reported. The efficacy of the second may be reduced because of instrument inaccuracy, difficulties associated with identifying individuals who are in an incubation period, and problems putting the policy into effect.

As for the absence of statistical significance for the set 3-2 results, we offer two possible explanations: the lack of familiarity with budgeting issues among the college student participants and/or the insufficient clarity of the simulation results on estimating the social costs.

6. Conclusions

The use of computer-based social simulations to explore social issues and disease epidemics has increased rapidly in the past two decades. They can also serve as powerful instructional tools for providing learners with rich and low-cost opportunities to construct comprehensive understandings of simulation problems. For this paper we designed three sets of experiments to evaluate the utility of CASMIM (a simulation system that meets the requirements of epidemiologists and public health specialists for analyzing potential epidemic prevention strategies) for training policy decision-makers and novice epidemiologists. Our results suggest that CASMIM exerts a significant impact on learner understanding of epidemic concepts. Furthermore, the results indicate that the interactive simulation process engages learners in studying real-world epidemic issues, thus helping them to construct new knowledge by adjusting prior knowledge according to simulation results. We have observed that different opinions expressed during follow-up discussions give learners a more thorough understanding of epidemic issues, thus helping them to form more comprehensive perceptions. We therefore suggest that the combination of CASMIM and the experimental sets described in this paper can help individuals with little simulation experience to construct models for studying past and emerging epidemics and to identify and test public health policies for epidemic suppression.

7. Appendix A: Scenario and Post-test

A.1 Experiment 1

A.1.1 Scenario

In 2002–2003, imported SARS cases from foreign countries increased early transmission rates via daily social contact networks. The increasing number of cases gained the attention of government authorities, which established control/preventive strategies to abate the epidemic (e.g., taking body temperature in public areas, stopping hospital visits, asking the general public to wear masks and to reduce public contact). With the execution of response policies, most countries successfully stopped SARS transmission. This lesson is aimed at teaching novices how to study SARS outbreak factors and to understand the efficacy of various interventions. After running simulations of outbreaks in Singapore and Taiwan, students should understand common characteristics of epidemic outbreaks and learn to prepare essential datasets for creating epidemic simulations

A.1.2 Instructional Procedure to Run the CASMIM Simulator

See Table A1. Please run simulations using the input datasets in Table A2 and A3.

A.1.3 Simulation Result Samples

Comparisons of actual and simulated epidemic data for the SARS outbreaks in Singapore and Taiwan are provided (see Figures A1 and A2). Blue bars represent actual reported cases, red line represents average results from 20 simulation runs.

A.1.4 Discussion

1. What differences or common features did you observe for the outbreaks in Singapore and Taiwan?
2. What datasets need to be prepared before running the above-mentioned simulations? Please mark all essential datasets in the following list:

   Time of imported case(s), number of imported cases, infectious rate of imported case(s), health policy execution time, health policy execution location, health policy execution record, number of deceased patients, number of infected individuals, daily number of deceased patients, daily imported cases, contact tracing information, daily number of suspicious cases.
3. How did this simulation approach help you to understand the SARS outbreak? If you did not think it was helpful, how could it be improved?

A.2 Experiment 2

A.2.1 Scenario

Efforts by the Taiwan and Hong Kong governments to promote general mask-wearing led to hoarding and panic buying. In Taiwan, this resulted in a serious shortage of professional-grade masks for medical staff and triggered a debate on the necessity of wearing N95 respirator masks outside of hospitals and clinics. Simulations of general public and healthcare mask-wearing policies at different protection levels are used to teach novices public health policy concepts.

A.2.2 Instructional procedure

See Table A4.

A.2.3 Simulation Result Samples

The following simulation results focused on the impact of mask-wearing by the general public and healthcare workers (Figures A3 and A4). Each mask-wearing policy was simulated at five protection levels: 0%, 50%, 70%, 90%, and 100%.

A.2.4 Discussion

1. Large numbers of citizens come into daily contact in public areas such as mass transportation system stations. In such environments, which mask protection level is sufficient to help the general public avoid infection?

   0% = no mask

   50% = regular surgical mask

   70% = activated carbon mask

   90% = N95 respiratory mask

   100% = perfect protection

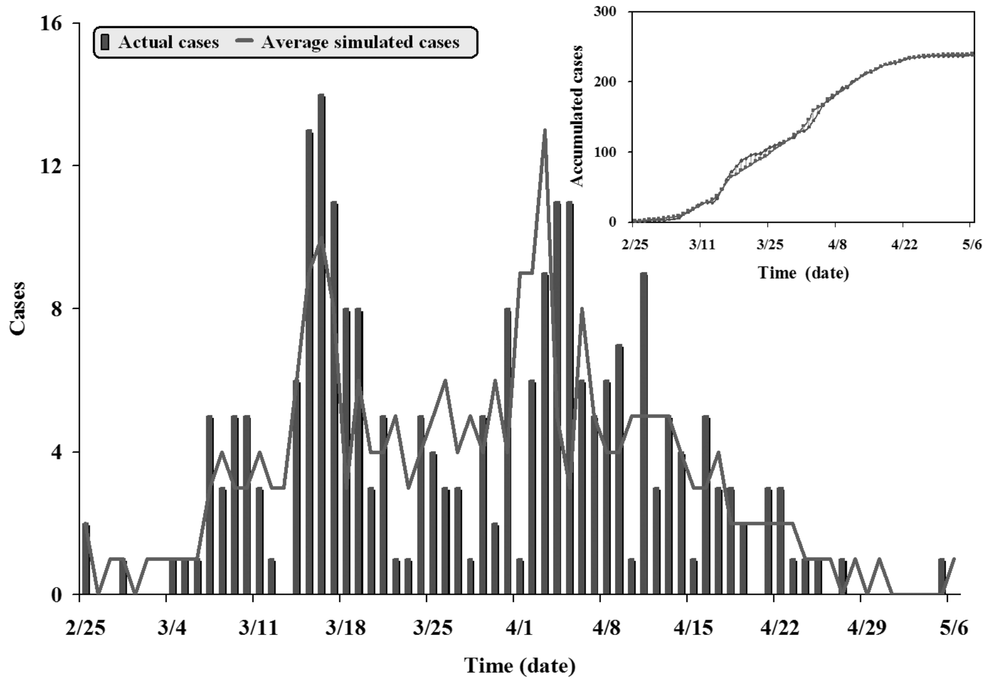

Figure A1. Comparison of actual and simulated epidemic results for SARS outbreak in Singapore

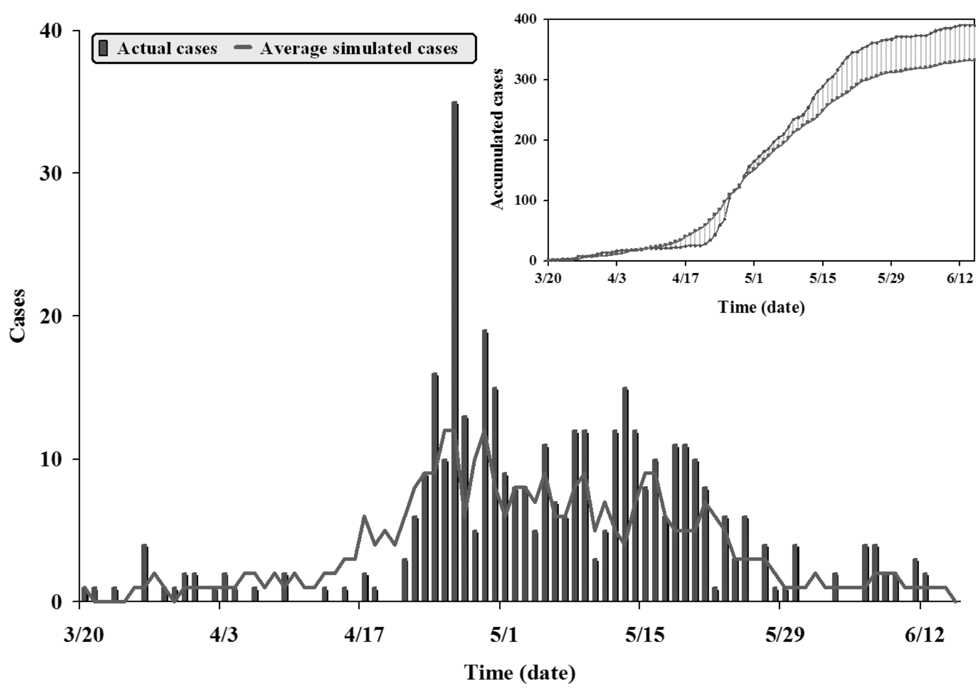

Figure A2. Comparison of actual and simulated epidemic results for SARS outbreak in Taipei

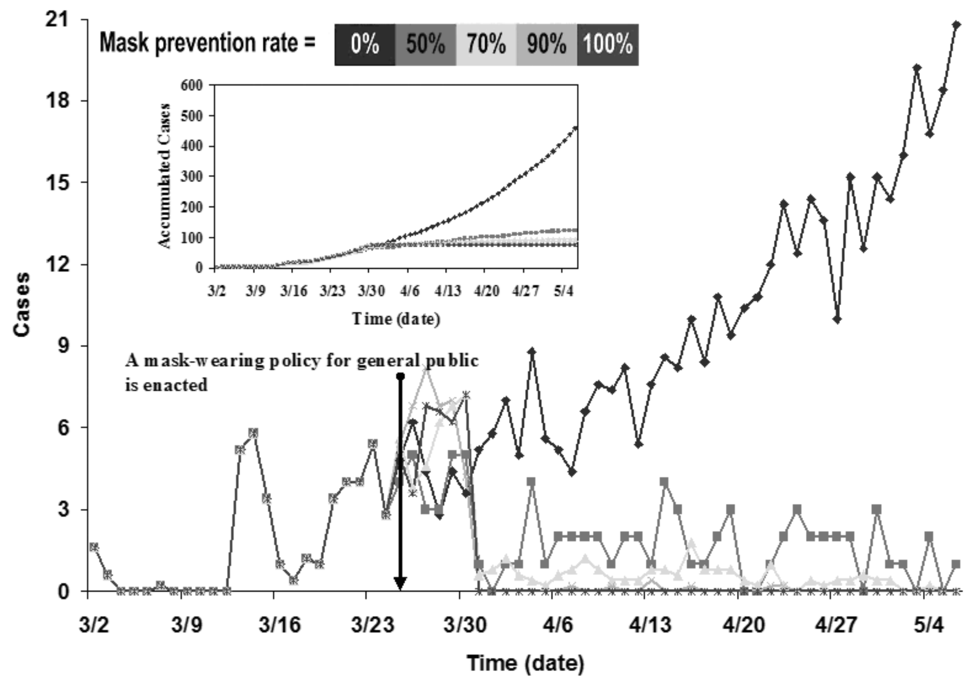

Figure A3. Simulation results for mask-wearing by general public

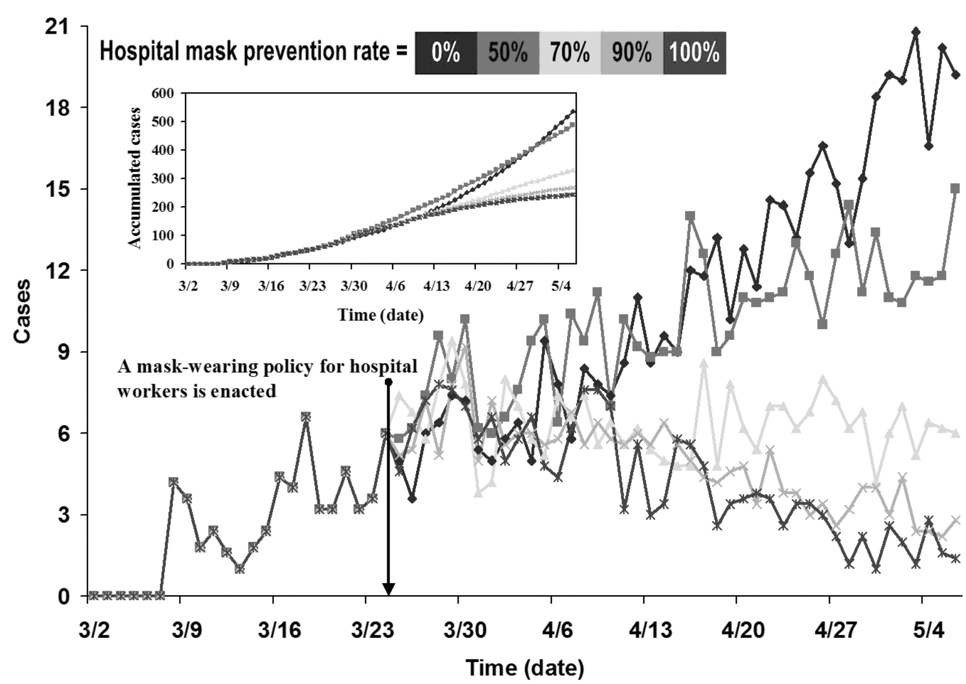

Figure A4. Simulation results for mask-wearing by healthcare workers

Table A1. Instructional procedure to run the CASMIM simulator

Step	Operation
1	Click on “Project1.exe” in sarsExp Folder to run simulation.
2	Click “Initialize” to start underlying contact network.
3	Modify parameters on “Epidemiological Parameter” panel according to datasets for different countries. Parameters can be found in given references.
4	Click “Import” to import infected or incubated cases according to chronologies released by national health authorities.
5	Click ”run” to run a multi-day simulation.
6	Activate public health policies on the “Health Policy” panel using reasonable ranges of prevention and participation rates.
7	Inspect “Micro-View” panel to observe how epidemic transmission occurs between individuals and their neighbors.
8	Look at “Reported Curve” panel to study outbreak trends.
9	Click “Stop” and “Finish” to end simulation.
10	Repeat steps 2–9 to run multiple simulations, then compare results for different countries.

Table A2. Singapore simulation input dataset

Step	Days	Operation
3/1	1	Click “Input” to enter infectious super-spreader (day 1).
2	2	Click “Input” to enter two infectious individuals (day 2). Click “Run” to run eight-day simulation (day 10).
11	11	Activate “Reduced Public Contact” policy on “Public Health Policy (2)” panel with 0.5 participation rate. Click “Run” to run four-day simulation (day 14).
15	15	Activate “mask-wearing by healthcare worker” policy on “Public Health Policy (1)” panel with 0.9 participation rate and 0.8 prevention efficacy rate. Click “Input” to enter incubated individual (day 15). Click “Run” to run six-day simulation (day 21).
22	22	Click “Input” to enter two incubated super-spreaders (day 22).
23	23	Activate “A-class home quarantine for 10 days” policy on “Public Health Policy (1)” panel with 0.9 participation rate. Activate “Restrict hospital visitation” policy on “Public Health Policy (1)” panel with 0.8 participation rate. Activate “Mask-wearing by general public” policy on “Public Health Policy (1)” panel with 0.5 participation rate and 0.6 prevention efficacy rate. Click “Run” to run two-day simulation (day 24).
25	25	Click “Input” to enter two infectious individuals (day 25). Click “Run” to run 26-day simulation (day 51).
4/21	52	Activate “Wide-scale body temperature-taking” policy on “Public Health Policy (1)” panel with 0.6 participation rate and 0.8 prevention efficacy rate. Click “Run” to run 19-day simulation (day 70).

Your choice ________

Explanation________________________________

2. Which mask protection level is sufficient to help healthcare workers avoid infection?

   Your choice is ________

   Explanation________________________________

A.3 Experiment 3

A.3.1 Scenario

When faced with a new disease outbreak, decision makers must consider various public health policies and decide when to activate them. The compound effects of different policy suites can differ a great deal according to each policy’s scale, efficacy, and targeted goal. Social costs must also be taken into consideration—for example, establishing cooperation between health authorities and enforcement agencies, the cost of a public relations campaign to encourage mask-wearing by the general public, etc.

A.3.2 Background for Health Policy Social Costs

When a home quarantine policy is enacted, authorities need to dispatch healthcare workers to monitor the activities of infected individuals and their families and to provide them with food and other essential goods. In Taiwan, a total of 4951 people were home quarantined during the 2002–2003 SARS outbreak.

When a policy restricting visits to the hospital is enacted, health authorities and law enforcement agencies work together to block access to hospitals that provide high-level medical treatment to SARS patients. Professional healthcare workers wearing high-level protective

Table A3. Taiwan simulation input dataset

Step	Days	Operation
3/20	1	Click "Input" to enter one infectious individual (day 1).
21	2	Click "Input" to enter four incubated individuals (day 2).
		Click "Run" to run six-day simulation (day 8).
28	9	Click "Input" to enter one incubated individual (day 9).
		Click "Run" to run one-day simulation (day 10).
30	11	Click "Input" to enter two infectious individuals (day 11).
31	12	Activate "A-class home quarantine for 10 days" policy on "Public Health Policy (1)" panel with 0.9 participation rate.
		Click "Input" to enter two infectious individuals (day 12).
		Click "Run" to run one-day simulation (day 13).
4/2	14	Click "Input" to enter one infectious individual (day 14).
		Click "Run" to run twelve-day simulation (day 26).
15	27	Activate "Mask-wearing by healthcare worker" policy on "Public Health Policy (1)" panel with 0.9 participation rate and 0.8 prevention efficacy rate.
		Click "Input" to enter one infectious individual (day 27).
		Click "Run" to run 19-day simulation (day 46).
5/5	47	Activate "Restrict hospital visitation" policy on "Public Health Policy (1)" panel with 0.8 participation rate.
		Click "Run" to run six-day simulation (day 52).
11	53	Activate "A-class home quarantine for 14 days" policy on "Public Health Policy (1)" panel with 0.9 participation rate.
		Activate "Mask-wearing by general public" policy on "Public Health Policy (1)" panel with 0.5 participation rate and 0.6 prevention efficacy rate.
		Click "Run" to run 21-day simulation (day 73).
6/1	74	Activate "A-class home quarantine for 10 days" policy on "Public Health Policy (1)" panel with 0.9 participation rate.
		Click "Run" to run 14-day simulation (day 87).
6/15	88	Activate "Wide-scale body temperature-taking" policy on "Public Health Policy (1)" panel with 0.6 participation rate and 0.8 prevention efficacy rate.
		Click "Run" to run 20-day simulation (day 107).

Table A4. Instructional procedure to understand the efficacy of each public health policy

Step	Operation
1	Click "Initialize" to start underlying contact network.
2	Click "Import" to import infected or incubated cases according to chronologies released by national health authorities. The Singapore chronology in Table A2 is recommended for an initial trial.
3	Activate "General Public Mask-Wearing" policy.
4	Click "Stop" to suspend simulation process.
5	Repeat steps 1–4 using different protection levels.
6	Activate "Healthcare Worker Mask-Wearing" policy.
7	Repeat steps 1, 2, 3 and 5 using different protection levels.
8	Compare results printed out as reported curves.

equipment are responsible for supplying food and other essential goods in hospitals. During the 2002–2003 SARS outbreak in Taiwan, three to four hospitals had to restrict visits.

When a large-scale body temperature-taking policy is enacted, health authorities must make large volumes of body temperature measuring equipment available. Local public or community organizations, business firms, and schools must invest time and money into hiring staff to take body temperatures.

When a reduced public contact and mask-wearing by the general public policies are enacted, health authorities must spend a great amount of money to run a publicity campaign (e.g., newspaper and TV advertisements) to persuade the public to comply.

A.3.3 Instructional procedure

See Table A5.

A.3.4 Simulation Result Samples

The results from simulations of various combinations of public health policies are shown in Figure A5 for further study.

Table A5. Instructional procedure to run the simulation of different combinations of health policies

Step	Operation
1	Click "Initialize" to start underlying contact network.
2	Click "Import" to import infected or incubated cases according to chronologies released by national health authorities. The Singapore chronology in Table A2 is recommended for an initial trial.
3	Activate multiple policies in different combinations. Four suggested combinations are provided for simulation.
4	Click "Stop" to suspend simulation process.
5	Repeat steps 1–4 for each health policy suite.
6	Compare results (in the form of reported curves) and discuss suite efficacies.

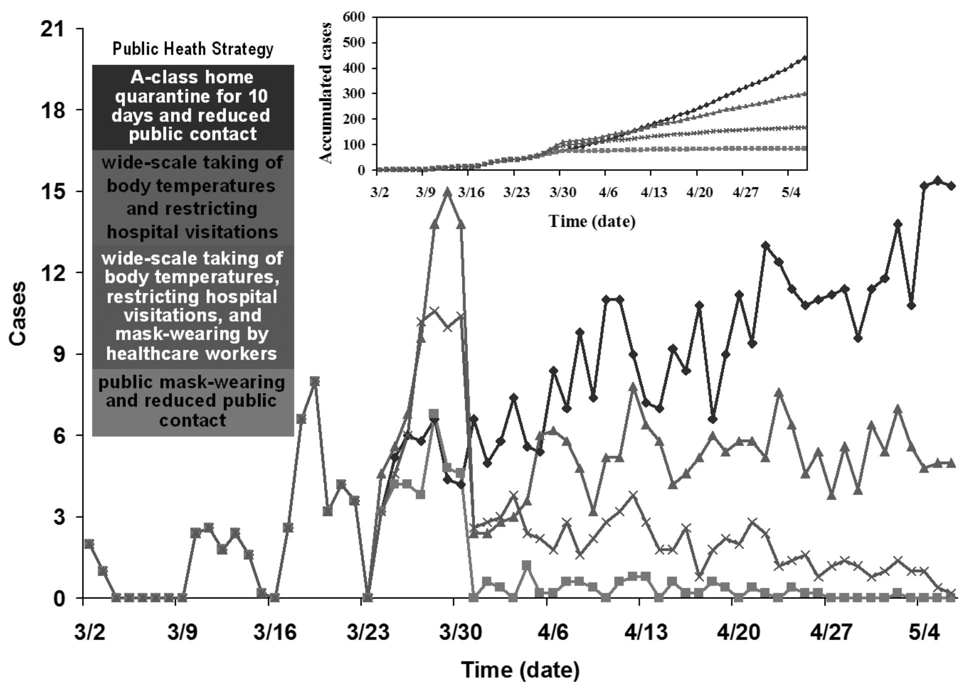

Figure A5. A comparison of various public health policy suites in the third instructional simulation experiment

A.3.5 Discussion

1. Which combinations of public health policies can not only abate the spreading of SARS efficiently but also avoid wasting more social cost?

   1st: A-class home quarantine for 10 days and reduced public contact

   2nd: Wide-scale taking of body temperatures and restricting hospital visitations

   3rd: Wide-scale taking of body temperatures, restricting hospital visitations, and mask-wearing by healthcare workers

   4th: Public mask-wearing and reduced public contact

   Please rank the efficiencies of four combinations from high to low___________________________

   Why do you rank in this order?___________________

   ____

   Please estimate and rank the social cost of four combinations from high to low____________________

   Why do you rank in this order?___________________

   ____

2. Could the above-mentioned simulation process help you form your combination which abates SARS spreading and avoid wasting more social cost at the same time? If not, please provide your personal opinion or suggestion.

8. Acknowledgments

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