Individual Decision Making Can Drive Epidemics: A Fuzzy Cognitive Map Study

Shan Mei, Yifan Zhu, Xiaogang Qiu, Xuan Zhou, Zhenghu Zu, A.V. Boukhanovsky, and P. M. A. Sloot

Abstract—**Existing studies on the propagation of infectious diseases have not sufficiently considered the uncertainties that are related to individual behavior and its influence on individual decision making to prevent infections, even though it is well known that changes in behavior can lead to variations in the macrodynamics of the spread of infectious diseases. These influencing factors can be categorized into emotion-related and cognition-related components. We present a fuzzy cognitive map (FCM) denotative model to describe how the factors of individual emotions and cognition influence each other. We adjust the weight matrix of causal relationships between these factors by using a so-called nonlinear Hebbian learning method. Based on this FCM model, we can implement individual decision rules against possible infections for disease propagation studies. We take the simulation of influenza A [H1N1] spreading on a campus as an example. We find that individual decision making against infections (frequent washing, respirator usage, and crowd contact avoidance) can significantly decrease the at-peak number of infected patients, even when common policies, such as isolation and vaccination, are not deployed.**

Index Terms—**Agent-based modeling, complex networks, fuzzy cognitive maps (FCMs), infectious diseases, influenza A [H1N1], unsupervised learning.**

I. Introduction

THE commonly used modeling methods to simulate infectious diseases include traditional system dynamics, agent-based methods, and complex-network-based methods. The latter two can be categorized into individual-based methodologies, which are used to investigate complex systems bottom-up and from an individual-collective or micro–macro perspective [1], [2]. Individual-based modeling and simulation, as a relatively new and practical method for epidemiological research, is suitable to capture the overall characteristics of propagation of infectious diseases [3]. In [4]–[7], its feasibility and validity is illustrated.

Recently, we have developed a novel complex agent network methodology to study the spreading of infectious diseases, and applied it to human immunodeficiency virus (HIV) and influenza A [H1N1] [8]–[10]. These studies did not consider the uncertainties that are related to individual behavior and their influence on individual decision making against infections. It is known, however, that microchanges in behavior can lead to variations in macrodynamics of infectious diseases' spreading.

Behavioral and neuroscience data have demonstrated that emotion and cognition not only interact but that their integrative operation is necessary for adaptive behavior [11], [12]. From the cognitive theory perspective, emotions are cognition dependent and contain cognitive components [13]. From the psychological perspective, any given mood state (negative or positive) may influence cognitive processing such that what humans think and remember matches (or is congruent with) that mood state. Although there are constant interactions between cognition and emotion in everyday life that determine human behavior, the fundamental aspects of emotion–cognition interactions have yet to receive much attention [12]. The focus of this study, therefore, is to unravel how emotions interact with and influence domains of cognition, in particular, attention, memory, and reasoning.

The factors that influence individual behavior can be categorized into emotion- and cognition-related aspects. Cognition represents individuals' perception and knowledge of the epidemiological situation, while emotions describe how individuals emotionally react to surrounding changes (pessimistic or optimistic, panic or calm) under conditions of epidemiological threats. These two jointly influence human behavior and decision making.

Fuzzy cognitive maps (FCMs) are suitable to describe the interrelations between emotions and cognition. FCMs, which originate from a combination of fuzzy logic and neural networks, are a modeling methodology for complex systems, supporting multicriteria decision making with dependence and feedback [14]. Kosko's pioneering work on FCMs stands as a milestone in the field [15]. As extensions of Kosko's model, new models have been presented and applied to fuzzy neural nets and fuzzy Petri nets [16]–[18]. Among many studies, a negative–positive–neutral (NPN) fuzzy set theory has been

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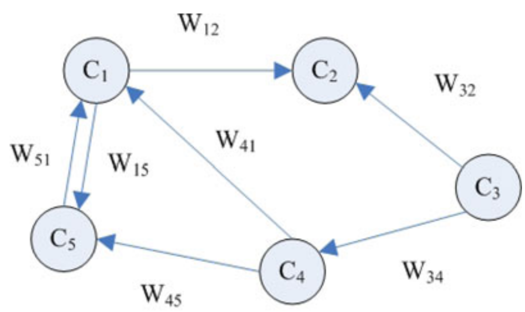

Fig. 1. Typical FCM.

proposed, which forms a computational framework for cognitive modeling and multiagent decision analysis [19]. Over the past few years, FCMs have been broadly applied in multidisciplinary decision making such as effect-based operations [20] and emotion modeling [21]. In [22] and [23], some extensions of FCMs have been studied. FCMs have several distinct characteristics to address the interplay of emotions and cognition. 1) The utilization of FCMs is simple and straightforward so that the underlying formalization and iterative calculation procedure can be easily understood; 2) FCMs can express and reason about the intercausal relationships between factors in a system; 3) FCMs can flexibly describe the knowledge and design of a system according to experts in different fields such as sociology, epidemiology and psychology; and 4) the view of a system can be continuously complemented by adding new factors into FCMs, even though the initial understanding of the system may be incomplete or inaccurate.

The aim of this study is to model the interrelations of emotions and cognition as well as investigate their influence on individual decision making against infections. We present an FCM denotative model to describe how the factors of individual emotions and cognition interact with each other. In addition, we adjust the weight matrix of causal relationships by using a so-called nonlinear Hebbian learning (NHL) method to achieve a well-trained FCM for our simulation case. Based on this FCM, we set individual decision rules against influenza A [H1N1] infections and investigate the effect on disease spreading by numerical studies.

II. Fuzzy Cognitive Maps

FCMs describe the behavior of a system in terms of concepts; each concept represents an entity, a state, a variable, or a characteristic of the system [24]. An FCM is developed by human experts who operate, supervise, or "know" the system and its behavior under different circumstances. Accumulated experiences and knowledge are integrated in a causal relationship between factors, characteristics, or components of the system [25].

The graphical representation of an FCM is a directed graph with feedback that consists of nodes and weighted interconnections. Signed and weighted links connect various nodes that represent the causal relationships that exist among concepts [26].

Fig. 1 shows a typical FCM consisting of five concepts where C_i is a concept with a state value A_i. A_i can be a fuzzy value within $[0, 1]$ that represents the active degree of a concept or a bivalent logic in $\{0, 1\}$ that represents a concept's open or closed state. The weight w_{ij} of a directed link indicates the influence degree from the cause concept C_i to effect concept C_j, which can be a fuzzy value within $[-1, 1]$ or a trivalent logic within $\{-1, 0, 1\}$ [27]. The adjacency matrix corresponding to the FCM is shown as

$$W = \begin{bmatrix} 0 & w_{12} & 0 & 0 & w_{15} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & w_{32} & 0 & w_{34} & 0 \\ w_{41} & 0 & 0 & 0 & w_{45} \\ w_{51} & 0 & 0 & 0 & 0 \end{bmatrix}, \quad -1 \leq w_{ij} \leq 1. \quad (1)$$

There are three possible types of causal relationships between concepts that correspond to values of w_{ij}.

1) $w_{ij} > 0$ indicates positive causality between concepts C_i and C_j, which means that an increase (decrease) in the value of C_i leads to an increase (decrease) in the value of C_j.
2) $w_{ij} < 0$ indicates negative causality between concepts C_i and C_j, which means that an increase (decrease) in the value of C_i leads to a decrease (increase) in the value of C_j.
3) $w_{ij} = 0$ indicates no relationship between C_i and C_j.

Given an FCM with a number of nodes $C_i (i = 1, \ldots, n)$, the value of each concept can be iteratively computed, according to the rule given as

$$A_i^{t+1} = f\left(A_i^t + \sum_{j=1, j\neq i}^{n} A_j^t w_{ji}\right) \quad (2)$$

where A_i^{t+1} is the value of concept C_i at time $t+1$, A_j^t is the value of concept C_j at time t, w_{ji} is a fuzzy weight between the two concepts, and f is a threshold function that transforms the result in the interval $[0, 1]$ wherein concepts take values. Yaman and Polat [20] list several common threshold functions. For example, $f(x) = \frac{1}{1+e^{-\lambda x}}$ $(\lambda > 0)$ is used to compute FCMs with concept values being continuous and within the range $[0, 1]$.

In Section III, we develop an FCM model and derive the adjacency matrix to be embedded into infectious disease simulations, taking into account emotion- and cognition-related factors that influence individual behavior.

III. Fuzzy Cognitive Map Denotative Model Describing Individual Emotions and Cognition

Human decision making is influenced by both human emotions and cognition. In this section, we elaborate on how to model human emotions and an individual cognitive assessment of the epidemiological situation, respectively. Then, we present an FCM denotative model that describes individual emotions and cognition for infectious disease simulations.

A. Human Emotions

Emotions play an important and indispensable role in affecting human memory, attention, and reasoning. Human intelligence enables not only rational thinking and logical reasoning but has strong emotional capabilities as well. Psychologically speaking, emotions stand for an individual's reaction to and evaluation of its own internal states and interactions between themselves and their environment [28]. As a type of intelligence and a psychological tool for agents to adapt to an environment as well as a means of communication, emotions can activate psychological and behavioral motives [29]. Damasio states that emotional capability is crucial to normal behavior, and it does not contradict rational thinking and logical reasoning [30]. In contrast, emotional capability is complementary to rational thinking and logical reasoning and vice versa. Additionally, in [31], emotional capability is regarded as a sign of human intelligence.

Artificial emotion recognizes and understands human emotions based on information science, which enable machines and virtual humans to have subhuman emotions and communicate with humans in a natural and harmonious way [32]. It emphasizes the influence of the internal states on artificial entities such as virtual persons. An internal emotion model is needed to construct emotional agents. In this model, the transition and mapping between stimuli, emotional status, and behavior is predefined in a given context [33]. Emotional agents that interact with an environment agent and with other agents can generate human-like emotion outputs, which subsequently affect decision making. The transition between emotions is related to outside stimuli and environment inputs, as well as current emotional status. Therefore, it is essential to investigate how external stimuli and internal status arouse emotion changes and how emotional changes affect behavior.

Human emotions can be psychologically categorized by three levels, i.e., primary emotions, secondary emotions, and senior emotions. Damasio [30] regarded primary emotions as intrinsic responses of a human to external stimuli; secondary emotions are triggered when primary emotions connect with current and past perception; senior emotions come into being during the course of long-term social contacts in a given environment.

Dao-Ping *et al.* [29] elaborate on the formation mechanism of emotions at different levels. Instantaneous emotions are intense and short-lasting, due to specific causes and perception content, and they easily transform into other statuses; therefore, instantaneous emotions are primary emotions. Moods are more mild, fuzzy, and long-lasting, which contain no specific perception content. Moods appear and vanish slowly with no obvious causes, and last short at emotional peaks. Thus, moods are secondary emotions. Society competence is relevant in each social and cultural environment, which forms more potential and underlying emotional context for people's cognition and behavior. The appearance and vanishing of society competence is more slowly compared with moods, which suggests that society competence is a senior emotion. Primary emotions are partially dominated by senior emotions, although they are mainly influenced by environmental stimuli and self-perception. The domination gets even more obvious when primary emotions conflict with senior emotions. For instance, an optimistic person (with respect to senior emotions) has less intensive instantaneous emotions (with respect to primary emotions) when facing frustrations (with respect to environmental stimuli). Additionally, there exist adjustments between emotions at the same level, which lead emotions to change toward an advantageous direction, as shown in Fig. 2.

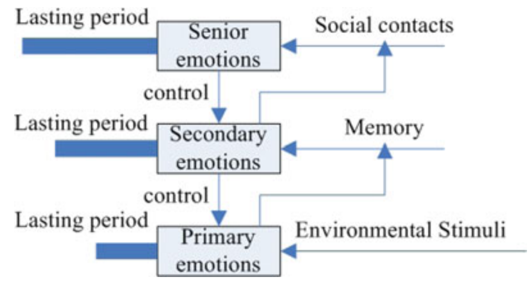

Fig. 2. Emotions at different levels and their interactions.

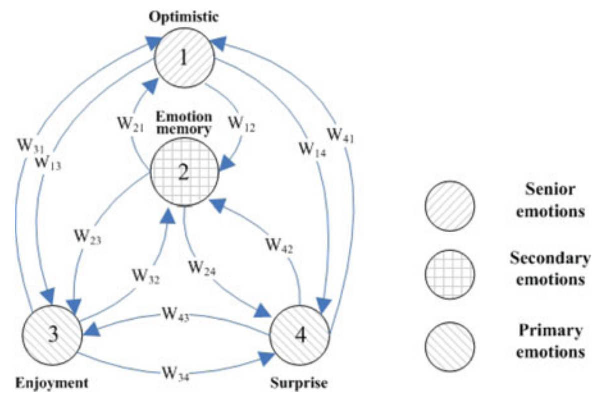

Fig. 3. Simple emotion FCM.

Human emotions, especially primary emotions, consist of eight types including anger, sadness, surprise, and enjoyment, and each type can be further categorized into subtypes which indicate how intense emotions are [34].

This study describes the human status in a continuous space, and selects an interested subset of primary emotions, such as enjoyment and surprise, to compose an emotion space. Besides primary emotions, secondary and senior emotions can also be appended as components to the emotion space, such as historical memory of emotion, which belongs to secondary emotions, and personality, which belongs to senior emotions. Let the emotion set be Emotion $= \{e_i | i = 1, \ldots, l\}$, where l is the total of involved components in the emotion space. Each component in the emotion space is mapped to a concept of which the value is in the range $[0, 1]$. Bigger values of concepts show that the corresponding basic components in the emotion space are more active. A simple example of an emotion FCM is shown in Fig. 3, where "Optimistic" belongs to senior emotions, "Emotion memory" belongs to secondary emotions, and "Enjoyment" and "Surprise" belong to primary emotions.

B. Individual Cognition of the Epidemiological Situation

Computational agents, which represent real-world individuals, are usually incapable of accurately obtaining the overall situation of disease spreading; therefore, they are assumed to collect local information and coarse global information (such as alert

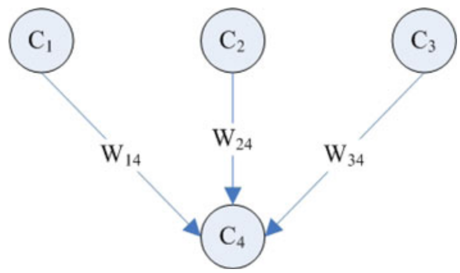

Fig. 4. Knowledge of the local epidemiological situation.

phases issued by WHO, i.e., the World Health Organization), instead of an accurate cognitive assessment of the epidemiological situation. This way, agents accumulate the knowledge and use it for later decision making against infections. We elucidate, in this section, the individual knowledge representation of the epidemiological situation from global and local aspects, respectively.

1) Knowledge of the Global Epidemiological Situation: We assume that agents base their own knowledge of a global situation on the six alert phases' description (the postpeak period and the postpandemic period ignored) issued by WHO.

1) In Phase 1, no viruses circulating among animals have been reported to cause infections in humans.
2) In Phase 2, an animal influenza virus circulating among domesticated or wild animals is known to have caused infection in humans, and is, therefore, considered to be a potential pandemic threat.
3) In Phase 3, an animal or human–animal influenza reassortant virus has caused sporadic cases or small clusters of disease in people but has not resulted in human-to-human transmission, which is sufficient to sustain community-level outbreaks.
4) Phase 4 is characterized by verified human-to-human transmission of an animal or human-animal influenza reassortant virus that is able to cause community-level outbreaks.
5) Phase 5 is characterized by human-to-human spread of the virus into at least two countries in one WHO region.
6) Phase 6, i.e., the pandemic phase, is characterized by community-level outbreaks in at least one other country in a different WHO region, in addition to the criteria defined in Phase 5.

In this study, the alert phase is taken as a concept in FCMs with phases 1–6 mapped to concept values 0.1, 0.2, 0.3, 0.5, 0.7, and 0.9, respectively.

2) Knowledge of the Local Epidemiological Situation: The individual cognition of a local epidemiological situation is greatly influenced by the infection status transitions of neighbors who interact with the agent during a given period. Increases in the proportion of the infected individuals intensify the agent's panic emotion; contrarily, increases in the proportion of the recovered individuals relieve panic emotion. Moreover, the changes of the agent's own disease status also influence the emotional transition.

Fig. 4 shows the representation of individual knowledge of the local epidemiological situation by using an FCM, wherein concepts take values in the range $[0, 1]$. Concept C_1 indicates the ratio of the infected to the total that interact with the agent under investigation. Concept C_2 indicates the ratio of the recovered to the total that interact with the agent. Concept C_3 indicates the disease status of the agent. The closer the value of C_3 is to 1, the more severe the disease status. Concept C_4 is influenced by C_1, C_2, and C_3 simultaneously and indicates the individual cognition of the local epidemiological situation. The closer the value of C_4 is to 1, the more threatening the epidemiological situation appears to this agent.

C. Denotative Fuzzy Cognitive Map Model and Unsupervised Learning for Infectious Disease Simulations

Taking into account individual (senior, secondary, and primary) emotions and cognition of the (local and global) epidemiological situation and expert knowledge, we construct a denotative FCM model for infectious disease simulations. The FCM model consists of Concepts $= \{C_i | i = 1, \ldots, n\}$ and interconcept causal strengths $W = \{w_{ij} | i, j = 1, \ldots, n\}$, where n is the totality of concepts. The value A_i of a concept C_i is within $[0, 1]$. The iterative computation of concepts values follows (2), and the threshold function $f(x)$ is selected to be $f(x) = \frac{1}{1+e^{-\lambda x}}$ $(\lambda > 0)$, which restrict concept values to be continuous and within $[0, 1]$.

We further distinguish concepts *inputs* (e.g., cognition of the epidemiological situation), *internal status* (e.g., emotions), and *outputs*, which need to be estimated for observation from outside. These *outputs* are called desired output concepts (DOCs), which are denoted by $\mathrm{DOC}_i (i = 1, \ldots, n1, n1 \leq n)$. DOCs stand for system factors and characteristics for which we want to estimate the values to describe the final state of the system. Suppose DOC_i takes values in the range $\mathrm{DOC}_i \in [\mathrm{DOC}_i^{\min}, \mathrm{DOC}_i^{\max}] \subseteq [0, 1]$.

The derivation of an FCM adjacency matrix is subject to the quantification of the causal strength between any two concepts. In this study, the causal interrelationships among concepts are defined as being negatively very strong ($w_{ij} \in [-1, -0.75]$), negatively strong ($w_{ij} \in [-1, -0.5]$), negatively medium ($w_{ij} \in [-0.75, -0.25]$), negatively weak ($w_{ij} \in [-0.5, 0]$), zero ($w_{ij} \in [-0.25, 0.25]$), positively weak ($w_{ij} \in [0, 0.5]$), positively medium ($w_{ij} \in [0.25, 0.75]$), positively strong ($w_{ij} \in [0.5, 1]$), and positively very strong ($w_{ij} \in [0.75, 1]$) (see also [35]). We set the weight between each pair of causally linked concepts by presuming the interrelationship type and then drawing randomly from the corresponding uniform distributions. For example, if the causal effect of C_i on C_j is presumed to be positively medium, a random number, which is drawn from a uniform distribution with bounds $[0.25, 0.75]$, will be assigned to w_{ij}. If there exists no cause and effect between C_i and C_j, w_{ij} will be set to zero.

Human knowledge and experience of the system under study helps to determine the initial weights of FCMs, which implicates heavy dependence of FCMs on experts' opinion, and uncontrollable convergence to undesired states of concepts. In order to stabilize concept values, ensure the values of DOCs to converge upon given ranges, and improve the efficiency and robustness of FCM-related computations, we utilize unsupervised learning to train weight matrices.

NHL, which is initially applied successfully in the training of artificial neural networks, has been proven to be applicable to support unsupervised learning of FCMs [35]–[37]. NHL is easy to use, fast converging, and stable. All concepts in the FCM model are simultaneously trigged and updated at each time step. Therefore, the computation of w_{ij}^t at time step t is relevant to w_{ij}^{t-1}, A_i^{t-1}, A_j^{t-1}, A_i^t, and A_j^t.

We adopt the general NHL rule for neural networks, introduced in [37]. It takes the form given by (3), putting together the values of concepts and weights in the FCM model. The coefficient η is a very small positive scalar factor called the "learning parameter" and is determined using an experimental trial and error method to optimize the final solution

$$\Delta w_{ji} = \eta A_i^{t-1}(A_j^{t-1} - w_{ji}^{t-1} A_i^{t-1}). \tag{3}$$

The NHL rule for our FCM model is shown in (4), according to which the weight matrix is updated at each time step

$$w_{ji}^t = \begin{cases} 0, & w_{ji}^{t-1} = 0 \\ \xi w_{ji}^{t-1} + \eta A_i^{t-1}(A_j^{t-1} - |w_{ji}^{t-1}| A_i^{t-1}), & w_{ji}^{t-1} \neq 0 \end{cases} \tag{4}$$

where ξ is the weight decay learning coefficient.

There are two complementary termination conditions of the NHL process [37]. The first termination function F_1 is defined as in (5), where DOC_i is the desired output value of C_i, and $\text{DOC}_i^{\text{expected}}$ is the expected value of DOC_i. Thus, one of the objectives of the training process is to find the set of weights that minimize function F_1

$$F_1 = \sqrt{\sum_{i=1}^{m1} (\text{DOC}_i^t - \text{DOC}_i^{\text{expected}})^2}. \tag{5}$$

It is required that DOC_i takes values in the range $\text{DOC}_i \in [\text{DOC}_i^{\min}, \text{DOC}_i^{\max}]$; therefore, we set the value of $\text{DOC}_i^{\text{expected}}$ as $\text{DOC}_i^{\text{expected}} = \frac{\text{DOC}_i^{\min} + \text{DOC}_i^{\max}}{2}$.

In addition to the first condition, the second condition is to terminate training after a limited number of iterations, taking the form $F_2 = |\text{DOC}_i^{t+1} - \text{DOC}_i^t| < \epsilon$. The determination of ϵ depends on experimental trial and error.

The unsupervised learning of the denotative FCM model, which is based on NHL, is shown in Algorithm 1.

IV. Individual Decision Making Against Infections

In this section, a specific FCM that describes human emotions and cognition, tailored for infectious disease simulations, is constructed. We initialize the weights and then resort to NHL to train the FCM, for the sake of stabilizing concept values and ensuring the values of DOCs to converge upon given ranges.

A. Fuzzy Cognitive Map Construction

We construct the FCM that describes human emotions and cognition, as shown in Fig. 5. For simplicity, only optimistic

Algorithm 1 Unsupervised learning of the denotative FCM model

1: Determine the initial weight matrix W^0 by quantifying the causal strengths between every two concepts;
2: Assign the values of concepts A_i^0 based on human knowledge;
3: Compute A_i^t according to Eq. 2;
4: Update the weight values W_{ij}^t according to Eq. 4;
5: If $W_{ij}^t > 1$ then set $W_{ij}^t = 1$ and if $W_{ij}^t < -1$ then set $W_{ij}^t = -1$, ensuring $W_{ij}^t \in [-1, 1]$;
6: Judge whether the two termination criteria F_1 and F_2 are met; if so then get the final weight matrix W^{NHL}, otherwise go to step 2.

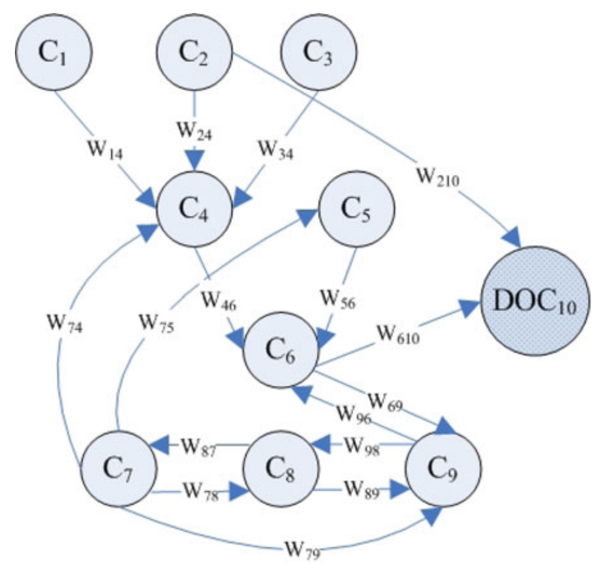

Fig. 5. FCM describing human emotions and cognition.

personality is considered for senior emotions, and panic emotion is considered for primary emotions, since these two are presumably more influential in individual decision making against infections. We do consider the influence of optimistic personality on panic emotion, but ignore the contrary influence. This is mainly because long-lasting senior emotions are absolutely superior to primary emotions within weeks or even months, while we investigate infectious disease spreading over a similar time span in this study.

The definition of C_i (with input, internal, or output concept type) is given in Table I. The definition of w_{ij} is given in Table II.

Consider an initial weight matrix as shown in (6); then, NHL is performed on the FCM with the aforementioned initial configuration. This utilization of unsupervised learning can overcome the lack of historical data for training. Suppose the values of concepts are $A^0 = \langle 0.3, 0, 0, 0, 0.3, 0, 0.5, 0, 0, 0.1 \rangle$ at time step 0, where $A_1^0 = 0.3$ indicates that the ratio of the number of the infected to the total who interact with the agent under investigation is 0.3, $A_5^0 = 0.3$ indicates that the current epidemic alert is in the third phase, $A_7^0 = 0.5$ indicates the degree to which the individual is optimistic, and $A_{10}^0 = 0.1$ indicates the

TABLE I
FCM CONCEPTS

C_i	**Description**	**Value Range**
C_1	Input concept, ratio of the infected to the total who interact with the individual	$[0,1]$
C_2	Input concept, ratio of the recovered to the total who interact with the individual	$[0,1]$
C_3	Internal concept, disease status of the individual	$[0,1]$. The closer the value is to 1, the more severe the disease status is.
C_4	Internal concept, cognition of local epidemiological situation	$[0,1]$. The more the value is close 1, the more threatening the local epidemiological situation is.
C_5	Input concept, coarse knowledge of the global epidemiological situation according to the alert phases issued by WHO	Initial value $\in \{0.1, 0.2, 0.3, 0.5, 0.7, 0.9\}$. The bigger the value is, the more threatening the global epidemiological situation is.
C_6	Internal concept, overall cognition of epidemiological situation due to both global and local information	$[0,1]$. The closer the value is to 1, the more threatening the individual assesses the epidemiological situation.
C_7	Internal concept, optimistic personality for senior emotions	$[0,1]$. The closer the value is to 1, the more optimistic the individual is.
C_8	Internal concept, memory of emotion for secondary emotions	$[0,1]$. The closer the value is to 1, the more easily the individual is influenced by emotion memory.
C_9	Internal concept, panic emotion for primary emotions	$[0,1]$. The closer the value is to 1, the more easily the individual panics.
C_{10}	Output concept, overall evaluation of current epidemiological situation taking into account emotions and cognition	$[0,1]$. The closer the value is to 1, the more the individual gets influenced by epidemiological situation. C_{10} is a desired output concept and also denoted as DOC_{10}.

TABLE II
FCM WEIGHTS BETWEEN CONCEPTS

w_{ij}	**Cause concept**	**Effect concept**	**Value Range**
w_{14}	C_1	C_4	$[0.25, 0.75]$ (positively medium)
w_{24}	C_2	C_4	$[-1, -0.75]$ (negatively very strong)
w_{210}	C_2	C_{10}	$[-1, -0.5]$ (negatively strong)
w_{34}	C_3	C_4	$[0, 0.5]$ (positively weak)
w_{46}	C_4	C_6	$[0.25, 0.75]$ (positively medium)
w_{56}	C_5	C_6	$[0.25, 0.75]$ (positively medium)
w_{69}	C_6	C_9	$[0.75, 1]$ (positively very strong)
w_{610}	C_6	C_{10}	$[0, 0.5]$ (positively weak)
w_{74}	C_7	C_4	$[-1, -0.75]$ (negatively very strong)
w_{75}	C_7	C_5	$[-1, -0.75]$ (negatively very strong)
w_{78}	C_7	C_8	$[-0.5, 0]$ (negatively weak)
w_{79}	C_7	C_9	$[-1, -0.75]$ (negatively very strong)
w_{87}	C_8	C_7	$[-0.25, 0.25]$ (zero)
w_{89}	C_8	C_9	$[-0.25, 0.25]$ (zero)
w_{96}	C_9	C_6	$[0, 0.5]$ (positively weak)
w_{98}	C_9	C_8	$[0, 0.5]$ (positively weak)

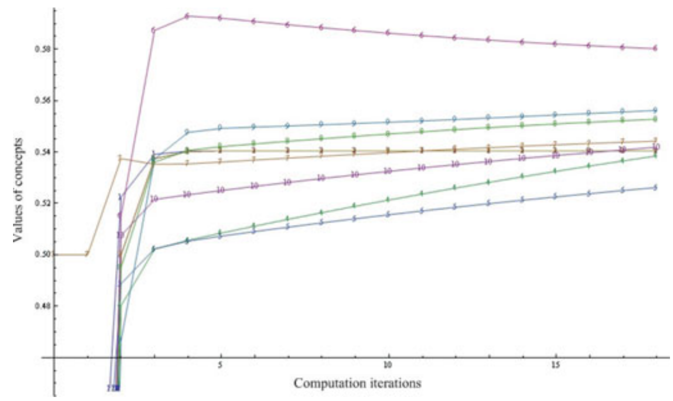

Fig. 6. Iterative values of concepts by using unsupervised learning on the FCM model (each curve with a number i on it maps to C_i).

individual's overall evaluation of the current epidemiological situation. Set $\xi = 0.95, \eta = 0.05, \mathrm{DOC}_{10} \in [\mathrm{DOC}_{10}^{\min}, \mathrm{DOC}_{10}^{\max}] = [0.3, 0.7]$ (excluding the cases that individuals are extremely optimistic or pessimistic), $\mathrm{DOC}_{10}^{\mathrm{expected}} = 0.5, \epsilon = 0.001$, and $f(x) = \frac{1}{1+\mathrm{e}^{-0.3x}}$ based on experimental trials. The values of concepts stabilize after 18 iterations and converge to the final weight matrix, as shown in (7). The iterative values of the concepts are shown in Fig. 6.

$$W = \begin{bmatrix} 0 & 0 & 0 & 0.62 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.81 & 0 & 0 & 0 & 0 & 0 & -0.7 \\ 0 & 0 & 0 & 0.18 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.66 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.68 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8 & 0.23 \\ 0 & 0 & 0 & -0.9 & -0.9 & 0 & 0 & -0.13 & -0.89 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -0.14 & 0 & 0.2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.1 & 0 & 0.12 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{6}$$

$$W^{\mathrm{NHL}} = \begin{bmatrix} 0 & 0 & 0 & 0.34 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.23 & 0 & 0 & 0 & 0 & 0 & -0.17 \\ 0 & 0 & 0 & 0.2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.35 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.35 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.41 & 0.23 \\ 0 & 0 & 0 & -0.27 & -0.27 & 0 & 0 & 0.11 & -0.27 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.11 & 0 & 0.22 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.19 & 0 & 0.19 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{7}$$

TABLE III
SUSCEPTIBLE INDIVIDUALS' DECISION RULES AGAINST INFECTIONS REGARDING INFLUENZA

A_{10}^t	**Behavior against infections**	**Coefficient** θ
$[0.3, 0.4)$	frequent hand washes and surrounding disinfection	$[0.8, 1]$
$[0.4, 0.6)$	mask wearing and preventive medication taking	$[0.5, 0.8)$
$[0.6, 0.7]$	crowd avoidance, self-quarantine and vaccination	$[0, 0.5)$

The comparison between the initial W and the resulting W^{NHL} shows that the influence of the proportion of the infected neighbors on the individual cognition of the local epidemiological situation, which is denoted as w_{14}, changes from 0.62 to 0.34; therefore, this influence is not as significant as expected; the negative influence of $w_{24}, w_{210}, w_{74}, w_{75}$, and w_{79} is not as significant as previously thought; the positive influence values of w_{46}, w_{56}, and w_{69} decreases after learning; noticeably, the values of w_{78} and w_{87} turn from slightly less than -0.1 to slightly greater than 0.1, implying that the causal interrelationship between emotional memory and panic emotion should take positively weak values.

To validate the final weight matrix W^{NHL}, we generate 10 000 random A^0 (the value of each of the ten concepts is randomly drawn from a uniform distribution with bounds $[0, 1]$) and compute A^1, according to (2). The results show that the values of DOCs, i.e., DOC_{10}, are always within the expected range $[0.3, 0.7]$. This validates the feasibility and robustness of applying NHL to FCM training.

B. Individual Decision Rules

Based on the computed A_{10}^t, which indicates the individual's overall assessment of the current epidemiological situation, we can set individual decision-making rules and the corresponding effect of lowering the probability of getting infected to further support simulations of infectious disease propagation. Taking influenza as an example, we can set susceptible individuals' decision rules against infections, as shown in Table III. The third column lists the coefficients of lowering the infection probability which are to be drawn from given distributions. For instance, if a susceptible person takes "frequent hand washes and surrounding disinfection," the probability that he/she gets infected is assumed to be decreased by multiplying the original probability and a coefficient θ drawn from a uniform distribution with bounds $[0.8, 1]$.

V. SIMULATING INFLUENZA A [H1N1] SPREADING

A. Complex Agent Network-Based Infectious Disease Simulations

Using a previously developed complex agent network method [8], [9], we hypothetically simulate the influenza A [H1N1] spreading among 5000 individuals using historical data [38], [39]. The virus isolated from patients in the United States was found to be made up of genetic elements from four different flu viruses: North American swine influenza, North American avian influenza, human influenza, and swine influenza virus typically found in Asia and Europe [38], [39]. Although it spreads well [40], infected patients manifest only mild symptoms, which are similar to those that occur in seasonal influenza.

The simplifying assumptions regarding the spreading dynamics for our simulations are as follows.

1) Each infected individual is equally infectious, excluding the case of super infectors.
2) The virulence of the pandemic influenza A [H1N1] virus remains unchanged during the course of spreading.
3) The immunity and susceptibility of each individual is identical, regardless of his/her age. This implies an assumption of homogeneous immunity and susceptibility structure in the population, which is valid for our study.
4) The duration of incubation follows a uniform distribution of one to two days, and patients during this period are assumed to be noninfectious.
5) The duration of the symptomatic period follows a uniform distribution of one to seven days. An individual will get diagnosed immediately after the symptoms appear and, finally, recovers at the end of the symptomatic period with no mortality.
6) The infectiousness of an infected individual remains unchanged during the course of symptomatic period (asymptomatic excluded).
7) We consider no demographical effect, i.e., we ignore the influence of people's inflow and outflow on the spreading of the virus. We presume that after a pandemic influenza A [H1N1] outbreak, the intercontacts within the population rather than the intercontacts between the population and the outside account for the greatest contribution to pandemic influenza A [H1N1] spreading.
8) Individuals become immune to the pandemic influenza A [H1N1] virus with no exception either after getting recovered from previous infection or with a delay of 14–21 days after being vaccinated.

We use social networks where the node degree follows a power-law distribution with small exponents to describe the complex social contacts between hosts. A social network is a set of people or groups of people with some pattern of contacts or interactions between them [41]. Many quantitative studies of the topology of networks abstracted from the real world suggest that most social networks are scale free [42]–[48], i.e., the node degree of these networks follows a power-law distribution $p_k = k^{-\gamma}$. In this study, $\gamma = 1.6$ is set for the power-law distributions' exponent, implying that networks have high connectivity which is beneficial to infectious disease propagation. For each node (individual) $m (m = 1, \ldots, 5000)$, its degree is denoted by k_m. Let the transmission probability within one day (this is equivalent to one time step in our simulations) across an edge which connects an infected individual and a susceptible individual be P. Let the number of infected contacts with whom this susceptible individual interacts within a given day

Algorithm 2 Simulation procedure

(1) Simulation initialization

  (1.a) Set each individual's infection status be susceptible

  (1.b) Randomly select an individual and set him be infected

  (1.c) Set each individuals's node degree k_m, following the power-law distribution $p_k = k^{-1.6}$

  (1.d) Set each individual's FCM as $FCM_m^{(0)} =< A_{1,m}^{(0)}, A_{2,m}^{(0)}, \ldots, A_{10,m}^{(0)} >$. In particular, the values of some internal concepts $A_{2,m}^{(0)}$, $A_{7,m}^{(0)}$, $A_{8,m}^{(0)}$ and $A_{9,m}^{(0)}$ need to be configured randomly, $A_{5,m}^{(0)}$ is set according to the WHO alert phase scenario during the simulation. The values of other concepts are set to be 0.

(2) Set TICK $= 1$ and time step $\triangle t = 1$ (day)

(3) If TICK $\leq t_f$ (termination time) then go to (4); otherwise go to (6)

(4) Update individual status and interactions, and record simulation data

  (4.a) Reshuffle the network, making each node m possess approximately k_m neighbors

  (4.b) **FOR** ($m = 1$ to 5000) **DO**

    (4.b.1) Set $\theta_m^{(\mathrm{TICK})} = 1$ (without individual decisions against infections)

    (4.b.2) Compute $\theta_m^{(\mathrm{TICK})}$ when considering FCM based decision

$$\begin{cases} A_{i,m}^{(\mathrm{TICK})} = f\left(A_{i,m}^{(\mathrm{TICK}-1)} + \sum_{j=1, j\neq i}^{10} A_{j,m}^{(\mathrm{TICK}-1)} W_{ji}^{\mathrm{NHL}}\right) \\ f(x) = \frac{1}{1+e^{-0.3x}} \\ \text{Compute } \theta_m^{(\mathrm{TICK})} \text{ according to the rules given in Table. III} \end{cases}$$

    (4.b.3) Compute the infection probability of susceptible individuals according to Eq. 9 and then update individual status

  ENDFOR

  (4.c) Record simulation data, e.g., the number of the infected

(5) Set TICK $=$ TICK $+ \triangle t$; go to (3)

(6) Termination of simulation

(simulation step t) be given by $I_m^{(t)}$ ($\leqslant k_m$). Thus, the susceptible individual gets infected at time step t with a probability

$$TP_m^{(t)} = 1 - (1-P)^{I_m^{(t)}}. \tag{8}$$

When incorporating individual decisions against infections into simulations, the coefficient of lowering the transmission probability due to the individual's behavior against infection is given by θ_m. Therefore, the susceptible individual gets infected with a probability

$$TP_m^{(t)} = 1 - (1-\theta_m^{(t)} P)^{I_m^{(t)}}. \tag{9}$$

The detailed simulation procedure is given in Algorithm 2 where individual decisions against infections are considered. For simulations where no individual decisions against infections are considered, steps *(1.d)* and *(4.b.2)* in Algorithm 2 are skipped.

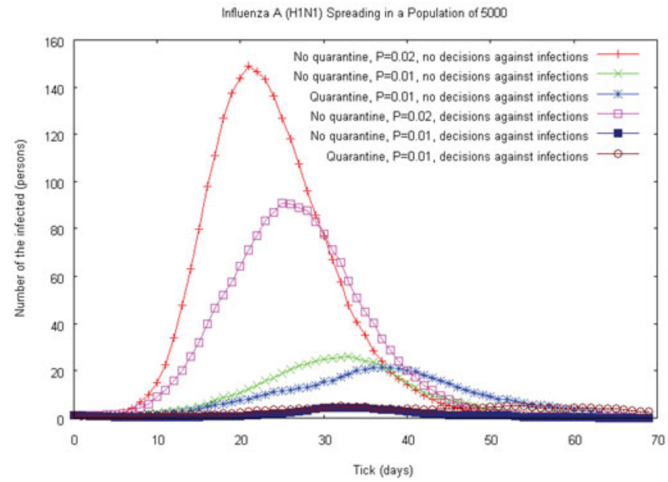

Fig. 7. Temporal evolution of the totality of infected individuals under six scenarios for combinations of quarantining (or not) infected individuals, different transmission probability P, and considering (or not) individual decisions against infections.

TABLE IV
RESULTING PEAK NUMBER AND OCCURRING DAY FROM SIMULATIONS OF SIX SCENARIOS

Scenario	Peak number	Occurring day	Influence of FCM-embedment
1	148.77	21st	
2	26.12	33rd	
3	21.23	36th	
4	90.92	25th	decreased by 38.9%
5	4.54	33rd	decreased by 82.6%
6	4.96	32nd	decreased by 76.6%

We compare the results of scenario 1 with that of scenario 4, scenario 2 with scenario 5, and scenario 3 with scenario 6, to examine the influence of FCM-embedment in terms of percentagewise decrease of peak number of the infected.

B. Results

Six scenarios are designed to simulate the influenza A [H1N1] spreading among 5000 individuals.

1) *Scenario 1:* not quarantining infected individuals, transmission probability $P = 0.02$, and *no* individual decisions against infections;
2) *Scenario 2:* no quarantining, $P = 0.01$, and *no* individual decisions against infections;
3) *Scenario 3:* quarantining, $P = 0.01$, and *no* individual decisions against infections;
4) *Scenario 4:* no quarantining, $P = 0.02$ with individual decisions against infections;
5) *Scenario 5:* no quarantining, $P = 0.01$ with individual decisions against infections;
6) *Scenario 6:* quarantining, $P = 0.01$ with individual decisions against infections.

Initially, a randomly chosen individual is set to be infected, and the time step is set to be one day. Fig. 7 shows the temporal evolution of the amount of infected individuals within 90 days (averaged over 30 realizations for each scenario).

The FCM model is embedded into Scenarios 4–6; therefore, we compare the results of Scenario 1 with that of Scenario 4, Scenario 2 with Scenario 5, and Scenario 3 with Scenario 6, to examine the influence of individual decisions. The moment in time and the peak number of infected individuals during the 90 simulation days are listed in Table IV. The results show that individuals' decisions against infections can significantly decrease the number of infections, for instance, from 148.77 (Scenario 1) to 90.92 (Scenario 4), with no noticeable influence on the time lag of the infection peaks.

VI. Conclusion

Epidemiologically, our FCM study indicates that pandemic influenza A [H1N1] will die out even with no quarantining intervention taken; individual decision making against infections (frequent washes, respirator usages, and crowd contact avoidances) can significantly decrease (by 38.9–82.6%) the peak of patients infected, even when common policies, such as isolation and vaccination, are not deployed. Individual decision making against infections has no noticeable influence on the time lag of the at-peak infected number of patients. Individual behavior, nevertheless, needs the proper guidance of government and media, for the sake of arousing no panic.

Technically, we conceptualize the relationships between emotions and cognition in the form of an FCM model and embed it into simulations of infectious diseases to examine the interplay of emotions and cognition for adaptively guiding behavior. The fundamental aspects of emotion–cognition interactions, especially as for how they act upon human behavior against infections, remains an open question. This study takes a large step by presenting an FCM denotative model and incorporating the influencing factors into emotion- and cognition-related elements; it provides a promising and reliable approach to model the influence of human emotions and cognition on decision making. The current FCM model contains topologically fixed links (with alterable weights) between emotions and cognition; future work will focus on the rewiring of links due to the fact that the links between emotions and cognition might be tuned through training and mental practice [12].

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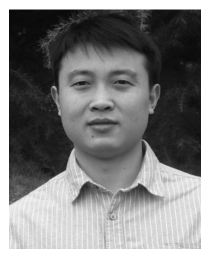

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