Simulation Analysis of Immunization Policy Diffusion in Social Network with ABM Approach

Jiao Xue, Takao Terano, Hiroshi Deguchi, and Manabu Ichikawa

Abstract—Immunization policy strives to promote vaccination coverage in population-wide social network of community by encouraging vaccination for a group of vulnerable population and accelerating health awareness diffusion in the personal networks of vaccinators. In order to determine the relative prognostic importance of the various factors predisposing to vaccination decision-making of individual and analyze diffusion of innovation in immunization policy adoption on overall social network architecture, this paper carries out an agent-based modeling (ABM) approach to construct a pandemic immunization simulation model for providing insights into immunization behavior modification of individual during social interaction in community. Simulation results give decision support to assess the relative impact of healthcare services for pandemic control and suggest that reasonable immunization policies tend to promote individual immunization behavior. Moreover, propagation path of immunization awareness inside the community can be reviewed in depth in the simulation result.

Index Terms—Agent-based Modeling, Vaccination Decisionmaking, Immunization Policy Diffusion, Pandemic Immunization Simulation, Social Network Interaction.

I. INTRODUCTION

Ordinarily, prophylaxis policies are carried out based on individual policy adoption decision-making rather than being mandatory. Immunization policies, as one of typical prophylaxis policies, often organize subsidies in order to obtain high vaccination uptake rates in community. The impetus for immunization policy diffusion comes with spread of innovation from one person to another, which process is known as diffusion of immunization awareness. Specifically, immunization policies encourage a group of vulnerable population to get vaccination firstly and expect vaccinators making publicity for immunization campaign to the other people in vaccinators' personal social networks.

Moreover, social norm in immunization system refers to a combination of perceived expectations from relevant individuals or groups along with intentions to comply with these expectations. In other words, if referents in personal network of individual are vaccinated, behavioral intention of the individual is likely to be influenced. The potential referents include family members, friends, and all people involved in personal network of the individual. Therefore, it is essential to take a consideration of social network structure and especially all personal networks in whole society when establish an immunization policy in healthcare system.

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I. Manabu are with Department of Health Crisis Management, National Institute of Public Health, 2-3-6 Minami, Wako-shi, Saitama 351-0197 JAPAN This paper focuses on the process of vaccination behavior change among social groups and presents a key to understand logic of social diffusion, in which immunization awareness or vaccination behavior of individual in community take off and spread throughout society. Moreover, by using agent-based simulation approach, we aim to provide a method to estimate diffusion path in the population-wide social network.

Similarly to our purpose, a lot of prior researches have claimed that interactions inside social network establish and maintain privacy awareness. In 2015, Artemis D. Avgerou and Yannis C. Stamatiou[1] introduced game theory to an innovative diffusion model, which showed that privacy awareness could be spread to a large population by taking advantage of individuals' social-network connections. Cain Mary, and Robert Mittman^[2] pointed out that choosing a right social network and a group with appropriate norms could maximize the pace of diffusion. Though all prior researches have provided us numerous rationales, social diffusion should depend on a specific subject and a defined network structure. Moreover, diffusion of innovation in immunization policy adoption cannot be well defined in previous works. Comparing with prior works, this paper propose to construct an analytic social network-based immunization model. The research method is based on subjective social norms models, and is capable of predicting future trends through analysis of social interactions between the community's members. We posit that individuals adopt vaccination based on their direct relations with others in community. This work aims to present the immunization awareness diffusion process in individual relationship network of human agent, which is a part of structural population-wide social network. Furthermore, subjective social norms will be illustrated through the well-defined network structure.

The structure of the paper is organized as follows: the details of pandemic immunization simulation model based on population-wide social network are discussed in Section II; Resulted simulation data analysis is conducted in both macro-level and micro-level in Section III; Section IV analyzes diffusion of innovation in immunization policy adoption on overall social network architecture via the immunization simulation model; In the final section of this paper, conclusion is proposed.

II. AGENT-BASED IMMUNIZATION SIMULATION BASED ON POPULATION-WIDE SOCIAL NETWORK

"Simulation is a technique to replace or amplify real experiences with guided experiences that evoke or replicate substantial aspects of the real world in a fully interactive

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manner"[3]. In this work, considering complex nature of epidemic system and immunization system corresponding to epidemic transmission phase, simulation is viewed as one of the most appropriate modeling technique for revival of the real situations about vaccination behavior of individuals and the realistic immunization system. Specifically, we adopt an agent-based modeling approach. Comparing with healthcare system researches with system dynamics approach[4][5][6], in which estimates are based on models with relatively simple assumptions about contacts among individuals in the population, agent-based simulation approach considers individuallevel heterogeneous contact patterns and takes advantage of population-level immunization diffusion model generation. In the model, all individuals in the community are viewed as independent agents. Their individual vaccination behavior and personal immunization policy adoption decision-making are the research subject in this work. All agents and their personal relationship networks constitute a population-wide social network and their vaccination behavior is component of an immunization system.

Besides, considering infectious risk, kinds of vaccination, inoculation pattern and possible immunization policies vary in a big way for different pandemic, this research focuses on one of a typical type of vaccination, seasonal influenza vaccination, which is usually paid as an out-of-pocket expense so that low vaccination coverage rates and high incidence are assumed to be a consequence of seasonal influenza vaccination in Japan[7]. The simulation is developed with the agentbased simulation language: SOARS (Spot Oriented Agent Role Simulator)[8], which is a Java based simulation tool. The details of the model are introduced in the following.

A. Population-wide Social Network

In the social community in the model, personal network of a human agent is a representation of the relationships between the agent and other human agents (friends, family, acquaintances, work colleagues, etc). Large populations and their personal networks compose a population-wide social network. This paper generates a population-wide social network for a specific area: Oshima, which is an isolated island under the administration of Tokyo. Variability among agents, social interactions, daily life, and in particular individual vaccination behavior are simulated on the social network in Oshima.

In the previous work, Ichikawa[9] has presumed the population-by-age composition and the household composition of the city based on city survey, geographic information and census data of Oshima and constructed a geography based virtual city model, in which people were related by social structure estimation from geographic information system and Japanese census data from portal site of official statistics of Japan. Besides, Xue[10] has analyzed features inside personal relationship networks inside real world based on the Japanese General Social Survey(JGSS) data and generated an intimacy-based population-wide social network in Oshima by applying the data analysis results to construct 7584 personal networks for the every human agent in Oshima.

Fig. 1 illustrates the visualization of the constructed social network. Each node in the graph represents one of the human agents. The edges in the graph are double arrows, which illustrate personal contact of each agent in the social network model. We generate this social network figure with Yifan Hu multilevel layout algorithm [11] by network graphs visualization software Gephi[12].



Fig. 1. Visualization of social network of Oshima

In the constructed population-wide social network. Each node represents an individual agent, Edges between them represent the relationship within them. TABLE. I gives a statistic of relationship types in the constructed Oshima social network. In addition, the details of a part of the social

 TABLE I

 Statistic of relationship types in the constructed network

relationship type	number		
family relationship	953		
parent - child relationship	2885		
couple relationship	1887		
schoolmate relationship	42645		
officemate relationship	14466		
friend relationship	14991		
Total rnumber	77827		

network is highlighted in Fig. 1. The relationship between each pair of the human agents is recorded on the edges. For example: 'VC_Human316' and 'VC_Human318' are children of 'VC_Human317'.('w'=wife; 'h'=husband; 'c'= child; 'o'= officemate; 'f'= friend;). Besides, the number written on the edge represents the intimacy degree.

B. Vaccination Decision-making

Each individuals living in the social network can use vaccination behavior modification mechanism to improve their pandemic vaccination decision-making performance. By characterizing the effect of personal values, health beliefs, and influence from interpersonal relationships within populationwide social network during the process of immunization decision modification, this paper purposes to evaluate the individual vaccination behavior intention in order to determine the relative prognostic importance of the various factors predisposing to immunization of individuals.

Specifically, to figure out prospective factors in vaccination decision-making and evaluate degree of the influence from the factors for each individual, the paper applies the variables of Theory of Reasoned Action (TRA) to distinguish vaccinators from non-vaccinators. According to the original component of TRA, an actual behavior is determined by behavior intention, which states that an individual's motivation to engage in a behavior is decided by [Attitude toward Behavior] and [Subjective Norms]. We embed the fundamental dimensions into the vaccination behavior. [Attitude toward Behavior], which is explained as human personal beliefs that immunization behaviors lead to certain outcomes and the his evaluation of these outcomes according to the decrease of rick after immunization, stands for risk and value cognition towards immunization. Conversely [Subjective Norms] represents normative beliefs and motivation to copy or comply with referents.

1) Subjective Attitude towards Vaccination: To quantify the risk and value cognition towards immunization, we define a parameter: [Willing to Pay]: C(pay), which is used to evaluate the expected payment of each individual. C(pay) can be calculated according to decision-making tree method, which considers parameters associating with pathology model. Besides, considering humans are possible to be lack of cognitive skill in reality, we introduce a subjective equation W(P) to reflect vaccination decision making in aspiration level. C(pay) can be calculated by parameters concerned with infection risk, which can be achieved from previous epidemic model[13] and economic lost of illness,

2) Subjective Norm: Subjective Norm reflects the influence of vaccination awareness from the social network individual lives in. Considering if intimate relevant people in the personal relationship network are vaccinated, the individual will develop tendency to inoculate, we quantitate the influence from Subjective Norm (ISN), which is viewed as a probability to decide whether human is affected or not. The value of ISN can be calculated from the leadership degree of each agent and the intimacy degree with their referents[10].

III. SIMULATION RESULT ANALYSIS

The immunization simulation with agent-based approach links micro-level individual vaccination intention analysis to macro-level immunization phenomena by making an insight of the properties of individual agents. In this paper, we are going to analyze the simulation results in a more comprehensive manner from both macro-level and micro-level perspectives. They will be represented separately in the following.

A. Macro-level Analysis: Epidemic Period, Infection Number and Immunization Coverage

Fig. 3 shows the simulation results of epidemic period, infection number and immunization coverage after executing the model 10 times. Fig. 3 represents ten possible situations



Fig. 2. Calculation of Behavior Intention

of epidemic period, corresponding infection number and immunization coverage. Every dot in Fig. 3 records the value of total infection number in pandemic season at horizontal axis and corresponding vaccination number at vertical axis.



	Average	Standard deviation	Coefficient variation	
Infection number	47	20.3	43.1%	
Vaccination number	629	90.6	14.3%	

Fig. 3. Epidemic period, infection number and immunization coverage

According to the simulation results in Fig. 3, simulation results are converged in the red circle eight times, which means epidemic period, infection number and immunization coverage inside the circle are much more likely to match with the real situations. For one thing, according to the statistic of value converged in the circle, the results implies that vaccination number is more stable than infection number. In other words, comparing with the prediction of transition of infectious disease, immunization coverage in the experimental results is more approximate well to reality. For another, there are still dots cannot converged in the circle, which means the probabilities of these possible epidemic period, infection number and immunization coverage inside the dots are very small.

Then, we separately pick up any two simulation results from the converged circle. The Epidemic transmission processes and the relative immunization coverage from these two results are shown in Fig. 4. According to the simulation results, vaccination number increases with a corresponding increase in infection number, whereas vaccination number tends to be stable when corresponding infection number decreases. In other words, vaccination popularity always finishes early before disease being stable. Specifically, in the result of 'Day18' epidemic period, there is a small amplitude of infection number from 'Day10' in pandemic season. The small amount of increase in infection number results in the growth in vaccination number. In contrast, the vaccination number changes to a stable state after 'Day16' when the infection number begins to drop down. Moreover, it is obvious that longer time the epidemic spreads, more substantial immunization coverage is likely to be.



Fig. 4. Epidemic transmission processes and the relative immunization coverage of converged results

B. Micro-level Analysis: Immunization Diffusion Process in Personal Network

Micro-level simulation result analysis attempts to explain internal decision-making of all agents and their vaccination behavior modification process. In the social network model, all 7584 personal relationship networks of every agent and vaccination state of them in the network are records per step (1step=15min). Output of the state change process in personal networks at per step is shown in Fig. 5.

Moreover, we set one example of the immunization awareness change process in the personal network of a specific human agent: 'Human418', whose personal network has already been visualized in Fig. 1. In the social network model, 'Human418' is a male, worker, 50 years old, and lives with his wife. The vaccination information in his personal social network is updated at every iteration. The diffusion process of his immunization awareness accompanies the vaccination

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Fig. 5. Personal networks and state change process per step

information change in his personal network at every iteration; we record these changes as states. The information in personal relationship network is update on time. Fig. 6 illustrates its transformation. (State1 \longrightarrow State2 \longrightarrow State3 \longrightarrow State4)



Fig. 6. Immunization diffusion process in a personal network

IV. EFFECT ESTIMATES OF IMMUNIZATION POLICIES

This section introduces several common immunization policies as scenarios into the constructed model. By estimating the effect of each immunization policy, diffusion of innovation in immunization policy adoption on overall social network architecture under each type of policy can be discussed as well.

A. Subsidy Amount, Epidemic Transmission Processes and Vaccination Coverage

Vaccination subsidy is one of the most widely operated immunization policy in Japan, which strives to provide financial support to a group of susceptible population. In the subsidy amount scenarios, this research analyzes the efficacy of 4 types of subsidy amount. Fig. 7 represents ten possible situations of epidemic period and corresponding infection number and immunization coverage when vaccine price goes down to 60%, 70%, 80% and 90% of original price. In Fig. 7, immunization coverage raises when price goes down. One reason of such result is because conformity involves changing behavior of



Fig. 7. Simulation results with different subsidy amount

human agents in order to "fit in" or "go along" with the other agents around them. If a lot of agents take immunization behavior under the subsidy, social influence forces agents to act like the majority of inoculated agents.

Besides, average number of vaccinators of each scenario at the beginning of pandemic season is shown as follows. It is notable that cheaper vaccine results in lager vaccinator number at the beginning of pandemic season.

TABLE II Average Initial vaccinator number

Scenario	60% price	70% price	80% price	90% price
Number	615.4	583.5	467.1	429.9

It is also notable that price between 70% and 80% is the best measure for immunization system with all due respect when considering immunization budget and infectious transition synthetically. In addition, the immunization coverage in '70% case' to '80% case' are shown in Figure. 8. In both '70% case' to '80% case', results with infectious period 'Day14' appeared several times. Though the infectious period is the same for these results, the total infection number and the total vaccination number are different. Especially, in the result of '70% case', total infection number is less than all results in '80% case'.



Fig. 8. Results of infectious period 'Day14'

B. Subsidy for Different Group of People

Ordinarily, government encourage vaccination to a specific group of people by providing them appropriate financial support. We specify herd immunity groups as: child (Primary school students and children in kindergarten), teenager (middle school students and high school students), elderly (people over 65 years old), and calculate the total immunization numbers for different age of agents. Number of immunization agents with half-price subsidy is shown as Figure. 9.



Fig. 9. Immunization number with different age under half-price subsidy

Fig. 9 implies that subsidy can promote immunization awareness of individuals, who are the target of the subsidy. Since different target groups lead to different immunization coverage, Selection of target group is a big mission for subsidy decision maker. In the simulation result, the immunization rate of teenagers doesn't present conspicuous difference even when teenagers are the target group of subsidy, which is because epidemic breakouts in high school. Most of the teenagers in the model are infected so that they cannot get vaccination.

Besides, pandemic immunization campaign or subsidy for a specific group of population would change the whole immunization coverage.

C. Herd Immunity and Budget Proposals

Herd immunity is a desperate measure in healthcare system. Though herd immunity for influenza vaccine is seldom operated for all population in community, herd immunity for students sometimes occurs in reality. In addition, the goal of herd immunity is to improve cost-effectiveness instead of enlarging the investment even beyond the limited budget proposals. In the specific area Oshima, the budget proposals for healthcare programs is 1,720,000 yen (US\$16723) according to the draft budget of Oshima in 2015. We assume immunization project will take 1/3 part of draft budget in the whole healthcare budget proposals and make use of the 1/3 budget to teenager herd immunity. As typical case studies, we estimate the immunization efficacy of herd immunity and compare the result in middle school and high school(Fig. 10).

In the model, there are 126 middle school students and 153 high school students in Oshima. Since pandemic starts from the unique high school and 5 students are infected at the initial step, the initial immunization number in high school



Fig. 10. 2 typical cases: herd immunity in middle school and high school

is 148. Mandatory vaccination for the high school students will cost 30.98% from the whole healthcare draft budget, while mandatory vaccination for the middle school students is 26.37%. Since the upper limit of cost is 1/3, both of mandatory subsidy policies can fit the bill and nearby 1/3.

In both cases, pandemic doesn't spread in the whole city and disappear in a relatively short time. Since pandemic starts from the high school students, pandemic season could stop quickly when high school student get vaccination. Specifically, the immunization actions of 126 middle school students affect 205 acquaintances to get the same immunization action as them. Especially 152 from 205 vaccinators are students.

V. CONCLUSION

This paper introduced an agent-based immunization system simulation and applied it to predict policy implementation. The simulation results about the pre-estimate of immunization policy efficacy suggested that different vaccination policies result in different degrees of influence on immunization system. Even the same subsidy may result in disparity benefits because of different subsidy amount and object. According to the results, reasonable subsidy tended to promote vaccination behavior modification and gives decision support to assess the relative impact of public health services for pandemic control. The model also certificated that diffusion of innovation in immunization policy adoption relied the overall social network architecture. Therefore, it is essential to consider the social network structure and population composition before implementation of immunization policy.

REFERENCES

- Artemis D. Avgerou, Yannis C. Stamatiou, Privacy Awareness Diffusion in Social Networks IEEE Security & Privacy, vol.13, no.6, p:44-50, 2015.
- [2] Cain, Mary, and Robert Mittman. Diffusion of innovation in health care Oakland CA: California Healthcare Foundation, 2002.
- [3] Gaba, David M. The future vision of simulation in health care Quality and safety in Health care 13.suppl 1, p:i2-i10, 2004.
- [4] Rwashana, AGNES SEMWANGA, and Ddembe Wileese Williams. Modeling the dynamics of immunization healthcare systems-the Ugandan case study The 26th International Conference of the System Dynamics Society; July 20-July. Vol. 24. 2008.

- [5] Arman Kussainov. Use of system dynamics and simulation in modeling and analysis of vaccine supply chain management Information technology, management and society 8(1) p:32-37, 2015.
- [6] Koelling, Patrick, and Michael J. Schwandt. *Health systems: A dynamic system-benefits from system dynamics* Simulation Conference, 2005 Proceedings of the Winter. IEEE, 2005.
- [7] Hiroaki Nobuhara, Yumi Watanabe, Yoshihiko Miura. Estimated influenza vaccination rates in Japan Japanese Journal of Public Health Vol. 61 No.7. p:354-359, 2014.
- [8] Tanuma, H., Deguchi, H., Shimizu, T. SOARS: Spot Oriented Agent Role Simulator Design and Implementation Agent-Based Simulation: From Modeling Methodologies to Real-World Applications, p.1-15, 2005.
- [9] Ichikawa, Manabu, Yuhsuke Koyama, and Hiroshi Deguchi. Virtual city model for simulating social phenomena Simulating Interacting Agents and Social Phenomena, Springer Japan, p:253-264, 2010.
- [10] Xue, Jiao, Manabu Ichikawa, and Hiroshi Deguchi. Agent-based Social Network Model of Construction through Analysis of Japanese General Social Survey Data Communications in Information Science and Management Engineering, Vol. 5 Iss.1, p:1-12, 2015.
- [11] Hu, Yifan. Efficient, high-quality force-directed graph drawing Mathematica Journal 10.1. p:37-71, 2005.
- [12] Bastian, M., Heymann, S., Jacomy, M, Gephi: an open source software for exploring and manipulating networks ICWSM, p:361-362, 2009.
- [13] Ichikawa, M., Hiroshi Deguchi, H. System of Virtual City Constructing Environment for Social Simulation (in Japanese) Proceedings of The Society of Instrument and Control Engineers, 7th Symposium of Technical Committee on Social Systems, p:91-94, 2014.

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