Simulations of the Diffusion of Innovation by Trust–Distrust Model Focusing on the Network Structure

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Received: 23 May 2022 / Accepted: 13 July 2022 / Published online: 17 August 2022
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Abstract
The purpose of this study is to examine the role of interaction between mass media and people in the diffusion of innovation using the Trust–Distrust model, one of the theories of opinion dynamics. Therefore, in this study, we ran simulations using the Trust–Distrust model to confirm the differences in opinion distribution across different network structures. We used the five adopter categories as the agents of the Trust–Distrust model and applied the random network, scale-free network, and small-world network as the networks for simulation. As a result, we confirmed that differences in network structure lead to differences in the diffusion of innovations (distribution of opinions).

Keywords Opinion dynamics · Trust–Distrust model · Diffusion of innovations · Five adopter categories · Network structure

1 Introduction
Due to the COVID-19 pandemic, we are paying attention to the transmission route of infectious diseases, that is, people’s connections and networks. The diffusion in society includes the spread of information in addition to infectious diseases. In the context of marketing communications, long before SNS became widespread, we used the Hypodermic needle model [1] and Two-step flow model [2] to discuss information diffusion and interpersonal networks.

The purpose of this study is to consider the role of interaction between mass media and people in the dissemination of innovation using the Trust–Distrust model, which is one of the theories of opinion dynamics. In the previous research [3–5], a simulation using a random network was executed, and it was confirmed that the

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spread of innovation (distribution of opinions) is biased by manipulating the connection probability of the link and the advertising variable. Therefore, in this research, we will develop the research so far, and by executing simulations applying scale-free networks and small-world network, we will examine the diffusion of innovation due to differences in networks and other variables (Advertising variable and initial value of opinion et al.) applied there.

2 Theory

Before running the simulation, this chapter defines and discusses “innovation”, “opinion dynamics”, and “network”.

2.1 About the Innovation and Its Diffusion

The dissemination of innovation is said to be the process by which innovation is transmitted among members of the social system over time through a communication channel [6].

Innovation refers to ideas, habits, or objects that are perceived as new by an individual or other unit of recruitment. iPhones, Greek yogurt Chobani, and the conversion of over-the-counter sales (OTC) to self-service in store sales are good examples of marketing innovation.

And it can be said that the essence of the spread of innovation is information exchange. In other words, we consumers recognize innovations such as new products and ideas through information exchange and convey them to others. The fastest and most efficient way to potentially convey information that innovation exists is in the mass media, and face-to-face information exchange is effective in persuading people to accept new ideas [6]. In addition, the superiority and inferiority of innovation and demand have a great influence on the diffusion of innovation, but the superiority and inferiority of innovation itself is not discussed in this paper. This paper focuses on the dissemination of innovation utilizing opinion dynamics. The variables to be manipulated are agents (consumers), advertising (exogenous) variables, and network types.

Here, we would like to mention the agents (consumers) who adopt innovation. In this study, we classify agents into five types and perform simulations according to Rogers’ adopter categories [6]. The adopter categories classify consumers into five categories based on innovation and distinguishes the members of the social system based on individual innovation. The recruitment categories are divided into (1) innovators, (2) early adopters, (3) early majority, (4) late majority, and (5) laggard, in order from the earliest adoption of innovation (Fig. 1).

Innovators are consumers who are adventurous and act as gatekeepers of social systems and are the earliest of the five employer categories to adopt innovation.

Early adopters are opinion leader consumers who are a source of innovation information for potential hires.
Although early majority is cautious when adopting innovation, it plays an important role in mediating the subsequent mass and innovation in the process of disseminating innovation. It is an important category that also plays a role of mutual liaison in interpersonal networks.

The late majority is skeptical of innovation and is a category that adopts innovation after the hiring rate exceeds 50%. Internal pressure is needed to motivate the adoption of innovation.

Laggard is the category that takes the longest time to adopt innovations and is considered to be the last category to adopt innovation in the social system.

Innovators are the first to adopt innovation in the market, but in general marketing, it is aimed at promoting the market penetration of innovations by disseminating information to opinion leaders rather than innovators. This is because innovators are generally regarded as just lovers of new things, adopting new innovations that are unknown. However, some have pointed out that innovators who adopt innovation the earliest are the ones who build the market [7], and it can be said that they cannot be ignored. In the previous research [5], we verified the spread of innovation by manipulating the confidence factor between agents. In this paper as well, we have increased the confidence factor of early adopters and set them to be trusted by other agents. In other words, when an early adopter adopts innovations, the early adopters are trusted, so the probability that other agents will adopt innovations increases, and in the opposite pattern, the diffusion of innovation does not increase.
2.2 Opinion Dynamics Theory

Opinion dynamics is a theory that analyzes the consensus building of opinions in a group, and various studies have been done since ancient times [8–13]. When dealing with the opinion dynamics with large-scale data such as the adopt (or reject) of innovation at the market, it is important to quantify opinions. As a method for this, there is a method of treating disagreements by polarizing them into discrete values of 0 and 1. A typical example of this theory is an application of Galam’s theory of magnetic physics [14]. The Ising model, which considers the direction of spin between atoms as +1 and −1, is applied to this.

There are also theories that treat opinions continuously rather than discretely. A typical example of this theory is the Bounded Confidence Model [15–17]. However, since the Bounded Confidence Model is a theory of consensus building, it only expresses the state from indifference to approval from 0 to 1, and does not consider dissenting opinions. Ishii and Kawahata have proposed a theory that develops this theory and solves its shortcomings [18, 19]. In this paper, we use the mathematical model proposed by Ishii and Kawahata. The following is the mathematical model.

\[
\Delta I_i(t) = -\alpha I_i(t) \Delta t + c_i A(t) \Delta t + \sum_{j=1}^{N} D_{ij} \Phi(I_i, I_j)(I_j(t) - I_i(t)) \Delta t, \#
\]

(1)

where

\[
\Phi(I_i, I_j) = \frac{1}{1+e^{(\beta(|I_i-I_j|)-b)}}, \#
\]

(2)

\( I \) expresses the strength of an individual’s opinion when quantifying the opinion on one theme, and expresses one as a positive value and the other as a negative value as the direction of the opinion. \( A \) is an exogenous variable, and is information added from social groups and the environment where there is a place for communication of opinions such as mass media. \( \alpha \) is a coefficient representing the forgetting rate of the exogenous variable, but in this simulation, it is set to zero because forgetting is not taken into consideration. \( D \) is a coefficient that expresses the susceptibility to the opinions of others. If the value of \( D \) is positive, it means that the person who asserted the opinion is trusted, and the person agrees with the opinion of the other person. On the other hand, if it is negative, you are wary of the other party and will oppose the other party’s opinion. \( D \) is represented by an \( N \times N \) matrix. The sum of the value of the coefficient \( D \) in all combinations of people who have opinions and the product of the opinions of the other party in the previous time step is the influence from others. By combining with \( A \), which is information from the outside, it is possible to express changes in opinions per individual time. \( C \) is a coefficient representing the reaction difference of each agent. The coefficient \( C \) can have a different value for each person, and \( C \) can be positive or negative.

The function \( \Phi(I_i, I_j) \) is a cut-off function that ignores opinions when disagreements exceed a certain level, and a sigmoid function is used. In the simulation of this paper, \( \beta \) is set to 10 and \( b \) is set to 1.
2.3 Regarding the Network

The components of society such as people and things have some kind of relationship, and when they are connected by lines as points (nodes) and expressed geometrically, they become a network. It can be said that the railway network has stations as points (nodes), and the air network has airports as points (nodes). The Internet and SNS can be said to be global information networks. A network is made up of points (nodes) and links (edges) connecting the points [20]. Networks have also been studied in the field of mathematics as graph theory and as a theory for expressing the connection of things [20–22].

There are various types of networks. A network in which all nodes are linked to all other nodes is called a complete graph (Fig. 2. Left side). A graph in which whether or not a link is established between two nodes is random and the probability that a link is established is $0 < p < 1$ is called a random graph (Fig. 2. Right side). By the way, A complete graph is obtained when $p = 1$.

The number of links from one node to another node is called degree, and the average number of links from each node is called average degree. A triangle in which three nodes are connected to each other by a link is called a cluster, and the clustering coefficient is a value indicating how closely the nodes connected by the link are connected to each other. The clustering coefficient ($C_i$) is defined below as the ratio of the combination of the number of triangles that can be formed in each node and the number of links in that node [20].

$$C_i = \frac{2L_i}{k_i(k_i - 1)}$$

where $L_i$ is the number of links between $K_i$ adjacent nodes of node $i$.

Graph theory graphs include complete graphs, random graphs, scale-free networks, and small world networks.

Fig. 2  Left side: complete graph ($n = 10$), right side: random graph ($n = 10, p = 0.5$)
2.3.1 Scale-Free Network (SF)

A scale-free network is a network whose order distribution can be approximated by a power rule and is a graph showing the existence of extremely many connections with others, which is often seen in the real world, considering growth and priority selection. Barabási and Albert point out that the relationship between train and airplane transportation networks, as well as the Internet and homepage links, follows the rules [21].

Figure 3 shows a scale-free network generated using a scale-free generative model called the Barabási-Albert model. The major features of scale-free are the degree distribution according to the power law and the existence of a node called a hub with a large order. It consists of a small number of nodes with a large number of edges and a large number of nodes with a small number of edges. Nodes with a particularly large number of edges are called “hubs” and play an important role in scale-free networks. Also in this paper, we call nodes with a small number of links as “local nodes”. Figure 4 is a histogram of nodes and edges. You can see a large

![Image of scale-free network](image_url)

Fig. 3 Scale free network: $N=300$, Average degree = 1
number of nodes with a small number of edges (local nodes) and a small number of nodes with a large number of edges (hubs).

### 2.3.2 Small-World Network (SW)

The small world network is known for the small world phenomenon of six degrees of separation [20] and is used to explain various networks in human relations and the natural world [20].

As for the small world, it is well known that the world is surprisingly small, such as Milgram’s postal experiment [20] and Six Degrees of Kevin Bacon (https://oracleofbacon.org/).

The characteristics of the small world network are that the shortest distance is short even if the number of nodes is large, and that there are many relationships with the inner circle in terms of human relationships.

Figure 5 shows a small world network generated using a small world generative model called the Watts–Strogatz model. Figure 6 is the histogram of Fig. 5. In the small world network, unlike the scale-free network, you can see a small number of nodes with a small number of edges and a large number of edges, and a large number of nodes with an average edge.

In this research, we perform a simulation using a random network, a scale-free network, and a small world network.
3 The Simulations

3.1 Trust–Distrust Model

First, the calculation results using the Trust–Distrust model of Ishii 2019 are shown (Fig. 7). In this simulation, $N = 300$, the agent network is a random network with a link connection probability of $50\%$, the initial value of the opinion is $\pm 30$, and the confidence coefficient $D_{ij}$ between 300 people is a random number between $-1$ and 1. The mass media effect $A(t)$ is set to zero.

The graph on the right side of Fig. 9 shows that people’s opinions are scattered into positive and negative categories. The left graph shows that the ratio of positive to negative opinions is approximately 50:50. Although the distribution is uniform, the center graph shows the existence of several opinion groups.

Fig. 5 Small World graph ($n = 300, k = 4, p = 0.1$)
3.2 Agent Categorization

One type of agent is used in the simulation in Ishii 2019, but agents are categorized into five and used in the simulation in Fujii Ishii [5, 6] (Fig. 8).

The adoption speed of innovation in each category will be put into the simulation with the time difference you see, using hyperbolic tangent (Fig. 9). The agent envisions a model that will participate in the simulation sequentially in the middle of the simulation.

Fig. 6 Histogram of nodes and edges in Fig. 5

Fig. 7 The calculation result of $N=300$. The human network is a random network with a link connection probability of 0.5. The left figure shows the evolution of the trajectory of opinions. The figure on the right shows the distribution of opinions at the end of this calculation. $D_{ij}$ is randomly set from $-1$ to $1$ so everyone trusts or distrusts everyone. Mass media effects are considered to be zero ($A(t) = 0$).
3.3 Simulation 1: Basic

Here, a simulation is performed using the Trust–Distrust model of a one-category agent that applies a random network, a scale-free network, and a small world network.

3.3.1 Simulation Using Random Network

The simulation result of applying the random network to the Trust–Distrust model is shown (Fig. 10). In this simulation, \( N = 300 \), the agent network is a random network with a link connection probability of 30\%, the initial value of the opinion is ±30, and the confidence coefficient \( D_{ij} \) between 300 people is a random number between −1 and 1. The mass media effect \( A(t) \) is set to zero. Although some opinion groups can be confirmed from the simulation results, the opinions are uniformly distributed positively and negatively. Moreover, since the mass media effect \( A(t) \) is set to 0, there is no bias and the positive and negative values are roughly balanced.
3.3.2 Simulation Using Scale-Free Network (SF)

The calculation result of applying SF ($N=500$, Average degree = 1) to the Trust–Distrust model of one agent is shown (Fig. 11). Except for the network structure, it is the same as the simulation with a random network. Checking the line graph on the right side of Fig. 11, the simulation is completed without changing the composition ratio, with the positive line remaining positive and the negative line remaining negative. Again, some groups can be found from the opinion distribution of the simulation results, but the opinions are uniformly distributed positively and negatively.

3.3.3 Simulation Using Small-World Network (SW)

The calculation result of applying SW ($n=300$, degree ($k$)=4, connection probability ($p$)=0.1) to the Trust–Distrust model with one-category agent is shown (Fig. 12). Again, Except for the network structure, the settings are the same as for the simulation using a random network. People’s opinions are uniformly distributed positively and negatively, but some opinion groups can be found.
3.3.4 Comparison of Simulation 1

At first glance, the three simulation results look the same, such as positive–negative balance and a uniformly distributed opinion. However, the difference between the three simulations can be seen in the widening of the tail of the data distribution. The spread of the hem is widening in the order of SF, SW, and random network. Positive and negative opinions seem to be determined by the initial value of the opinion, but it is thought that the ease of interaction between agents affects the spread of opinions.

3.4 Simulation 2: Basic with Advertising Variables

In the simulation 1, the advertising effect variable \( A(t) \) was calculated as zero, but here, \( A(t) \) is set to 3 and the simulation biased in the positive direction is executed. The settings other than \( A(t) \) are the same as in Simulation 1.
3.4.1 Simulation Using Random Network

A simulation in which \( A(t) = 3 \) is added to the simulation of the random network in simulation 1 is shown (Fig. 13). Since the bias is applied in the positive direction, the positive ratio increases with each step of the simulation. At the 15 steps where the simulation was completed, the result was 77% positive and 23% negative.

3.4.2 Simulation Using Scale-Free Network (SF)

In the SF of Simulation 1, \( A(t) = 0 \) is set, but here \( A(t) = 3 \) is set and the simulation is executed (Fig. 14). Since this simulation is also biased in the positive direction, the positive ratio increases as the simulation progresses. It can be confirmed that the positive ratio has reached 80% in 5 steps. Since this simulation is also biased in the positive direction, the positive ratio increases as the simulation progresses. The majority have positive opinions, but there are still multiple opinion groups.
3.4.3 Simulation Using Small-World Network (SW)

A simulation was run with \( A(t) = 3 \) for the SW simulation in Simulation 1 (Fig. 15). Since this simulation also has a positive bias, the opinions become more positively biased as the simulation progresses. 6 steps in, we can see that the percentage of positives reaches 80%. The final result was 98% positive and 2% negative.

3.4.4 Comparison of Simulation 2

The random network has a different opinion distribution shape than the other network structures, while the SF and SW have similar results. These two network structures have more efficient communication penetration compared to the random network. It is speculated that the function of hubs in the network may boost the communication effect more.

3.5 Simulation 3: 5 Adapter Categories

Simulation with Trust–Distrust model with 5-adapter categories as agents, with random network, SF, and SW.

3.5.1 Simulation Using Random Network

This is a simulation of the Trust–Distrust model with 5 adapter categories applied to the agents and a random network as the network (Fig. 16). The number of agents is \( N = 1000 \), and the distribution of the number of agents in the five adopter categories follows Rogers [6]: Innovators: \( n = 25 \) (2.5%), Early Adopters: \( n = 135 \) (13.5%), Early Majority: \( n = 340 \) (34%), Late Majority: \( n = 340 \) (34%), and Laggards: \( n = 160 \) (16%). Each agent is dropped into the simulation with a time lag, as shown in Fig. 9. The initial value of the innovator’s opinion that is first dropped into the simulation is set in the range of ±30, while the initial values of the other agents are set to zero. The mutual trust coefficient \( D_{ij} \) between agents is determined by a uniform random

![Fig. 16](image_url) Calculation result of \( N = 1000 \). The human network is a random network with a link connection probability of 0.5. The figure on the left shows the time evolution of the opinion trajectory of each adopter category (Red: Ninn, Light blue: Nea, Blue: Nem, Green: Nlm, Pink: Nlg). The central figure shows the distribution of opinions at the end of this calculation. The figure on the right shows the time-series change in the ratio of adopt (+) and reject (−), and red indicates adopt (+) and blue indicates reject (−). \( D_{ij} \) is randomly set from −1 to 1, so everyone trusts or distrusts everyone. The media effect is zero (\( A(t) = 0 \)) (color figure online)
number between $-1$ and $1$. The mass media effect $A(t)$ is set to zero, so there is no bias to bias opinions.

Thus, the ratio of positive to negative opinions at the end of the simulation is very close. Agents are also uniformly distributed, but again, some opinion groups can be identified. The adoption curve is S-shaped, which could not be observed in a simulation with only one category of agents, and is caused by the sequential dropping of five adopter categories of agents into the simulation.

### 3.5.2 Simulation Using Scale-Free Network (SF)

Here is a simulation with SF set up as a Trust–Distrust model network (Fig. 17). The parameter settings are the same as in the simulation with the random network, except for the network structure.

According to Rogers, early adopters are noted to function as opinion leaders, so hubs with many links (top 135) are set as early adopters. However, in this simulation, the ratio of positive and negative opinions is close, since the trust coefficient between agents is also set to neutral, including the communication effect variable. Although the agents’ positive and negative opinions are close, the majority of agents’ opinions are zero. This is a feature not seen in other simulation results.

### 3.5.3 Simulation Using Small-World Network (SW)

Here is a simulation with the SW set to a Trust–Distrust model network (Fig. 18). The parameter settings other than the network structure are the same as in the simulation with the random network.

In this simulation as well, the top 135 hubs with the most links are set as early adopters. However, in this simulation, we have not set any bias in the agents’ decision making, so the agents’ opinions are approximately equal between positive and negative.

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**Fig. 17** Calculation result of $N=1000$. The human network is a scale free network with average degree $=1$. The figure on the left shows the time evolution of the opinion trajectory of each adopter category (Red: Ninn, Light blue: Nea, Blue: Nem, Green: Nlm, Pink: Nlg). The central figure shows the distribution of opinions at the end of this calculation. The figure on the right shows the time-series change in the ratio of adopt (+) and reject (−), and red indicates adopt (+) and blue indicates reject (−). $D_{ij}$ is randomly set from $-1$ to $1$, so everyone trusts or distrusts everyone. The media effect is zero ($(A(t) = 0)$ (color figure online)
3.5.4 Comparison of Simulation 3

We set up 5 adapter categories for the agents and ran simulations with different network structures. In the three simulations, the ratio of positive to negative opinions is close. The major difference between the three simulations is the distribution of opinions. The distribution of opinions in the simulation with the random network was flatter (scattered around zero), while in the SF simulation it was more sharply distributed (data concentrated around zero). The opinion distribution in SW had a distribution in between them. It is thought that the difference in the distribution of opinions was caused by the fact that the interaction between agents differed from network to network.

4 Results and Future Challenges

Simulations were performed with the Trust–Distrust model with the adopter category as the agent, and random networks, scale-free networks, and small-world networks were applied and compared. In the simulations, the initial distribution of opinions and mass media effects were set and manipulated. It was confirmed that the SW tended to be more widely distributed than the SF, although not as widely as the random network. This implies that differences in the network structure cause differences in the dispersion of opinions. In addition to the advertising (exogenous) variables, the respondents’ own opinions are considered to be influenced by face-to-face information exchange and contact with others. The weight of mass media will increase. Fake and extreme opinions can be found on the Internet. It is highly likely that they will be greatly influenced by such things. There may be a risk of being influenced by propaganda.

The elucidation of the mechanism of opinion transition in the adoption category based on the Trust–Distrust model is useful for research on marketing and mass media, and we proposed a computational social science method that takes network
differences into account. However, the media influences on people’s decision-making are diverse, including mass advertising, digital advertising, and social networking services, and their influence is not uniform. The timing of people’s adoption also depends largely on the level of involvement of individual consumers but is assumed to be constant for the sake of convenience in this paper.

Remaining issues include heterogeneity of media effects, setting $D_{ij}$ for each adopter category, and constructing a model that takes seasonality into account. By resolving these issues, we hope to develop this research into a future study of marketing communications that makes use of opinion dynamics.

Acknowledgements This paper is based on joint research with Professor Akira Ishii of Tottori University at the webinar “Cross-sectional study group with economy and society” held by The Canon Institute for Global Studies (“CIGS”) in December 2021. This paper was originally intended to be co-authored, but due to his sudden death before the webinar, we were unable to co-author or even jointly report on the research. However, this paper has developed a discussion based on the knowledge about opinion dynamics gained under the guidance of Professor Ishii. I would like to express my deepest gratitude to Professor Ishii, who gave me great guidance throughout his career as a supervisor, and I pray for his soul from the bottom of my heart.

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