IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 16 October 2022, accepted 27 October 2022, date of publication 1 November 2022, date of current version 8 November 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3218719

RESEARCH ARTICLE

Multiagent Diffusion and Opinion Dynamics Model Interaction Effects on Controversial Products

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ABSTRACT When controversial products are introduced, effective promotion efforts and eventual public acceptance require consideration of multiple factors such as existing social network structures, numbers of pioneers and their locations, and appropriate methods for product information diffusion. These factors have been the focus of marketing, investment and other studies for many years, most recently in computer information science. Researchers are especially motivated to understand diffusion processes for new technologies and controversial products within and across social networks. While many product diffusion simulation models have been proposed, most suffer from assumptions of unchanging internal agent attitudes toward products, no opinion exchanges between agents, and non-significant relationships between agent internal opinion attitudes and diffusion thresholds. In this paper we propose an opinion dynamics model that assumes both agent interaction and changes in agent attitudes over time. Social psychology theory is used to explain interactions between opinion and diffusion dynamics, with changing agent attitudes and behaviors affected by interpersonal relationship factors. Simulations were used to study dynamic diffusion processes involving controversial products (e.g., vaccines and genetically modified foods) in different social networks. Results indicate that the proposed model accurately reflects several kinds of social phenomena, including pioneer influences, rural marketing strategies, and the influence of social network structure. This effort to identify instances of product diffusion under various social conditions is offered in support of research in communication dynamics and social media-centered marketing strategies.

INDEX TERMS Opinion dynamics model, diffusion dynamics model, controversial products, social simulation, multiagent system, cognitive dissonance, theory of reasoned action.

I. INTRODUCTION

As E. M. Rogers notes in Diffusion of Innovations (1995), it is rare for large segments of social systems to agree on accepting new products or concepts [1], since product acceptance generally results from successive adoption events. This process entails a group of individuals who are willing to be the first to accept new and possibly controversial products or ideas—without their support, the odds of acceptance and successful dissemination are low. Pioneer quantity is considered key to product popularity and ease of promotion, with product diffusion rates rapidly increasing when the number of product adopters reaches a "critical mass," [2], [3] a concept based on Mancur Olson's Logic of Collective Action theory [4]. According to the idea of "perceived critical mass" proposed a decade later, the behaviors of individuals are affected by the number of friends who adopt the same behaviors [5]. When developing his diffusion of innovation theory, Rogers used this idea to define critical mass as the minimum number of users required to support innovative behaviors or products [1].

From a sociological perspective, individuals experiencing perceived critical masses are affected by a mix of objective facts plus normative influences that support recognition of

The associate editor coordinating the review of this manuscript and approving it for publication was Qiang Li.

TABLE 1. Comparison of critical mass and reasoned action theories.

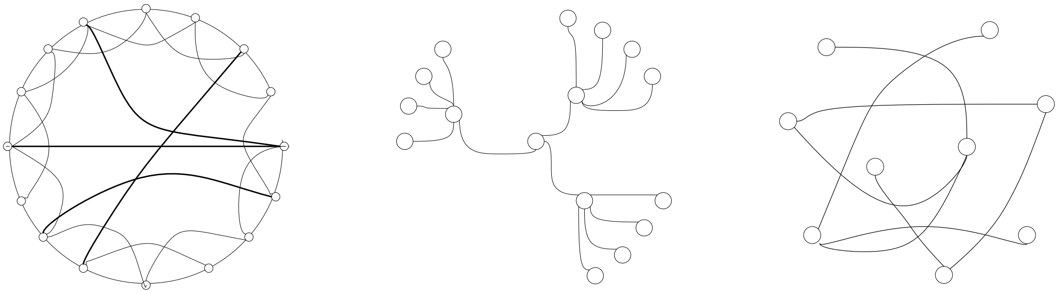
	Critical Mass	Reasoned Action
Theoretical Basis	Use long-term observations of social phenomena to locate time points at which product adopter numbers increase sharply.	Individual behaviors are determined by a mix of internal attitudes and external pressures.
Disadvantages	Researchers are limited to static observations of social situations. Dynamic interactions between individuals are not described in detail.	Researchers are limited to static evidence of individual potential to act at certain time points. Does not depict or explain the dynamic behaviors of individuals over time.

the expectations of others [6]. An economics concept similar to critical mass is "network externality," defined as the increasing consumption value or utility that occurs when user numbers increase [7]. According to Metcalfe's Law, network value (proportional to the square of the number of connected users of a system [8]) increases exponentially when user scale reaches a critical mass, thus attracting additional users. Common technologies such as telecommunications, fax machines, email platforms, websites, and apps such as Line and Facebook Messenger all reflect network externality [9]. Until recently, critical mass studies have required long periods of social observations and the use of questionnaires to collect indirect information on the psychological states of individuals. Today it is possible to apply social simulation tools (as we did for the present study) to observe dynamic changes in agent behaviors and attitudes in a manner that supports an understanding of technology, product, or concept acceptance, as well as subsequent effects under various social conditions [10].

For several decades social psychologists have used Fishbein and Ajzen's theory of reasoned action (TRA) to study the decision-making behaviors of individuals [11]. According to TRA, such behaviors are affected by a combination of internal attitudes and external subjective norms; Ajzen later added a volitional control factor when creating his theory of planned behavior (TPB) [12]. Davis et al.'s TRA-based technology acceptance model (TAM) considers ease of use and the utility of new technologies in determining new product acceptance [13]. Subsequent studies have generally been based on these models and theories, along with the addition of modifications and parameters deemed necessary for understanding decision-making behaviors [14]; a comparison is shown in Table 1. Since the details of behaviors and human interactions change over time, we added a social simulation tool from information science to create an agent-based model that includes a time axis. This supports an understanding of factors leading to the acceptance or rejection of controversial technologies, products and ideas.

Some researchers have used agent-based diffusion models to examine internal attitudes and external pressures in product adoption decisions [15], [16], [17], as well as when designing customizable simulation models capable of meeting the requirements of individual environments. However, almost all of these models suffer from the drawback of fixed agent attitudes toward products or concepts, regardless of agent interaction content or duration. Real world individuals must deal with internal attitudes and external pressures when examining controversial issues such as experimental vaccines and genetically modified foods. Such issues share at least three commonalties: a lack of consensus among experts, incomplete information, and inconsistent applications of existing data, recommendations, and predictions [18]. According to rational action theory [19], the behaviors of individuals are strongly affected by internal mentality (attitudes) and external social pressure (subjective norms). For this study we added an opinion dynamics mechanism when simulating changes in internal attitudes resulting from interpersonal communication. Regarding subjective norms, we also added a threshold model to simulate various levels of situationally determined social pressures [20] in order to simulate the dynamic interactive influences of attitudes and behaviors.

In this paper we describe a simulation model that more closely reflects real-world scenarios—that is, one that considers dynamic changes in internal attitudes and external pressures at different time points. Our proposed model can be applied to marketing and communication studies of product or concept diffusion involving long-term tracking for analyzing growth in the number of users or acceptors. However, research in this area is limited in terms of understanding the internal attitudes of consumers and the effects of opinion exchanges on acceptance rates. Since our model supports observations of interactions between opinion exchanges and product acceptance, simulation results can be used to identify which social conditions exert the greatest impacts on product acceptance. Our model can also be applied to social psychology and computer information science problems. Social psychologists can use it to observe interactions between psychological theories and to analyze the details of individual theories. Whereas computer information scientists



(a) Small world (b) Scale-free (c) Random

FIGURE 1. Illustrations of three complex networks.

are accustomed to simulating the diffusion of new products in the same manner as viral infections [21], our proposed model uses social psychology principles to consider the influences of internal attitudes and external social pressures. We expect that the model will evolve in step with new research on product diffusion.

Regarding the structure of this paper, in the following section we describe research efforts in the areas of artificial social networks, cognitive dissonance theory, opinion dynamics models, diffusion threshold models, and diffusion of innovation. In the third section we introduce the simulation model design, including equations, basic settings, relationship networks and their construction, agent attributes, experimental procedure, public opinion dynamic mechanisms, and related algorithms. Section IV discusses five sets of reference group characteristics: an external pressure threshold with a normal distribution, the geographic distribution or concentration of pioneers, high-controversy products, changing interpersonal networks, and impact degree. A conclusion is offered in the final section.

II. RELATED WORKS

Sociologists use network structure simulations to analyze social interactions [22], [23], [24], [25], with individuals represented as points or nodes and relationships as lines or links [26], [27], [28]. Since individual, group, societal and national social networks are complex (with relationships involving friendliness, hostility or neutrality), we incorporated two social network definitions: (a) a specific connected network of individuals with a structure that influences social behaviors [29], and (b) a group of social actors (individual or collective) with special ties reflecting different levels of cooperation or opposition [11], [30], [31], [32].

Researchers generally agree that all social networks consist of a minimum of three elements:

- Points (actors) with network-specific roles, meaning that social networks can break down when actors leave for any reason.
- Links indicating relationship content, direction, or strength. Content can be organized as one of eight directional or non-directional categories: family affection, social role, emotion, cognition, action, flow, distance, or co-occurrence [33]. Strength can be assessed as duration, depth of conversation, or degree of familiarity, among other measures.
- Actors with ties indicating more than one relationship type [34]. For example, ties between actors who are both classmates and friends can be individually classified as weak or strong [35].

Sociologists frequently use two concepts for their network analyses: degree of separation, referring to the average shortest path length between any two points, and clustering coefficient, used to measure the degree to which graph nodes tend to gather. Two characteristics of social networks are high degree of clustering and low degree of separation. For many years only two types of artificially constructed networks were considered—regular and random—but today's researchers also work with small world and scale-free networks. Watts and Strogatz's small world network has been characterized as having qualities between regular and random networks [36], [37], and Barabasi's scale-free network features a power law distribution of branch degree [38]—Facebook and other social media are said to have this characteristic (Fig. 1). Our focus in this study is on small world networks because they more closely resemble real-world networks in terms of high degree of clustering and low degree of separation.

A. SMALL-WORLD NETWORKS

Fig. 2 shows the small-world network creation process, starting with a regular network consisting of n nodes and k degrees of connection. Each network edge has potential for breaking off and reconnecting to a randomly selected network node—a process resembling real-world social networks. Determining whether the resulting network is a small-world type requires verification of a high degree of clustering and low degree of coefficient separation. Within a society designated as G, v_i denotes network nodes and k_i their respective degrees, C(v_i) the clustering coefficient of each node, and *Ei* the number of edges connecting all *vi* neighbors. C(v_i) is defined as E_i divided by $k_i(k_i - 1)/2$, and network clustering coefficient C(G) is defined as the average C(v_i) value for all nodes. Each

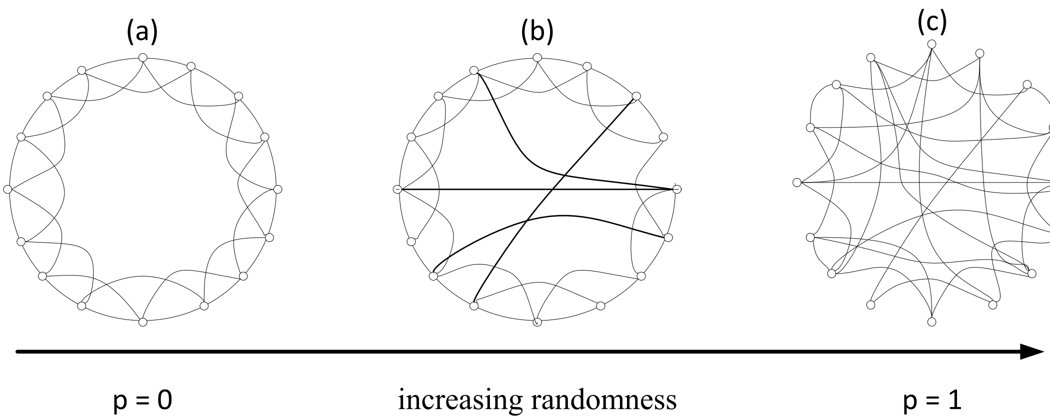


FIGURE 2. Small world network evolution: (a) regular, (b) small world, (c) random.

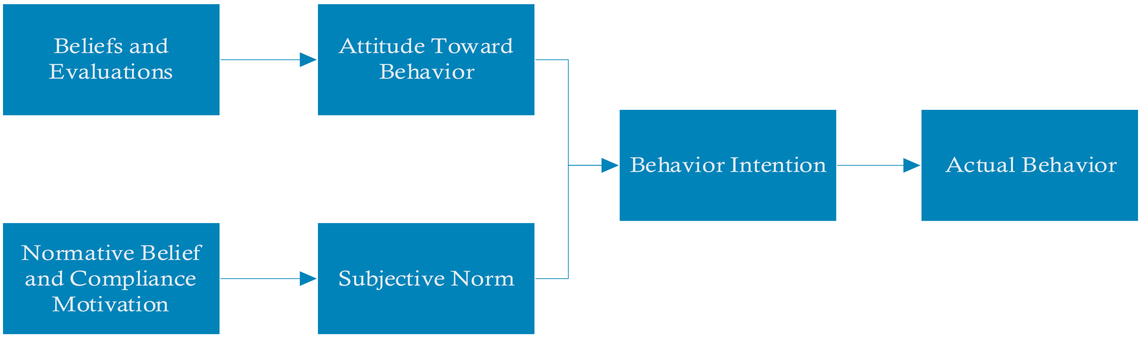


FIGURE 3. Theory of Reasoned Action model diagram.

$C(v_i)$ clustering coefficient is expressed as

$$C(v_i) = (2E_i)/(k_i(k_i - 1)) \tag{1}$$

with $S(v_i, v_j)$ representing the shortest path between any two points v_i and v_j, and S(G) the separation coefficient for the entire network—that is, the average of the shortest paths between any two points in the network [39], [40].

B. COGNITIVE DISSONANCE AND THEORY OF REASONED ACTION (TRA)

Social psychologists study the behavioral adjustments of individuals in situational contexts [41], [42]. When analyzing the impacts of group processes on individual decisions, their observations and research methods focus on social perceptions (personal attributes, attitudes, and changes in attitudes) and social influences (including the ideas of conformity and compliance, among others). The social psychologist Leon Festinger (best known for his theories of cognitive dissonance and social comparison) observed that most people see themselves as rational individuals, therefore when they perceive that their behaviors are viewed as unreasonable or worse, they are likely to take one of four actions: change their behavior to become consistent with other's thoughts; change the dissonant thought to restore consistency; add other consonant thoughts that justify or reduce the importance of the dissonant thought, thereby diminishing inconsistency; or trivialize the inconsistency, making it less important and less relevant [43], [44]. According to Festinger's theory, individuals are likely to change their attitudes (including rationalization) to resolve dissonance associated with perceived inconsistencies. We used this theory when defining simulation parameters as part of our examination of interactions between behaviors and attitudes, the effects of cognitive dissonance, and consequent adjustments.

TRA assumes that behaviors are determined by intention, which in turn is determined by a combination of inner attitude and subjective norms [11]. A structural diagram of the TRA operational mode is shown in Fig. 3. Definitions for its component parts include

1. Behavioral intention, referring to the strength of an individual's intention to perform a certain behavior. When looking at the relationship between intention and actual behavior, the latter is measured in terms of the former and labeled as "intention mode."

2. Attitudes toward behaviors, referring to an individual's perception of behaviors being good/bad or positive/negative. Attitudes toward specific behaviors are affected by beliefs and evaluations that are generated during execution.

3. Beliefs that executing certain behaviors will produce specific results.

4. Evaluations of behavioral results. Note that the attitude of individual A regarding a specific behavior equals the sum of behavior belief and result evaluation—expressed as $A = \Sigma b_i e_i$, with b denoting beliefs and e evaluation.

5. Subjective norms (SN), meaning perceived social pressures when engaging in certain behaviors. SN is determined by a mix of normative beliefs and compliance motivation, expressed as SN$= \Sigma m_i n_i$, with n denoting normative beliefs and m the compliance motivation.

6. Normative beliefs, referring to the influence of a social environment on individual behavioral intentions—that is, an individual's perception regarding the extent to which others who are important to them believe they should or should not perform particular behaviors.

7. Compliance motivation, meaning degree of individual compliance in reaction to the opinions of other individuals or groups.

In addition to social issues, several researchers have confirmed the ability of TRA to predict and explain why users are likely to adopt new information systems, specifically in research fields that emphasize technological acceptance [13]. Examples include the use of TRA to predict the acceptance of genetically modified foods and to analyze the weights of various factors affecting individual behaviors [45].

C. OPINION DYNAMICS MODEL

Researchers use multi-agent opinion dynamics models to simulate opinion exchanges [46], [47]. Such models encode opinions as real number ranges with sets known as opinion spaces—some continuous ([0, 1]), others discrete ($\{-1, +1\}$). Agents who are connected according to a model's social network structure have opportunities to exchange opinions. Individual agents are given inner opinion values during model initialization, after which opinions are exchanged according to one or more rules (note our interchangeable use of "agent attitude" and "agent opinion"). Models then show changes in group opinion dynamics that produce consensus, polarization, or dispersion. An important limitation of the bounded confidence (BC) model [48] is that only agents with similar opinions communicate with one another, with communication automatically stopping when opinion differences exceed a threshold. The Hegselmann-Krause (HK) [49], [50], [51], [52] model expresses opinion value as a real number with a [0, 1] interval, with the uncertainty ε parameter synonymous with bounded confidence in the BC model. During each round of communication, evolving agent opinions represent the average of all opinions held by friends. The continuously repeated simulation process supports observations of opinion distributions. Since the HK model does not have an interpersonal relationship network structure, any two agents can exchange similar opinions.

Several extensions have been added to the BC model, including social structure, dynamic networks [53], and multi-issue communication dynamics [54]. These additions support model applications to scenarios involving mass media [55] and the spread of extreme opinions [56]. The relative agreement model (RA, sometimes referred to as the D model) was created to study the prevalence of extreme opinions [57]. There are two important differences between the RA and HK models: RA opinion spaces are defined as $[-1, +1]$, and RA opinion exchanges are two-way, with both sides capable of modifying their opinions. For the opinion exchange process we randomly selected two agents. When the opinion distance between them is within the bounded confidence interval, they communicate opinions that are close to each other according to the following calculations [58]:

$$x_j = x_j + u_i(h_{ij}/u_i - 1)(x_i - x_j) \tag{2}$$

$$u_j = u_j + u_i(h_{ij}/u_i - 1)(u_i - u_j) \tag{3}$$

Agent i has an x_i opinion and u_i uncertainty; for agent j they are x_j and u_j, respectively. The bounded confidence interval between the two agents is denoted as h_{ij}. Accordingly, individuals change their opinions more frequently as their attitudes become more uncertain, reflecting real-life scenarios in which individuals who strongly insist on their own opinions are less affected by the opinions of others. When studying the spread of radicalism, the RA model includes both extreme and moderate agents, with the former characterized by low uncertainty. This is a very different assumption from the HK model, which treats all agents as moderate.

D. DIFFUSION THRESHOLD MODEL

Individuals are affected by personal experiences, impressions, prejudices, and social pressures [59]. Watts' threshold rule [36] states that individuals are likely to choose wrong answers to problems even when they are obviously wrong, as long as they perceive agreement from a threshold number of others. According to a comparison of reasoned action theory and the diffusion threshold model shown in Table 2, the theory's subjective norms are affected by a combination of normative beliefs and compliance motivation corresponding to the number of neighbors and threshold values found in the model [60].

E. DIFFUSION OF INNOVATION

Technology adoption research can be traced to a 1960 survey of community group responses to innovative technology products [61]. Subsequent technology adoption life cycle studies have distinguished among different times of adoption, resulting in curves approximating normal distributions (Fig. 4) [62]. Adopters are now categorized as innovators, early adopters, early majority, late majority, or laggards [69], each with different personality traits. Early adopters have positive attitudes toward change, new ideas, and innovative products. Significant effort is being made to determine how to best use the internet to communicate the benefits and advantages of innovative products to early adopters as an initial step in the diffusion process [63], [64].

TABLE 2. Comparison of reasoned action theory and a diffusion threshold model.

	Reasoned Action	Diffusion Threshold
Normative Beliefs	Refers to social environment influences on individual behavior intentions—i.e., certain actions that most others believe one should adopt.	Increased external belief that one should engage in behaviors as more friends adopt them.
Compliance Motivation	The degree to which individuals follow the opinions of others.	Stronger individual responses to others' opinions indicate lower external pressure thresholds and greater likelihood of being influenced by those opinions.

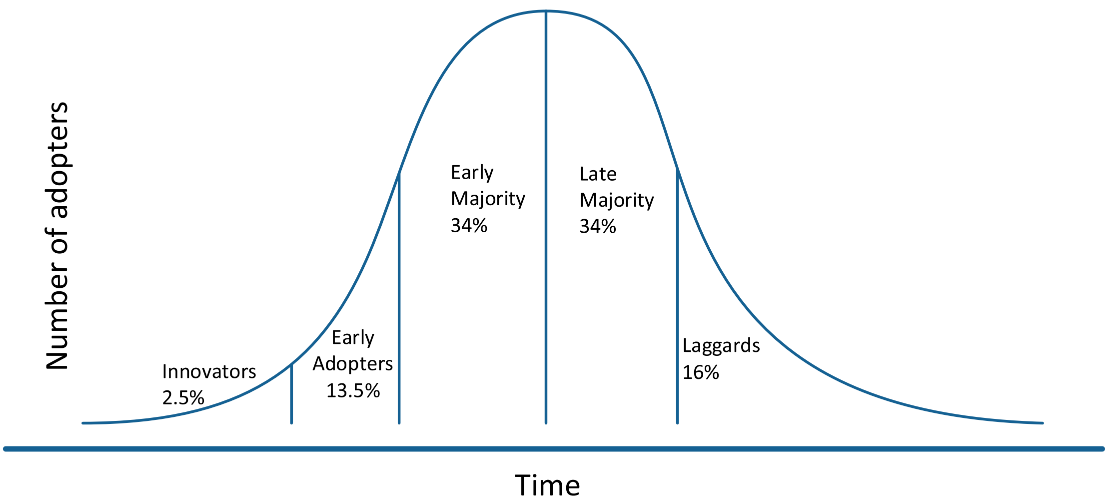


FIGURE 4. Technology adoption life cycle [62].

Technology markets for innovative high-tech products can be categorized as early (innovators and early adopters), mainstream (early and late majority) and late (laggards) (Fig. 5) [65], [66], [67]. Marketers view the gap between early and mainstream markets as problematic—some new technology products adopted by innovators fail to grab the attention of users in other categories. Success in bridging this gap can determine product acceptance and profitability [68],, but the task requires a thorough understanding of differences between early and mainstream markets in order to identify and successfully execute gap-bridging strategies. Some companies purposefully pursue a strategy of identifying technology innovators and helping them express their approval to early adopters. The motivations are to build early majorities, trigger maximum turnover in mainstream markets, and earn recognition as maintainers of product standards. When product sales enter the mainstream stage, marketers must consider the influence of market contrarians [69], [70].

F. GAPS BETWEEN AND WITHIN EXISTING STUDIES

Innovation diffusion studies have been performed with Fishbein and Ajzen's TRA, Ajzen's TPB, Davis et al.'s TAM, and decision-making behaviors [11], [12], [13], [14]—all discussed in an earlier section. However, social science studies require large amounts of data collected over long time periods, often with questionnaires designed to gather information on peoples' internal feelings. Data frequently reflect specific decision-making behaviors within limited time frames. Since individuals tend to continually adjust their attitudes based on opinion exchanges over time [71], time point-focused data collection methods such as questionnaires frequently produce data that do not accurately portray opinion dynamics. To address this shortcoming, some computer science researchers apply agent-based and network-oriented simulation approaches to measure the effects of various factors on decision-making behaviors [49], [57], [72].

A number of computational social science researchers have experimented with opinion dynamics and adoption threshold models of innovation diffusion to examine opinion exchanges and consensus formation [36], [49], [57], [73]. However, many opinion dynamics model studies emphasize agent opinion exchanges without discussing follow-up actions, and many adoption threshold model studies only address individual decisions that depend on proportions of friend and

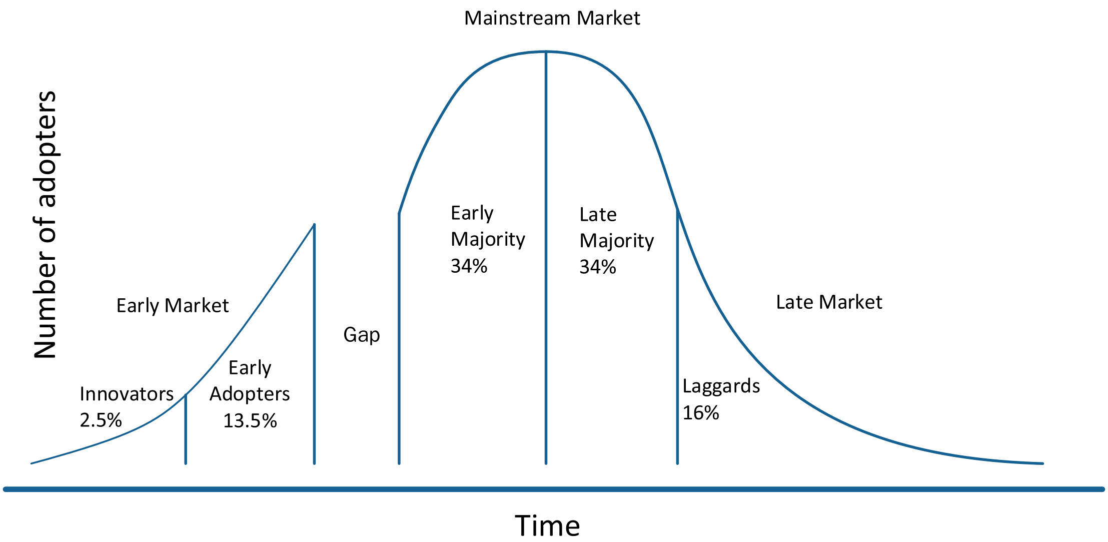


FIGURE 5. Technology adoption life cycle model and market phases [65], [66], [67].

neighbor outcome behaviors, without considering opinion differences in internal agent attitudes. To our knowledge, no attempts have been made to combine the two model types when simulating opinion exchanges and observing their effects on decisions and agent actions. Our motivation in this paper is to combine the two in order to achieve a broader understanding of opinion exchanges and product acceptance.

III. MODEL DESIGN

Definitions for all system parameters and agent attribute values discussed in this section are given in Table 3.

A. EQUATIONS MODEL DESCRIPTION AND BASIC SETTINGS

The experiment design was based on four assumptions:

1. All social communication occurs within small-world networks.

2. All individuals have their own positive, negative or neutral opinions that influence the adoption or rejection of controversial products and issues.

3. Based on cognitive dissonance theory, individuals who adopt controversial products or ideas only exchange opinions with agents who are equally or more accepting of them, thus increasing the positive strength of the initial agent's opinion.

4. Individuals with negative attitudes never consider adopting controversial products.

B. BUILDING RELATIONSHIP NETWORKS

An artificial society based on $N \times N$ 2D cellular automata with a toroidal structure was created (Fig. 6). As stated above, small-world networks resemble human networks in terms of high clustering, low separation, and normal connectivity distribution [21]. To increase the clustering degree, we used the Moore model [74] to add links to neighbors surrounding each node. To achieve low separation, we re-wired all connections according to a probability calculated as $\{x|x \in \mathrm{Q}, 0 < x < 1\}$.

C. SETTING AGENT ATTRIBUTES AND EXPERIMENTAL PROCEDURE

A single-issue model served as the basis for the main experiment. These kinds of issues—for example, acceptance/rejection of COVID-19 vaccines or genetically modified food—are the most likely to trigger opinions and attitudes ranging from 0 (extremely negative) to 100 (extremely positive). In our simulations, individual agents were given values for four characteristics: attitude (att), meaning internal evaluation of an idea or product; bounded confidence (d), a determinant of ongoing communication between two agents; external pressure threshold (u_threshold), a conformity indicator (i.e., whether an agent adopts a product/idea due to the number of friends who adopt it); and action (action), indicating whether an agent has adopted a product/idea, after which it only communicates with agents holding a similar positive opinion.

The experiment consisted of three stages:

1. Initialization, meaning the establishment of a small world network and its agents. After setting the att, d, u_threshold and action parameters, a small number of positive pioneers who had already adopted the product were added. According to our proposed model, pioneers can be randomly scattered throughout a social network, or concentrated in one or more areas.

2. Opinion exchanges, all implemented in accordance with RA model rules [36]. Two agents with attitudes within a predetermined bounded confidence range can communicate and modify their opinions to be closer to each other. After randomly selecting a friend from a network, each agent

TABLE 3. System and agent parameters.

Parameter	Type	Description	Range	Interval
no-pioneers	integer	Number of pioneers.	[0, 100]	1
clustered-pioneers	boolean	Whether pioneers are clustered.	true/false	
max-opinion-distance	integer	Communicable range indicating whether agents can tolerate differences in friend attitudes. The larger the range, the greater the agent tolerance. Smaller ranges indicate conservative or exclusive perspectives.	[1, 100]	10
convergence-rate	real	Proportion of agents moving toward each other.	[0.1, 1.0]	0.1
avg-attitudes	integer	Public evaluation of an issue or product. Larger values indicate more positive attitudes.	[1, 100]	10
std-attitudes	integer	For normally distributed agent attitudes, larger SD values indicate more dispersed public opinions.	[0, 30]	5
avg-thresholds	integer	An agent conformity measure. Larger values indicate greater societal conservatism and caution. Lower values indicate more openness and willingness to take risk.	[1, 100]	10
std-thresholds	integer	For normally distributed agent thresholds, larger SD values indicate greater differences in public personality traits.	[0, 30]	5
max-time	integer	Maximum simulation iterations.	[50, 1000]	300
iterations	integer	Individual experiment iterations.	[10, 1000]	100
att	integer	Agent evaluation of a product.	[0, 100]	1
d	integer	Bounded confidence interval.	[0, 100]	1
u_threshold	integer	Agent conformity.	[0, 100]	1
Action?	integer	Boolean value indicating whether an agent has adopted a product.	true/false	
Ready?	Integer	Boolean value indicating whether the opinion values of two agents are within the bounded confidence interval.	true/false	

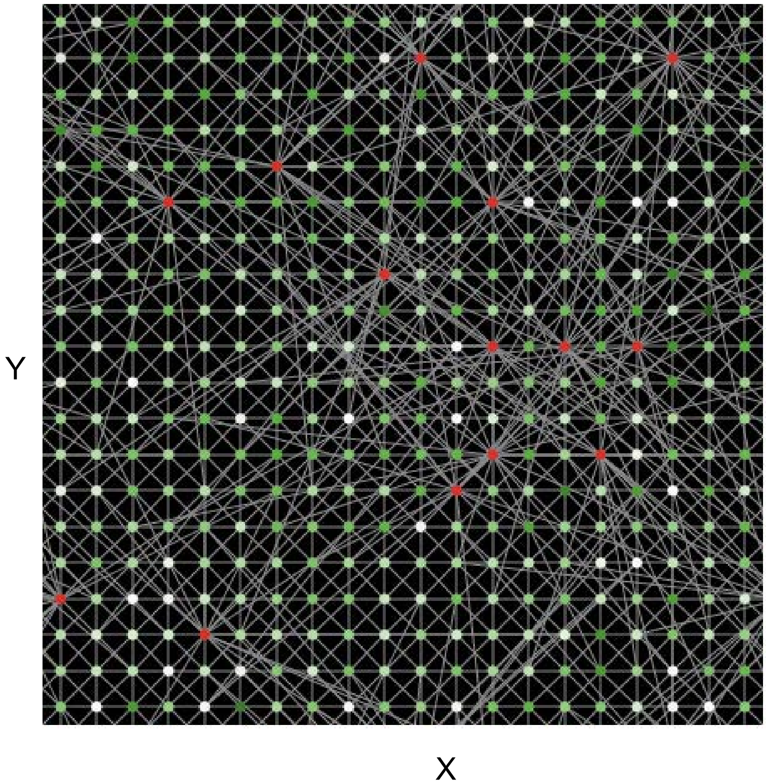


FIGURE 6. Two-dimensional representation of circular cellular automata.

determines which behavior should be performed based on one of four conditions:

a. If the agent and friend reject the controversial product, they influence and adjust each other's attitudes as long as the distance between their opinions is within the bounded confidence interval.

b. If an agent has already adopted a product but the friend hasn't yet done so, and if the friend's opinion value is lower than the agent's, then only the friend's attitude value is affected by an exchange of opinions. If the friend's opinion value is higher than the agent's, the attitudes of both are influenced by an exchange of opinions. Again, this is only true when the two parties' opinions are within the bounded confidence interval.

c. In situations where both parties adopt a product, if the friend's attitude value is higher but within the bounded confidence interval, then only the attitude of the original agent is affected. If the friend's attitude value is lower but within the bounded confidence interval, only the friend's attitude value is affected.

d. If the agent hasn't adopted the product but the friend has, and if the agent's attitude value is lower than the friend's but within the bounded confidence interval, only the agent's attitude is affected. If the agent's attitude is higher than the friend's, the attitude values of both parties are affected by exchanges of opinion.

3. Execution decision stage. According to rational action theory, agent behaviors are affected by a mix of internal attitudes and external social norms. The u_threshold parameter is defined as the threshold value for an agent to decide whether or not a product should be adopted. If the agent has a positive attitude and the number of friends who have already adopted the product is higher than the parameter u_threshold, the agent also adopts it.

D. PUBLIC OPINION DYNAMIC MECHANISM

Implementing this mechanism entails three parameters. For att, a range from 0 to 50 indicates a negative attitude and from 51 to 100 a positive attitude. For the bounded confidence interval, attitude values for two agents (as calculated in section II(C)) determine whether or not they have an opportunity to communicate; for additional agents, those with certain attitude values may be able to communicate with one or more agents but not with others. The third parameter, convergence, indicates the degree of opinion aggregation. In all cases the attitudes of two agents move closer to each other after exchanging opinions, as expressed in equation 4,

$$x_i = x_i + \text{convergence} \times (x_j - x_i) \tag{4}$$

where x_j denotes the attitude of agent j, x_i the attitude of agent i, and convergence the system parameter convergence rate.

TABLE 4. One-way persuasion and two-way communication scenario descriptions discussed in section III(e).

<table>
<tr><th>Agent_i / Agent_j</th><th colspan="2">Not adopted</th><th colspan="2">Adopted</th></tr>
<tr><td>Not adopted</td><td colspan="2">Two-way communication (Case 1)</td><td>One-way persuasion (Case 2)</td><td>Two-way communication (Case 3)</td></tr>
<tr><td>Adopted</td><td>Two-way communication (Case 4)</td><td>One-way persuasion (Case 5)</td><td colspan="2">One-way persuasion (Case 6 or 7)</td></tr>
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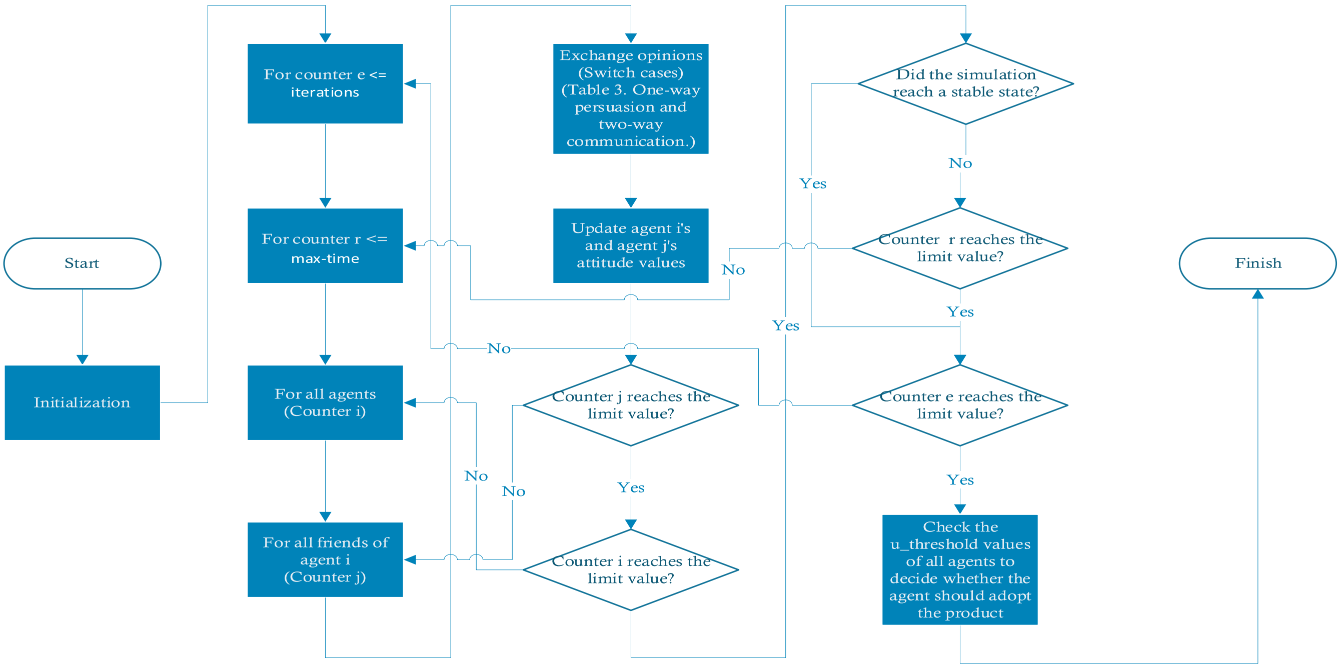

FIGURE 7. Algorithm flowchart.

This study looks at two types of communication. One-way communication occurs when an agent has already adopted a product and a friend has a lower attitude value; in those cases the agent's attitude is not affected even if their attitude values are within the bounded confidence interval. According to cognitive dissonance theory, the friend's attitude becomes slightly more positive in such situations. Illustrations of one-way and two-way communication timing are presented in Table 4.

E. ALGORITHMS AND PSEUDOCODE

A flow chart depicting the algorithm process is presented as Fig. 7. The following pseudocode is for the model design and algorithm for simulating the evolution process:

1. Build a social network
**Each highly abstract real society is represented as a network. In the network model, all individuals are shown as nodes. Edges between nodes indicate interactions/relationships between social individuals.*
**Set the network to one of four types: regular (cellular automata, CA), random (RN), small world (SWN), or scale-free (SFN).*
(Set system parameter "Network_type" as SFN/SWN/CA/RN with "Rewiring_probability.")
**Initialize all agent attributes (agent.att, agent.d, agent.u_threshold, agent.Action?, agent.Ready?)*
2. Initialize system parameter "no-pioneers," "clustered-pioneers," "max-opinion-distance," "convergence-rate," "avg-attitudes," "std-attitudes," "avg-thresholds,"

"std-thresholds," "max-time," and "iterations." For system parameters see descriptions in Table 4.
3. Perform opinion exchange and diffusion simulations:
Loop "iterations"
Loop "max-time":
For Agent_i in the social network:
For Agent_j as friend of agent i :
If(|Agent_i.att − Agent_j.att| <= "max-opinion-distance") then:
// Table 3. One-way persuasion and two-way communication.
Switch case: (Agent_i.Action? and Agent_j.Action?)
Case 1: (Agent_i.Action? == false and Agent_j.Action? == false)
Agent_i.att = Agent_i.att + convergence-rate(Agent_j.att – Agent_i.att);*
Agent_j.att = Agent_j.att + convergence-rate(Agent_i.att – Agent_j.att)*
Break switch;
Case 2: (Agent_i.Action? == true and Agent_j.Action? == false) and (Agent_i.att > Agent_j.att)
Agent_j.att = Agent_j.att + convergence-rate(Agent_i.att – Agent_j.att);*
Break switch;
Case 3: (Agent_i.Action? == true and Agent_j.Action? == false) and (Agent_i.att <= Agent_j.att)
Agent_i.att = Agent_i.att + convergence-rate(Agent_j.att – Agent_i.att);*
Agent_j.att = Agent_j.att + convergence-rate(Agent_i.att – Agent_j.att);*
Break switch;
Case 4: (Agent_i.Action? == false and Agent_j.Action? == true) and (Agent_i.att >= Agent_j.att)
Agent_i.att = Agent_i.att + convergence-rate (Agent_j. att – Agent_i.att);*
*Agent_j.att = Agent_j.att + convergence-rate *(Agent_i. att – Agent_j.att);*
Break switch;
Case 5: (Agent_i.Action? == false and Agent_j.Action? == true) and (Agent_i.att < Agent_j.att)
Agent_i .att = Agent_i.att + convergence-rate (Agent_j. att – Agent_i.att)*
Break switch;
Case 6: (Agent_i.Action? == true and Agent_j.Action? == true) and (Agent_i.att > Agent_j.att)
Agent_j.att = Agent_j.att + convergence-rate (Agent_i.att –Agent_j.att);*
Break switch;
Case 7: (Agent_i.Action? == true and Agent_j.Action? == true) and (Agent_i.att <= Agent_j.att)
Agent_i.att = Agent_i.att + convergence-rate (Agent_j. att - Agent_i.att)*
Break switch;
End switch case
End if then
End Agent_j as friend of agent i
End Agent_i in the social network
4. Agent decides whether to adopt the product:
For Agent_i in the social network:
IF (Agent_i.att >= Agent_i.u_threshold), then
Agent_i.Action? = True;

IV. SIMULATION EXPERIMENTS

Simulation experiments were grouped according to separate variables to determine their respective effects. The iterations parameter was set to 1000 and max-time to 300. The mainframe computer used in this project had an Intel® Core (TM) i7-8565U CPU @ 1.80GHz 1.99 GHz processor (16.0 GB RAM, x64-type) with an Intel® UHD 620 graphics card (Microsoft Windows 11 Pro Version 21H2). The software was written in NetLogo 4.0.5; source code is available from the corresponding author. The six simulation experiment groups are described in the rest of this section.

A. REFERENCE BENCHMARK EXPERIMENT GROUP

To ensure high clustering, low separation, and a normal degree of distribution (i.e., number of agent friends), "small world" was used as the default network for this group (100 × 100cellular automata with a re-wiring value of 0.3). The M=50, SD=25 att parameter indicates a moderate (non-extreme) public attitude toward a widely distributed product, while the constant value of 30 for opinion_distance (bounded confidence interval) indicates a conservative public attitude. For controversial issues or products there is greater likelihood that agents will only exchange strong opinions with friends holding similar opinions. Pioneers were initially distributed so as to avoid concentrations in certain areas. The u_threshold low-controversy product parameter was set to 30%, indicating a lower product adoption threshold—that is, agents adopted products when 30% of their friends used them. The u_threshold value for a separate high-controversy product was set to 50%—in other words, 50% of an agent's friends had to express support for a product before the agent considered adopting it.

Next, a simulation program was used to observe how many product adopters emerged from different pioneer percentages, with the numbers of final product adopters equal to average values obtained after 40 simulation rounds. Throughout the experiment we observed pioneer ratios at which the number of recipients increased significantly, indicating the speed at which a product became popular (i.e., achieved critical mass). The above-described settings were used to establish two types of product standards: low-controversy and high-controversy. These benchmarks were used to adjust social parameters for observing dynamic product spreading. As shown in Fig. 8, for low-controversy products (u_threshold = 30%) pioneer proportions of 6-8% were sufficient to trigger rapid product popularity. As shown in Fig. 9, for high-controversy products (u_threshold = 50%) the required pioneer proportion for a similar rapid expansion was 20%. According to the two figures, different adoption curves were produced depending on the degree of product or idea controversy. Low pioneer proportions were unlikely to trigger the rapid spread of a

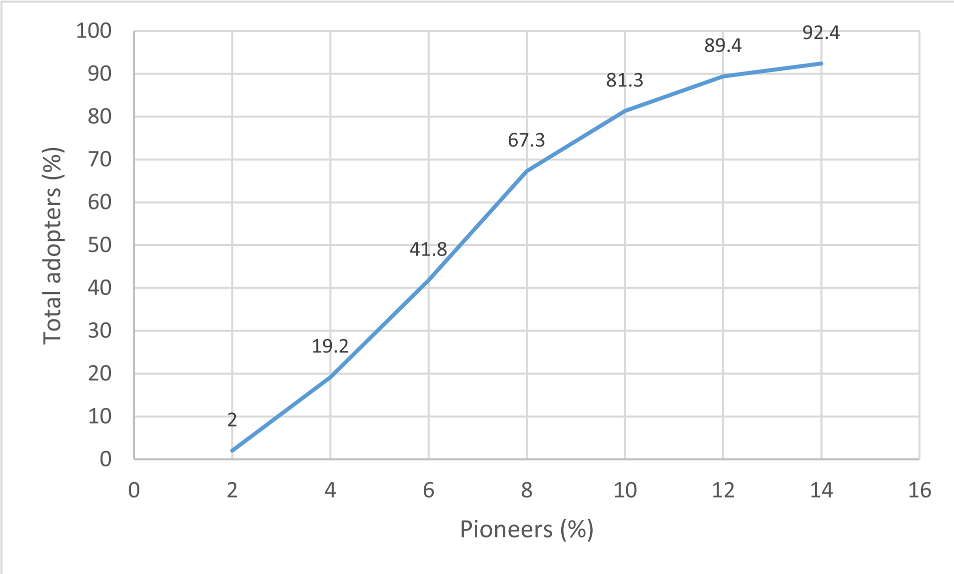

FIGURE 8. Simulation results for a low-controversy product benchmark in a small world network at a u_threshold of 30%.

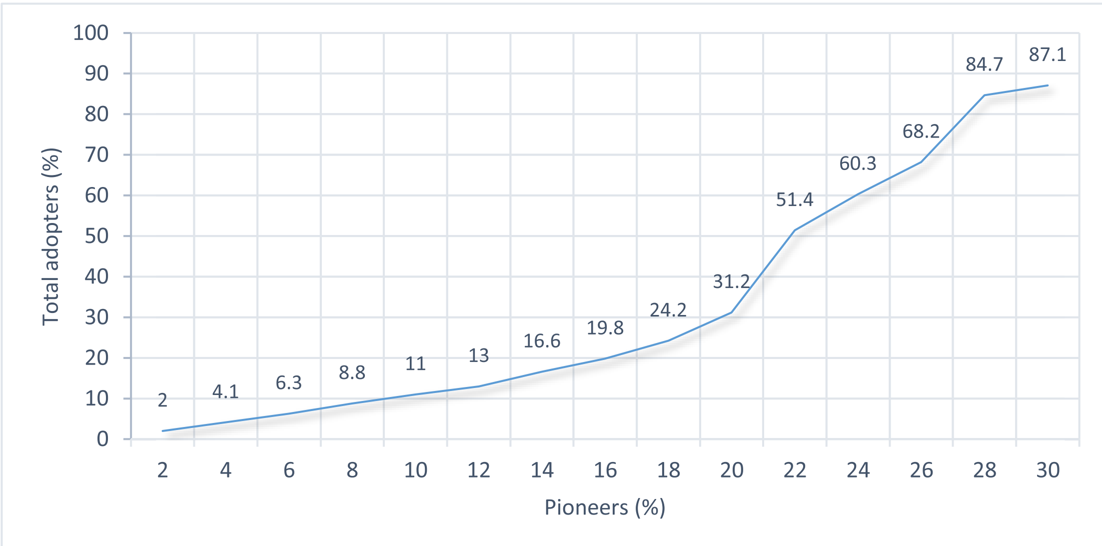

FIGURE 9. Simulation results for a low-controversy product benchmark in a small world network at a u_threshold of 50%.

high-controversy product, but a surprisingly small number of pioneers may have been sufficient to trigger the rapid spread of a low-controversy product. All subsequent results were compared to this benchmark experiment.

B. EXTERNAL PRESSURE THRESHOLD IN A NORMAL DISTRIBUTION

Since public doubts about controversial products tend to show normal distributions, we set the agent u_threshold parameter to normal with a 30% mean value (SD=10) for low-controversy products and 50% mean value for high-controversy products (SD=25). As shown in Fig. 10, for low-controversy products the diffusion rate for the normal threshold distribution curve was faster than for the constant threshold value. A normal threshold value distribution indicates a percentage of individuals with lower threshold values who are the first ones to be influenced when pioneer proportions are small. Since they increase the potential for product acceptance or adoption by a larger percentage of a population, the degree of diffusion will likely be much higher than in situations marked by a constant threshold value. Accordingly, when the proportion of pioneers grows to a medium or large size, the likelihood of a product spreading throughout a society increases sharply, even when agent thresholds remain constant. Stated differently, there is little difference in the total number or percentage of adopters when pioneer proportions

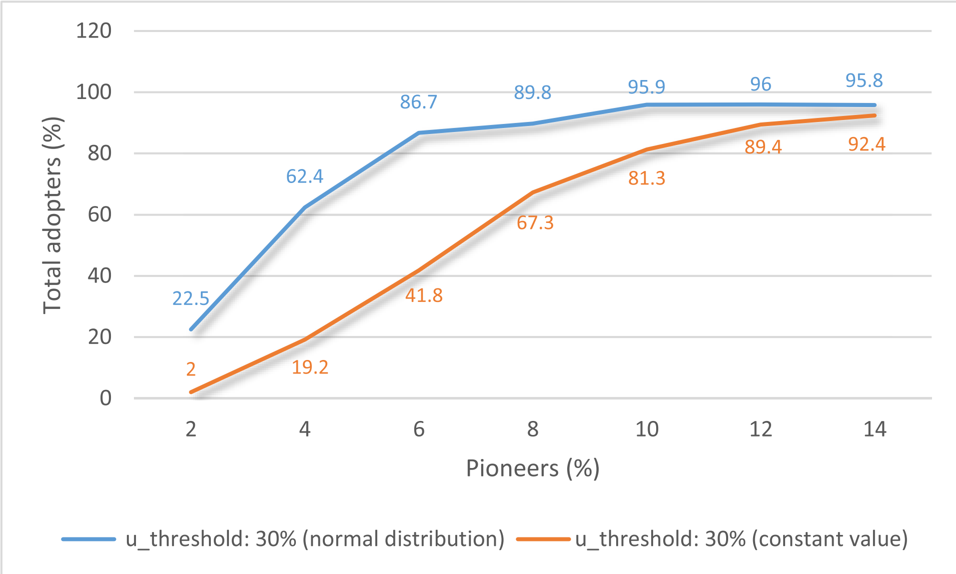

FIGURE 10. Small-world network simulation results for low-controversy products with a u_threshold of 30% (normal distribution) compared to a benchmark u_threshold of 30% (constant value).

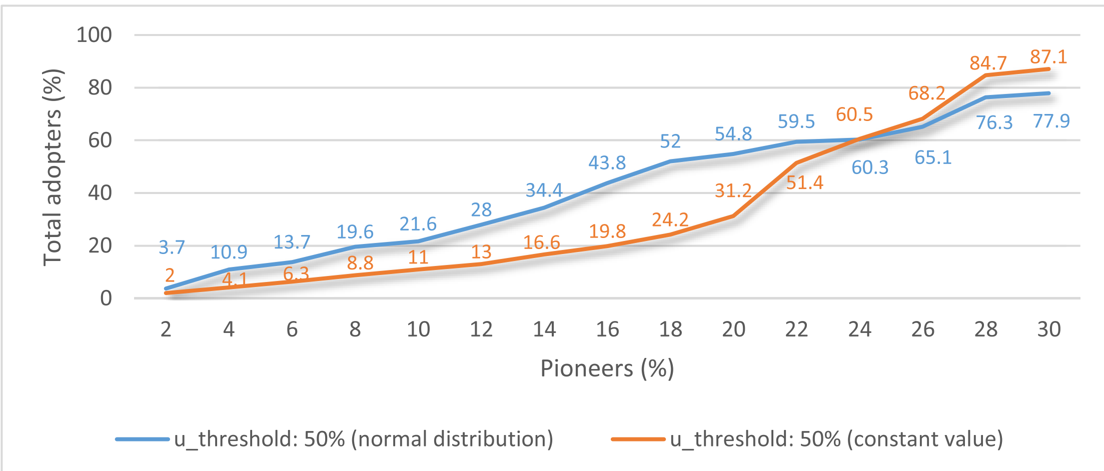

FIGURE 11. Small world network simulation results for high-controversy products at a u_threshold of 50% with a normal distribution compared to a benchmark u_threshold of 50% with a constant value.

are large, regardless of whether the pioneer threshold value is a normal distribution or a constant.

We analyzed a normal distribution with a 50% mean threshold value and SD=25 in three scenarios; results are shown in Fig. 11. At a <20% level of pioneers, a normal threshold value distribution indicated a higher number of agents who were the first to be influenced and the first to influence a large number of others. However, pioneers are not always capable of influencing low-threshold agents. If the agent threshold value is a constant, the degree of influence on others is exceptionally limited. In other words, when the proportion of pioneers is small and accompanied by a normally distributed threshold value, a stronger product diffusion effect occurs. Note that when the proportion of pioneers reached 21-24%, the number of adopters influenced a larger number of agents, even at a constant agent threshold—62.4% at a 24% pioneer percentage. A normal distribution threshold does not significantly support diffusion in such situations. When the pioneer proportion was >24% and the agent threshold value was normally distributed, diffusion did not benefit as much as when the threshold value was constant, since a normal threshold distribution indicated the presence of agents with higher threshold values who were not easily affected by pioneers. Looking at the end of the curve shown in Fig. 10, note that 100% diffusion was difficult to achieve when the threshold was a normal distribution due to the number of high-threshold agents—there was greater chance of reaching 100% at a constant threshold value of 50%. In short, when

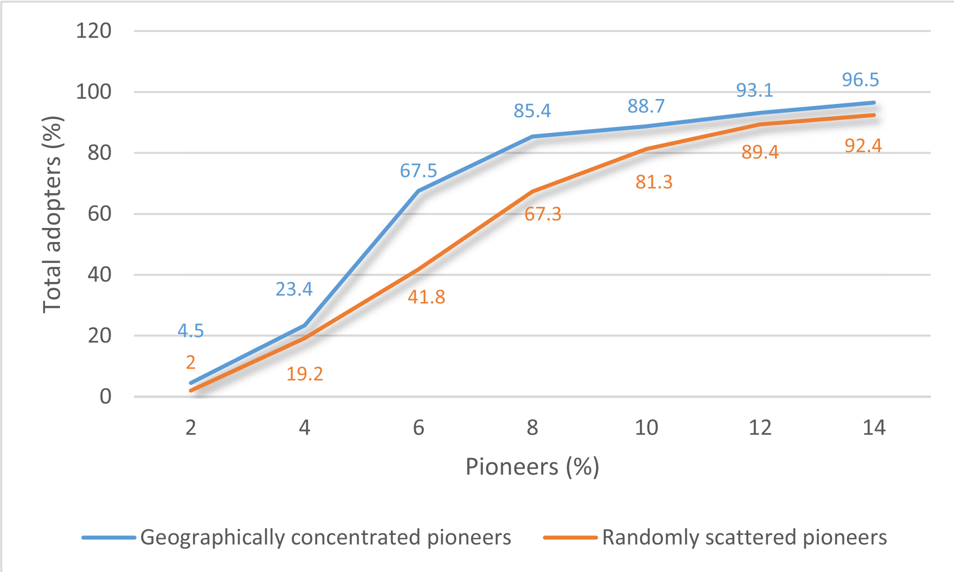

FIGURE 12. Small world network simulation results for low-controversy products (u_threshold = 30%) with either geographically concentrated or randomly scattered (benchmark) pioneers.

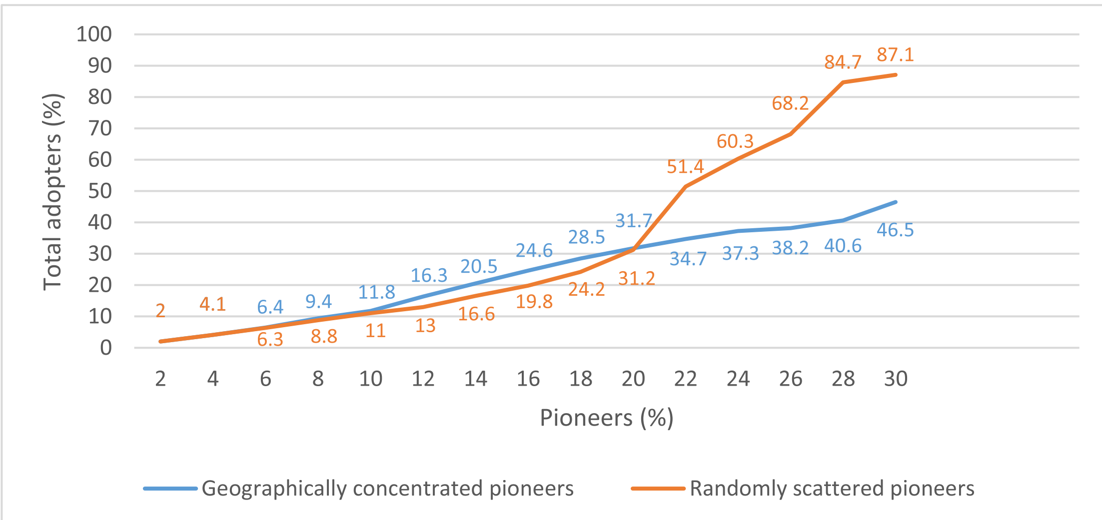

FIGURE 13. Small world network simulation results for high-controversy products with a u_threshold of 50% and either geographically concentrated or randomly scattered (benchmark) pioneers.

the number of pioneers was sufficiently large, diffusion was likely to be greater at a constant threshold.

C. GEOGRAPHIC CONCENTRATION OF PIONEERS

Marketers understand the potential benefits of concentrating pioneers in specific areas to develop a sense of product acceptance or popularity that can spread to other areas. We used simulations to examine this tactic at various pioneer concentrations. Fig. 12, which presents our results for low-controversy products, shows that concentrating pioneers in one area accelerated an increase in the number of adopters. The largest difference between adopter proportions in the two curves was observed at pioneer ratios of 6-8%, after which the two curves gradually converged.

A key pioneer proportion for high-controversy products (50% threshold) was 20%; below this level, few agents other than pioneers adopted them. Thus, the initial influence of pioneers on an overall population remained weak when they were concentrated in one area, but they were still likely to influence nearby agents. A sharp increase in the curve occurred when the pioneer proportion exceeded 20%. As shown in Fig. 13, the curve for scattered pioneers increased much more rapidly than the curve for concentrated pioneers, indicating that the former was more successful in terms of spreading their influence. Thus, the figure shows

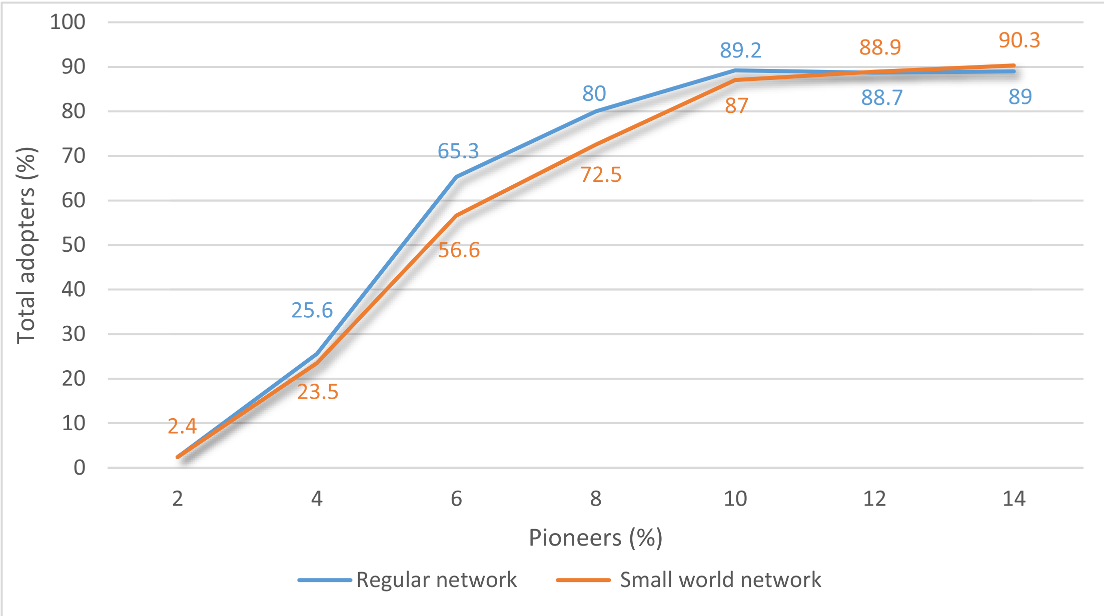

FIGURE 14. Comparison of regular and small world network simulation results for low-controversy products (u_threshold = 30%).

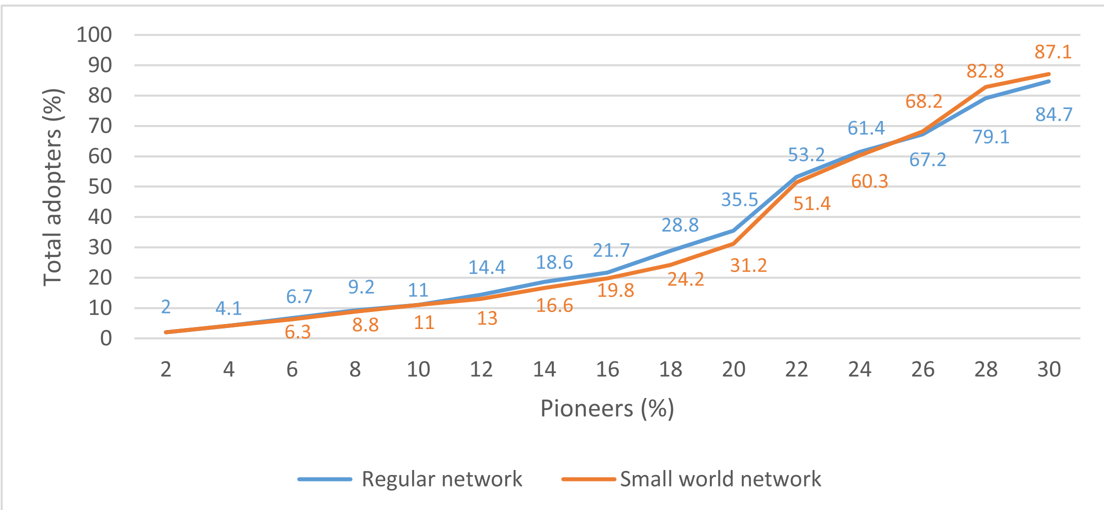

FIGURE 15. Comparison of regular and small world network simulation results for high-controversy products (u_threshold = 50%).

that diversifying the geographic locations of pioneers is a better strategy for building initial product popularity once the proportion of pioneers reaches a sufficiently high level.

D. CHANGE IN INTERPERSONAL NETWORK STRUCTURE

The focus of the above-described experiment was on small world network connections featuring high clustering, low separation, and normal agent degree distributions. We modified the experiment to better observe the impacts of social networks on the spread of controversial products. A regular network with high clustering and high separation characteristics was established; this type of model has been used to simulate the effects of various epidemic isolation policies, home-and-work movement and lifestyle changes, and degree of isolation (i.e., interactions limited to those occurring at home). Individuals in this type of network only interact with adjacent neighbors.

Our motivation was to observe the impacts of interpersonal relationship separation on product diffusion. According to the results shown in Figs. 14 and 15, similar curve trends were produced whether the threshold was high or low. At a low initial percentage of pioneers, the eventual number of adopters from the population of all potential adopters was higher than that produced by the small world network, indicating greater

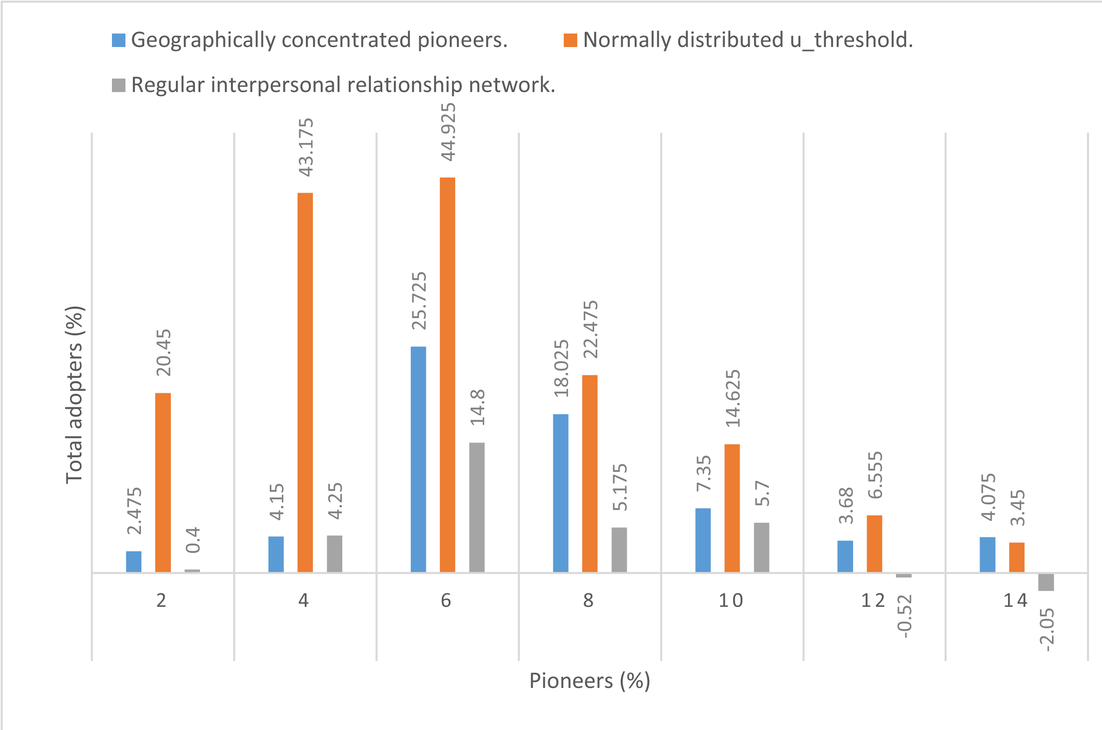

FIGURE 16. Comprehensive comparison chart for low-controversy products (u_threshold = 30%).

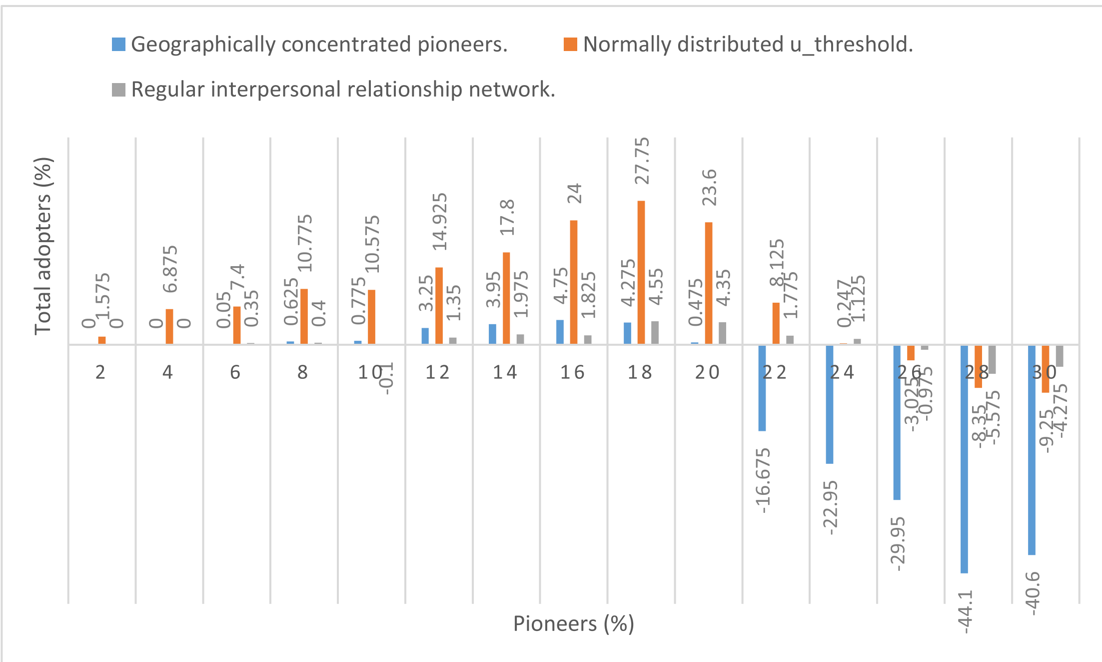

FIGURE 17. Comprehensive comparison chart for high-controversy products (u_threshold = 50%).

influence from higher concentrations of pioneers. But when the initial pioneer proportion was high, both the size and geographic spread of influence via interpersonal relationships in a regular network remained low. In brief, the low-separation characteristic of the small world network was more conducive to spreading positive influence to other areas.

E. COMPARATIVE ANALYSIS OF IMPACT DEGREE

The red bars in Figs. 16 and 17 indicate differences in the total numbers of adopters between normal threshold distributions and benchmark constant threshold values. Blue bars indicate differences between total number of adopters in a regular network and a benchmark small-world human relationship network. Green bars show differences between total numbers of adopters according to pioneer concentrations and a benchmark scattering of pioneers throughout a network. The Fig. 16 chart is for low-controversy products (30% external pressure threshold). According to these data, threshold distribution was the most important factor determining the number of adopters, and the presence or absence of a regular network was the least important—the latter even exerting a negative effect when the pioneer proportion was large.

According to the Fig. 17 comparison chart for high-controversy products (50% external pressure threshold), when the percentage of pioneers was small (<20%), the influence of a control group on product adoption was consistently positive. The greatest influence occurred with a normal distribution of adoption threshold value (red bar). We also observed a negative control group effect on the number of product adopters at an initial pioneer level of >20%. The blue bar shows the strongest negative effects of pioneer concentration.

Two conclusions can be derived from these charts:

1. In normal distribution cases, the external pressure threshold exerted the greatest positive impact on product adoption.

2. For high-controversy products, pioneer concentration exerted a strong negative impact on product proliferation when the number of pioneers was large.

V. CONCLUSION

The main study motivation was to clarify issues involved in getting support for controversial ideas or products. Sociologists and marketing researchers have previously emphasized the importance of pioneers during the initial introduction stage. We combined social simulation methods taken from information science with a dynamic opinion dissemination model to identify key processes and factors in product adoption. Our results indicate that traditional marketing activities were ineffective, especially the practice of concentrating influential pioneers to influence the purchase/adoption decisions of specific groups of consumers—in other words, product or idea pioneer scattering may be a more successful strategy for influencing acceptance behavior. A combination of the two approaches may have the greatest potential for success—that is, concentrating pioneers in specific areas at the very beginning of a marketing or dissemination effort, but distributing them across a larger geographic area (or number of media platforms) when the proportion of pioneers begins to show positive growth. In this manner, product or idea adoption can be monitored in greater detail.

This study makes three contributions to the fields of computer information, marketing, and communications:

1. The experimental results under different social conditions help explain how certain factors affect the acceptance of controversial products or ideas. The main benefit for marketing and communications researchers and practitioners is support for building a better understanding of the internal attitudes of consumers. Our proposed model simulates changes not only in attitudes triggered by exchanges of agent opinions, but also changes in agent attitudes over time. The study data also support an understanding of how dynamic public opinion processes clarify the diffusion dynamics underlying innovative product adoption.

2. We believe our proposed model can be modified for purposes of using computer simulations to predict internal changes of opinion—for example, changes in attitudes regarding vaccines and consequent effects on willingness to be vaccinated. It is our hope that the model can be used in public health scenarios in support of increasing public acceptance of disease prevention and mitigation policies.

3. Based on our effort to accurately simulate real-world opinion exchanges, we believe our proposed model is capable of simulating four kinds of social networks corresponding to topologies reflecting the actual characteristics of interpersonal networks. Computer information scientists may be interested in expanding our model to enhance the practical reference value of simulation results.

Our goals of supporting improvement in existing opinion dynamics models and identifying interaction mechanisms involving opinion and diffusion dynamics models demands consideration of a complex mix of societal factors requiring simplification. After clarifying basic model characteristics, our next task is to identify and add features for purposes of making the model more realistic. Three areas for expansion and improvement stand out:

1. The addition of media communication and opinion leader model factors to reflect their respective influences on real-world opinion formation and exchanges. Whereas past opinion leaders generally consisted of celebrity endorsers of products and ideas, today the category also includes mass and niche media figures such as social media-based influencers [75], [76]. Researchers have identified three primary characteristics of opinion leaders [76], the first being the potential for their innovative behaviors and normative influences to affect adoption rates via social pressure and social support [77]. A second group of opinion leaders exerts influence by providing advice and directions to other consumers, thereby increasing the speed and range of information diffusion via sources such as Facebook, Twitter, and TikTok, among others. Third, opinion leaders can share their experience, expertise, and involvement when evaluating products, thereby translating marketing messages presented in newspapers, magazines, and videos into word-of-mouth recommendations that many recipients perceive as more reliable sources of information compared to paid advertisements [78].

2. In simulations, social network edges can be modified and used as a "strength attribute." Real-world opinion strengths for individual connections vary widely, with close friends and professionals exerting the strongest influences in their roles as consultants. Researchers can use the strength attribute in their models to reflect the degree of importance of friends, acquaintances, and specialists.

3. Scale-free networks [69], [70] can be modified to reflect one-to-many and one-way relationships such as those

between internet celebrities/social media influencers and their fans. Future researchers may be interested in adding a "contrarian" factor to scale-free networks to consider the effects of anti-mainstream thinking. There are numerous examples of contrarian views regarding computer, communication and consumer (3C) electronics products. The numbers of contrarians are far below those of supporters of individual brands, yet it remains unclear how much influence they exert on product popularity and acceptance.

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