# A Multiplex Network Perspective of Innovation Diffusion: An Information-Behavior Framework

**QIAN YU, ZHEHAO YU[iD], AND DING MA[iD]**

School of Economics, Wuhan University of Technology, Wuhan 430070, China

Corresponding author: Ding Ma (mading@whut.edu.cn)

**ABSTRACT** Information transmission of innovation and peer effect among firms have significant impacts on innovation adoption decisions of firms, but those effects usually depend on the different types of inter-firm networks. Therefore, the diffusion of innovation (DOI) can be regarded as a process occurring in complex systems composed of different types of interactions, which can be categorized into links belonging to different layers of multiplex networks. This study aims to shed light on the complexity of innovation diffusion from the perspective of an information-behavior framework based on multiplex networks. The process of technology innovation adoption is formulated into two stages including information perception and decision making, and a novel innovation diffusion model based on duplex inter-firm networks, in which one layer has influence on information transmission and the other carrys the peer effect, is further proposed in this study. The simulation experiments indicate that the random-scale-free duplex networks are favourable to the diffusion speed while scale-free-scale-free duplex networks are conducive to the diffusion range. Moreover, within the scale-free-scale-free duplex networks, the diffusion speed will increase with the increasing of the power law index in the information network and decrease with the increasing of the power law index of the behavior network. The study contributes to the literature by establishing duplex network model that distinguishes links between information and behavior networks, and offers insights concerning optimization of network configuration in the promotion of DOI.

**INDEX TERMS** Multiplex networks, diffusion of innovation, information-behavior framework, agent-based modeling.

## I. INTRODUCTION

The theory of propagation dynamics has been extensively applied in many fields, including epidemic spreading [1], the emergence and evolution of cooperative behavior [2], herd behavior in the markets [3], the spread of new products and technologies [4], etc.. The diffusion of innovation (hereafter DOI), being one important branch of propagation dynamics, bears theoretical and practical importance. DOI is usually defined as a process through which innovation is carried out in different channels of time by a member of social system. And it is widely recognized as the materialization of innovation and determines the value of innovation. Accordingly, rich literature has been accumulated seeking to explain how a new technology or product is disseminated, which includes the

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formation of diffusion process [5]–[7], mining of driving or inhibiting factors [8], [9], and most recently the microscopic exploration of innovation adoption [10]–[12].

In the early stage of the DOI research, the behavior of individuals are assumed to be homogenized, and Bass model (or Bass diffusion model) is developed by Frank Bass to describe how a new product is adopted in a population through differential equation modeling [13]. After then this kind of models has been studied and widely used in forecasting, especially new products' sales and technology adoption. Beyond that, scholars also noticed that innovation diffusion will be affected by interaction among the heterogeneous individuals. And the spatial structure has been taken account of in the studies. The relationship between network architecture and diffusion performance is investigated to infer that system performance exhibits clear small-world properties, in that the steady-state level of average knowledge is maximal when the structure is

a small-world. These studies enlighten us that the intricate relationship in DOI can be captured in the model of complex networks.

As we known, individuals in the social systems often interact in multiple ways with others to form a multi-layered networks [14] For example, social network is composed of several different types of relationships such as friendship, proximity, kinship, membership, or colleague relationship [15]. In the inter-urban transportation system, the road network, the railway network, and the aviation network are coupled to each other to form a multi-level transportation network. Within the existent multiplex network literature, the prevailing construct of two-layer network are composed of online information network and offline physical contact network [16], [17]. The spread of epidemics is modeled by two-layer multiplex networks of awareness diffusion and epidemic propagation. The awareness diffusion induces informed individuals to take actions to prevent infection, hence influencing the infection threshold of disease spreading [18]. Regarding to information diffusion, the online information network is similar to the preferential attachment process due to the user attention mechanism, and its structure conforms to the scale-free network, while the offline reality network shows the characteristics of small-world. The coupling relationship enables information to spread faster [19]. In the diffusion of green behaviors, reference [20] finds that choosing individuals with high popularity in information network to be initial spreaders is not a necessary condition for the widespread of green behavior but choosing those with popularity under turning point is inadvisable.

However, most of the research on DOI concentrates on a single-layer network, which neglects the multiplexity of real world systems [21]. In particular, few studies portray DOI from the perspective of multiple networks, which ignore the similarities between DOI and other diffusion themes such as disease propagation, information diffusion, and behavior evolution in the field of multiplex networks. DOI share similarities with epidemic spreading, which involves the interaction between influencing adopters and potential adopters and the time path could be depicted with a similar S-curve. Scholars have established the single-layer DOI models such as SI, SIR, and SIRS. In addition, DOI is similar to the spreading of green behavior in that information plays an important role in the adoption of new technology. With economic development and technological advancement, the relationship within innovation network is complicated, information exchange and capital operation are coupled in multiple dimensions of social relations, exhibiting more complex diffusion topology and features. For example, in the early stage of DOI, individuals can only base their adoption decisions on the information they acquired, so information transmission among individual imposes the largest impact on innovation adoption; in the subsequent stages of DOI, individuals' adoption decisions are determined by experience and knowledge from those they are closed related [22]. The networked information perception and resources or knowledge sourcing implies duplex relationships within DOI. Therefore, the ignorance of multiplexity could neither fit the reality well nor consider the interactions or joint effect of duplex networks.

Motivated by the discussion above, this study establishes the duplex networks for DOI based on an information-behavior framework, dividing the individuals' behavior into two stages of information acquisition and adoption decision-making. The interactions of information acquisition will occur on the layer of the so-called information networks but the interactions of adoption decision-making will occur on the layer of the so-called behavior networks. Since agent-based modeling provides a way to explicitly specify the micro-level processes that drive the adoption of innovation, thus revealing the macro adoption dynamics from aggregated individual behavior and interactions between agents [1]. This paper establishes an agent-based model to formulate the intra-layer connection and inter-layer interaction mechanisms, and the decision algorithm underlying our model allows heterogeneity among decision-makers and duplex network construction. Since network structure is the substrate of DOI, an understanding of network structure toward efficient DOI is of paramount significance. A number of simulations are performed on Anylogic software to compare across different topologies of duplex networks qualitatively and to measure the quantitative impacts of topological parameters, and finally time paths in different topological scenarios are obtained. The simulation experiments shed lights on the following three questions: (1) What type of duplex networks are most conducive to DOI? (2) What are the independent effects of the topological characteristics of each network on the speed and range of DOI? (3) How does the combined topological characteristics of duplex networks affect the speed and range of DOI? Our results partly lend support to some previous results on single-layer network, and most importantly reveal some unique features of DOI contours in multiplex networks. This study presents a feasible attempt to explore DOI using multiplex networks, which extends the application scenarios of multi-layer network theory and offers a versatile framework in future multiplex networked DOI literature.

The layout of the paper is as follows: we introduce the model in Section 2. The experiment design and simulation result analysis are presented in Section 3. Finally, conclusions are presented in Section 4.

## II. DUPLEX NETWORK DOI BASED ON INFORMATION-BEHAVIOR FRAMEWORK
### A. AN INFORMATION-BEHAVIOR FRAMEWORK
Given the fact that the links inside biological, social, information, and technological networks are synchronized in multiple layers [1], the multilayer network framework has offered a promising insight to the elucidating of real world phenomenon [23], [24]. Accordingly, recent years have witnessed a rapid growth of the multilayer network studies, manifesting in the domains of epidemic spreading [1], [24],

neutral science [25], finance [26], transportation [27] and so on. A typical distinctive duplex network observed are probably the information and behavior networks.

Information network refers to the networked relationships which capture the flow of information or knowledge through media communications [28]. Despite the varying forms in terms of citation networks, co-citation networks, and co-word networks, information network is intrinsically the invisible channel and process of information transmission. The key point of relevant studies is how to determine network connections, and can be roughly classified into network topology and diffusion mechanism studies [29]. The first strand of research focuses on the identification of topologies of various information networks or the influence of topologies exerted on information diffusion [30], [31]. Reference [32] investigated diffusion dynamics in small-world networks and identified a critical penetration threshold in information diffusion, whereas reference [33] found no percolation threshold in infinite scale-free networks. Scholars have also investigated the bearing of other structural features on diffusion dynamics, such as community structure [34] and multiplex networks [35]. The other line of studies pay attention to the excavation of mechanism of information dissemination dynamics, and design diffusion model to capture or reproduce information diffusion phenomenon [29]. Some models focus on the detection of diffusion cascade and propagation paths of information diffusion [36], [37]. Other models try to predict the quantity of infected users, depth and scale of information diffusion [38], [39].

Innovation diffusion is a typical social process of high uncertainty, in which other individuals exert significant effect on one's innovation decision. Such influences of social interactions have been named by many terms, including 'social learning', 'imitation', 'peer influence', 'conformity', 'peer effect', or 'interdependence preference' [22]. In this study, we choose to use behavior network to represent the social interactions involved in innovation adoption decision. And our operational definition of a behavior network is a nexus of relationships that exerting various influences over the innovation adoption decision. Such network encompasses all kinds of relationships as long as they are originated from stakeholders who exerting critical effects on individual innovation motives or capabilities. The typical relationships are R&D collaboration, supply chain partnership, parent-subsidiary relationship, industry alliance, government-enterprise, and even competitors. Several theoretical paradigms concerning innovation have underscored the importance of stakeholder effect. In terms of institutional theory, the impact of institutional environment on the legitimacy, social acceptance, and access to resources of an organization's form, structure, or behavior is called institutional pressure, which is further classified into regulatory pressure, normative pressure, and competitive pressure [40]. This implies regulators, alliance partners, and competitors as important stakeholders in innovation diffusion. In the social network paradigm, collaborative ties embedded in R&D networks, alliance, or supply
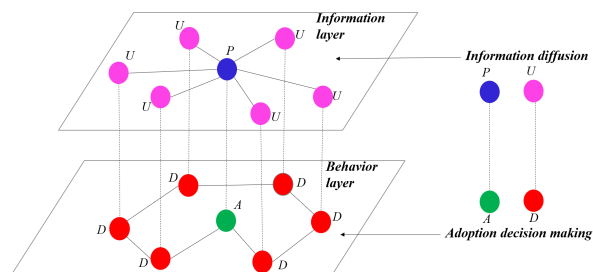


**FIGURE 1.** The information-behavior framework. Note: the upper layer describes the information diffusion, and it contains two types of nodes, in which the purple node represents the unaware state and the blue node denotes aware state of innovation related information. The lower layer is the behavior layer consist of two types of nodes: innovation adopter in green and non-adopter (including both potential adopter and dis-adopter) in red.

chain partnerships will assist in resources access, reputation establishment, opportunity detection, and knowledge absorption that are prerequisites for the adoption of innovation [41]. In addition, contemporary innovation is characterized as an open innovation paradigm due to the increased specialization of knowledge production, indicating the imperative of networked relationships for creating and profiting from technology [42].

Rather than encompassing information and behavior network into a holistic setting of peer network like other study does [22], our study makes a distinction between these two layers of networks due to two reasons. On the one hand, the topological structures are assumed to be different between information and behavior networks according to the stylized facts. Information network is the one that exhibits characteristics of high degree assortativity, small shortest path lengths, large connected components, high clustering coefficients, and a high degree of reciprocity, whereas an information network is a structure where the dominant interaction is the dissemination of information along edges characterized by large vertex degrees, a lack of reciprocity, and large two-hop neighborhoods [43]. On the other hand, the priority differs between information and behavior networks. In the early stage, information transmission matters the most as individuals can only base their adoption decisions on the basic information available; in the later stage, individuals' adoption decisions heavily rely on the experiential knowledge and resources accessible from those closely linked with [22]. Therefore, the distinguishing of these two layers is necessary for the design of cascade networks toward DOI. The information-behavior framework is exhibited in Fig. 1.

## B. THE DIFFUSION DYNAMICS IN DUPLEX NETWORK
In the seminal work of reference [10], the innovation adoption activity of individual is depicted by an awareness-motivation-capability (hereafter AMC) framework. Based on the overarching Complex Adaptive System (CAS) theory, AMC interconnects DOI element (i.e., the innovation, communication channels, time, and the social system) via three

behavior drivers: agents' awareness, motivation, and capability, and turned it into an elegant yet comprehensive model for empirical examination [10]. Despite being confined in only one layer network, AMC lays a theoretical foundation for the information-behavior framework in our study. Specially, we describe awareness in the information network. Awareness represents individual's understanding of an innovation, which depends on the dissemination and diffusion speed and range of information network. The information manifests in many terms, including publications reported by research institute, new product release by industry leaders, citation of patents, etc.. With the continuous reception of external information, the individual's understanding of an innovation will gradually change from unawareness to awareness, which is a prerequisite for innovation. Motivation and capability are described in behavior network. Motivation can be expressed as the individual's anticipation of expected returns resulted from the adoption of an innovation, and also reflects the competitive pressure [10], [44]. Capability represents the level of relevant competence required to adopt an innovation. To materialize an innovation, the innovator must engage in innovation-related cognitions and behaviors. The accumulation of capability could either through autonomous learning, or from interactive learning with other individuals in the behavior network [45], [46]. Motivation and capability are intertwined in the process of innovation-related behaviors, such as the value exchange in supply chains or the peer-driven social learning [47].

Accordingly, an agent-based simulation model is developed to computationally represent DOI in duplex inter-firm networks. In our model, agents are divided into focal groups and external groups, in which external groups are the external environment for innovation diffusion. And focal groups are potential adopters of new technologies which are the observation objects in our model. In order to describe individual states and behavioral rules, we assign five state attributes to each individual to describe their awareness, motivation, capability indicators, and their value and signal levels. Each individual plays both the roles of innovation adopter and disseminator, and its behavior rules are as follows:

First, as a potential innovation adopter, individuals will compare their awareness indicators of innovation with their neighbors in the information network, and update their awareness indicators at the next time according to the rules of social learning. Then, individuals will compare their motivation and capability indicators of innovation with those of their neighbors in the behavior network that send out innovation signals, and update their own motivation and capability indicators in accordance with their own value and signal level at the next moment.

Second, for an innovation adopter, its level of innovation signal is determined by its motivation level and incremental value gained from innovation adoption. When its signal level is above the threshold, it becomes the disseminator of innovation and the learning object of neighbors in behavior networks, i.e., the lower the threshold, the easier the spread.

At the end of each moment of behavior evolution, each individual updates its state attributes according to the information interaction, motivation formation, capability accumulation rules, and the results of innovation adoption.

We use $A = \{a_{ij}\}$ to represent the information network in the form of the adjacency matrix. Behavior network is denoted by $B = \{b_{ij}\}$. Since the awareness dynamic reflects the process of information exchange, which is triggered by the information difference. The awareness difference is calculated in information network as the following:

$$awareness\ difference = \frac{\sum a_{ij} A_j(t)}{\sum a_{ij}} - A_i(t) \qquad (1)$$

Meanwhile, the motivation and capability diffusion are calculated in behavior network:

$$\begin{cases} motivation\ difference = \dfrac{\sum b_{ij} M_j(t)}{\sum b_{ij}} - M_i(t) \\ capability\ difference = \dfrac{\sum b_{ij} C_j(t)}{\sum b_{ij}} - C_i(t) \end{cases} \qquad (2)$$

where $A_i(t)$ is agent $i$'s awareness stock at time $t$, and $M_i(t)$, $C_i(t)$ represent the Agent $i$'s motivation stock and capability stock respectively.

Agent $i$'s incremental awareness $\Delta A_i(t+1)$ at time $t+1$ is described as the following:

$$\Delta A_i(t+1) = \begin{cases} \left( \dfrac{\sum a_{ij} A_i(t)}{\sum a_{ij}} - A_i(t) \right) \cdot \delta_i, \\ \qquad if\ \exists j,\ A_j(t) - A_i(t) > 0 \\ 0, \quad if\ \forall j,\ A_j(t) - A_i(t) \leq 0 \end{cases} \qquad (3)$$

$$A_i(t+1) = A_i(t) \cdot \eta_i^A + \Delta A(t+1) \cdot \lambda_i' \qquad (4)$$

$$\delta_i = \frac{N_i + 1}{N_i} \qquad (5)$$

where $\delta_i$ indicates the time coefficient of innovation's influence on agent $i$ over time, $a_{ij}$ is the element in the temporary matrix which indicates whether there is a link between the node $i$ and node $j$, $\eta_i^A$ represents the forgetting coefficient of the awareness stock of agent $i$, $\lambda_i'$ indicates the efficiency of agent $i$'s learning from its neighbors, $N_i$ represents the duration of agent $i$'s adoption of this innovation.

Agent $i$'s incremental motivation stock $\Delta M_i(t+1)$ at time $t+1$ is described as the following:

$$\Delta M_i(t+1) = \begin{cases} \left( \dfrac{\sum b_{ij} M_j(t)}{\sum b_{ij}} - M_i(t) \right) + \Delta V_i(t), \\ \qquad if\ \exists j,\ M_j(t) - M_i(t) > 0 \\ \Delta V_i(t), \quad otherwise \end{cases} \qquad (6)$$

$$M(t+1) = M_i(t) \cdot \eta_i^M + \Delta M(t+1) \cdot \lambda_i' \qquad (7)$$

$$\Delta V_i(t) = \begin{cases} (1 + r_i(t)) \cdot \delta_i \cdot \xi, & if\ Adoption_i = 1 \\ 0, & if\ Adoption_i = 0 \end{cases} \qquad (8)$$

where $V_i(t)$ is the value agent $i$ gains at time $t$ from innovation adoption. When agent $i$ adopts the innovation, the incremental value gains from the adoption of innovation will increase due

to the adoption of its neighbors, and $r_i(t)$ represents the ratio of innovators in agent $i$'s neighbors at $t$.

Agent $i$'s incremental capability $\Delta C_i(t+1)$ at time $t+1$ is described as the following:

$$\Delta C_i(t+1) = \begin{cases} \left( \dfrac{\sum b_{ij}C_j(t)}{\sum b_{ij}} - C_i(t) \right) \cdot \xi, \\ \qquad \exists j, C_j(t) > C_i(t) \text{ and } Signal_j = 1 \\ 0, \quad otherwise \end{cases} \quad (9)$$

$$C_i(t+1) = C_i(t) \cdot \left( \eta_i^C + \lambda_i \right) + \Delta C_i(t+1) \cdot \lambda_i' \quad (10)$$

where $\xi$ is a random number, reflecting the volatility caused by market uncertainty, $\lambda_i$ indicates the efficiency of the agent $i$'s learning from itself. An Agent only learns about capability from the signaling neighbors, the signaling behavior indicates that the Agent has been noticed by its neighbors because its revenue and related indicators have reached a certain level, and $Signal_j = 1$ indicates that neighbor $j$ has sent a signal.

Agent $i$'s state of signaling $Signal_i$ is described as the following:

$$Signal_i = \begin{cases} 1, & if \ S_i(t) > T_i^S \\ 0, & otherwise \end{cases} \quad (11)$$

$$S_i(t) = M_i(t) \cdot \Delta V_i(t), \quad if \ A_i(t) \geq T_i^A \quad (12)$$

where $S_i(t)$ is agent $i$'s signal stock at time $t$ and when it exceeds its threshold $T_i^S$, agent $i$ will send a signal to let itself be noticed by its neighbors, causing the neighbors to learn from Agent $i$. $S_i(t)$ is determined by its motivation stock $M_i(t)$ and incremental value gained from adoption $\Delta V n_i(t)$.

Agent $i$'s state of adoption $Adoption_i$ is described as the following:

$$Adoption_i = \begin{cases} 1, & if \ A_i(t) > T_i^A, \ M_i(t) > T_i^M, \ C_i(t) > T_i^C \\ 0, & otherwise \end{cases} \quad (13)$$

where $T_i^A, T_i^M, T_i^C$ are the thresholds of awareness, motivation, and capability respectively of agent $i$. Agent $i$ will adopt this innovation when its awareness, motivation, and capability stock exceed the respective thresholds simultaneously.

## III. SIMULATION DESIGN AND ANALYSIS
### A. SIMULATION EXPERIMENT DESIGN
In order to observe the DOI process in the duplex networks based on the information-behavior framework, we design the agent-based model to simulate diffusion behavior of individuals in social networks in terms of technology innovation, including information awareness, motivation formation and capability accumulation. This model examines the impact of duplex network topology on DOI, and we execute the simulation experiments based on the Anylogic software.

In the simulation, we examine the duplex networks formed by the combination of random networks, small-world networks, and scale-free networks. The nine topology combinations are denoted by the acronyms of random network (RD),

scale-free network (SF), and small-world network (SW) in the form of hyphen-connected symbols, such as RD-RD, SF-SW, and SF-SF. Random network, small-world network, and scale-free network are generated according to the following algorithms.

Random network: Specify the number of nodes N and the average number of connections L, so that each node establishes a connection with L nodes on average in a random connection manner, thereby generating a random network.

Small-world Network: Based on the WS small-world network generation algorithm [48], the number of nodes N, the number of connections L, and the reconnection probability p are specified. Firstly, each agent establishes a connection to the nearest L nodes to form a regular network. This connection is reconnected to another random node with probability p, thereby generating a small-world network.

Scale-Free Network: Based on the BA scale-free network generation algorithm [49], the number of nodes N, the number of initial nodes $K_0$, and the number of newly established connections in each iteration $K$ are specified. The network initially has $K_0$ nodes and randomly establishes connections. Then, in each iteration a new node is added, and the new node selects $K(K \leq K_0)$ nodes from the current network to connect with, and the probability $p(v_i)$ of a node $v_i$ being selected is proportional to the size of the node degree $d_i$, that is $p(v_i) = \frac{d_i}{\sum_j d_j}$. It is incremented until the total number of nodes equals to $N$, resulting in a scale-free network.

In our simulation experiments, agent completes the decision of information awareness, motivation formation and capability accumulation in each iteration, and updates its own state indicators according to the behavior evolution rules. At the end of each iteration, the system counts the speed of innovation adoption and the range of innovation diffusion. Among them, we observe the occurrence of critical conditions through significant changes in the diffusion curve [50], and use the time taken to reach the adoption rate of 50% to characterize the diffusion speed [51]. The cumulative adoption rate after a certain number of iterations represents the size of the diffusion range [52].

The simulation steps are designed as follows:

Step 0: Set the population size, generate duplex networks according to the structure type and topological characteristics, initialize the system parameters, and complete the parameter settings of the focal population and external population.

Step 1: According to the agents that have adopted innovative technology in the entire network, obtain the incremental value gained from innovation adoption and update the signal stock.

Step 2: In the focal population, each potential innovation adopter compares awareness indicators about innovation with its neighbors in the information network, and updates its awareness indicators according to formulas (3) and (4) at the next iteration. Then the individual will compare the motivation and capability indicators of innovation with the

**TABLE 1.** Basic statistics of simulated networks.

| Network Type | Number of Nodes | Average Degree | Average Path Length | Clustering Coefficient |
|---|---|---|---|---|
| RD network | 1000 | 5.994 | 4.107 | 0.005 |
| SW network | 1000 | 6.074 | 5.986 | 0.451 |
| SF network | 1000 | 5.982 | 3.496 | 0.028 |

neighbors who sent the innovation signal in the behavior network, and combine their own value and signal level to update their motivation and capability indicators according to formulas (6) to (10). Then, each potential innovation adopter makes decision based on whether the AMC indicator level reaches the adoption threshold.

Step 3: Update the statistical indicators in the system, and calculate the innovation adoption rate and innovation diffusion speed.

Step 4: Determine whether the iteration termination condition is reached. If the condition is reached, the simulation stops.

The detailed experimental process is shown in Fig. 2:
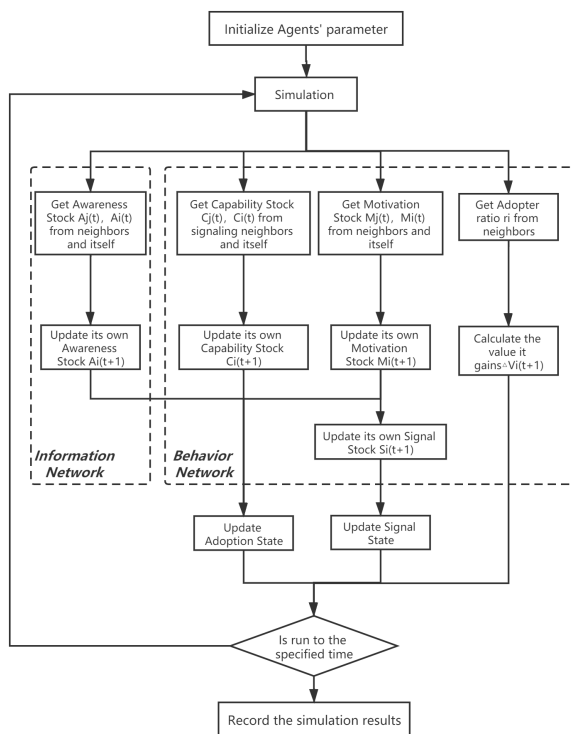


**FIGURE 2.** Flow chart of simulation experiment.

## B. IMPACT OF TOPOLOGICAL TYPES ON DOI IN DUPLEX NETWORKS

To investigate the impact of topological types on DOI in duplex networks, we generate three kinds of basic networks (random networks, small-world networks, scale-free networks) with nodes number N = 1000 and average degree of 6,

and combine them into 9 different types of duplex networks such as RD-RD(random-random), SF-SW, SF-SF, etc. We use the RD network with $L = 6$, SW network with $p = 0.1$ and $L = 6$, SF network with $K = K_0 = 3$, the basic statistics of the simulated networks are exhibited in Table 1. Two hundred steps are iterated in 9 kinds of duplex networks in the simulation experiment, the results are shown in Fig. 3.

According to the simulation results above, we find that the S-curves of the homogeneous duplex networks (a,e,i) conform to the regular pattern of DOI, validating our model in the description of DOI in case of homogeneous duplex networks. In the pairwise combination of different networks, scale-free-scale-free (SF-SF) duplex networks (i) have the widest diffusion range, and random-scale-free (RD-SF) duplex networks (g) have the fastest diffusion speed. The experimental results are also consistent with the literature that there is a positive correlation between the speed of knowledge diffusion and the degree of randomization in the network, that is, the greater the degree of randomization of the network, the faster the speed of knowledge diffusion in the network [53]. In the process of knowledge diffusion that does not continuously generate new knowledge, random networks show better performance [54]. The knowledge dissemination performance of scale-free social networks is better than that of uniform social networks with the same average degree [55].

In addition, the diffusion speed and range of DOI in the network combination containing small-world network (b, d, e, f, h) are relatively inferior. Diffusion efficiency in duplex networks is affected by the network topology of each layer. Although it can have relatively good diffusion performance in scale-free or random homogeneous networks, diffusion range and speed in the heterogeneous duplex networks will be slower once it is combined with a small-world network.

In a word, experimental results show that in the duplex networks of different topological types, the scale-free network and scale-free network combination (SF-SF) is advantageous for diffusion range of innovation. The combination of random networks and scale-free networks (RD-SF) is comparatively superior in terms of diffusion speed. And it is necessary to meet the effective diffusion of both information and behavior. Deficiencies in any of these levels will lead to a significant reduction in the overall speed and range of DOI.

## C. IMPACT OF TOPOLOGICAL PARAMETERS ON DOI

Considering that the performance of DOI is most prominent in the SF-SF duplex networks, we further analyze the
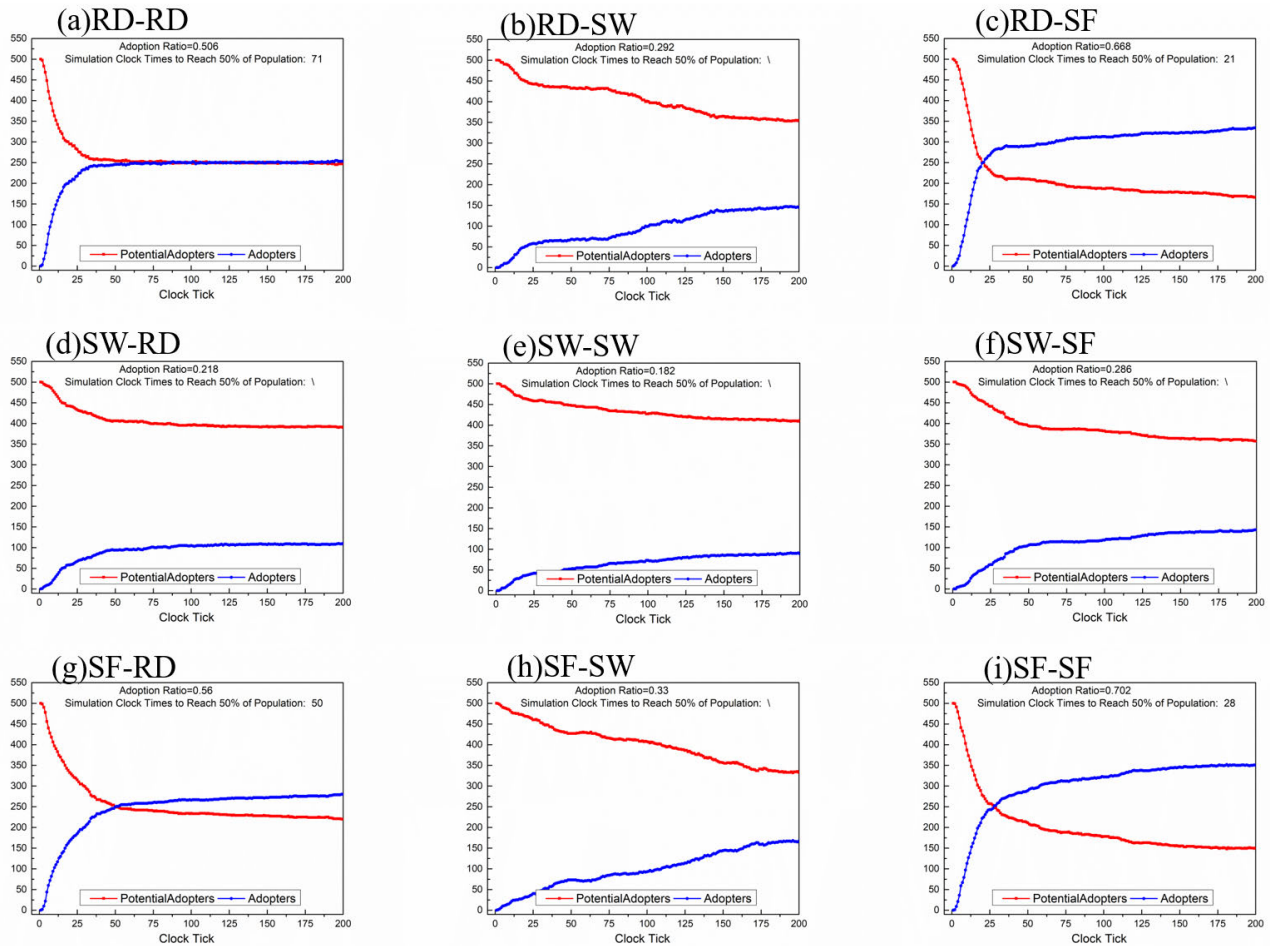
**FIGURE 3.** DOI in duplex networks of different topological types.

influence of the topological parameters of the network on DOI in the SF-SF duplex networks, focusing on network density and power law index. Network density characterizes the density of interconnected edges between nodes in the network, and is measured by the average degree in the network [56]. The power law index reflects the non-uniformity of the degree distribution and is calculated from the slope of the regression line in the hyperbolic coordinate system of the degree distribution [57]. In order to investigate the impact of the topological characteristics on DOI in a SF-SF duplex networks, we conduct two sets of experiments by fixing the information or behavior layer and adjust the topological characteristics of the other layer. Then we report the impact on DOI due to changes in network density and power law index in each layer of duplex networks.

### 1) IMPACT OF INFORMATION NETWORK TOPOLOGICAL CHARACRERISTICS ON DOI

First, in order to examine the influence of the network density of information network on DOI, we select information networks with different network densities to build duplex

networks with fixed behavior network parameters, perform simulation experiments on the network, and observe the critical conditions, range, and speed of DOI. The selection rules of experimental data are based on BA scale-free network generation algorithm, and the parameter $K_0$ is fixed at 3. By adjusting parameter K, a set of network data with power law index approximately equal to 1.95, and the average degree ranges from 1.998 to 15.872 is generated, exhibiting a monotonically increasing trend along K. At the same time, we record the average path length which ranges from 2.681 to 7.964. The detailed statistics are shown in Table 2.

We choose a scale-free network with K = 3 as the behavior network, adjust the average degree of the information network and perform sensitivity analysis, and intercept the diffusion curve at t = 100. We observe from the diffusion curve in Fig. 4 that the adoption rate increases with the change of the parameter K, and there is a critical value. When parameter K exceeds a certain value, the diffusion curve tends to be stable. Early in the increase of K (K = 1,2), both the diffusion range and speed show a rapid increase, but the diffusion curve is stable near a certain range in the middle and late stages of K increase (K ≥ 3).

**TABLE 2.** Topological characteristic of each layer.

| Network | K | Power Law Index | Average Degree | Average Path Length |
|---|---|---|---|---|
| Information Network | 1 | 1.85 | 1.998 | 7.964 |
| | 2 | 1.94 | 3.992 | 4.142 |
| | 3 | 1.94 | 5.982 | 3.496 |
| | 4 | 1.97 | 7.968 | 3.199 |
| | 5 | 2.00 | 9.95 | 3.007 |
| | 6 | 1.95 | 11.928 | 2.848 |
| | 7 | 1.95 | 13.902 | 2.755 |
| | 8 | 1.95 | 15.872 | 2.681 |
| Behavior Network | 3 | 1.94 | 5.982 | 3.496 |

**TABLE 3.** Power law index for innovation diffusion experimental data.

| K | Power Law Index | Average Degree |
|---|---|---|
| 3 | 2.012 | 5.986 |
| 4 | 1.836 | 5.986 |
| 5 | 1.94 | 5.982 |
| 6 | 1.884 | 5.982 |
| …… | …… | …… |
| 27 | 1.596 | 6.212 |
| 28 | 1.547 | 6.214 |
| 29 | 1.593 | 6.312 |
| 30 | 1.504 | 6.246 |
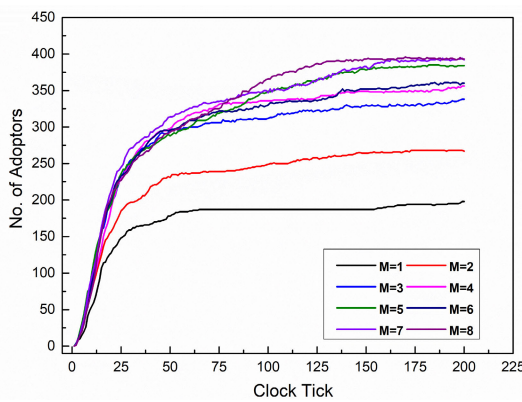


**FIGURE 4.** Sensitivity analysis of network density on DOI in information networks.



**FIGURE 5.** Time for the adoption rate to reach 50% with varying power law indexes.

The experimental results show that under the condition that the behavior network is fixed, as the information network density increases, the nodes are more densely connected to each other, and the average path length is gradually shortened. There are two reasons for the "saturation point" of innovation diffusion. On the one hand, the interaction between nodes is more frequent due to the increase in network density, which makes the speed and range of diffusion increase, but the marginal increase is gradually decreasing. On the other hand, in the duplex networks coupling process, although the increase in network density has made information dissemination more rapid and widespread, the motivations and capabilities associated with innovation decisions in behavior networks have not reached saturation, which restricts the overall diffusion process. This is consistent with the conclusions in section B of part III.

We execute 100 simulation experiments in each different sample networks, and use the average time of adoption rate reaching 50% under different power law indexes to proxy the speed of innovation diffusion. The experimental results are shown in a scatter plot in Fig. 5. Its horizontal axis is the power-law index of the sample network, and its vertical axis is the average time for 28 sample networks to reach 50% adoption rate in 100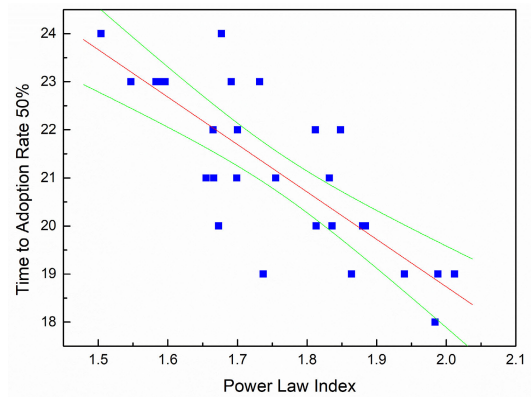 simulation experiments. From the fitted straight line in Fig. 5, the time required for the adoption rate to reach 50% decreases as the power law index increases, that is to say, the speed of innovation diffusion increases with the increase of power law index.

We also record and linearly fit the experimental results of the time taken for the adoption rate to reach 10%, 20%, 30%, 40%, and 50% under different power law indexes. From the linear fitting results in Table 4, we can see that the slope is only $-0.0619$ when the adoption rate is 10%, and the slope is $-11.15$ when the adoption rate is 50%. The growth rate of the diffusion speed with the power law index increases with the adoption rate, which means the influence of the power law index on the diffusion speed is not obvious in the early stage, but gradually increases with the diffusion process.

We observe the range of DOI by recording the adoption rate at time t = 100 under different power law indexes. We find from Fig. 6 that the data points of the innovation diffusion range with different power law indexes are scattered, and the fitted straight line indicates no obvious trend.

Two conclusions can be drawn from the above experiments. Firstly, the unevenness degree distribution of information network has a significant role in promoting the speed of innovation diffusion. This effect becomes more pronounced as the diffusion process evolves. This highlights the role of

**TABLE 4.** Linear fitting results of time to the specified adoption rate under different power law indexes.

| Adoption Rate | Linear Fit Results f(x) = p1*x + p2 (with 95% confidence bounds) | |
| --- | --- | --- |
| | p1 | p2 |
| 10% | -0.0619 (-1.654, 1.53) | 6.892 (4.073, 9.71) |
| 20% | -0.7004 (-2.709, 1.309) | 10.67 (7.114, 14.23) |
| 30% | -2.405 (-5.109, 0.2977) | 16.16 (11.37, 20.94) |
| 40% | -4.601 (-7.177, -2.025) | 23.55 (18.99, 28.11) |
| 50% | -11.15 (-13.48, -8.816) | 40.94 (36.8, 45.07) |
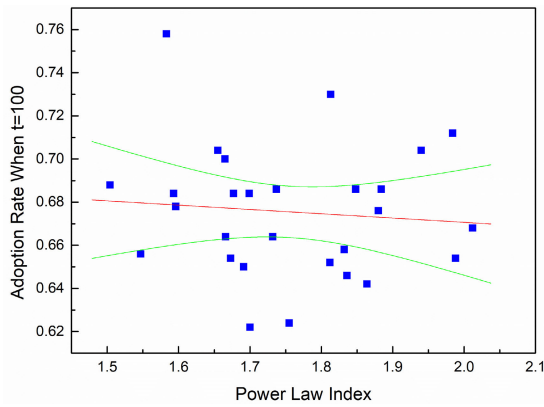


**FIGURE 6.** Adoption rate at t = 100 with varying power law indexes.
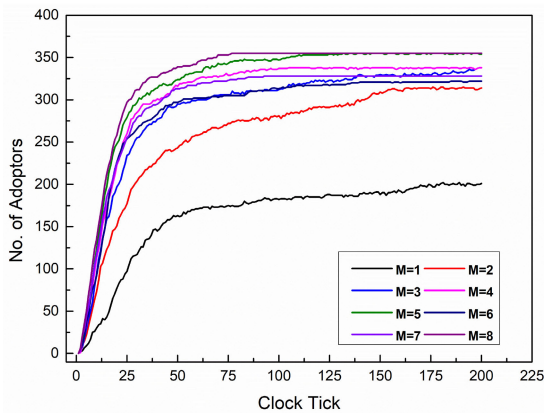


**FIGURE 7.** Sensitivity analysis of network density on DOI in behavior networks.

opinion leaders or influential central nodes in information network in that speed of diffusion will be accelerated given information disseminated through these nodes. Since these central nodes gradually participate and have an impact in diffusion process. Therefore, the positive effect of the power law index on the diffusion speed is gradually significant. Secondly, the change in the power law index has little effect on the range of DOI. This is mainly because the overall network density and average path length have not changed significantly, the tightness between nodes has not been improved.
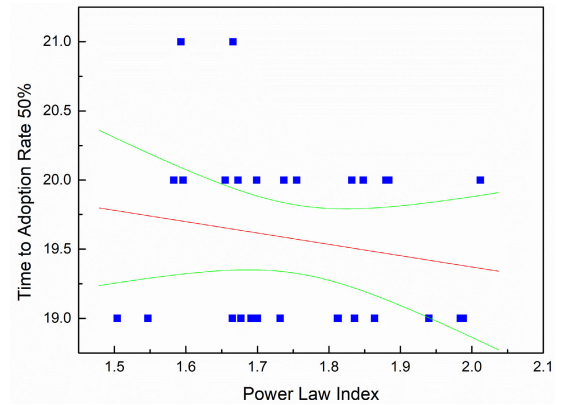


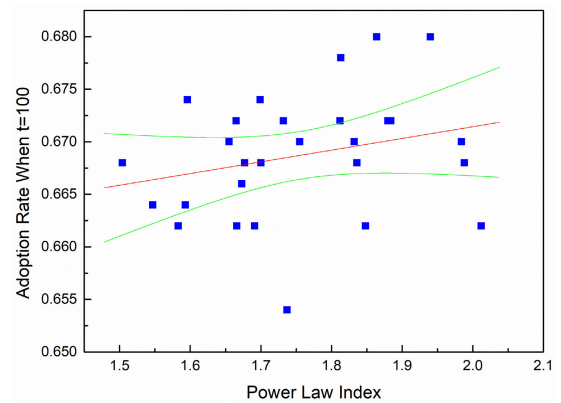**FIGURE 8.** Time for the adoption rate to reach 50% with varying power law indexes.



**FIGURE 9.** Adoption rate at t = 100 with varying power law indexes.

### 2) IMPACT OF BEHAVIOR NETWORK TOPOLOGICAL CHARACTERISTICS ON DOI

First, in order to examine the impact of network density of the behavior network on DOI, we select information networks with different network densities to build a duplex networks with fixed information network parameters, perform simulation experiments in this network and observe the critical conditions, range, and speed of diffusion. Selection rules of experimental data are the same as in section (1) of part C. The detailed data are similar with those in Table 2 except for the exchange between information networks and behavior networks.

We select a scale-free network with K = 3 as the information network, adjust the average degree of the behavior network to perform the sensitivity analysis and intercept diffusion curve at t = 100. We observe from the diffusion curve in Fig. 7 that the adoption rate shows an increasing trend with the change of the parameter K. There is a critical value, when the parameter K exceeds a certain value, the diffusion curve stabilizes. The result is similar to the information network. Therefore, whether it is an information network responsible for information dissemination or a behavior network driven by decision-making related peer effects, as the network density increases, the average path length between
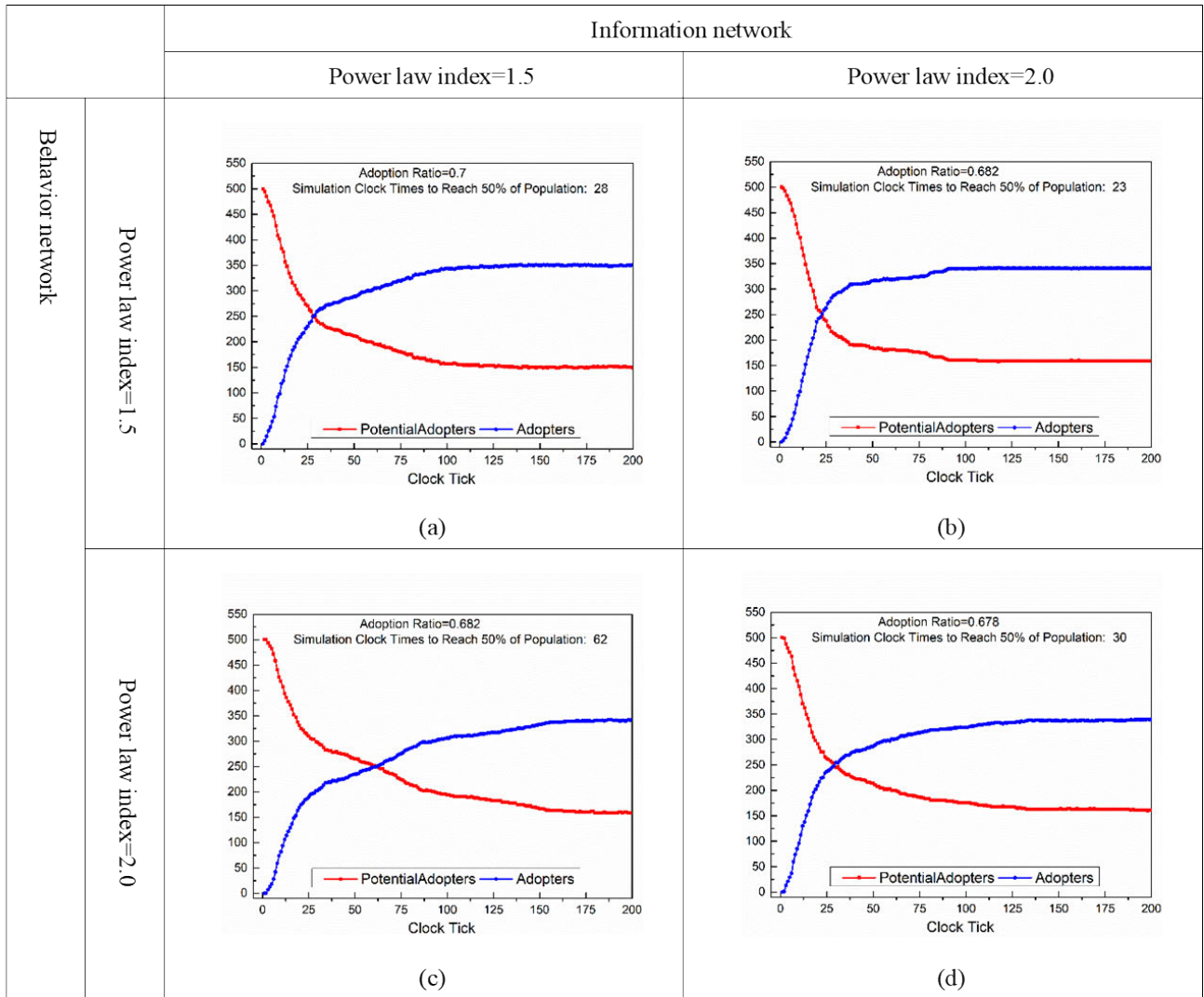
**FIGURE 10.** Impact of interactions on DOI in duplex networks.

nodes shortens, and the adoption rate of DOI increases to a certain threshold, driving by diminishing marginal benefits and coupling of duplex networks.

Second, in order to investigate the impact of the uneven distribution of the behavior network on DOI, we select behavior networks with different power law indexes to build duplex networks and perform two sets of simulation experiments, record the effects on diffusion speed and range separately in the case of a fixed behavior network. We executed 100 simulation experiments in each sample networks, and record the average time of adoption rate to reach 50% under different power law indexes to observe the speed of innovation diffusion. The experimental results is shown in a scatter plot in Fig. 8. Its horizontal axis is the power law index of the sample network, and its vertical axis is the average time for 28 sample networks to reach 50% adoption rate in 100 simulation experiments. The fitting curve shows a slight downward trend, considering that the two data points

except $t = 21$ are excluded, all other data points are $t = 19$ or $t = 20$, and there is no obvious change pattern with the power law index. This is different from the experimental results in the information network.

In Fig. 9, the range of DOI is observed by recording the adoption rate at $t = 100$ with different power law indexes.

Although the fitted straight line indicates that the diffusion range increases with the increase of the power law index, the impact is small, and the data points of the innovation diffusion range under different power law indexes are scattered and do not exhibit a clear trend. Therefore, the power law index has little effect on the diffusion speed and range in the behavior network. Comparing the experimental results with information network, it can be found that the change of the power law index in the information network has a significant effect on the diffusion speed, whereas the effect in the behavior network is not obvious. This indicates that in the information-behavior framework, although information and
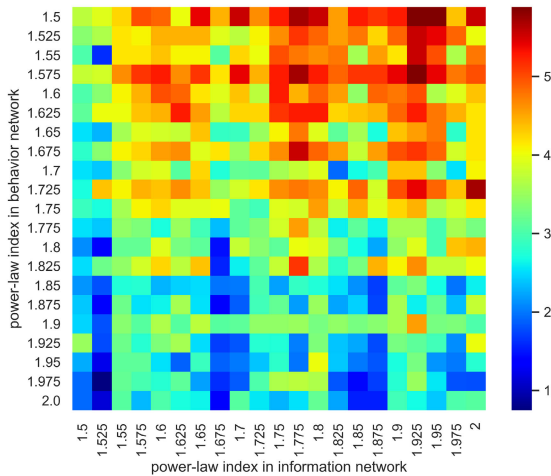
**FIGURE 11.** Heatmap of the interaction of duplex networks on DOI.

**TABLE 5.** Experiment summary.

| | Conclusion |
|---|---|
| 1 | The combinations of RD-SF networks and SF-SF networks have the best performance on diffusion speed and diffusion range respectively; |
| 2 | The optimal combination for diffusion speed is composed of information network with high power law index and behavior network with comparatively low power law index; |
| 3 | The change of power law index has little effect on the range of DOI; |
| 4 | Diffusion scale and speed increase with the increase of network density, but this effect wears off after network density reaches a certain point. |

behavior activities are carried out in two layers of networks and determine innovation decisions at the same time, the spread of information is faster than the diffusion of behaviors, which makes the spread of information dominates the process of innovation diffusion.

## D. INTERACTIVE EFFECTS OF THE DUPLEX NETWORK TOPOLOGICAL CHARACTERISTICS ON DOI

In order to investigate the impact of network interaction on innovation diffusion in duplex network, we adjust the power law index of the information network and the behavior network simultaneously. First, we select two scale-free networks with power law indexes of 1.5 and 2.0. The two groups are combined for simulation experiments. The results are shown in the Fig. 10.

According to the experimental results in Fig. 10, the duplex network (b), which is a combination of the information network with power index of 2.0 and the behavior network with power law index of 1.5, has the fastest diffusion speed (time = 23), and the duplex network (c), which is a combination of 1.5 and 2.0, has the slowest diffusion speed (time = 62). The network (a) with double layers of 1.5 has the largest diffusion range, and the network (d) with double layers of 2.0 has the smallest diffusion range.

It can be found that when the parameters in the information network are fixed, the diffusion range and speed decrease as the power law index of the behavior network increases. When the parameters in the behavior network are fixed, the diffusion range decreases as the power law index in the information network increases, but the diffusion speed increases.

Further, we generate 21 scale-free networks with power law exponential distributions ranging from 1.5 to 2.0, and combine them in pairs to form 21*21 experimental sample networks. We perform 200 iterations respectively, and exhibit the simulation results in Fig. 11. In order to compare the magnitude of the diffusion speed more clearly, we calculate the time T used to reach the adoption rate of 50% as a speed of $\frac{200}{T}$ and display the results by heatmap.

As Fig. 11 indicates that the fastest diffusion speed in a duplex network is generated by an information network with a power law index at [1.6, 2.0] and a behavior network with a power-rate index at [1.75, 2.0]. The diffusion speed increases with the increase of the power law index in information network, and decreases with the increase of power law index in the behavior network. In other words, the duplex networks constructed by an unevenly distributed information network and a uniform behavior network have better DOI performance.

We summarize the conclusions of all experiments as follows in Table 5:

## IV. CONCLUSION AND RECOMMENDATIONS

Information transmission and peer effect have significant impacts on innovation adoption decisions of firms, but those effects usually occur in the different types of inter-firm networks. Considering the multiplexity of DOI, this paper is built on the information-behavior framework to establish an agent-based model, formulating the distinguished relationships in information perception layer and peer-driven behavior decision layer. To explore the time paths of DOI across different topological setting, simulations are performed in terms of qualitative comparison among topology combinations and quantification of effects induced by the change of topological parameter. Simulation experiments results verify some conclusions in the current literature and most importantly reveal some unique insights concerning network architecture optimization in duplex network, thus indicating a validity of the established model and the necessity to explore DOI in multiplex networks. This study enriches the academic finding in DOI and benefits those practitioners with policy implications.

### A. MAIN FINDINGS

The main findings of our study illuminate two interesting questions concerning DOI efficiency. One is why DOI is advisable to model in duplex networks comprised by

information transmission and behavior decision networks. The other is what topologies are conducive to the outbreak and adoption fraction of DOI.

(i) For the necessity of taking multiplexity into consideration, the duplex network of information transmission and behavior decision built on the theoretical framework of AMC provide a superiority and flexibility of the agent-based modeling in DOI, which is a further extension on the AMC framework proposed by reference [10]. First, it formulates the sequential two stages in DOI, which is intrinsically in line with the information, experience, and externality mechanism proposed by reference [22] from their case studies of DOI, proving our model's consistency with reality. Our model further elaborate reference [22]'s propositions in that the model captures the causal links from individual influences and adoption behaviors to multiplex networked movements of innovation-related signals, and eventually to collective adoption patterns, thus providing a flexible way to incorporate elements unfolding at both the microscopic and macroscopic levels associated with DOI. Most importantly, the simulation experiments indicate that the outbreak and adopted fraction of DOI is highly contingent on the topology of information transmission network. This conclusion corroborates the results of reference [20] on the key role played by information dissemination in DOI cascades, therefore the selection of initial spreaders of innovation is of paramount significance. Any single layer networked analysis is susceptible to underestimate the effect of information diffusion.

(ii) For the topologies conducive to DOI, qualitative analysis predicts faster adoption of innovation for the combination of random network in the layer of information dissemination and scale-free network in the layer of behavior decision, whereas the widest range of diffusion occurs in the combination of scale-free networks in both layers. This result is remarkably different to many previous results on single-layer network which state DOI is more likely to fail in a random network than in a highly clustered network [58]. One possible explanation is that random graph or scale-free network in the information transmission layer is more conducive to the awareness perception of new idea or product, since they are not inhibited by the path dependence or rigid knowledge or cognitive framework induced by small-world network. After the identification of facilitating architectures of duplex networks, the effects of topological parameters on the speed and range of DOI is quantified. Simulation results reveal that network density in both layers are beneficial to efficient DOI, validating density as an acceleration of early-period adoption rates. This is in line with current literature on the notion that density improves knowledge transfer and absorption efficiency [59]. However, this effect wears off after network density reaches a certain point when information is redundant. Another network parameter investigated is power law index, which characterizes the degree of heterogeneity of scale-free networks. In the information network, the diffusion speed increases with the increase of the power law index whereas

in the behavior network the diffusion speed decreases as the power law index increases. The adjustment of the power law index has little effect on the range of diffusion. The simulation results of duplex network interaction show that the information network with big power law index and the behavior network with comparatively small power law index offer a duplex network structure most conducive to DOI.

## B. PRACTICAL IMPLICATIONS

From a practical perspective, this study is of certain value for people who want to induce more efficient diffusion of certain innovations (such as the policy makers who contribute to the increasing of eco-friendly technology propagation), since it provides the guidance for duplex network configuration toward efficient DOI. There are mainly two suggestions: First, the effect of opinion leader or influential hub actors in the information network should be fully exploited due to their paramount significance in DOI. The government can endow more inputs to the cultivation of opinion leaders in the information network though stimulation or administrative measure and strengthen the information radiation range of the hub organizations through the promotion of information platform, industry association and strategic alliance. Second, for the second layer of duplex networks, government can amplify the demonstration effects of advanced actors and promote the cooperation between hubs and potential adopters at the same time. For example, the government can guide the hub actors to undertake R&D, test, demonstration and marketization stages of innovation, widening the range of technology diffusion at multiple levels of innovation and facilitate the catch-up of non-hub actors.

The paper also has some limitations need to be addressed in future studies. First, the interaction of inter-layers is described by the adoption rule in which adoption occur only in the joint exceeding of intra-layer thresholds. More sophisticated model is expected to formulate the complex relationship between information transmission layer and behavior decision layer and to explore the influence exerted by the interplay between different layers on DOI. In addition, this study uses a same set of nodes in the duplex networks, which take into consideration only intra-layer heterogeneity rather than inter-layer heterogeneity such as population. This simplified setting can conceal important micro-level characteristics affecting DOI thresholds. Future studies should take account of individual heterogeneity across different networks, which may provide more detailed investigation of time-dependent effects regarding a variety of social or technical factors on DOI.

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**QIAN YU** received the M.Sc. degree in applied mathematics and the Ph.D. degree in systems engineering from Wuhan University, Wuhan, China, in 2003 and 2006, respectively. He is currently a Professor with the School of Economics, Wuhan University of Technology. His research interests include economic behavior and game, cooperative innovation, and enterprise networks.

**ZHEHAO YU** is currently pursuing the Ph.D. degree with the Wuhan University of Technology. In this article, he is responsible for the establishment of models and data processing. His main research interests are in complex networks, complexity adaptive systems, and innovation diffusion.

**DING MA** received the M.Sc. degree in finance from Loughborough University, U.K., in 2008, and the Ph.D. degree in management science and engineering from the Wuhan University of Technology, Wuhan, China, in 2016. She is currently a Lecturer with the School of Economics, Wuhan University of Technology. Her research interests include complex networks, enterprise networks, and technology diffusion.

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