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REGULAR ARTICLE

Social culture and innovation diffusion: a theoretically founded agent-based model

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Abstract
This study proposes an agent-based model to theoretically investigate the effects of social culture on innovation diffusion. The model assumes that social culture (i.e., individualism, power distance, and uncertainty avoidance from Hofstede's cultural dimension theory) has a direct effect on the small-world network structure and individual characteristics. We further explore how the characteristics of innovation influence the diffusion process. We find that individualism has a positive effect on the diffusion speed in the early stage, whereas uncertainty avoidance and power distance have negative effects on innovation diffusion. The effect of uncertainty avoidance on the diffusion speed turns positive after the early stage of diffusion and the negative effect of power distance becomes positive in the late stage. We compare real-world diffusion data with the proposed agent-based model, finding some similarities in the diffusion patterns. The characteristics of innovation affect innovation diffusion when the uncertainty avoidance is high. However, when both uncertainty avoidance and individualism are low, the effect of the characteristics of an innovation on diffusion is restricted.

Keywords Hofstede · Social culture · Diffusion of innovation · Agent-based modeling · Computational method

JEL classification O33 · C63 · Z10 · D11

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1 Introduction

Schumpeter (1939) finds that innovation is an essential driver of economic dynamics. He divides the innovation process into four phases, namely invention, innovation, diffusion, and imitation (Burton-Jones 1999; Schumpeter 1934), and shows that the diffusion and imitation processes have great impacts on the economy (Schumpeter 1934; Śledzik 2013). The diffusion of a new product is as important as its invention. To conduct a successful diffusion, organizations invest considerable effort in advertising and marketing. According to the statistics published by Gartner, marketing expenditure represents 11.2% of revenue on average globally (McIntyre and Virzi 2018). The retail industry allocates the highest percentage, 21.9%, of expenditure to advertising. With the development of information and communication technology, advertising and marketing behaviors in online social networks are more effective than offline (Evans 2009). According to the report of PwC, Global Entertainment & Media Outlook 2019–2023, in 2018 digital advertising expenditure in the United States is $30 billion higher than TV advertising expenditure (van Eeden and Chow 2019). Organizations tend to target directly individual social networks to improve marketing efforts when introducing an innovation (Peres et al. 2010). According to Roger's theory, four main factors affect innovation diffusion: (1) the characteristic of the innovation, (2) time, (3) the communication channel, and (4) the social system (Rogers 2010). The first three factors depend on the change agency, namely the body that introduces the innovation into society (e.g., enterprises and governments). The change agency decides what, when, and how to introduce the innovation. However, the social system, which includes the social network structure, social norms, social culture, and opinion leaders, is simply presented to the change agency. Therefore, it is important to understand how the characteristics of the social system affect innovation diffusion dynamics. From the social system aspect, numerous studies examine the effect of the social network structure, social norms, opinion leaders, and weak ties on innovation diffusion (Valente and Rogers 1995). Delre et al. (2007) find that innovations diffuse faster in a more clustered social network because individuals are more exposed to a social influence. Bohlmann et al. (2010) state that the effect of the network structure on innovation diffusion is significant as individuals' adoption threshold increases. Loch et al. (2003) emphasize that a social norm can both inhibit and encourage innovation diffusion. Schwarz and Ernst (2009) and Sopha et al. (2013) consider social norms in their empirical studies of the diffusion of innovations. Van Eck et al. (2011) find that opinion leaders, who have a more central network position than others, possess more accurate knowledge about an innovation and are more innovative, which increases the speed of innovation diffusion. Valente and Davis (1999) also emphasize the importance of an opinion leader for accelerating the diffusion of innovations. Goldenberg et al. (2001) indicate that the influence of weak ties on information diffusion is as strong as the influence of strong ties. In most cases, individuals within the social system conduct adoption behavior. Numerous studies in the literature also examine the effect of consumption behavior on innovation diffusion (Chircu and Mahajan 2009; Desiraju et al. 2004; Iyengar et al. 2009).

In a social system, the emergence of a social phenomenon such as the diffusion of an innovation is driven by aggregated individual behaviors as well as the interactions between individuals. Individuals provide a society with unique social culture through historical integration. Conversely, social culture affects the social network system as well as individuals' characteristics. Evidence shows that individuals adjust their behaviors to reach the generalized expectations of others within a social group (Cialdini and Goldstein 2004). For example, people tend to behave differently when public scrutiny is absent (Belk 1988). Individuals in the same society tend to share a similar language, history, religion, and sense of identity at the national level (Dawar and Parker 1994; Hofstede 1980). Although there is a huge variance between individual personalities within a society, people from different societies display systematically different behaviors. Social norms and social culture have a tremendous influence on an individual's decision behavior (Cialdini and Goldstein 2004; Rogers 2010); therefore, the adoption pattern of a new product in one society differs from those of another (Yalcinkaya 2008).

Evidence shows that the diffusion patterns of an identical product differ by country (Ganesh 1998; Mahajan and Muller 1994). Several factors have been investigated to explain these variations (Yalcinkaya 2008): a country's place in a multi-country roll-out (Ganesh et al. 1997), a country's cultural context (Takada and Jain 1991), socioeconomic factors (Lindberg 1982), and social mobility (Gatignon et al. 1989). Aside from geographic, economic, and political factors, cultural factors are one of the most important characteristics that differentiate one society from another. Helsen et al. (1993) argue that macro-level variables cannot fully explain the difference in the diffusion of an innovation across countries. Social culture has a tremendous influence on individual behavior and different cultural aspects affect individual consumption behaviors differently (Roth 1995). Hence, understanding how cultural differences drive the differences in diffusion patterns among countries is a key point to capture the influences of a social system on innovation diffusion.

Traditional innovation diffusion studies are generally based on the Bass model (Bass 1969), which forecasts consumer durable goods at the industry level. Using aggregated sales data, the Bass model can capture the S-shaped diffusion pattern. It assumes a fully connected and homogeneous social network. The increase in adopters over time is driven by external influences such as advertising and internal influences such as word-of-mouth. As a diffusion model, however, the Bass model cannot capture individual interactions and overlooks decision variables. Although some of these drawbacks have been addressed (Mahajan et al. 2000; Meade and Islam 2006), aggregated models still lack explanatory power and require sufficient data to increase predictability (Chandrasekaran and Tellis 2007). Moreover, social culture influences the social structure and individual behavior simultaneously, which is a complex social process. Aggregated models have limitations in dealing with individual heterogeneity and interactions. Additionally, factors that affect an individual's decision and communication process are rarely informed by empirical data (Zhang and Vorobeychik 2019).

Since "innovation does not lend itself to description in terms of a theory of equilibrium" (Schumpeter 1928), innovation diffusion must be understood as a dynamic process driven by social influences (Kiesling et al. 2012). Individual-level models such as agent-based models, which can deal with complex emergent phenomena and individual interactions, have emerged as a natural approach for diffusion studies (Zhang and Vorobeychik 2019). Incorporating individual heterogeneity and interactions, agent-based models have been adopted by numerous studies of innovation diffusion, thereby providing theoretical explorations and political decision support (Kiesling et al. 2012).

Applying an agent-based model, this study investigates the effect of social culture on innovation diffusion by incorporating cultural factors into the social structure and individual characteristics. Psychological factors such as the number of adopted neighbors and need for identity significantly affect innovation diffusion (Janssen and Jager 2001). Individual utility when adopting an innovation depends on not only the functional advantage of the innovation, but also the social image of its usage (Janssen and Jager 2001). This study further explores the effect of different characteristics of innovation on diffusion in different social cultures. The remainder of this paper is structured as follows. Section 2 reviews previous studies, Section 3 introduces the proposed model, and Section 4 specifies the simulation experimental settings and simulation results, while Section 5 provides further discussion and concludes.

2 Literature review

2.1 Theory of social culture

Culture is a complex social-specific phenomenon that lacks a commonly accepted definition (Tian et al. 2018). Kluckhohn et al. (1953) define culture as "patterned ways of thinking, feeling and reacting that constitutes the distinctive way of life of a group of people." Similarly, Hofstede et al. (2010) consider culture as "the collective programming of the mind that distinguishes the members of one group or category of people from others" and Adler and Gundersen (2008) further state that the collective programming of the mind can be "handed down from one generation to the next through means of language and imitations."

Hofstede's cultural dimension theory has been widely applied in studies of national and organizational culture. It has a profound impact on empirical studies of culture (Sivakumar and Nakata 2001) and could be the most influential theory of cultural classification (Kirkman et al. 2006). Hofstede's social cultural dimension was developed based on data from over 116,000 surveys of over 88,000 IBM employees distributed across more than 50 countries from 1967 to 1973 (Kirkman et al. 2006). Table 1 shows Hofstede's cultural dimension scores for selected countries and regions (Hofstede 1984). The cultural dimension scores are scaled from 0 to 100, with lower scores indicating a lower level of cultural dimensions. Hofstede's original cultural dimensions include individualism, power distance, uncertainty avoidance, and masculinity (Hofstede 1984). Another dimension, long-term orientation, was defined in a later study (Hofstede and Bond 1988).

Hofstede's cultural dimension theory has a wider scope than those of Trompenaars, Hampden-Turner, and Hall (Roozmand et al. 2011). Since social culture changes little in a short period, mainstream studies that have explored the effect of social culture on innovation (Tian et al. 2018) and consumer behavior across countries (Van den Bulte and Stremersch 2004) use Hofstede's cultural dimensions. Tellis et al. (2003) investigate the effect of uncertainty avoidance on the diffusion of 10 durable goods in 16 European countries, finding that uncertainty avoidance has a negative impact on innovation diffusion take-off. Dwyer et al. (2005) study the diffusion of seven technological innovations in 13 European countries and find positive relationships between internal influence described in the Bass model and masculinity and power distance, but

Table 1 Cultural Dimension Scores of Selected Countries and Regions

Region	Country and Region	Individualism	Power Distance	Uncertainty Avoidance
Asia	China	20	80	30
	Hong Kong	25	68	29
	South Korea	18	60	85
	Japan	46	54	92
	Philippines	32	94	44
	Thailand	20	64	64
	Singapore	20	74	8
America	United States	91	40	46
	Venezuela	12	81	76
Europe	Denmark	74	18	23
	Sweden	71	31	29
	Germany	67	35	65
	Netherlands	80	38	53
	Norway	69	31	50
	Turkey	37	66	85

Source: Hofstede (1984)

a negative relationship with individualism. Van den Bulte and Stremersch (2004) conduct a meta-analysis covering 28 countries and 52 products and show that lower uncertainty avoidance and individualism and higher power distance accelerate innovation diffusion. Yeniyurt and Townsend (2003) investigate the relationship between the penetration rate of new products and national culture in 56 countries, finding that power distance and uncertainty avoidance hinder the adoption of new products. Yaveroglu and Donthu (2002) explore the effect of individualism, power distance, and uncertainty avoidance on innovation diffusion, while Jain and Maesincee (1997) and Steenkamp et al. (1999) study the effects of individualism and uncertainty avoidance.

The aforementioned literature shows that at least three cultural dimensions directly affecting innovation diffusion: individualism, power distance, and uncertainty avoidance. Individualism is the extent to which "people from birth onwards are integrated into strong, cohesive ingroups" (Hofstede 2001). Individualism is one of the most studied cultural dimensions when discussing an individual's susceptibility to social influences (Hofstede 1980; Kim et al. 1994; Mourali et al. 2005). Individualists have loose social ties, are independent, focus on themselves (Tian et al. 2018), and seek variety and hedonistic experiences (Roth 1995). Collectivists (opposite to individualists) tend to consider themselves as parts of groups, are more easily influenced by social norms, place more attention on the group (e.g., family, friends, coworkers), pursue more belongingness to the group (Kacen and Lee 2002), and are more sensitive to group pressures (Cialdini and Goldstein 2004). Individualists are more motivated by their own preferences and group conformity (Triandis 1995) and harmony is less important; therefore, they are less sensitive to group pressure (Broekhuizen et al. 2011). Individualists tend to evaluate an innovation from their own perspective and are less affected by the adoption decisions of others.

Power distance is "the extent to which the less powerful members of society expect and accept that power is distributed unequally" (Hofstede 2001). Power and inequality are fundamental social factors. All societies have unequal power distributions, but some are more unequal than others (Roozmand et al. 2011). Power distribution is strongly correlated with the distribution of social status and social wealth. In a high power distance culture, people tend to have stronger relationships with those in their own social circle and are less likely to have a relationship with those not close to their social status. In a high power distance culture, people have needs to maintain and increase their power-related factors such as social status and social wealth (De Mooij 2004; Roozmand et al. 2011; Roth 1995). In a low power distance culture, where class differences and social aspirations are not important, the tendency toward social status is low (Roozmand et al. 2011).

Uncertainty avoidance is the "extent to which members of a society feel threatened by uncertainty and ambiguity" (Hofstede 2001). People in a high uncertainty avoidance culture try to alleviate the uncertainty from unknown situations and unclear futures by relying on social norms, rituals, and bureaucratic practices (House et al. 2002). People in a low uncertainty avoidance culture are more likely to accept competition and dissent (Tian et al. 2018).

Among all factors, social culture is the only one that affects innovation diffusion. When studying the effect of social culture on innovation diffusion empirically, it is almost impossible to control for all the other factors that affect innovation diffusion, such as the time of the innovation's introduction, the price of the innovation, related policies, and the marketing efforts by the change agency. Moreover, empirical studies cannot capture how cultural factors affect individual characteristics and the interaction between individuals, which are the main drivers of innovation diffusion (Yalcinkaya 2008). Individual-level models such as agent-based models are thus ideal for this topic because they are capable of investigating the effect of social culture on innovation diffusion at the individual level.

2.2 Agent-based diffusion models

Since agent-based models focus on theoretical development (Gilbert 1997), many aim to understand diffusion processes in a highly abstract sense. Numerous theoretical agent-based models of innovation diffusion focus on individual heterogeneity (Faber et al. 2010; McCoy and Lyons 2014), social influence (Kaufmann et al. 2009; McCoy and Lyons 2014; Schwarz and Ernst 2009; Sopha et al. 2013), the effectiveness of promotional strategies, endogenous innovation, coevolution, and competitive diffusion (Kiesling et al. 2012).

Kiesling et al. (2012) review more than 150 theoretical and empirical studies associated with the agent-based simulation of innovation diffusion and Zhang and Vorobeychik (2019) review 43 papers (23 papers published after 2011) of empirical agent-based models. However, these two comprehensive review papers do not cover any study that applies Hofstede's cultural dimensions to agent-based diffusion models. Kirkman et al. (2006) review 180 empirical studies published from 1980 to 2002 that incorporate Hofstede's cultural dimensions, including studies of individual decision making, social networks, and organizational innovation. There is no study discussing diffusion directly and no study of agent-based diffusion models incorporating

Hofstede's cultural dimensions. To the best of the authors' knowledge, few studies embed Hofstede's cultural dimensions into agent-based diffusion models.

Desmarchelier and Fang (2016) follow Rogers' diffusion theory and build a cultural agent-based model to explore the effect of individualism and uncertainty avoidance on the diffusion process. Roozmand et al. (2011) simulate consumers' automobile decision-making process based on power distance and personality using three automobile characteristics: social status, social responsibility, and price. An individual's utility depends on his/her power distance level, social status, and personality. Broekhuizen et al. (2011) introduce an agent-based model to investigate individuals' movie selection decisions. In their model, an individual's decision is probabilistic based on his/her utility, which is a weighted sum of individual utility and social utility. Social utility is divided into two separated social influences: the influence of the past behavior of unknown others and the influence of the individual's social network. They further analyze differences in social influence in different cultures based on individualism.

The above studies embed social culture into individual characteristics but neglect the effect of social culture on the social network structure. Bohlmann et al. (2010) examine the effects of various network structures and relational heterogeneity on innovation diffusion in market networks, specifically network topology and the strength of the communication links among market segments. The study proves that the network structure has an important effect on the diffusion process and that the speed of diffusion varies significantly according to within- and cross-segment communication in a heterogeneous network. Delre et al. (2007) study how social processes affect diffusion dynamics and how the speed of diffusion depends on the network structure and individual heterogeneity. This theoretical study shows that the speed of diffusion changes with the degree of randomness in the network and that individual heterogeneity accelerates the diffusion process. Wolf et al. (2012) propose an agent-based model of the adoption of electric vehicles in Germany. In their simulation, the social network structure is determined by individuals' characteristics including age, sex, income, education, place of residence, lifestyle, and social radius. Palmer et al. (2015) consider socioeconomic factors while generating a small-world social network in their agent-based model of solar photovoltaic system diffusion in Italy. They adjust the connection probability between and within different social groups based on the Sinus-Milieus adopter categories.

Theoretically grounded agent-based diffusion models lack the capacity to represent real-world situations. On the contrary, empirically grounded agent-based diffusion models that consider the effect of socioeconomic factors on social structures are built for specific situations and they heavily rely on individual-level survey data (for a review, see Zhang and Vorobeychik (2019)). A compromise is thus needed to study the effect of social culture on innovation diffusion.

2.3 Social influences from the characteristics of innovation

Duesenberry (1949), who introduces the relative income effect, states that an individual's utility from consumption behavior depends not only on the amount of consumption, but also on the consumption level of others (Clark and Oswald 1994; Neumark and Postlewaite 1998). Veblen (1934) suggests that "conspicuous consumption behavior" exists and argues that the intrinsic value of an innovation may be less important than its social image (Chao and Schor 1998). Evidence shows that individuals' satisfaction increases when consuming the same products as their neighbors and that adoption decisions are largely driven by social comparison and imitation (Janssen and Jager 2002). Deffuant et al. (2005) design a model for innovations in which both social values and individual payoffs are considered and find that innovations with high social value and low individual benefit have a greater chance of succeeding than innovations with low social value and high individual benefit. Xiong et al. (2016) study peer effects including the information effect (awareness of an innovation), experience effect (knowledge or resource gained from earlier adopters' actual practice of the innovation), and externality effect (externalities generated by the adoption behavior of peers). These three effects could occur through different types of relationships in a social network, and each plays a different role at different stages of a diffusion process.

Within the innovation diffusion process, Peres et al. (2010) find two types of social influences on an innovation: the functional signal, which represents information on the functional attributes of a product, and the social signal, which indicates the social information that individuals infer from the adoption behavior of others. A potential adopter may not need word-of-mouth communication to detect the functional signal of an innovation (Peres et al. 2010). A typical functional signal is a network externality, which exists when the utility of a product depends on the number of its adopters (Katz and Shapiro 1985). The number of users of the same product increases utility as adopting the product increases, especially for telecommunication products such as fax, phone, and email. Network effects thus affect the diffusion of interactive communicational innovations (Mahler and Rogers 1999).

The social signal from an individual's aspiration group is transmitted to that individual (Van den Bulte and Joshi 2007; Van den Bulte and Wuyts 2007). It can be subdivided into a vertical social signal, which indicates the status of the adopter, and a horizontal social signal, which represents group identity. The vertical social signal is a crucial driver of innovation diffusion. Under certain conditions, an individual's social status has more impact on diffusion than his/her social ties (Van den Bulte and Stremersch 2004). Empirical evidence shows that one purpose of an individual's purchasing behavior of luxurious and prestigious products is to enhance his/her social status (De Mooij 2004). The horizontal social signal indicates that the adoption behaviors of individuals in a group emphasize group identity. An individual sensitive to group belongingness faces stronger pressure on his/her adoption behavior. Finally, the social influence from the characteristics of innovation also plays an important role in innovation diffusion. A better understanding of how the characteristics of innovation affect social interaction enables the change agency to deliver more efficient marketing strategies.

3 Model specification

To investigate the effect of social culture on innovation diffusion, the proposed model assumes that social culture directly affects the structure of social networks and individual characteristics. Figure 1 illustrates the general frame of the proposed model, which has three parts: the social network, individuals, and the innovation. First, the effect of social culture on the structure of social networks is discussed. Second, the individual agent's behavior is introduced by partitioning the decision process into the knowledge stage, persuasion stage, and decision stage. The mechanism of how the characteristics of innovation affect the innovation diffusion process is then derived.

3.1 Building social networks

Individuals "tend to be linked to others who are close to them in physical distance and who are relatively homophilous in social characteristics" (Rogers 2010). In a social network, individuals are more likely to cultivate a relationship and communicate with individuals who share similar characteristics such as beliefs, education, and socioeconomic status. A social network has two typical features: the clustering effect and the small-world effect (Newman 2000). The clustering effect indicates that an individual's social network is highly clustered, which means that a friend of an individual is likely to be a friend of another friend of the individual. Milgram (1967) confirms the small-world phenomenon, which suggests that most people are separated by only six degrees on average. In a social network, compared with the whole network size, an individual has limited links, mostly with family members, friends, and coworkers, and he/she needs only a few steps to reach another unknown individual. Among the various networks in graph theory, the small-world network proposed by Watts and Strogatz (1998) possesses these two features of social networks. According to Watts and Strogatz (1998), a small-world network starts with a regular and circular network, as shown on the left of Fig. 2. Then, rewire the links between two agents to a randomly selected agent with a certain probability with parameter p, which is named the rewiring probability. If $p = 0$, the network is highly clustered and it takes longer steps to reach other agents. If $p = 1$, the network is completely "random". When $0 < p < 1$, the network exhibits both the clustering effect and the small-world effect.

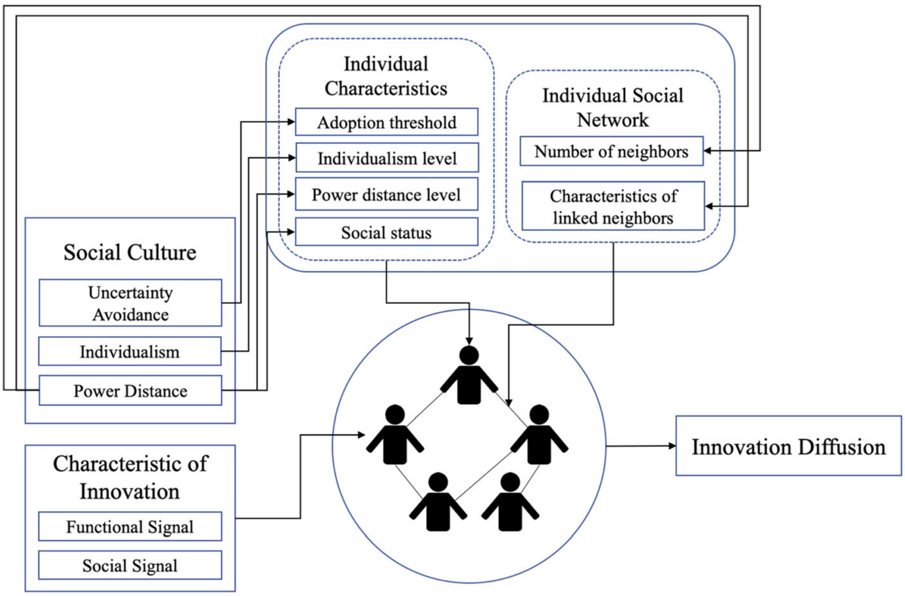

Fig. 1 Overview of the Proposed Model

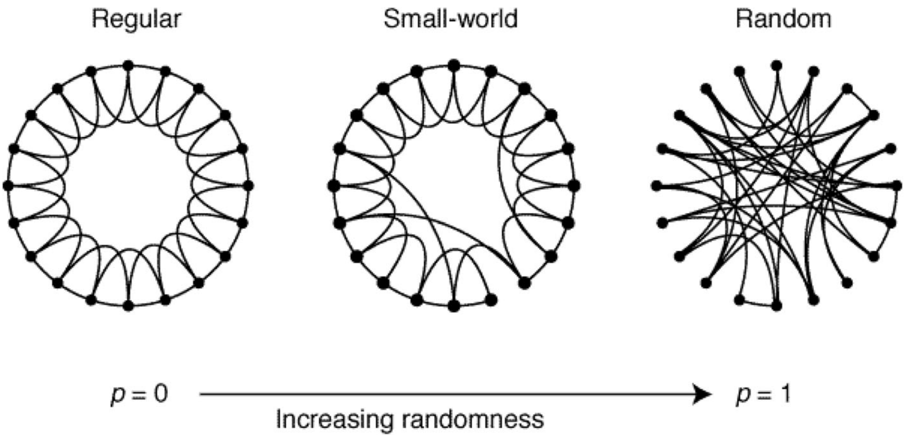

Fig. 2 Small-World Network with 20 Agents ($k = 4$). Source: Watts and Strogatz (1998)

If each agent in the small-world network represents an individual and the links between agents represent mutually recognized social relationships, the network structure of a high power distance society is much closer to a regular network, as shown on the left of Fig. 2, which consists of limited links among social classes. On the contrary, the network structure of a low power distance society is relatively close to a random network with more links among social classes. The parameter p adjusts the randomness of the network structure. Therefore, it is reasonable to assume that the power distance is negatively correlated to the rewiring probability p.

For different network topologies, a social network of 1000 agents is sufficiently large to observe the dynamics (Cowan and Jonard 2004). The agent-based model we build comprises a population of 1000 individuals ($N = 1000$); each individual i links with 10 agents ($k = 10$) in every simulation run on average. The rewiring probability is usually between 1% and 10% of all links to represent a social network (Watts and Strogatz 1998). To observe a more diverse social structure, we assume that the rewiring probability varies according to power distance (*PDI*) level in a linear sense:

$$p = \varphi_p \times PDI + \eta_p \tag{1}$$

where $\varphi_p = -0.00099$ and $\eta_p = 0.1$. When power distance is high/low ($PDI = 100$ *or* $PDI = 0$), the rewiring probability is very low/high ($p = 0.001$ *or* $p = 0.1$), and only a few links (or a lot of links) are rewired.

3.2 Individual agents' behavior

Rogers (2010) indicates that the "innovation adoption decision is the process through which an individual passes in sequence from (1) gaining initial knowledge of an innovation, (2) to forming an attitude toward the innovation, (3) to making the adopt-or-reject decision, (4) to implementing the new idea, and (5) to finally confirming the decision." Considering the nature of the decision sequence, Rogers (2010) introduces a five-stage innovation decision process: knowledge, persuasion, decision, implementation, and confirmation. Our model is built on the first three stages based on the widely accepted assumption that an individual's adoption behavior is influenced by personal characteristics, social influences, and innovation characteristics (Gatignon and Robertson 1985). Individual i in our model has three states: uninformed ($inform_i = 0$), informed ($inform_i = 1$), and adopted ($adopt_i = 1$). We incorporate three social cultural dimensions, namely individualism, power distance, and uncertainty avoidance, into the individual characteristics that affect the individual's innovation decision process. Individual i's characteristics include his/her individualism level (idv_i), power distance level (pdi_i), and adoption threshold level (τ_i), which are directly affected by the social individualism level (IDV), social power distance level (PDI), and social uncertainty avoidance level (UAD), respectively; i's social status ($status_i$), number of linked neighbors, and characteristics of linked neighbors are indirectly affected by the social power distance level (PDI). All individual characteristics vary in the range [0,1]. Detailed explanations are provided next. Appendix A presents the specific variables of the individual characteristics.

3.2.1 Knowledge stage

In this stage, individuals are informed about the existence of the innovation either from external information such as advertising or from internal information such as word-of-mouth. In the early stage of innovation diffusion, such information generally flows from outside the social system. Individuals informed in the early stage of diffusion generally have a higher level of innovativeness, which shows how open an individual is to new ideas compared with other members of the system. Rogers (2010) divides potential adopters into five segments according to their time of adoption: innovators, early adopters, early majorities, later majorities, and laggards. Innovators and early adopters usually possess a high level of innovativeness and "earlier adopters have higher social status than do later adopters" (Rogers 2010). As social status is highly correlated with innovativeness, it is reasonable to assume that individuals with higher social status are more likely to be informed by external information. In our model, 1% of the population are informed about the innovation by external information. The probability of being informed by external information depends on an individual's social status: individuals with higher social status have a higher probability of being informed by external information.

3.2.2 Persuasion stage

In the persuasion stage, individuals form an attitude toward the innovation or the expected utility of innovation adoption. As discussed earlier, the characteristics of innovation can be divided into functional and social signals and the social signal can be subdivided into vertical and horizontal social signals. An individual's utility is the weighted sum of the three characteristics of innovation above. The utility of the functional signal and social signal is defined as individual utility and social utility, respectively, and the weight of these two utilities is the individual's individualism level. If the individual's individualism level is high, his/her utility depends more on the functional signal and his/her own characteristics. If the individual's individualism level is low, his/her utility depends more on the decisions of others and social status-related factors. Individual i's utility function is defined as

$$
\begin{aligned}
U_i = {} & idv_i \cdot (1 - exp(-idv_i \cdot info\_f)) \\
& + \ (1 - idv_i) \cdot \left((1 - exp(-\alpha)) + \left(1 - exp\left(-\sqrt{pdi_i \cdot status_i} \cdot info\_s \right) \right) \right)
\end{aligned} \tag{2}
$$

The exponential form of the utility function is inspired by Jager (2000) and Roozmand et al. (2011), which is capable of modeling diminishing marginal utility and restricting the utility value between [0,1]. idv_i, pdi_i, and $status_i$ are individual i's individualism level, power distance level, and social status, respectively. $info\_f$ and $info\_s$ indicate the functional signal and vertical social signal of the innovation, respectively. $\sqrt{pdi_i \cdot status_i}$ means that if individual i's power distance level is high or social status is high, the vertical social signal has a stronger impact on his/her social utility. On the contrary, if individual i's power distance level or social status is low, the vertical social signal has a limited influence on his/her social utility. The square root offers a balanced mean of the two variables. α represents the horizontal social signal, which is the ratio of the number of adopted neighbors and the total number of neighbors:

$$
\alpha = \frac{number\ of\ adopted\ neighbors}{number\ of\ total\ neighbors} \tag{3}
$$

Individual i's idv_i and pdi_i are drawn from a normal distribution with means of $IDV/100$ and $PDI/100$, respectively. To allow for differences in the individual's personality, standard deviation is fixed to 0.2. Individual i's social status, $status_i$, is assigned in the order of his/her ID number in the simulation according to the following equation (where $N = 1000$ is the population number):

$$
status_i = (i/N) - (i/N) \cdot \left(1 - {}^{i}/_{N} \right)^{\left(1 - {}^{PDI}/_{100} \right)} \tag{4}
$$

Equation (4) aims to generate a Lorenz curve, which is commonly used in inequality distribution-related studies. Morgan (1962) states that the Gini index is one of the best measures of inequality, and most measurement of income inequality is derived from the Lorenz curve (Gastwirth 1972). Since social status is strongly correlated with other socioeconomic factors such as income, education, and occupation, it is reasonable to assume that the distribution of social status also follows a Lorenz curve. Social mobility is relatively low in a high power distance society. The randomness of the network structure depends on power distance, as discussed earlier. We also introduce the randomness of social status as follows:

1. Assign individual i's social status, $status_i$, in the order of his/her ID number according to eq. (4).
2. Randomly choose individual j.
3. Exchange individual i's social status with individual j's social status with a probability of p.

Figure 3 shows the distribution of social status with social power distance levels of 0, 30, 50, and 70. Every dot in the sub-figures represents an agent. The x-axis indicates

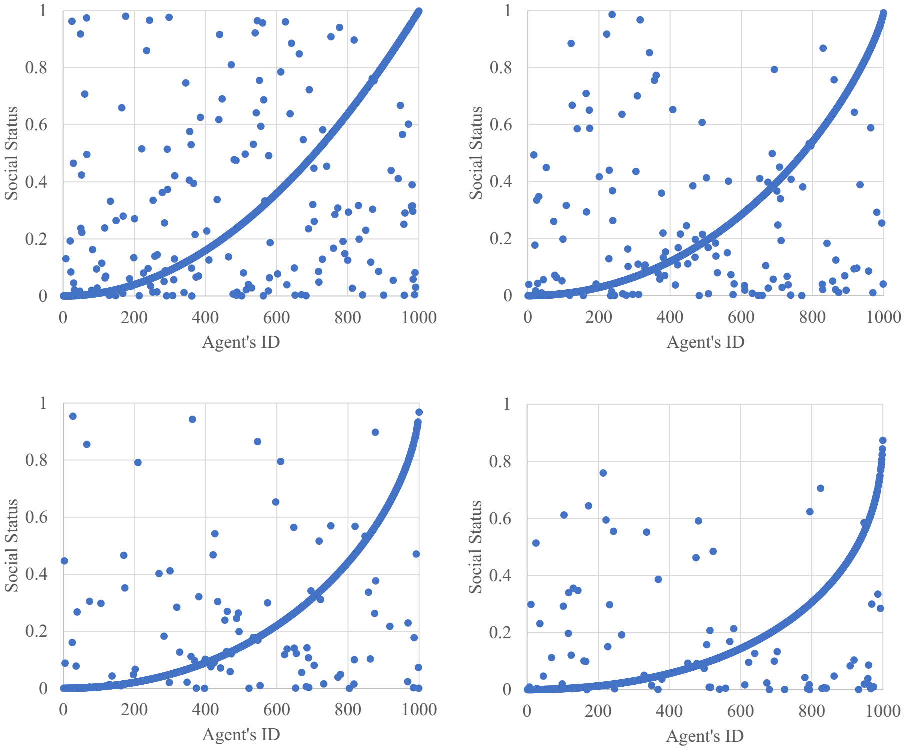

Fig. 3 Distribution of Social Status. Note: upper-left: power distance = 0; upper-right: power distance = 30; lower-left: power distance = 50; lower-right: power distance = 70. If agent i's ID is around 300, his/her social status is probably around 0 to 0.2; agent i's social status then has a probability greater than 0.2 if his/her social power distance level is low. Consider agent i's ID is around 900. Then, his/her social status is probably located around 0.8 if PDI = 0 and around 0.4 if PDI = 70

agents' ID and the y-axis indicates social status. There are 1000 agents in the simulation and their social status ranges from 0 to 1. More randomness can be observed with a lower social power distance level (i.e., more random dots). Social status is distributed more equally with a lower social power distance level.

3.2.3 Decision stage

In the decision stage, an individual makes an adopt-or-reject decision according to his/her utility. We apply the adoption threshold concept widely used in the social sciences, especially for modeling collective behaviors (Granovetter 1978). The threshold model can be applied to many social phenomena, including innovation, rumor, and epidemiology (Rogers 2010). Diffusion models incorporating the threshold model suggest that an individual adopts the innovation when his/her utility surpasses his/her threshold level. Individual i thus adopts the innovation when his/her utility exceeds his/her adoption threshold: $U_i > \tau_i$.

Innovation diffusion is a process of social learning under uncertainty. An individual with a strong uncertainty avoidance propensity needs a higher level of expected utility of innovation adoption to overcome the corresponding doubts of innovation risks. Low uncertainty avoidance societies are more willing to take risks (Yalcinkaya 2008). The adoption threshold is correlated with an individual's uncertainty avoidance level. In a high individualism society, people more seek diversity; therefore, the variance of the threshold distribution is larger than in a low individualism society. The adoption threshold of individual i, τ_i, is drawn from a normal distribution with a mean and standard deviation as defined below:

$$\begin{aligned} mean\_TH &= \varphi_{mean} \times UAD + \eta_{mean} \\ \mathrm{SD}_{\mathrm{TH}} &= \varphi_{sd} \times IDV + \eta_{sd} \end{aligned} \tag{5}$$

where $\varphi_{mean} = 0.006$, $\eta_{mean} = 0.2$, $\varphi_{sd} = 0.004$, and $\eta_{sd} = 0.1$. Since a threshold under 0.2 or over 0.8 cannot observe a typical diffusion process, the mean of the threshold distribution varies from 0.2 to 0.8, while the social uncertainty avoidance level varies from 0 to 100. A standard deviation smaller than 0.1 makes individuals highly homogeneous in their threshold levels and one larger than 0.5 makes them overly heterogeneous, which loses the meaning of the uncertainty avoidance level. Therefore, the standard deviation ranges from 0.1 to 0.5 and the social individualism level varies from 0 to 100. Figure 4 shows the initial threshold distribution with a mean of 0.5 and standard deviations of 0.1, 0.2, 0.3, and 0.5.

High-income individuals are more likely to adopt an innovation because their marginal disutility of price (innovative products are usually more expensive than other

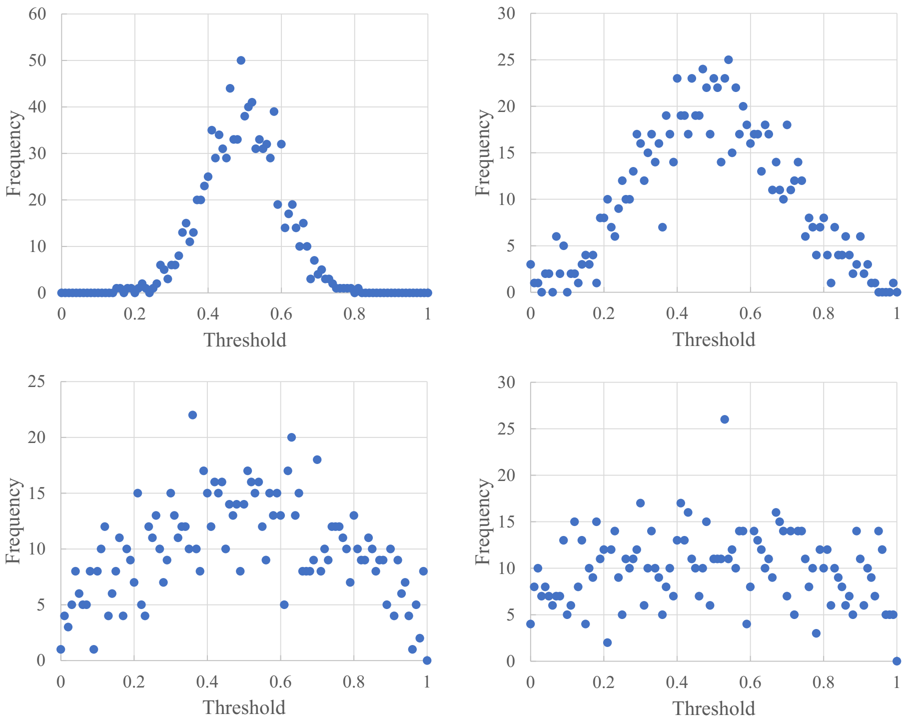

Fig. 4 Initial Threshold Distribution. Note: upper-left: SD_TH = 0.1; upper-right: SD_TH = 0.2; lower-left: SD_TH = 0.3; lower-right: SD_TH = 0.5

products in the market) is much lower than that of low-income individuals. Furthermore, highly educated individuals are more skilled in dealing with the uncertainty of innovation adoption. Since social status is highly correlated with other socioeconomic factors, we assume that an individual's threshold level is correlated with his/her social status. We also introduce randomness into the threshold distribution after drawing the individual's threshold values from a normal distribution:

1. Sort the drawn threshold values into decreasing order.
2. Assign individual i's threshold, τ_i, in the order of his/her ID number. (Higher social status values are matched with a lower adoption threshold.)
3. Randomly choose individual j.
4. Exchange individual i's adoption threshold with individual j's adoption threshold with a probability of p.

3.3 Characteristics of innovation

As mentioned in the persuasion stage, we divide the characteristics of innovation into the functional signal, vertical social signal, and horizontal social signal. Empirical studies show that individuals' utility is affected by the decisions of their neighbors in their own social networks (Cowan et al. 2004). The horizontal social signal is represented by the number of adoptions in one's social network. By contrast, the functional signal and vertical social signal are embedded in innovation. For simplicity, we assume that the sum of the functional signal and vertical social signal is 1. Although the absolute levels of those characteristics are important for innovation diffusion, sometimes the absolute level can be meaningless. For example, an innovation with a high functional signal and a high vertical signal diffuses faster than one with a low function signal and a low vertical signal. The comparison of relative levels brings about more implications, such as which diffuses faster in a certain type of society (an innovation with a high functional signal and a low vertical signal or one with a low functional signal and a high vertical signal) To address the above questions, we assume that the vertical social signal, $info\_s$, varies from 0 to 1 and the functional signal is $info\_f = 1 - info\_s$.

3.4 Simulation process

The simulation of the proposed model begins by setting the values for the social cultural dimensions and the characteristics of innovation (Step 1). The initialization process is needed to build the simulation environment. First, build a social network according to the social power distance level (Steps 2 and 3). Second, initialize all individuals' characteristics such as social status, adoption threshold, and cultural characteristics (Steps 4–6). Third, initialize all individuals' states (Steps 7 and 8). After initializing all the parameters, randomly choose an agent and update his/her state (Step 9). Then, randomly choose an agent among the informed agents, check whether he/she wants to change his/her state (Step 10), and update his/her adoption threshold (Step 11). Repeat the state and adoption threshold update process (Steps 9–11) 10,000 times. Ten thousand iterations are sufficient to obtain a distinct diffusion process for a network with 1000 agents (see Appendix B). The details of the simulation process are described below:

1. Confirm the social cultural dimension scores (individualism (IDV), power distance (PDI), and uncertainty avoidance (UAD)) and characteristics of innovation (vertical social signal (*info _ s*)).
2. Build a regular network with a population of 1000, $N = 1000$; the average number of linked neighbors is 10, $k = 10$.
3. Calculate the rewiring probability, p, according to the following equation; then, rewire the links between individuals with a probability of p:

$$p = \varphi_p \times PDI + \eta_p$$

4. Generate agents' social status values, $status_i$, according to the following equation; then, apply randomness with a probability of p:

$$status_i = (i/N) - (i/N) \cdot \left(1 - {}^{i}/_{N}\right)^{\left(1 - {}^{PDI}/_{100}\right)}$$

5. Draw agents' adoption threshold values, τ_i, from a normal distribution with the following mean and standard deviation; then, apply randomness with a probability of p:

$$mean\_TH = \varphi_{mean} \times UAD + \eta_{mean}$$
$$SD\_TH = \varphi_{sd} \times IDV + \eta_{sd}$$

6. Draw agents' cultural characteristics, idv_i and pdi_i, from a normal distribution with means of $IDV/100$ and $PDI/100$, respectively and a standard deviation of 0.2.
7. Set all individuals' state as uninformed ($inform_i = 0$).
8. Randomly select 1% of the population to be informed about the innovation ($inform_i = 1$). Individuals with higher social status are more likely to be selected.
9. Randomly select individual i. If individual i is uninformed and one of the linked individual j is informed ($inform_j = 1$) or adopted ($adopt_j = 1$), individual i is informed ($inform_i = 1$); otherwise, stay uninformed ($inform_i = 0$).
10. Randomly select informed individual i ($inform_i = 1$) and calculate his/her utility according to the following equation. If $U_i > \tau_i$, then individual i adopts the innovation ($adopt_i = 1$); otherwise, stay informed ($inform_i = 1$):

$$U_i = idv_i \cdot \left(1 - exp\left(-idv_i \cdot info_f\right)\right) + (1 - idv_i) \cdot \left((1 - exp(-\alpha)) + \left(1 - exp\left(-\sqrt{pdi_i \cdot status_i} \cdot info\_s\right)\right)\right)$$

11. The threshold of individual i, τ_i, decreases exponentially as the number of adopted neighbors increases: $\tau_{i,t} = \tau_i \cdot e^{-10\alpha}$
12. Repeat Steps 9 to 11 10,000 times.

Finally, repeat the whole process 20 times to control for the random effect. All the simulation results reported in Section 4 are averaged over 20 independent runs. Appendix A lists the parameters and variables.

4 Simulation experiments and results

We first examine the effect of each cultural dimension and the vertical social signal on innovation diffusion. Then, the diffusion process according to different combinations of cultural dimensions is simulated. After examining the basic features of the proposed model, we investigate the effect of social culture on the innovation diffusion process by analyzing the effect of the cultural dimensions on the adoption level and diffusion speed in the different stages. The effects of the cultural dimensions are further explored by comparing the real-world diffusion data with the diffusion patterns generated by the model. Then, the effects of the characteristics of innovation on the diffusion process are discussed.

4.1 Basic features

To verify the dynamics of the proposed model, we first conduct simulations that modify one cultural dimension from 0 to 100 each time, while the other cultural dimensions are fixed at 50 and the vertical social signal ($info\_s$) is fixed at 0.5. Then, we modify the vertical social signal from 0 to 1, with all the cultural dimensions equal to 50. Figure 5 presents the simulation results and Appendix C reports the standard deviations of each simulation. The results show that a higher level of individualism has a positive effect on innovation diffusion, whereas a higher level of power distance and uncertainty avoidance as well as a higher vertical social signal have a negative effect on innovation diffusion. The effects of individualism and uncertainty avoidance on the innovation diffusion process are similar. A decrease in individualism has a larger negative effect on innovation diffusion than the positive effect of uncertainty avoidance. When power distance exceeds 60, the diffusion processes are strongly hindered. Power distance has only a limited effect on innovation diffusion when it is less than 60. Compared with the cultural dimensions, the characteristics of innovation do not exhibit a strong effect on innovation diffusion in the early stage.

To investigate the effect of different combinations of the cultural dimensions, Table 2 presents eight cases. We conduct simulations on each case with the vertical social signal fixed to 0.5. Figure 6 presents the experimental results and Appendix C reports the standard deviations.

Innovation diffuses rapidly when individualism is high and the other dimensions are low (Case 6). Since uncertainty avoidance is low, individuals' threshold level is relatively low, and this allows them to adopt the innovation easily. Lower power distance indicates more cross social class links, which allows information to transform in the social network more quickly. Additionally, the high individualism level indicates higher individual heterogeneity, which accelerates innovation diffusion. This explains why Case 8 diffuses slightly more slowly than Case 6. When both uncertainty avoidance and power distance remain high and individualism is low (Case 3), innovation diffusion tends to be slow. A low individualism level makes individuals focus more

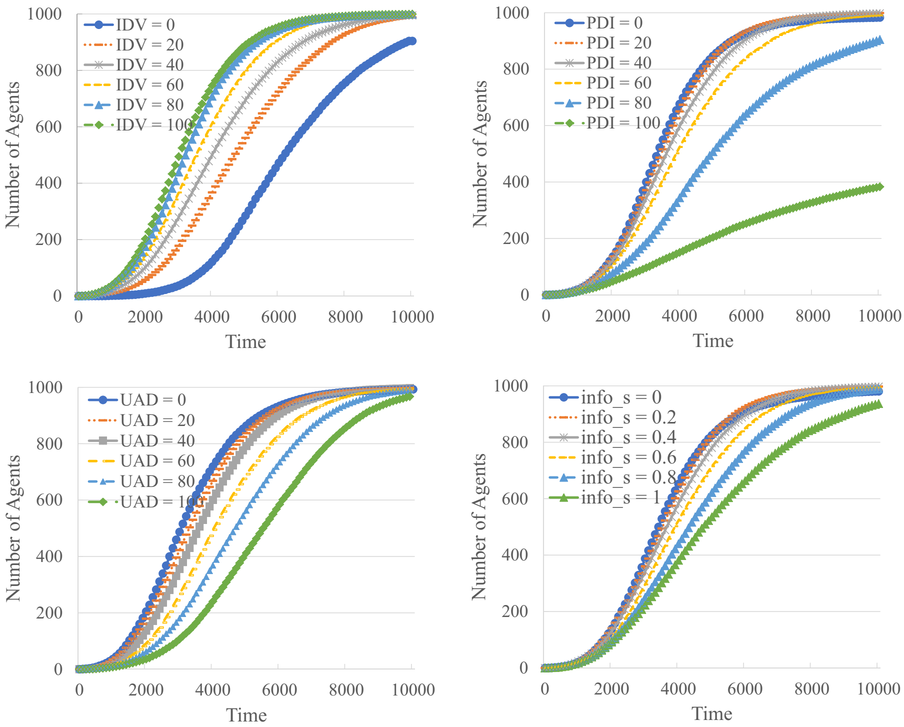

Fig. 5 Effect of Social Culture on Innovation Diffusion. Note: upper-left: individualism adjusted; upper-right: power distance adjusted; lower-left: uncertainty avoidance adjusted; lower-right: info_s adjusted

on the decisions of others, whereas a high level of uncertainty avoidance makes the majority of individuals risk averse when adopting the innovation. In addition, a high level of power distance further suppresses the diffusion process. As only limited links exist between social classes, the information flow is restricted in an almost regular social network. If individualism is high (Case 1), the situation is relieved. Indeed, although the take-off is slower than in the low power distance case, the final adoption

Table 2 Combination of Cultural Dimensions

	Uncertainty Avoidance	Individualism	Power Distance
Case 1	High	High	High
Case 2	High	High	Low
Case 3	High	Low	High
Case 4	High	Low	Low
Case 5	Low	High	High
Case 6	Low	High	Low
Case 7	Low	Low	High
Case 8	Low	Low	Low

*Note: High = 80, Low = 20

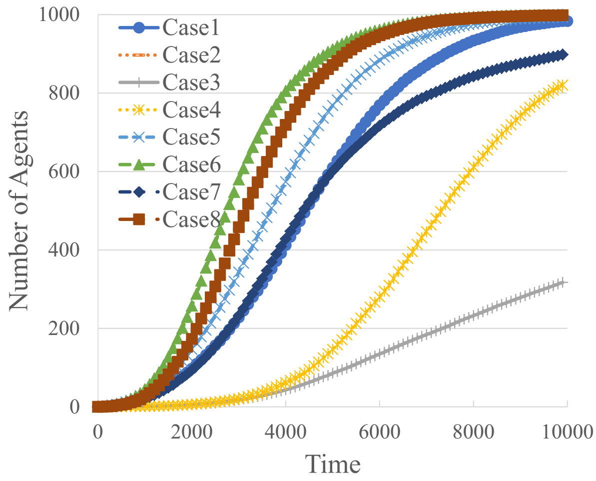

Fig. 6 Diffusion Process with Eight Combinations of the Cultural Dimensions. *Note: All simulation runs with $info\_s = 0.5$

level is much more optimistic. Power distance has a strong effect on innovation diffusion. When it is low and the levels of uncertainty avoidance and individualism differ (Cases 2 and 8), an innovation diffuses faster than in other cases. When a social network has sufficient inter-social class links, the drawbacks of a high uncertainty avoidance level can be mitigated by highly heterogeneously distributed individuals. Moreover, when the population lacks heterogeneity and is highly affected by other individuals, as in the case of low individualism (Cases 7 and 8), if the uncertainty avoidance level is sufficiently low, the fatal effect of power distance can be alleviated to a certain extent.

Overall, the results show that the differences in diffusion patterns are due to the differences in both the cultural dimensions and the characteristics of innovation. In a low power distance society, it would be ideal to introduce innovations to high social status individuals. Such individuals tend to have a low threshold, and low threshold individuals need less information to adopt an innovation. Since higher social class individuals are interlinked with lower social class individuals, their adoption behavior can affect the latter. In a high power distance society, targeting individuals with relatively low social status and a low threshold might be a good strategy. Since the adoption behavior of the higher social class hardly affects the lower social class, encouraging effective adoption behavior by the lower social class can boost the diffusion process. On the contrary, introducing the experience of the higher social class to the lower social class may have a positive effect on diffusion.

4.2 Effect of social culture on the innovation diffusion process

To investigate how social culture affects innovation diffusion, we examine the effect of the cultural dimensions on the diffusion level and diffusion speed of the innovation in the different diffusion stages. The three cultural dimensions (individualism, power distance, and uncertainty avoidance) vary from 0 to 100 in intervals of 20 and the characteristics of innovation vary from 0 to 1 in intervals of 0.2. There are 1296 cases in total. Each simulation result is averaged over 20 independent runs to control for the random effect. The diffusion process is divided into 10 intervals (Fig. 7). The diffusion level in each interval is the number of adoptions; for example, the diffusion level of $g1$ is the number of adoptions at time $g1$. The diffusion speed in each interval is the linear slope of an earlier time point; for example, the diffusion speed of $g4$ is the linear slope between times $g3$ and $g4$. Then, we use two ordinary least squares models to estimate the effects of the cultural dimensions on the diffusion level (AL) and diffusion speed (SL):

Model 1:

$$SL_g = \beta_0 + \beta_1 \cdot IDV + \beta_2 \cdot PDI + \beta_3 \cdot UAD + \varepsilon \qquad \forall g = 1, 2, \cdots, 10$$

$$AL_g = \beta_0 + \beta_1 \cdot IDV + \beta_2 \cdot PDI + \beta_3 \cdot UAD + \varepsilon \qquad \forall g = 1, 2, \cdots, 10$$

Model 2:

$$\begin{aligned} SL_g = {} & \beta_0 + \beta_1 \cdot IDV + \beta_2 \cdot PDI + \beta_3 \cdot UAD + \beta_4 \cdot IDV \times PDI + \beta_5 \cdot IDV \times UAD \\ & + \beta_6 \cdot PDI \times UAD + \beta_7 \cdot \cdot IDV \times PDI \times UAD + \varepsilon \qquad \forall g \\ = {} & 1, 2, \cdots, 10 \end{aligned}$$

$$\begin{aligned} AL_g = {} & \beta_0 + \beta_1 \cdot IDV + \beta_2 \cdot PDI + \beta_3 \cdot UAD + \beta_4 \cdot IDV \times PDI + \beta_5 \cdot IDV \times UAD \\ & + \beta_6 \cdot PDI \times UAD + \beta_7 \cdot IDV \times PDI \times UAD + \varepsilon \qquad \forall g \\ = {} & 1, 2, \cdots, 10 \end{aligned}$$

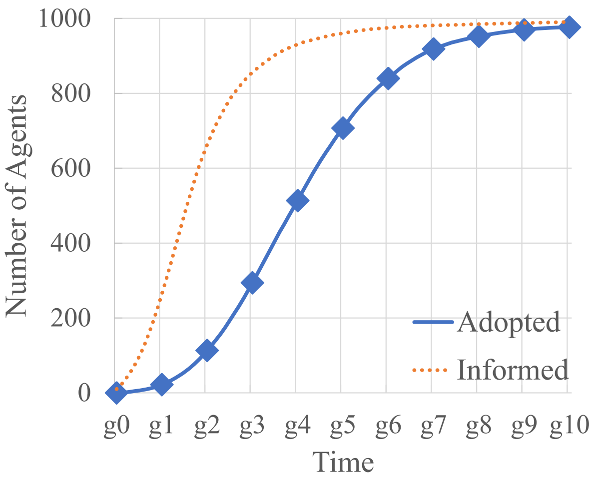

Fig. 7 Intervals in the Diffusion Process. *Note: Simulation run with individualism = power distance = uncertainty avoidance = 50 and $info\_s = 0.5$

Tables 3 and 4 show the effects of the cultural dimensions on the diffusion speed and diffusion level in each interval, respectively. Figure 8 shows the coefficients of the estimation results. The interpretations of the results are based on Model 2 that provides more statistically significant information. In the early diffusion stage, individualism has a positive impact on the diffusion speed, whereas power distance and uncertainty avoidance have negative impacts. In the middle stage, the negative effect of power distance and uncertainty avoidance decreases and the effect of individualism turns negative. In the late stage, individualism has only a limited effect on the diffusion speed. On the contrary, uncertainty avoidance and power distance have a positive effect. Individualism has a positive effect on the diffusion level in the early stage of diffusion and the effect gradually turns negative over time. Uncertainty avoidance and power distance have strong negative effects on the diffusion level before the middle stage, which are alleviated thereafter.

To raise reliability, we display the real-world diffusion data and proposed model with the following innovations: mobile phones, television sets, cable television, personal computers, and fax machines. Figure 9 provides the real-world diffusion example and corresponding diffusion patterns with the proposed model. The diffusion data of the above innovations are published by the World Bank. The diffusion patterns are the only focus of this comparison, not the diffusion level or diffusion starting point. The real-world diffusion data are normalized to [0,1] and ignored any difference in diffusion starting time. The cultural dimensions of the selected countries are distinct from those of others countries and there are sufficient real-world data on them. Table 1 lists the cultural dimension scores of the considered countries.

Mobile phones, personal computers, and fax machines are innovations with strong network externalities. As the number of adopters increase, the advantages of innovation increase exponentially. Innovations with network externalities present stronger functional signals. Most people adopt these innovations to enjoy their functional advantages rather than flaunt their social status. Nowadays, without these innovations, daily life might face huge inconveniences. Therefore, the vertical social signals of these innovations are relatively low and is assumed to be around 0.3. Television sets and cable televisions are innovations with only indirect network externalities. The advantages of these innovations do not directly increase as the number of adopters increase, as more content providers compete in the market and therefore the quantity and quality of content increase. Adoption utility increases as more favorable content increases. Most people use television sets and cable television to gain information and for leisure time. As the utility of television sets and cable television depends on providing content rather than on the number of adopters, the functional signal is not as strong as it is for mobile phones and fax machines. The vertical social signal of television sets and cable television is assumed to be around 0.5.

The diffusion of mobile phones in Denmark and the United States is faster than that in China and South Korea in the model. However, the diffusion process in South Korea is faster in the real world, perhaps because of policies that have promoted the development of the ICT infrastructure. The real-world diffusion patterns of television sets are identical to the patterns simulated by the model, while

Table 3 Estimation Results of the Effect of the Cultural Dimensions on the Diffusion Speed

	SL_g1		SL_g2		SL_g3		SL_g4		SL_g5		SL_g6
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1
IDV	0.029***	0.026***	0.106***	0.062***	0.133***	−0.07***	0.078***	−0.172***	0.019***	−0.136***	−0.012***
	(75.2)	(19.31)	(61.75)	(11.16)	(50.55)	(−8.48)	(30.64)	(−21.68)	(8.86)	(−19.4)	(−6.34)
PDI	−0.011***	−0.018***	−0.086***	−0.138***	−0.149***	−0.281***	−0.117***	−0.224***	−0.062***	−0.081***	−0.025***
	(−28.18)	(−13.6)	(−50.12)	(−24.87)	(−56.86)	(−34.26)	(−46.39)	(−28.25)	(−28.67)	(−11.52)	(−13.78)
UAD	−0.026***	−0.045***	−0.112***	−0.258***	−0.161***	−0.464***	−0.115***	−0.348***	−0.044***	−0.111***	0.005**
	(−66.47)	(−34.04)	(−65.72)	(−46.61)	(−61.49)	(−56.59)	(−45.39)	(−43.87)	(−20.07)	(−15.75)	(2.73)
IDV*PDI		−0.00005*		−0.000112		0.0013***		0.002***		0.0012***	
		(−2.2)		(−1.2)		(9.69)		(14.77)		(9.81)	
IDV*UAD		0.0002***		0.0018***		0.0048***		0.0045***		0.0021***	
		(8.65)		(18.82)		(34.36)		(33.62)		(17.95)	
PDI*UAD		0.0003***		0.0019***		0.0034***		0.0016***		−0.0006***	
		(11.64)		(20.62)		(24.19)		(12.3)		(−5.08)	
IDV*PDI*UAD		−0.0000***		−0.0000***		−0.0000***		−0.0000***		−0.0004	
		(−3.72)		(−9.81)		(−17.61)		(−13.21)		(−1.85)	
_cons	2.442***	3.107***	13.542***	18.615***	24.375***	37.715***	23.78***	36.626***	17.053***	22.864***	10.575***
	(67.55)	(39.38)	(85.89)	(56.78)	(100.72)	(77.72)	(101.93)	(78.12)	(85.19)	(54.94)	(62.69)
Adjusted R^2	0.5764	0.5999	0.5713	0.6324	0.545	0.6373	0.392	0.5132	0.14	0.2629	0.0285

	SL_g6	SL_g7		SL_g8		SL_g9		SL_g10	
	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
IDV	−0.068***	−0.022***	−0.018**	−0.023***	0.011*	−0.019***	0.021***	−0.014***	0.022***
	(−11.31)	(−14.77)	(−3.47)	(−18.08)	(2.53)	(−18.18)	(6.03)	(−16.64)	(7.69)

Table 3 (continued)

	SL_g6	SL_g7		SL_g8		SL_g9		SL_g10	
	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
PDI	0.016**	−0.005**	0.058***	0.006***	0.067***	0.012***	0.06***	0.014***	0.05***
	(2.72)	(−2.98)	(11.6)	(5.03)	(16.1)	(11.54)	(17.6)	(16.63)	(17.44)
UAD	0.05***	0.027***	0.117***	0.031***	0.124***	0.028***	0.104***	0.023***	0.079***
	(8.22)	(17.68)	(23.15)	(25.06)	(29.84)	(27.86)	(30.4)	(28.06)	(27.85)
IDV*PDI	0.0003**		−0.0002*		−0.0004***		−0.0005***		−0.0004***
	(2.95)		(−2.52)		(−6.11)		(−7.84)		(−8.32)
IDV*UAD	0.00024*		−0.0008***		−0.0011***		−0.0010***		−0.0008***
	(2.35)		(−8.84)		(−15.26)		(−17.25)		(−16.67)
PDI*UAD	−0.0017***		−0.0019***		−0.0016***		−0.0012***		−0.0008***
	(−16.91)		(−22.47)		(−23.13)		(−20.51)		(−16.64)
IDV*PDI*UAD	0.0000***		0.0000***		0.0000***		0.0000***		0.0000***
	(6.87)		(12.07)		(14.17)		(13.69)		(11.96)
_cons	10.576***	6.089***	3.229***	3.359***	−0.265	1.748***	−1.509***	0.863***	−1.713***
	(29.57)	(43.5)	(10.82)	(29.17)	(−1.07)	(18.62)	(−7.43)	(11.2)	(−10.17)
Adjusted R^2	0.1344	0.063	0.1561	0.109	0.1893	0.1341	0.197	0.1435	0.1893

*Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4 Estimation Results of the Effect of the Cultural Dimensions on the Diffusion Level

	AL_g1		AL_g2		AL_g3		AL_g4		AL_g5		AL_g6
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1
IDV	0.295***	0.258***	1.351***	0.876***	2.678***	0.181	3.453***	−1.537***	3.645***	−2.902***	3.529***
	(75.2)	(19.31)	(64.69)	(12.82)	(58.5)	(1.24)	(52.59)	(−7.41)	(46.82)	(−11.79)	(41.72)
PDI	−0.111***	−0.181***	−0.967***	−1.56***	−2.46***	−4.37***	−3.634***	−6.609***	−4.256***	−7.419***	−4.508***
	(−28.18)	(−13.6)	(−46.33)	(−22.81)	(−53.74)	(−29.87)	(−55.35)	(−31.85)	(−54.67)	(−30.15)	(−53.3)
UAD	−0.261***	−0.454***	−1.384***	−3.037***	−2.998***	−7.678***	−4.147***	−11.155***	−4.583***	−12.263***	−4.533***
	(−66.47)	(−34.04)	(−66.3)	(−44.41)	(−65.5)	(−52.49)	(−63.16)	(−53.76)	(−58.86)	(−49.83)	(−53.58)
IDV*PDI		−0.0005*		−0.00162		0.0118***		0.0316***		0.0432***	
		(−2.2)		(−1.4)		(4.78)		(9.01)		(10.4)	
IDV*UAD		0.0012***		0.0196***		0.0672***		0.1123***		0.134***	
		(8.66)		(16.94)		(27.19)		(32.01)		(32.12)	
PDI*UAD		0.0027***		0.022***		0.0555***		0.0712***		0.0659***	
		(11.64)		(18.98)		(22.44)		(20.51)		(15.85)	
IDV*PDI*UAD		−0.0000***		−0.0000***		−0.0006***		−0.001***		−0.0009***	
		(−3.72)		(−8.67)		(−13.93)		(−14.86)		(−13.06)	
_cons	24.421***	31.075***	159.84***	217.23***	403.59***	594.37***	641.39***	960.64***	811.92***	1189.3***	917.67***
	(67.54)	(39.38)	(83.02)	(53.7)	(95.63)	(68.68)	(105.96)	(78.25)	(113.12)	(81.69)	(117.67)
Adjusted R^2	0.5764	0.5999	0.5732	0.6264	0.5703	0.6417	0.5514	0.6342	0.5198	0.6083	0.4827

	AL_g6	AL_g7		AL_g8		AL_g9		AL_g10	
	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
IDV	−3.586***	3.305***	−3.761***	3.079***	−3.655***	2.894***	−3.448***	2.769***	−3.251***
	(−13.33)	(37.53)	(−13.32)	(34.34)	(−12.63)	(32.06)	(−11.76)	(30.65)	(−11.04)

Table 4 (continued)

	AL_g6	AL_g7		AL_g8		AL_g9		AL_g10	
PDI	−7.255***	−4.554***	−6.67***	−4.491***	−5.998***	−4.373***	−5.394***	−4.248***	−4.947***
	(−26.96)	(−51.71)	(−23.63)	(−50.09)	(−20.72)	(−48.44)	(−18.4)	(−47.02)	(−16.79)
UAD	−11.766***	−4.264***	−10.598***	−3.951***	−9.354***	−3.668***	−8.31***	−3.457***	−7.597***
	(−43.73)	(−48.43)	(−37.55)	(−44.07)	(−32.31)	(−40.63)	(−28.35)	(−38.26)	(−25.79)
IDV*PDI	0.0463***		0.0441***		0.0398***		0.0353***		0.0317***
	(10.18)		(9.25)		(8.14)		(7.12)		(6.36)
IDV*UAD	0.136***		0.1285***		0.1177***		0.1077***		0.1005***
	(29.91)		(26.93)		(24.06)		(21.74)		(20.18)
PDI*UAD	0.0486***		0.0295***		0.0132**		0.0013		−0.0059
	(10.69)		(6.18)		(2.69)		(0.26)		(−1.19)
IDV*PDI*UAD	−0.0008***		−0.0006***		−0.0005***		−0.0003***		−0.0002**
	(−10.4)		(−7.76)		(−5.53)		(−3.85)		(−2.8)
_cons	1295.0***	978.6***	1327.3***	1012.1***	1324.7***	1029.6***	1309.6***	1037.4***	1294.2***
	(81.36)	(120.53)	(79.48)	(122.44)	(77.35)	(123.7)	(75.5)	(124.54)	(74.25)
Adjusted R^2	0.5728	0.4459	0.5352	0.4134	0.5008	0.3861	0.4715	0.3661	0.4498

*Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

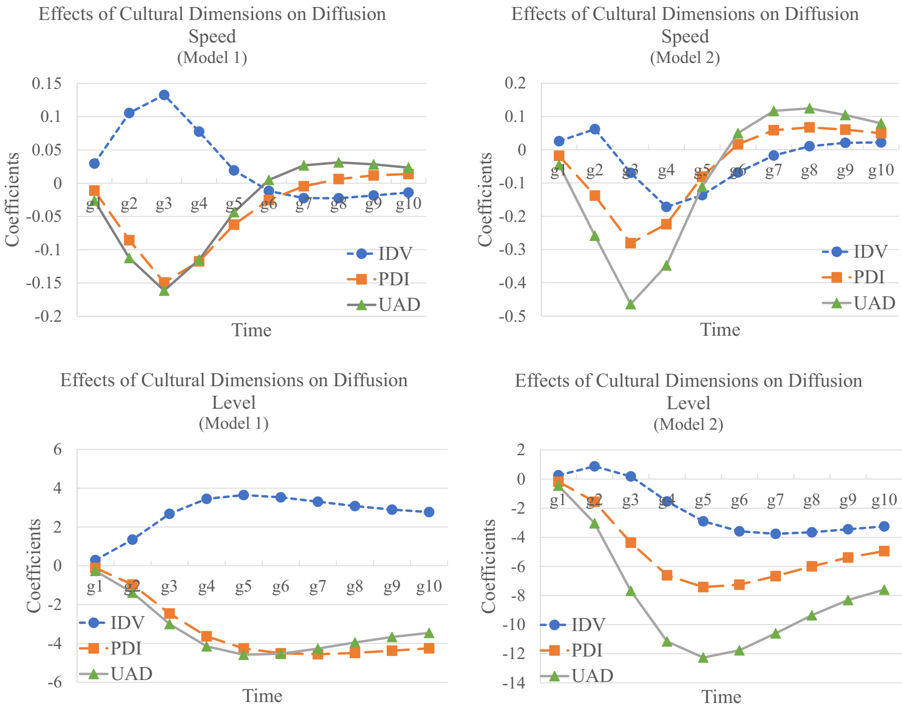

Fig. 8 Effects of the Cultural Dimensions on the Diffusion Speed and Diffusion Level

the simulated diffusion pattern of cable television in the United States is faster than the real-world diffusion pattern. Geographic factors might inhibit the diffusion of cable television in the United States. In China, personal computers diffuse much slower than the model expects, perhaps because of the lack of economic development. The diffusion of fax machines in Hong Kong is much faster than the model expected. This may be because of the structure of its industry, since Hong Kong is a global financial center. Although some cases exhibit different diffusion patterns to the proposed model, real-world diffusion and that of the proposed model are still somewhat similar. Since many factors affect the diffusion of an innovation in each country (e.g., political, geographic, economic, and industrial factors), it is not surprising that the real-world diffusion patterns are distinct from those of the proposed model. This study focuses on gaining theoretical insights into how social culture affects interpersonal communications and thus the innovation diffusion process.

Generally, individualism has a positive effect on both the diffusion speed and the diffusion level in the early stage. This effect gradually turns negative thereafter. When the individualism level is high, individuals focus more on the functional signal of the innovation rather than on the decisions of other individuals. Therefore, innovations can diffuse rapidly in a high individualism society in the early stage. However, after the early stage, diffusion is driven by the word-of-mouth effect. Since individualists pay less attention to other agents, the word-of-mouth effect is inhibited, which explains why individualism has a negative effect on the

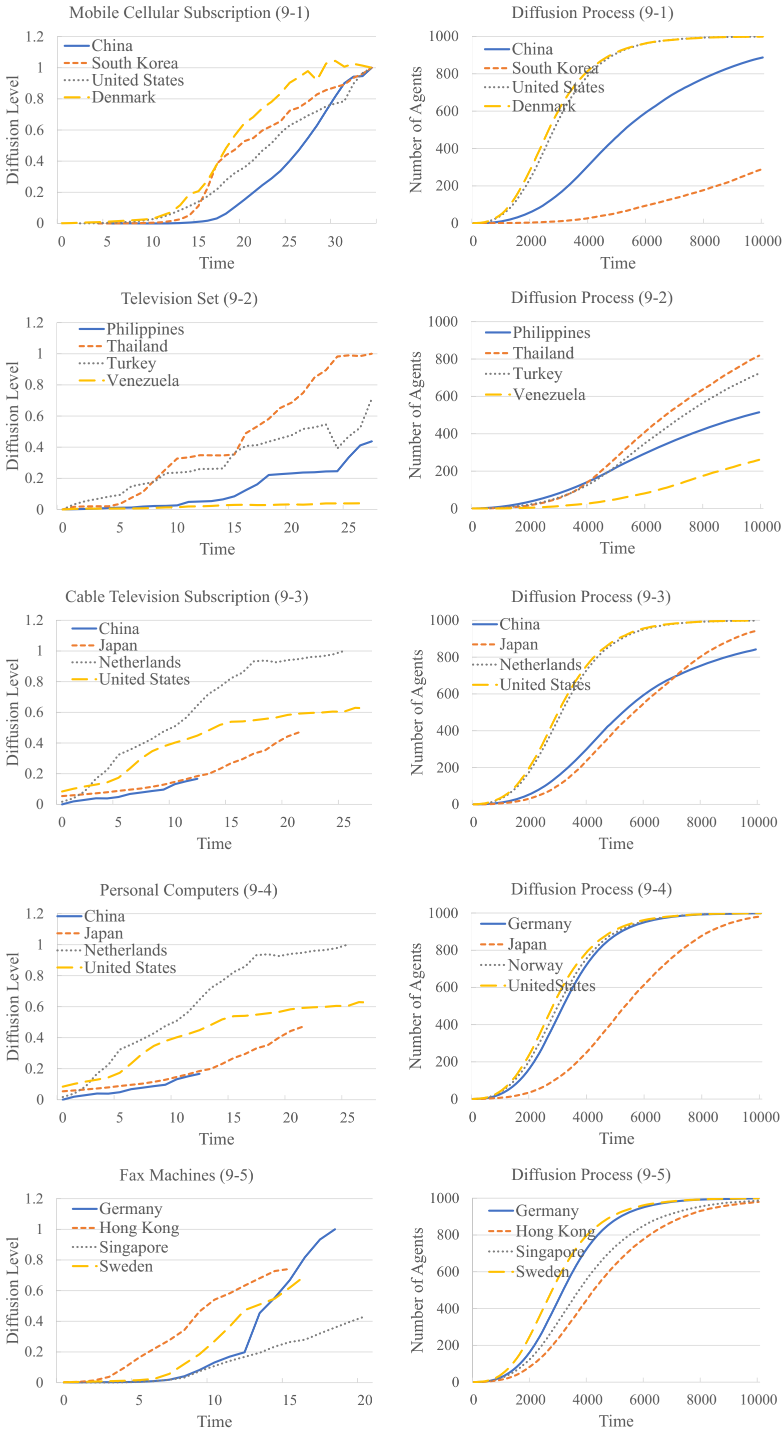

Fig. 9 Real-World Diffusion and Diffusion Patterns of the Proposed Model. *Note: info_s = 0.3 in the diffusion processes of 1, 4, and 5; info_s = 0.5 in the diffusion processes of 2 and 3

rate of diffusion after the early stage. As shown in Fig. 9-1, although the United States has a higher level of power distance and uncertainty avoidance than Denmark, its diffusion process is only slower than that of Denmark in a limited range. This might be due to the positive effect of individualism (since the United States has a higher level of individualism than Denmark) or the characteristics of the innovation. As shown in Fig. 9-2, Thailand and Turkey have similar power distance scores. Turkey has a slightly higher individualism and uncertainty avoidance levels, but diffusion is slower in Turkey than in Thailand, probably because of its higher uncertainty avoidance. Considering the limited differences between the two diffusion processes, individualism may affect the diffusion process positively.

Uncertainty avoidance has a negative effect on both the diffusion speed and the diffusion level before the middle stage and uncertainty avoidance has a positive effect on the diffusion speed thereafter. Innovation adoption behaviors usually accompany uncertainty. Therefore, individuals in a high uncertainty avoidance society need more information, either from the characteristics of innovation or from other agents, to make their adoption decisions. Information from the characteristics of innovation is fixed over time. The adoption behaviors of other individuals are a reliable way to gain more information about an innovation. Only a few individuals adopt the innovation in the early stage. Hence, uncertainty avoidance has a negative effect on the rate of diffusion in this stage. However, as the number of adopters increase, individuals find it easier to obtain information from other individuals thereafter. Since the word-of-mouth effect controls diffusion progress after the early stage, individuals with high uncertainty avoidance tend to interact with other agents more intensively. This enhanced interaction among agents accelerates the diffusion process, explaining why uncertainty avoidance has a positive effect on the diffusion rate after the early stage. As shown in Fig. 9-1, although China has a higher power distance level than South Korea, the diffusion process in South Korea is much lower than that in China because of its high level of uncertainty avoidance. Mobile phone diffusion in South Korea is fast, largely owing to government policies. The diffusion of recent high-tech innovations such as mobile payments and Uber face problems in South Korea. As shown in Fig. 9-4, Germany and Norway have similar individualism and power distance scores. Since innovations diffuse faster in Norway than in Germany and the power distance of these two countries is identical, the negative effect of uncertainty avoidance arises. Moreover, as shown in Fig. 9-4, a high level of uncertainty avoidance and a relatively low level of individualism make the diffusion process in Japan slower than those in other countries. The negative effect of uncertainty avoidance is also shown in Fig. 5. Hong Kong has a similar level of individualism and power distance to Singapore, but a lower level of uncertainty avoidance; hence, innovations in Singapore diffuse faster than in Hong Kong.

Power distance has a strong negative effect on the diffusion level at all times as well as a strong negative effect on the diffusion speed before the late stage. Power distance affects the rewiring probability of social networks, distribution of social status, and initial distribution of agents' thresholds. High power distance indicates a low rewiring probability, more unequally distributed social status, and the lower probability of agents with low social status having a low threshold. A low rewiring probability indicates a high clustering coefficient and long path length. Agents are more likely to link to other agents who have similar social status. The information flow under this network structure is slow. Unequally distributed social status aggravates this situation. High power distance means that most linked agents have similar social status. Social pressure boosts adoption behavior, especially when power distance is high and most neighbors adopt the innovation. Thus, power distance has a positive effect on the diffusion speed in the late stage. As shown in Fig. 9-2, Venezuela and Thailand have similar individualism and uncertainty avoidance levels, whereas diffusion in Venezuela is much slower than that in Thailand. The higher level of power distance may have hindered Venezuela's diffusion process. Although Japan has much higher uncertainty avoidance than China (Fig. 9-3), its diffusion level is higher than that of China because it has much lower power distance, which has a positive effect on the diffusion speed in the late stage. Singapore has a low uncertainty avoidance score compared with Germany and Sweden (Fig. 9-5), whereas its diffusion is slower than that of the other countries due to its high power distance.

4.3 Effect of the characteristics of innovation on the diffusion process

To explore the effect of the characteristics of innovation on diffusion, we adjust the vertical social signal ($info\_s$) to the eight cultural dimension combinations presented in Section 4.1. Figure 10 shows that the vertical social signal has a significant effect on innovation diffusion in Cases 1–4, a relatively small effect in Cases 5 and 6, and a limited effect in Cases 7 and 8.

If both uncertainty avoidance and individualism are high (Cases 1 and 2), the decrease in the vertical social signal can help the diffusion process. On the contrary, if both individualism and uncertainty avoidance are low (Cases 5 and 6), a vertical social signal greater than 0.6 would dampen the process. When individualism is high, an individual's utility is more dependent on personal utility than on social utility; therefore, the vertical social signal cannot increase his/her utility. A rise in the vertical social signal accelerates the diffusion process when uncertainty avoidance is high and individualism is low (Cases 3 and 4). In a low individualism culture, individuals are more sensitive to social factors such as social status and the decisions of others within one's personal network. Enhancing the vertical social signal of an innovation thus increases the social utility of individuals. In societies with both low uncertainty avoidance and low individualism, the vertical social signal has a limited effect on innovation diffusion. However, a high vertical social signal can boost the diffusion speed marginally.

An innovation's diffusion process is not only affected by social culture; the characteristics of the innovation also play an important role. When introducing a new innovation in a society with both a high level of uncertainty avoidance and a high level of individualism, decreasing the vertical social signal might be a more effective strategy. If the individualism level is relatively high, focusing the content

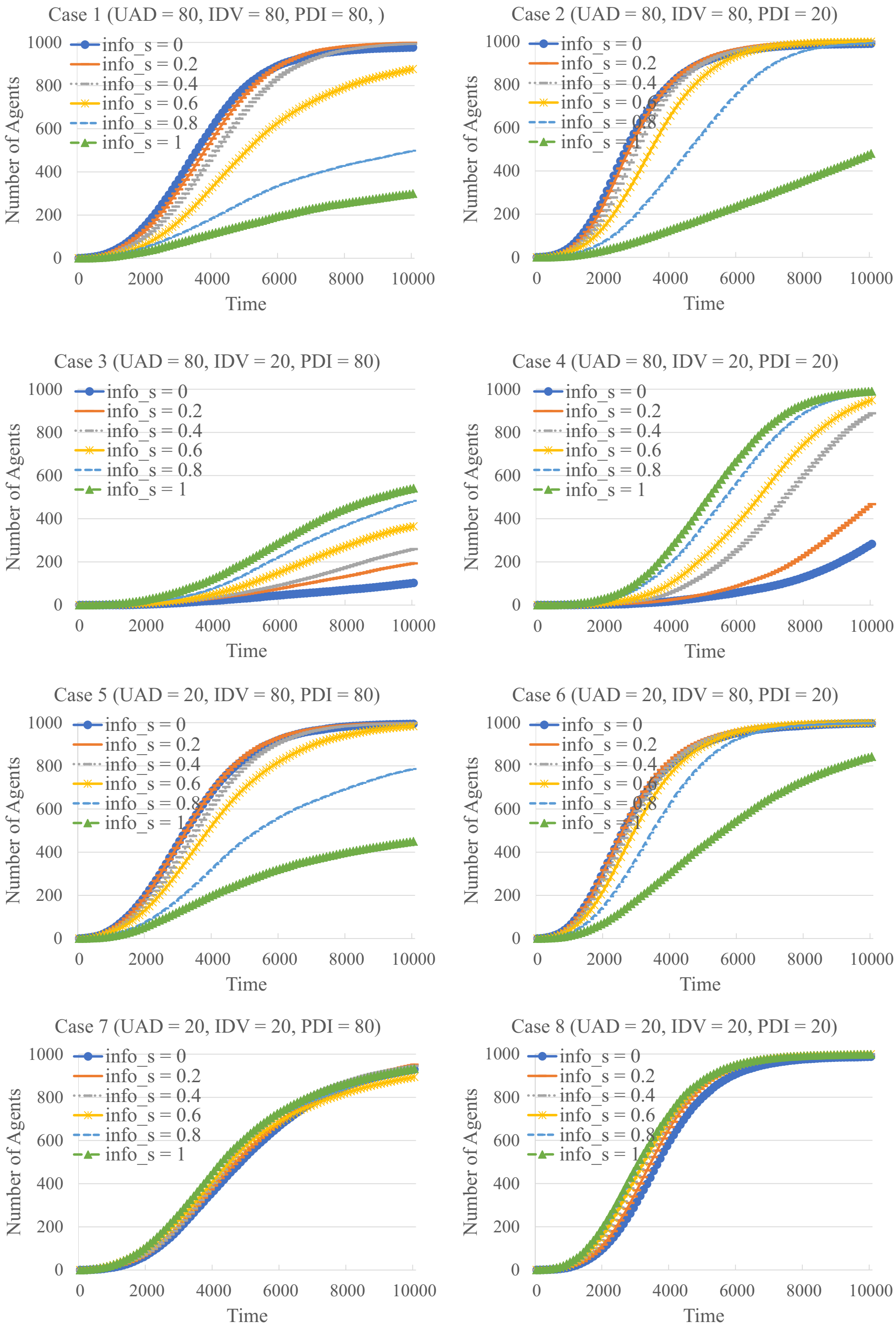

Fig. 10 Diffusion Process with Different Characteristics of Innovation

of an advertising campaign on the functional signal might help the diffusion process. If the individualism level is relatively low, granting more social status-related characteristics to the innovation could stimulate individuals' pressure to adopt an innovation. If the individualism of the targeted society is relatively high, ensuring that the vertical social signal remains at a relatively low level may help the diffusion of an innovation.

5 Conclusion

5.1 Main findings

This study investigated the effect of social culture on innovation diffusion using agent-based models. We embedded Hofstede's cultural dimension theory and Rogers' innovation diffusion theory into the network structure and individual characteristics. We considered three of the five cultural dimensions that directly affect innovation diffusion: individualism, power distance, and uncertainty avoidance. From Rogers' innovation diffusion process, we considered the knowledge stage, persuasion stage, and decision stage to realize a diffusion process in a theoretical situation.

Since individuals are more likely to have links with others who are similar to themselves and high power distance indicates unequally distributed power and social status, we assume that power distance affects the rewiring probability (i.e., the probability of turning a regular network into a random network). When making decisions, individualists are less affected by their surrounding environment (e.g., family and friends), which means they are more focused on their own thoughts and feelings. On the contrary, collectivists place more weight on others' opinions than their own. Because individuals weight their own feelings and others' behaviors differently, we defined individual utility as the weighted sum of individual utility and social utility. Moreover, since innovation is always accompanied by uncertainty, the propensity toward uncertainty avoidance largely affects an individual's adoption time. People with high innovativeness have a lower propensity to avoid uncertainty and innovativeness is highly correlated with social status. We included these features in the diffusion model to study the effect of social culture on innovation diffusion.

We presented eight diffusion patterns with different cultural dimension combinations to confirm the effect of social culture on innovation diffusion. Furthermore, we investigated the effect of social culture on the diffusion speed and diffusion level in different diffusion stages. Some of our results support those of previous studies of this topic; for example, individualism has a positive effect on innovation take off, whereas uncertainty avoidance suppresses diffusion in the early stage. Desmarchelier and Fang (2016) suggest that uncertainty avoidance has a positive effect on innovation diffusion by generating a word-of-mouth effect. Our results support this point of view: uncertainty avoidance has a positive effect on the diffusion speed after the early stage. The effect of power distance on innovation diffusion is more complicated. Van den Bulte and Stremersch (2004) insist that an innovation must not be adopted too early to avoid appearing presumptuous about one's place in a high power distance society. Burt (1987) states that people tend to adopt an innovation quickly if it is adopted by people with similar status and they fear that such adoption might harm their present status. Our result supports both opinions: power distance has a positive effect on the diffusion speed in the late stage. However, previous studies do not show the effect of power distance on the social network structure. Power distance not only affects the status distribution, but also links the social structure. While the high social class has already adopted the innovation for different purposes, the low social class may have not even had the chance to know about it.

We further considered the effect of the characteristics of innovation on the diffusion process. We found that the characteristics of an innovation strongly affect its diffusion when uncertainty avoidance is high. However, there is only a limited effect when both uncertainty avoidance and individualism levels are low. Moreover, the vertical social signal stimulates innovation diffusion when the individualism level is low. We suggest that in a low power distance society, the introduction of an innovation to the high social class may be the most effective diffusion strategy. On the contrary, in a society with high power distance but low individualism, enhancing the vertical social signal of the innovation might be a more efficient mode of introduction. If individualism is high, focus should instead be placed on the functional signal for both high and low social class members, especially low social status members with a low adoption threshold.

5.2 Limitations and future research

The study investigated traditional face-to-face interactions among individuals. Hence, the further study of online and negative word-of-mouth is needed, which may alter the effect of social culture on innovation diffusion under certain conditions. In Rogers' innovation diffusion theory, there are five stages of adoption behavior: information, persuasion, decision, implementation, and confirmation. This study simulated how individuals are informed, are persuaded, and make decisions. After adoption, behaviors may also influence innovation diffusion due to a change in attitude toward the innovation, re-adoption, or stopping usage.

We could not include all the cultural dimensions in this model because of the limited evidence in the previous literature. A dearth of studies explores how the other cultural dimensions (e.g., masculinity) affect innovation diffusion. Future empirical analysis of the proposed model with suitable cross-national data would contribute to extending our knowledge on this subject.

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Appendix A

Parameters and variables in the proposed model are shown in Table 5.

Table 5 Parameters and variables in the proposed model

Network related parameters		
N	Number of individuals in the network	1000
k	Number of average links	10
p	Rewiring probability	$p = \varphi_p \times PDI + \eta_p$ (where $\varphi_p = -0.00099$ and $\eta_p = 0.1$)
t	Simulation steps	10,000
Social cultural dimensions		
IDV	Social individualism level	<input value> [0,100]
PDI	Social power distance level	<input value> [0,100]
UAD	Social uncertainty avoidance level	<input value> [0,100]
Individual state related variables		
$inform_i$	Inform state of individual i	1, if individual i get informed about the innovation 0, o.w
$adopt_i$	Adoption state of individual i	1, if individual i adopt the innovation 0, o.w
Individual characteristic related variables		
idv_i	Individual individualism level	Drawn from normal distribution with $mean\_CUL = IDV/100$, $SD\_CUL = 0.2$
pdi_i	Individual power distance level	Drawn from normal distribution with $mean\_CUL = PDI/100$, $SD\_CUL = 0.2$
τ_i	Individual adoption threshold level	Drawn from normal distribution with $mean\_TH = \varphi_{mean} \times UAD + \eta_{mean}$ $SD\_TH = \varphi_{sd} \times IDV + \eta_{sd}$ (where $\varphi_{mean} = 0.006\eta_{mean} = 0.2\varphi_{sd} = 0.004$and $\eta_{sd} = 0.1$)
$status_i$	Individual social status	$status_i = (i/N) - (i/N) \cdot \left(1 - {}^{i}/_{N}\right)^{\left(1 - {}^{PDI}/_{100}\right)}$

Table 5 (continued)

α	(horizontal social signal) Proportion of adopted neighbors among all neighbors	$\alpha = \frac{number\ of\ adopted\ neighbors}{number\ of\ total\ neighbors}$
U_i	Individual utility function	$U_i = idv_i \cdot \left(1 - exp\left(-idv_i \cdot info_f\right)\right) + (1 - idv_i)\left((1 - exp(-\alpha)) + \left(1 - exp\left(-\sqrt{pdi_i \cdot status_i} \cdot info\_s\right)\right)\right)$
Characteristics of innovation		
$info\_f$	Functional signal of innovation	$info_f = 1 - info\_s$
$info\_s$	Vertical social signal of innovation	<input value> [0,1]

Input values in simulations are shown in Table 6.

Table 6 Input values in simulations

Figure 5	IDV adjusted	PDI = UAD = 50; IDV = 0 ~ 100	info_s = 0.5
	PDI adjusted	IDV = UAD = 50; PDI = 0 ~ 100	info_s = 0.5
	UAD adjusted	IDV = PDI = 50; UAD = 0 ~ 100	info_s = 0.5
	info_s adjusted	IDV = PDI = UAD = 50	info_s = 0 ~ 1
Figure 6	Case 1	UAD = 80; IDV = 80; PDI = 80	info_s = 0.5
	Case 2	UAD = 80; IDV = 80; PDI = 20	info_s = 0.5
	Case 3	UAD = 80; IDV = 20; PDI = 80	info_s = 0.5
	Case 4	UAD = 80; IDV = 20; PDI = 20	info_s = 0.5
	Case 5	UAD = 20; IDV = 80; PDI = 80	info_s = 0.5
	Case 6	UAD = 20; IDV = 80; PDI = 20	info_s = 0.5
	Case 7	UAD = 20; IDV = 20; PDI = 80	info_s = 0.5
	Case 8	UAD = 20; IDV = 20; PDI = 20	info_s = 0.5
Figure 7	Adopted	IDV = 50; PDI = 50; UAD = 50	info_s = 0.5
Figure 10	Case 1	UAD = 80; IDV = 80; PDI = 80	info_s = 0 ~ 1
	Case 2	UAD = 80; IDV = 80; PDI = 20	info_s = 0 ~ 1
	Case 3	UAD = 80; IDV = 20; PDI = 80	info_s = 0 ~ 1
	Case 4	UAD = 80; IDV = 20; PDI = 20	info_s = 0 ~ 1
	Case 5	UAD = 20; IDV = 80; PDI = 80	info_s = 0 ~ 1
	Case 6	UAD = 20; IDV = 80; PDI = 20	info_s = 0 ~ 1
	Case 7	UAD = 20; IDV = 20; PDI = 80	info_s = 0 ~ 1
	Case 8	UAD = 20; IDV = 20; PDI = 20	info_s = 0 ~ 1

Appendix B

We adjusted simulation time from 10,000 to 100,000. As shown in Fig. 11, the system with 10,000 iterations is large enough to identify the whole diffusion pattern with $N = 1000$. Population number is adjusted from $N = 1000$, $N = 5000$, $N = 10{,}000$ with simulation time $t = 10{,}000$, $t = 50{,}000$ and $t = 100{,}000$, respectively. Table 7 shows the proportion of averaged final adoption level and standard deviation. Average final adoption proportion does not change with the population number. We further adjust average number of linked neighbors k from 3 to 20 with population number $N = 1000$. As shown in Table 8, the system converges to a steady state with k larger than 8, and the increase in k does not reduce the standard deviation.

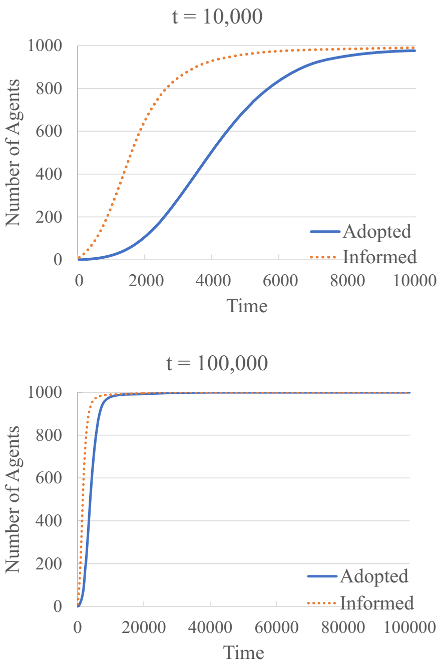

Fig. 11 Sensitivity to Iteration Time

Table 7 Sensitivity to Number of Population

	N = 1000	N = 5000	N = 10,000
Average Final Adoption Proportion	0.9817	0.9908	0.9864
Standard Deviation	0.0580	0.0306	0.0447

Table 8 Sensitivity to Number of Average Links

k	Average Final Adoption level	Standard Deviation	k	Average Final Adoption level	Standard Deviation
3	538.8	142.227	12	983.5	42.658
4	792.35	152.841	13	990.6	14.173
5	942.6	128.175	14	990.9	24.320
6	958.5	131.758	15	980.15	68.599
7	957.6	98.778	16	985.7	48.978
8	969	96.061	17	977.15	69.343
9	968.25	76.365	18	990.75	28.959
10	970.4	47.684	19	990.7	25.958
11	984.2	37.241	20	984.3	54.960

Appendix C

Standard deviation of simulations of Fig. 4, Fig.5 and Fig. 9 are shown in Table 9, Table 10 and Table 11, respectively.

Table 9 Standard deviation of simulations of Fig. 4

Simulation		SD	Simulation		SD
IDV adjusted	IDV = 0	64.367	UAD adjusted	UAD = 0	2.091
	IDV = 20	10.875		UAD = 20	2.218
	IDV = 40	7.434		UAD = 40	3.207
	IDV = 60	2.016		UAD = 60	4.562
	IDV = 80	1.813		UAD = 80	7.779
	IDV = 100	1.316		UAD = 100	33.407
PDI adjusted	PDI = 0	1.524	info_s adjusted	info_s = 0	1.261
	PDI = 20	1.410		info_s = 0.2	1.881
	PDI = 40	1.653		info_s = 0.4	3.549
	PDI = 60	15.625		info_s = 0.6	3.878
	PDI = 80	67.328		info_s = 0.8	10.502
	PDI = 100	51.980		info_s = 1	35.081

Table 10 Standard deviation of simulation of Fig. 5

Simulation	SD	Simulation	SD
Case1	23.519	Case5	10.985
Case2	0.991	Case6	1.219
Case3	97.066	Case7	51.910
Case4	76.234	Case8	1.119

Table 11 Standard deviation of simulation of Fig. 9

Simulation		SD	Simulation		SD
Case1	info_s = 0	2.552	Case2	info_s = 0	1.234
	info_s = 0.2	2.716		info_s = 0.2	0.923
	info_s = 0.4	3.238		info_s = 0.4	1.414
	info_s = 0.6	60.212		info_s = 0.6	1.552
	info_s = 0.8	87.630		info_s = 0.8	4.321
	info_s = 1	68.795		info_s = 1	103.439
Case3	info_s = 0	65.320	Case4	info_s = 0	202.366
	info_s = 0.2	90.503		info_s = 0.2	298.500
	info_s = 0.4	70.253		info_s = 0.4	212.255
	info_s = 0.6	117.236		info_s = 0.6	62.157
	info_s = 0.8	101.550		info_s = 0.8	13.177
	info_s = 1	91.186		info_s = 1	10.177
Case5	info_s = 0	1.410	Case6	info_s = 0	1.218
	info_s = 0.2	1.780		info_s = 0.2	1.465
	info_s = 0.4	3.052		info_s = 0.4	1.276
	info_s = 0.6	25.708		info_s = 0.6	1.395
	info_s = 0.8	76.343		info_s = 0.8	1.860
	info_s = 1	63.303		info_s = 1	57.133
Case7	info_s = 0	52.235	Case8	info_s = 0	1.755
	info_s = 0.2	38.324		info_s = 0.2	1.638
	info_s = 0.4	49.525		info_s = 0.4	1.261
	info_s = 0.6	54.908		info_s = 0.6	2.245
	info_s = 0.8	58.608		info_s = 0.8	1.683
	info_s = 1	54.272		info_s = 1	1.531

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