International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-18

https://doi.org/10.70917/ijcisim-2026-0175
Article

The Digital Transformation Path of Cross-Border E-Commerce cross-Cultural Communication on the "Digital Silk Road" under the Perspective of Enterprise Operation Synergy

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Abstract: This paper first introduces the basic characteristics of networks and the evolutionary process of complex network models. Building upon complex social networks and traditional SIR models, it introduces two key factors—content homogeneity and dynamic change rates—to propose a dynamic information propagation model with a content homogeneity mechanism, analyzing approaches to addressing information content homogeneity. Through comparative experiments between scale-free networks and small-world networks, it explores the propagation mechanisms of homogeneous information in cross-border cultural networks. The results indicate that the number of edges, average path length, and clustering coefficient in cross-border cultural transmission networks decrease as the threshold increases. Through experiments, the threshold, average path length, and clustering coefficient of cross-border cultural transmission e-commerce networks were ultimately determined to be 0.5, 2.59039, and 0.42242, respectively. The effectiveness of cross-border cultural transmission marketing is enhanced by increases in market size, infection rate, and information survival time, while recovery rate and the number of competitors significantly weaken the effectiveness of cross-border cultural communication marketing.

Keywords: SIR model; scale-free network; small-world network; homogeneous information; cultural communication

1. Introduction

In the context of globalization, cross-border e-commerce has become an important form of international trade [1-2]. However, due to differences in language, culture, and legal systems between different countries and regions, successfully expanding e-commerce operations into international markets is no easy task [3-5]. Therefore, cross-cultural communication plays a crucial role in the operation of cross-border e-commerce, as it can help businesses overcome cultural barriers and enhance market competitiveness [6-7]. However, as market competition intensifies and consumer demands continue to evolve, traditional cross-border e-commerce cross-cultural communication models may no longer fully meet market needs. Consequently, a digital transformation of cross-border e-commerce cross-cultural communication is necessary [8-11].

Digital transformation holds significant importance for cross-border e-commerce cross-cultural communication [12]. First, digital transformation enables businesses to better meet consumers' growing demands [13]. By establishing robust cross-border e-commerce platforms, consumers can browse and purchase products anytime, anywhere, significantly enhancing the convenience and efficiency of shopping [14-16]. Second, digital transformation brings more business opportunities to companies [17]. Through data analysis and artificial intelligence technology, companies can better understand consumer needs and purchasing habits, thereby accurately positioning themselves in the market and promoting their products [18-20]. Finally, digital transformation makes companies more competitive [21].

Companies have improved production efficiency and supply chain management through digital means, reduced costs, and further improved product quality and service levels [22-23].

In network science research, the topological structure of a network plays a crucial role in studying it. To further understand the properties of complex networks, this paper defines fundamental topological properties, including node degree and degree distribution, average path length, clustering coefficient, and metrics related to the evolution of complex networks. Subsequently, taking homogeneous information propagation as the research object, the H-SIR dynamic information propagation model is proposed. This model incorporates a propagation mechanism based on content homogeneity and defines dynamic change rates based on user interest lock-in and fatigue levels. Through simulation experiments, the propagation process of homogeneous information in social networks is simulated, and the effects of different parameters on propagation outcomes are observed. Additionally, the model was fitted with real-world data on cross-border e-commerce cross-cultural information dissemination and compared with traditional models to validate its effectiveness. Finally, measures such as strengthening scientific and technological innovation, precise data collection, optimizing information management, improving talent cultivation mechanisms, and deepening industrial integration were proposed to promote the widespread dissemination and sustainable development of Digital Silk Road culture, contributing to the inheritance and development of excellent traditional culture.

2. Modeling online behavior communication based on cross-cultural communication in cross-border e-commerce

2.1. Modeling the spread of network behavior

2.1.1. Basic Properties of Networks

(1) Degree and average degree of nodes

One of the key attributes of nodes is degree, which is also one of the hot topics in node research. The degree of node i is the number of other nodes it is connected to.

Assume that the adjacency matrix $A=(a_{ij})_{N\times N}$ of network G. From this matrix, we can obtain:

$$k_i=\sum_{j=1}^{N}a_{ij} \tag{1}$$

In a network, the average degree of all nodes is the average degree of the network, denoted as $\langle k\rangle$. The average degree is an important attribute of a network. For an undirected network, let the number of nodes in the network be N and the number of edges in the network be M, then we have:

$$\langle k\rangle=\frac{2M}{N} \tag{2}$$

In the study of directed networks, it is necessary to distinguish between the in-degree and out-degree of nodes. The in-degree k_i^{in} represents the number of links pointing from other nodes to node i, while the number of links pointing from node i to other nodes is defined as the out-degree k_i^{out}. Thus, we can derive the degree of node i as:

$$k_i=k_i^{in}+k_i^{out} \tag{3}$$

For example, in the World Wide Web, the out-degree k_i^{out} of a web page represents the number of web pages it links to, while the in-degree k_i^{in} represents the number of web pages that link to it. In a directed network, the total number of links is:

$$M=\sum_{i=1}^{N}k_i^{in}=\sum_{i=1}^{N}k_i^{out} \tag{4}$$

In a directed network, let the number of edges in the network be M. The average in-degree $\langle k^{in}\rangle$ and the average out-degree $\langle k^{out}\rangle$ of the network are the same, so the average degree $\langle k\rangle$ of a directed network is defined as:

$$\langle k \rangle = \frac{M}{N} \tag{5}$$

(2) Degree distribution

In network propagation, the degree distribution p_k represents the probability of randomly selecting a node from the network with a degree of k. This is what we refer to as the degree distribution. Since the degree distribution is a probability value, it should satisfy normalization, that is:

$$\sum_{k=0}^{\infty} p_k = 1 \tag{6}$$

In a directed network, its degree distribution is divided into the out-degree distribution $P(k^{out})$ and the in-degree distribution $P(k^{in})$. Here, the out-degree distribution is the probability of the out-degree k^{out} of a randomly selected node in the network, and the in-degree distribution is the probability of the in-degree k^{in} of a randomly selected node in the network.

In research, we commonly encounter discrete probability distributions $p(k)$, such as the binomial distribution and the Poisson distribution. The Poisson distribution satisfies the following, where the parameter $\lambda > 0$:

$$P(k) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{7}$$

For a network with N nodes, its degree distribution can be normalized as follows:

$$p_k = \frac{N_k}{N} \tag{8}$$

Here, N_k refers to the number of nodes with degree k. Therefore, we can see that the number of nodes with degree k can be calculated based on the degree distribution, i.e., $N_k = Np_k$.

After the discovery of scale-free networks, scholars found that degree distribution plays an important role in network science. The average degree of a network can be written as:

$$\langle k \rangle = \sum_{k=0}^{\infty} k p_k \tag{9}$$

(3) Average path length

Paths play a central role in network science. Next, we will explore some important properties of paths. The length of the shortest path between node i and node j is usually referred to as the distance between node i and node j, denoted as d_{ij} or simply d. There may be multiple shortest paths of the same length between the same pair of nodes.

The average path length L of a network refers to the average distance between nodes in the network. For a network containing N nodes, we have:

$$L = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \geq j} d_{ij} \tag{10}$$

The average path length in a network is also referred to as the characteristic path length or average distance.

(4) Clustering coefficient

In a network, the clustering coefficient characterizes the density of connections between the neighboring nodes of a node. For a node i with degree k_i, we define the clustering coefficient of node i as:

$$C_i = \frac{E_i}{\frac{k_i(k_i-2)}{2}} = \frac{2E_i}{k_i(k_i-1)} \tag{11}$$

Here, E_i represents the number of links between the k_i neighbors of node i.

In network propagation, we characterize the clustering coefficient of the entire network using the average clustering coefficient $\langle C \rangle$. The average clustering coefficient refers to the probability that two neighbors are connected when a node is randomly selected. We define it as:

$$\langle C \rangle = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{12}$$

2.1.2. Evolution of Complex Network Models

(1) Regular Networks

The regular networks commonly encountered in our research are those with regular structures and regular topological properties. The three most common types of regular networks are as follows:

1) Globally coupled networks [24]. In our research, any two nodes in the network are directly connected by an edge, and we define such a network as a globally coupled network.

2) Nearest-neighbor coupled networks. In network propagation, nodes in the network are only connected to their neighboring nodes, and we define such a network as a nearest-neighbor coupled network.

3) Star-shaped coupled network. A star-shaped coupled network refers to a network where there is only one central node, and all other nodes in the network are connected to this central node, with no connections between these nodes.

(2) Random networks

We consider a random network to be a network consisting of N nodes, where the probability of any two nodes being connected is p. The steps for constructing a random network are as follows:

1) Start with N isolated nodes.

2) Select a pair of nodes and choose a random number between 0 and 1. If the random number is less than p, then there is a link between the two nodes. Otherwise, the nodes are not connected.

3) Repeat step 2) for all $N(N-1)/2$ pairs of nodes.

(3) Small-world network model

In general, we define the small-world property as:

$$\langle d \rangle \approx \frac{\ln N}{\ln\langle k \rangle} \tag{13}$$

The total number of nodes is N, $\langle d \rangle$ is the average distance of randomly selected nodes, and $\langle k \rangle$ is the average degree of the network. This formula describes the relationship between the average distance of nodes and the size and average degree of the network.

(4) Scale-free network model

When studying the World Wide Web, we found that its degree distribution is not a Poisson distribution. In a double-logarithmic coordinate system, the degree distribution of the World Wide Web approximates a straight line. This indicates that the degree distribution of the World Wide Web can be approximated as:

$$p_k \sim k^{-\gamma} \tag{14}$$

This formula is called the power-law distribution. We need to distinguish between degree distributions with different degrees and in-degrees. In the World Wide Web, the power-law distribution with approximate in-degrees and out-degrees is:

$$p_{k_{in}} \sim k^{-\gamma_{in}} \tag{15}$$

$$p_{k_{out}} \sim k^{-\gamma_{out}} \tag{16}$$

Among them, γ_{in} and γ_{out} are the degree exponents of the in-degree distribution and out-degree distribution, respectively. Generally speaking, the degree exponent of the in-degree distribution and the degree exponent of the out-degree distribution can be different.

In a scale-free network with N nodes, the average path length in this scale-free network is:

$$L \approx \frac{\ln N}{\ln \ln N} \tag{17}$$

The clustering coefficient can be expressed as:

$$C = \frac{m^2 (m+1)^2}{4(m-1)} \left(\ln \frac{m+1}{m} - \frac{1}{m+1} \right) \frac{(\ln t)^2}{t} \tag{18}$$

The degree distribution function obtained through the unscaled network construction process is:

$$P(k) = 2m^2 \frac{t}{m_0 + t} \frac{1}{k^3} = 2m^2 k^{-3} \tag{19}$$

2.2. Modeling cross-cultural communication in e-commerce based on content homogeneity

2.2.1. Construction of a dissemination model

The SIR model [25] is a typical model used in infectious disease research. However, the traditional SIR model cannot accurately explain the process of homogeneous information transmission. Therefore, we created the H-SIR dynamic information transmission model. In the H-SIR transmission model, the two main factors affecting the effective transmission rate and effective recovery rate of homogeneous information are as follows:

(1) Content homogeneity: In the new information transmission landscape, the degree of homogeneity in information content has a profound impact on information transmission.

(2) Dynamic change rate: In the process of information dissemination on social networks, when people encounter homogeneous information, their interest lock-in and fatigue levels will constantly change. Therefore, we also designed the concepts of individual interest level $P(i)$ and fatigue level $F(i)$ to reflect this, and incorporated them into the effective dissemination rate.

2.2.2. Content homogeneity

This paper first describes how homogeneous information influences each other, simulating a network diagram with 8 nodes $\{a,b,c,d,e,f,g,h\}$, 11 edges, and only 3 pieces of homogeneous information. For these nodes, there are only three states: S, I, R . When in the I state, nodes will choose whether to change states based on the degree of homogeneity of the information content.

For these pieces of information, it is assumed that the degree of homogeneity between Information 1 and Information 2 is high, the degree of homogeneity between Information 1 and Information 3 is low, and the degree of homogeneity between Information 2 and Information 3 is high.

The detailed propagation process is as follows:

(1) In the initial state, there are three infected nodes $\{e, f, g\}$ that have received Information 1, Information 2, and Information 3, respectively, while the remaining five nodes $\{a,b,c,d,h\}$ are in the susceptible state.

(2) After multiple rounds of transmission, some susceptible nodes are infected by surrounding infected nodes. For example, node h comes into contact with both Information 2 and Information 3, becoming an infected node that knows both Information 2 and Information 3.

(3) After several more rounds of transmission, node e was exposed to information 2, meaning it now knows both information 1 and information 2. Node b was exposed to both information 1 and information 2, transitioning from a susceptible state to an infected state.

(4) In the final round of transmission, nodes b and e became immune nodes. For simplicity, the similarity between multiple homogeneous information is defined as:

$$Sim(m) = \frac{\eta \sum_{i=1}^{n} (\prod_{j}^{num(m)} m_i)}{num(m)} \tag{20}$$

In this formula, m represents the number of homogeneous information items, $num(m)$ represents the total number of homogeneous information items, n represents the number of common themes, m_i represents the proportion of the theme in the i th homogeneous information item out of the m homogeneous information items, and η represents the optimization parameter for the degree of homogeneity. The larger $Sim(m)$, the higher the degree of homogenization. Conversely, the smaller $Sim(m)$, the lower the degree of homogenization.

To distinguish between high and low degrees of homogenization, i.e.:

$$\rho(Inf) = \begin{cases} high, & Sim(m) \geq \theta \\ low, & Sim(m) < \theta \end{cases} \tag{21}$$

In the above equation, θ is a threshold used to determine the degree of homogenization, which can be modified based on the similarity of the actual data.

2.2.3. Dynamic Change Rate

As the amount of homogeneous information increases, two situations may arise. In one situation, the degree of homogeneity among homogeneous information is low, and users will be very interested due to the richness of the information topics. In the other situation, the degree of homogeneity among homogeneous information is high, and users will pay slightly less attention to this type of information. Introduction of reward and punishment measures:

$$\delta(i) = \varepsilon \log_{10} e^{Sim(m)} \tag{22}$$

Based on the above description, the interest degree $P(i)$ of user i is defined as:

$$P(i) = \alpha_0 + \delta(i) \tag{23}$$

α_0 and $\delta(i)$ represent the initial interest value and the effect of content homogeneity on user interest, respectively. Here, ε is a constant used to control penalties and rewards.

If content homogeneity is low, users will experience less fatigue and continue to accept this type of information, remaining in an infected state:

$$\omega(i)_t = \begin{cases} \omega(i)_{t-1} + 1, & \rho(Inf) = high \\ \omega(i)_{t-1}, & \rho(Inf) = low \end{cases} \tag{24}$$

Based on the above description, the fatigue level $F(i)$ of user i is defined as:

$$F(i) = ae^{bt} + \lg(num(m)^{Sim(m)} + k) \tag{25}$$

For the time-dependent accumulation effect in fatigue, ae^{bt} is used for simulation, where a and b are constants. For the content homogeneity mechanism in fatigue, $num(m)$ represents the amount of homogenized information, $Sim(m)$ represents the degree of homogeneity among homogenized information, and k represents a constant used to ensure the effectiveness of the lg function.

2.2.4. Transmission threshold analysis

By incorporating the above interest level $P(i)$ and fatigue level $F(i)$ into the new model, we obtain the dynamic change rates, namely the infection probability $\beta(i,t)$ and recovery probability $\gamma(i,t)$, thereby deriving the differential equations of the improved H-SIR model:

$$\begin{cases} \dfrac{ds(t)}{dt} = -[\beta_0 + P(i)]i(t)s(t) \\ \dfrac{di(t)}{dt} = [\beta_0 + P(i)]i(t)s(t) - [\gamma_0 + F(i)]i(t) \\ \dfrac{dr(t)}{dt} = [\gamma_0 + F(i)]i(t) \end{cases} \tag{26}$$

$s(t), i(t), r(t)$ represent the proportion of people who have not been exposed to homogeneous information, the proportion of people who have received homogeneous information, and the proportion of people who have lost interest in homogeneous information, respectively. Information spreaders transition to immune information spreaders with probability $\gamma(i,t)$. The initial state of the nodes is:

$$N = S_0 + I_0 + R_0 \tag{27}$$

$$\begin{cases} S_0 = N - I_0 \\ I_0 = [\beta_0 + P(i)]N \\ R_0 = 0 \end{cases} \tag{28}$$

S_0, I_0, R_0 are the initial values of the unknown information carrier, the information transmitter, and the immune information carrier, respectively. N is the total number of nodes in this network. It can be derived that:

$$\frac{1}{s}\frac{ds}{dt} = -\frac{\beta_0 + P(i)}{\gamma_0 + F(i)}\frac{dr}{dt} \tag{29}$$

Differentiating with respect to time, we obtain:

$$s = s_0 e^{-\frac{[\beta_0 + P(i)]r}{\gamma_0 + F(i)}}, s_0 = s(0) \tag{30}$$

Substituting $i = 1 - s - r$ and formula (30) into formula (26) yields the following solution:

$$\frac{dr}{dt} = [\gamma_0 + F(i)] \times \{1 - r - s_0 e^{-\frac{[\beta_0 + P(i)]r}{\gamma_0 + F(i)}}\} \tag{31}$$

For a given set of constant values, the steady-state value of the number of immune individuals can be calculated using $\frac{dr}{dt} = 0$:

$$r = 1 - s_0 e^{-\frac{[\beta_0 + P(i)]r}{\gamma_0 + F(i)}} \tag{32}$$

The definition of the transmission threshold $\lambda(i,t)$ is given by formula (33), which represents the average number of susceptible individuals that an infected individual, taking into account individual interest and fatigue, can transmit information to before recovering:

$$\lambda(i,t) = \frac{\beta_0 + P(i)}{\gamma_0 + F(i)} \tag{33}$$

That is:

$$\lambda(i,t) = \frac{\beta_0 + \alpha_0 + \varepsilon \log_{10} e^{Sim(m)}}{\gamma_0 + ae^{bt} + \lg(num(m)^{Sim(m)} + k)} \tag{34}$$

In large networks, it is often assumed that only a portion of the population is initially infected. That is, at the initial moment, there are no immune individuals in the network, so $s_0 \approx 1, i_0 \approx 0, r_0 \approx 0$.

Then, substituting equation (33) into equation (32), we have:

$$r = 1 - s_0 e^{-\lambda(i,t)r} \tag{35}$$

For the improved H-SIR model with a critical propagation threshold $\lambda = 1$, we can conclude that:

(1) If $\lambda < 1$, then $r = 0$, meaning that homogeneous information cannot propagate.

(2) If $\lambda > 1$, then $r > 0$, meaning that as the value of λ increases, the value of r also increases, indicating that the propagation range of homogeneous information in the network expands.

2.2.5. Network Model Construction

In order to better analyze and verify the effectiveness of the H-SIR model, the network model construction process took into account the real characteristics of real life. First, people's social circles exhibit small-world characteristics. Second, there are superstars and a large number of ordinary people in real life. Therefore, we constructed two network models: WS small-world networks and BA scale-free networks.

3. The effectiveness of cross-cultural communication in cross-border e-commerce and the path to digital transformation

3.1. Static geometric characteristics and topological properties of cross-border e-commerce networks

3.1.1. Static geometric characteristics of cross-border e-commerce networks

Construct a series of cross-border e-commerce networks established under different parameter thresholds and use the software to calculate the average path length, clustering coefficient, and number of edges in the network. The static geometric characteristics of the cross-border e-commerce network are shown in Table 1. In the network construction process, the threshold variable serves to control the number of edges between nodes in the network, which essentially represents the degree of correlation between cross-border e-commerce and cross-cultural communication returns. As the threshold value increases, the number of edges in the network decreases, and the average path length and clustering coefficient also decrease with the increase in the threshold value. When the threshold is set to 0.5, the number of edges and nodes in the network stabilizes. Ultimately, a threshold of 0.5 was selected to construct the cross-border e-commerce network, with an average path length of 2.59039 and a clustering coefficient of 0.42242.

Table 1. The static geometry of the cross-border e-commerce network.

Threshold value	Mean path length	Concentration coefficient	Network node number	The number of edges in the network
0.1	1.24302	0.80396	239	12041
0.2	1.79719	0.69781	230	7759
0.3	2.01544	0.58513	211	4035
0.4	2.22536	0.52377	174	1724
0.5	2.59039	0.42242	153	793
0.6	2.66691	0.39413	142	589

3.1.2. Topological Properties of Cross-border E-commerce Networks

Degree distribution is an indispensable statistical measure in complex network models, encompassing as many nodes as possible (cross-border e-commerce cross-cultural communication). Using R software, we plotted the degree distributions of networks with different parameters (cross-border e-commerce cross-cultural communication) and found that when the threshold equals 0.4875, the cross-border e-commerce network exhibits scale-free properties. The degree distribution of the cross-border e-commerce network is shown in Figure 1, and the double-logarithmic distribution of the cross-border e-commerce network is shown in Figure 2. It can be observed that the degree distribution curve of the network is approximately a straight line in the double-logarithmic coordinate system, indicating that the cross-border e-commerce network has a higher number of hub nodes at a threshold of 0.5, and this portion of cross-border e-commerce cross-cultural communication possesses significant influence. The degree distribution of the network follows a power-law distribution, thus the cross-border e-commerce network established in this study is a scale-free network.

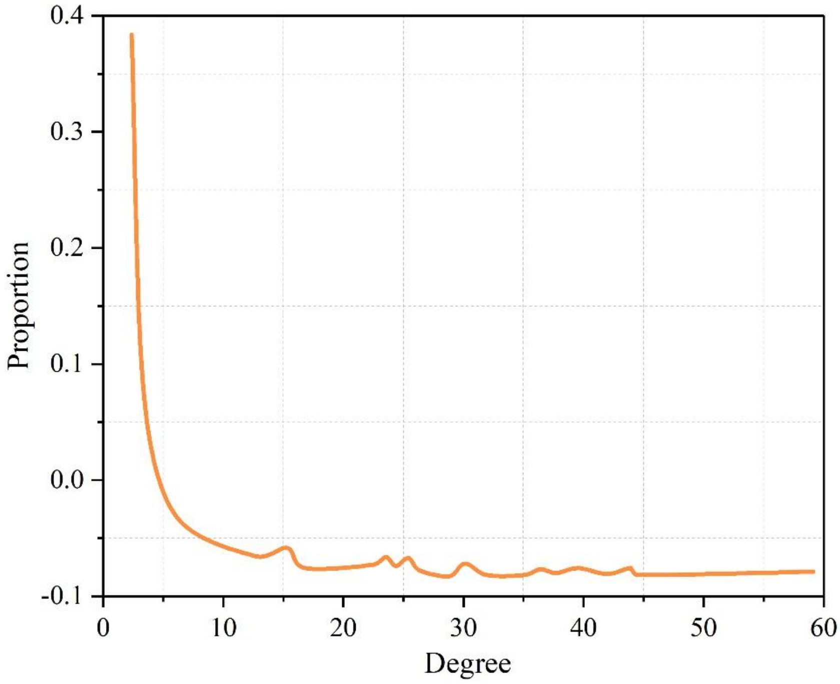


Figure 1. The distribution of cross-border e-commerce network.

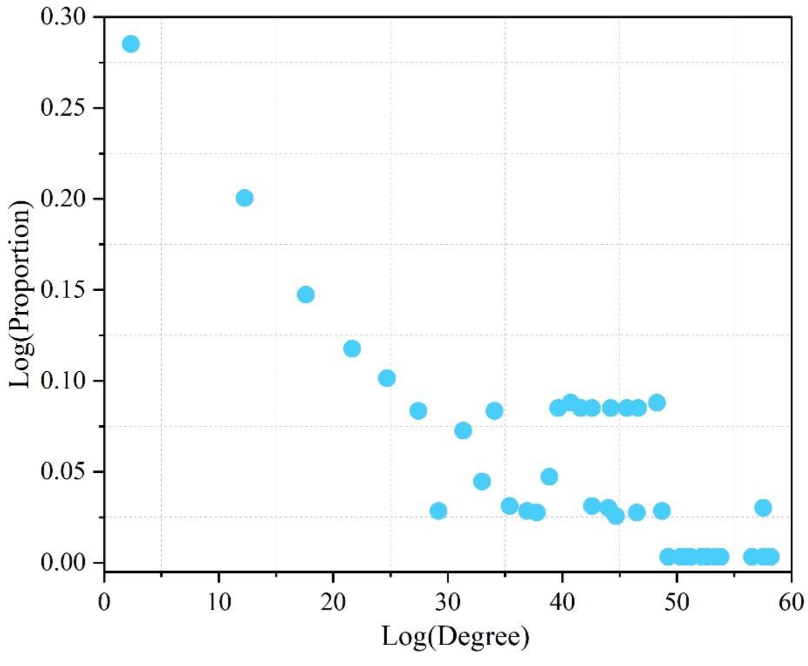


Figure 2. The logarithmic distribution of cross-border e-commerce networks.

A small-world network is a complex network with a small average path length and a large clustering coefficient. We now construct a random network with 155 nodes and compare it with the cross-border e-commerce network established in this paper. The comparison results between the cross-border e-commerce network and the random network are shown in Table 2. It can be seen that, when compared to a random network, the average path length and clustering coefficient of the cross-border e-commerce network are as follows: the average path length of the constructed cross-border e-commerce network is

2.65629, which is smaller than that of the random network. A smaller average path length indicates that any two cross-border e-commerce cross-cultural communication contents can be easily connected within the network; the clustering coefficient is 0.43012, which is larger than that of the random network. a higher clustering coefficient implies that fluctuations in the prices of cross-border e-commerce cross-cultural communication content are more likely to spread and influence neighboring groups within a specific cross-cultural community. Therefore, it can be concluded that the cross-border e-commerce network exhibits small-world characteristics and is a small-world network.

Table 2. Cross-border e-commerce and random networks.

Network	Number of network nodes	The number of edges in the network	Average path length clustering coefficient	Number of network nodes
Random network	153	775	3.03459	0.37566
Stock network	153	797	2.65629	0.43012

3.2. Model Simulation and Implementation

3.2.1. Setting Model Parameters

In the SIRepiDEM model for online marketing information dissemination, we added three consumer characteristics: relationship links (Lk), movement speed (Sp), and response to marketing information encountered (Re). Therefore, we set the links between network nodes as follows:

$$Lk = \begin{cases} 0 & \text{The entire network does not have links between nodes} \\ 1 & \text{The entire network has links between nodes} \end{cases} \tag{36}$$

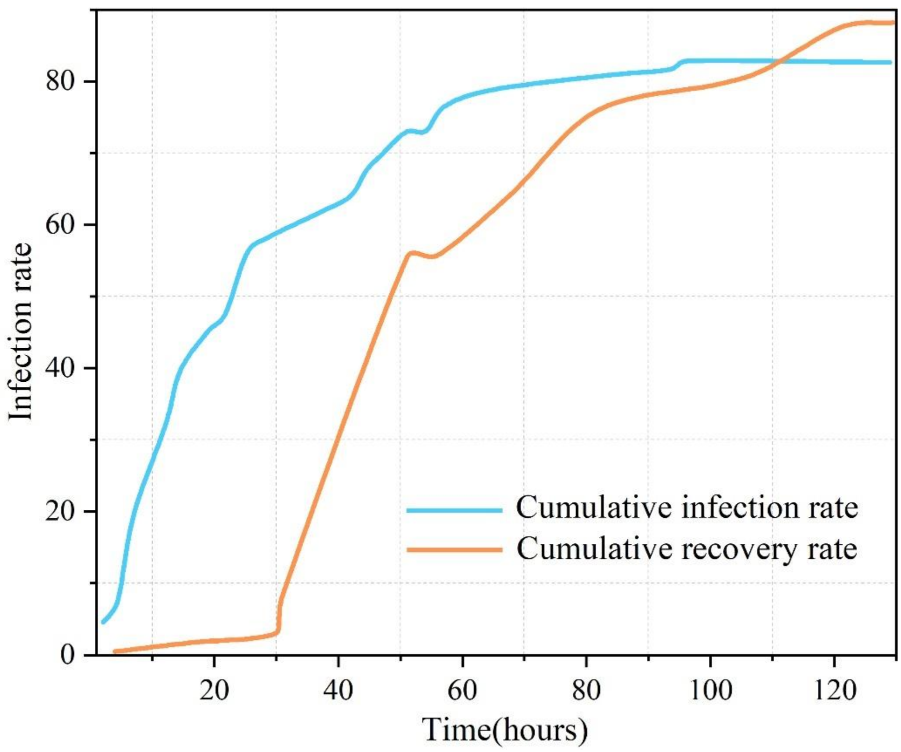
Meanwhile, the node's movement speed $Sp = [v_1, v_2]$, where v_1 represents the minimum movement speed, set to 0, and v_2 represents the maximum movement speed, set to 1/hour; consumers' response to marketing information Re directly affects the number of consumers in the direct immunity state n ; and $\gamma = n / N$, therefore, $Re \in [n_1, n_2]$, where n_1 denotes the minimum number of consumers with the opportunity to become directly immune, set to 0; n_2 denotes the maximum number of consumers with the opportunity to become directly immune, set to 30; therefore, $\gamma \in [0, 0.30]$.

3.2.2. Implementation of Simulation

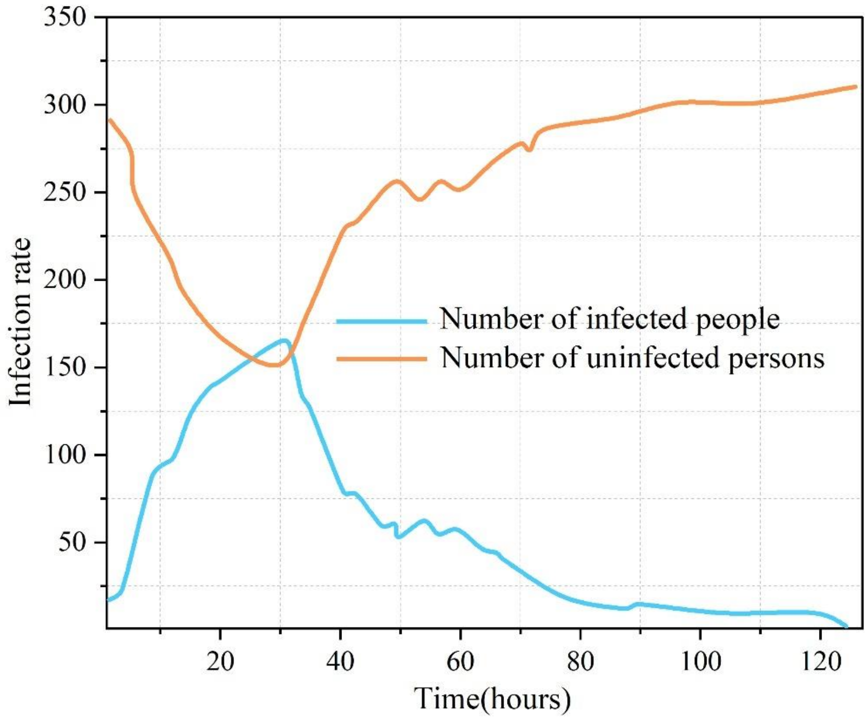
(1) Experiment 1

The simulation in this paper was also implemented using Netlogo software. At the start of the experiment, an initial reference experiment 1 was set up, which was the original SIRepiDEM model, with an initial market size of $N = 300, \alpha = 0.10, \beta = 0.20, \overline{r_t} = 50, v = 0.1 / h$ and all other parameters set to 0.

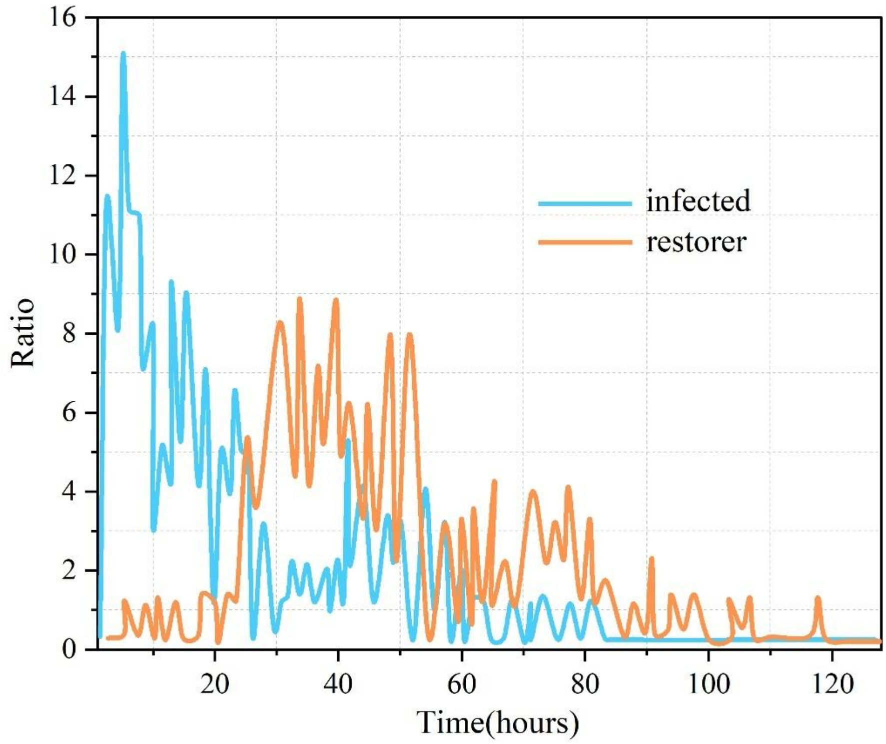
The simulation results of Experiment 1 are shown in Figure 3, where (a) to (c) represent the cumulative infection rate (CIR) and cumulative recovery rate (CRR), changes in the number of infected individuals (I) and recovered individuals (R), and changes in the ratio of infected to recovered individuals. After consumers are exposed to the marketing information being disseminated, the number of infected individuals gradually increases, with the growth rate beginning to decline around 25 hours, reaching nearly 0 by around 88.4 hours. When the initial number of infected individuals is 0, it reaches its maximum value around 30 hours and then rapidly decreases to 0 by 123.8 hours. The rate of change in the number of infected individuals stops changing by 83.4 hours, while the rate of change in the number of recovered individuals nearly stops changing after 107.5 hours, but another fluctuation occurs at 120 hours. It is evident that the process from the initial entry of information into the system to its eventual disappearance from the population is a lengthy one, and the rate of change for recovered individuals lags significantly behind that of infected individuals. This also indicates that marketing information persists in the consumer population for an extended period even after its transmission has ceased. Businesses must not only leverage the process of information transmission but also capitalize on the duration during which information remains in consumers' minds.



(a) Cumulative infection rate and cumulative recovery rate



(b) Changes in the number of infected and restorers



(c) Changes in the ratio of infected and restorer

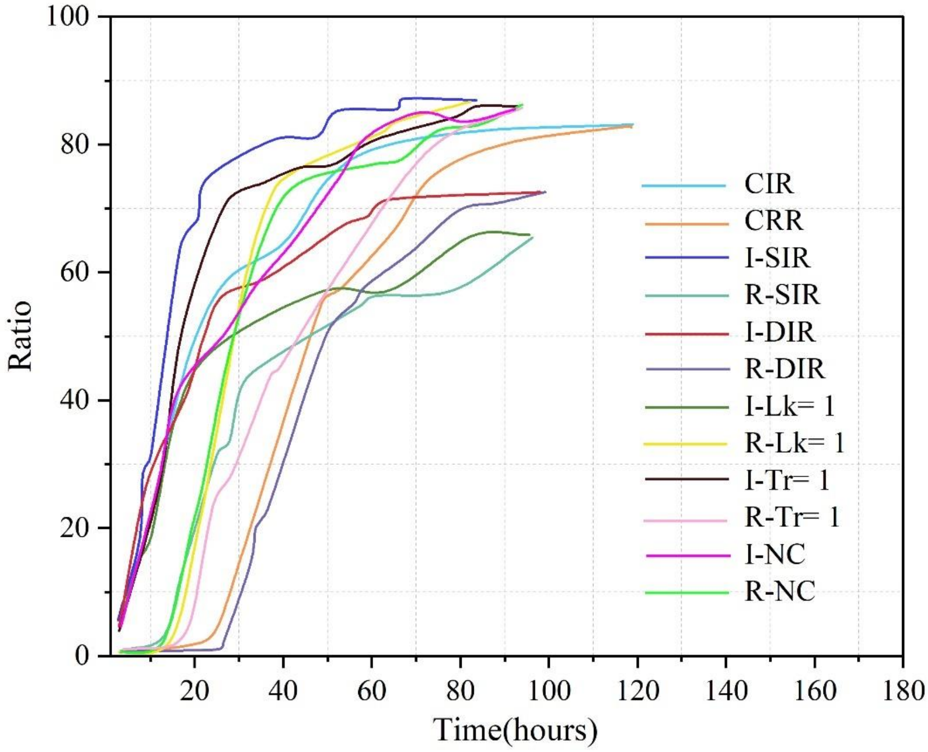
Figure 3. Simulation results of experimental one.

(2) Experiment 2

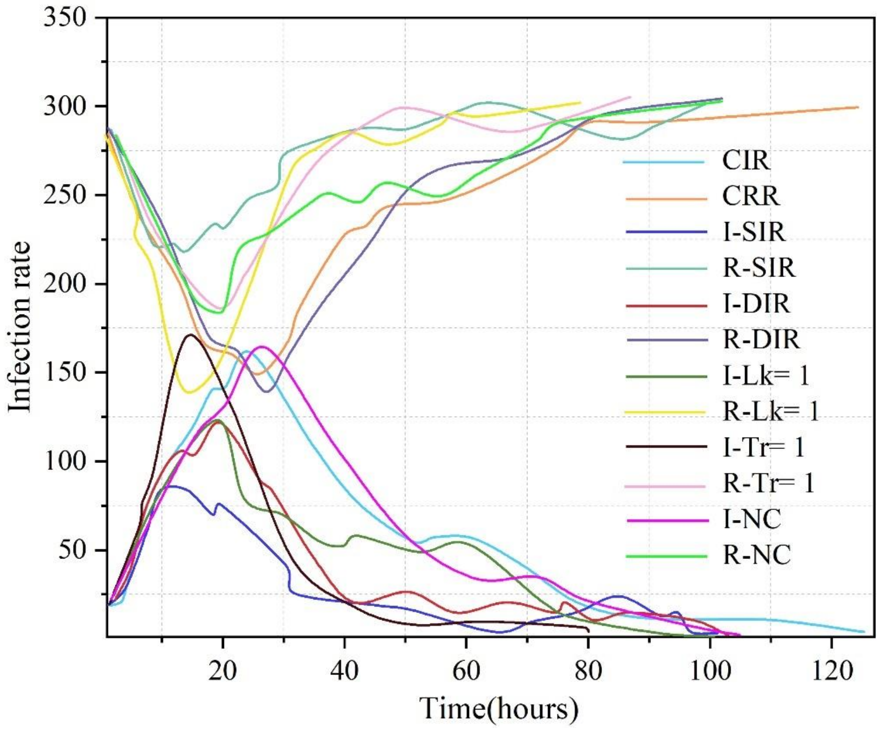
Based on Experiment 1, a second set of experiments was designed. During the experiment, the average probability of consumers entering the direct immune state (DIR) was set to 5%, the average probability of entering the self-isolation state (SIR) was set to 5%, the relationship link between consumers was set to $Lk = 1$, the consumer cross-market mobility function was set to $Tr = 1$, the number of competitors (NC) is 1. The results obtained from five sets of experiments are shown in Figure 4, where (a) to (d) represent the cumulative infection rate and cumulative recovery rate, changes in the number of infected and recovered individuals, changes in the infection rate, and changes in the recovery rate, respectively.

The time required for the cumulative infection rate and cumulative recovery rate to reach their maximum values are 100.3 hours, 66.8 hours, 79.9 hours, 102.5 hours, and 91.4 hours, respectively. The maximum values of the cumulative infection rate and cumulative recovery rate are 73.45%, 65.08%, 87.24%, 86.09%, and 81.99%, respectively. The time lag between the cumulative recovery rate ceasing to change and the cumulative infection rate ceasing to change, i.e., the time from when the information stops spreading to when it completely disappears, is 30.5 hours, 15.7 hours, 15.5 hours, 16.5 hours, and 13.9 hours, respectively. When compared with the initial state of 130.2 hours, 82.26%, and 23.8 hours, it is found that in all five scenarios, the time to reach the final stable state is shorter than that of the initial state, to some extent indicating that consumers' attitudes toward marketing information, relationship links, cross-market mobility, and the number of competitors reduce the time marketing information remains in the system under the current parameter conditions. Consumers' attitudes, relationship links, and competitors have a significant impact on the time it takes for marketing information to cease spreading and be completely eliminated.

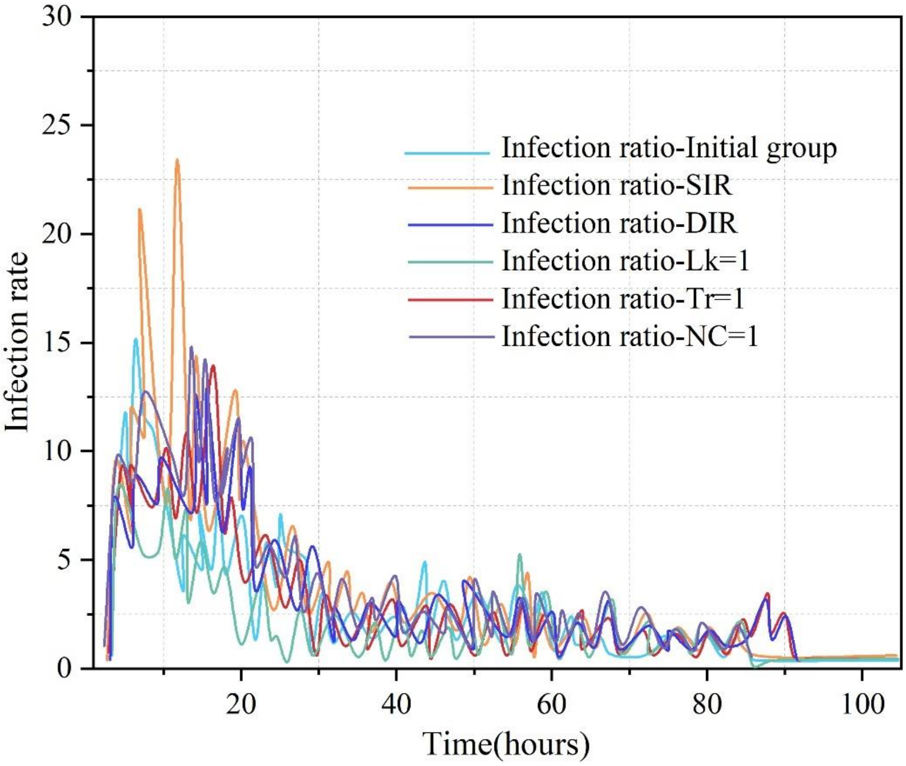
When the average probability of entering the direct immunity state is 5%, the fit with the initial state is highest, and when the average probability of entering the self-isolation state is 5%, the fit with the initial state is lowest. Cross-market mobility and the presence of one competitor also exhibit lower fit with the initial state. In the initial experiment, the highest infection rate was 16.12%, and the highest recovery rate was 11.73%, both reaching 0 at 102 hours. The experimental group with network connections exhibited significantly higher frequencies of high infection and recovery rates compared to other groups, but their time cycles were significantly shorter than those of other groups. Relationship network links can accelerate the spread of information but also promote its disappearance. Compared to the initial experimental group, information in other experimental groups was forgotten or disappeared more quickly.



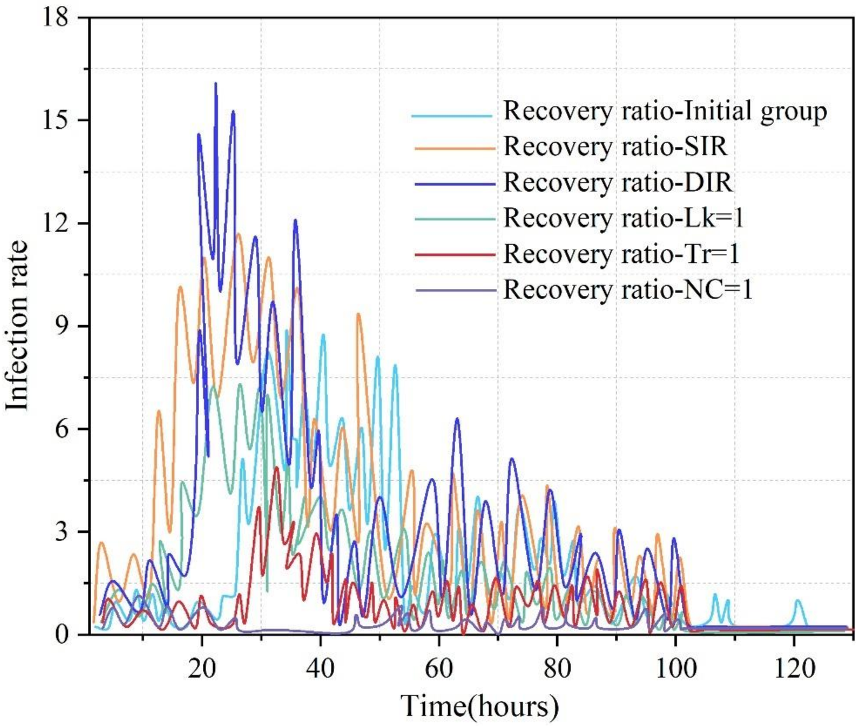
(a) Cumulative infection rate and cumulative recovery rate



(b) Changes in the number of infected and restorers



(c) Ratio variation



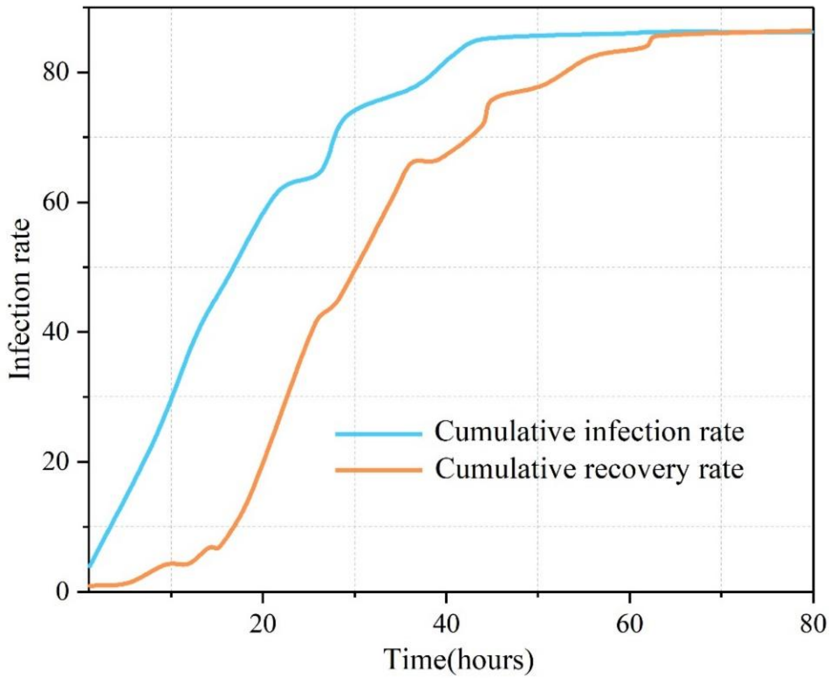
(d) The recovery ratio changes

Figure 4. Results obtained by 5 groups.

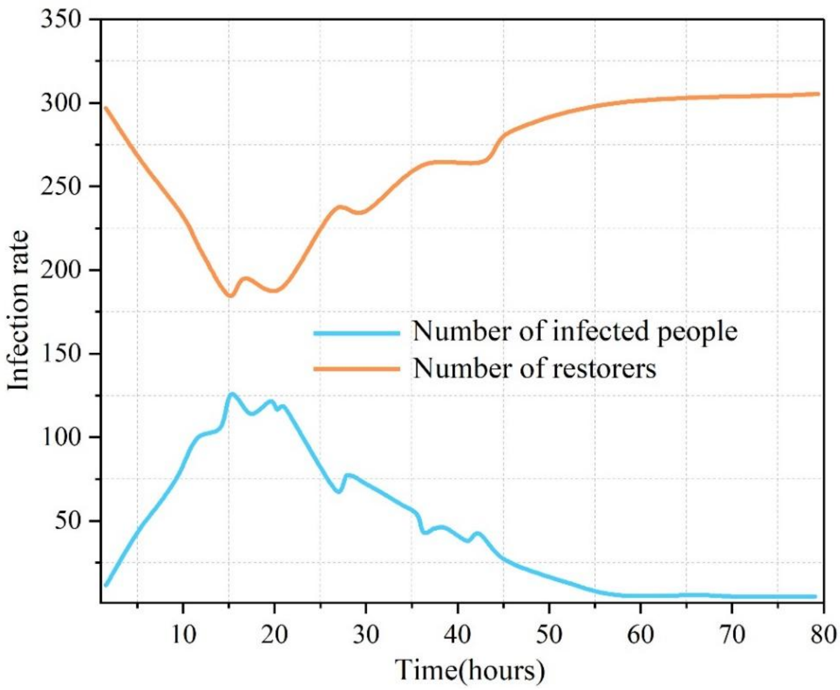
(3) Experiment 3

Next, we conducted the third set of experiments, simultaneously setting the five states from the second set of experiments to obtain the reference experiment group 2. The simulation results of Experiment 3 are shown in Figure 5, where (a) to (c) represent the cumulative infection rate and cumulative recovery rate, changes in the number of infected and recovered individuals, and changes in the ratio of infected to recovered individuals, respectively.

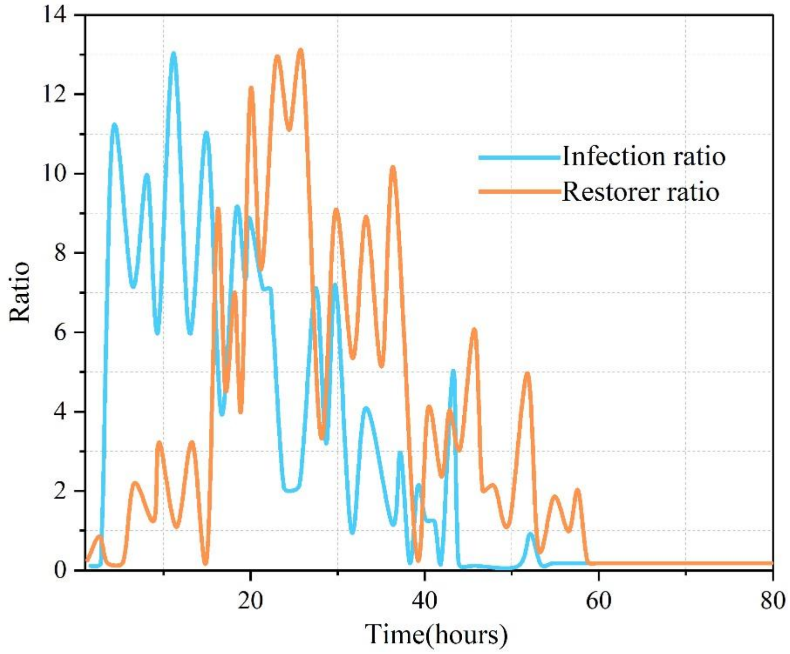
Comparing the results with Experiment 1, the final values of the cumulative infection rate and cumulative recovery rate differ by 0.83 percentage points, but the time to reach the final equilibrium differs by 45 hours, indicating that the cycle of marketing information in Experiment 3 is significantly shorter than in Experiment 1. The maximum number of infected individuals in Experiment 3 is 126, while in Experiment 1 it is 165, clearly lower than in Experiment 1. The time difference between the cessation of changes in the number of infected and recovered individuals was only 12 hours in Experiment 2, whereas it was 28 hours in Experiment 1, indicating that the information in Experiment 3 disappeared faster after ceasing to spread compared to Experiment 1. Overall, this suggests that when all five conditions occur simultaneously, the number of consumers reached by the information being transmitted decreases most significantly.



(a) Cumulative infection rate and cumulative recovery rate



(b) Changes in the number of infected and restorers



(c) Changes in the ratio of infected and restorer

Figure 5. Experimental three simulation results.

3.3. The Digital Silk Road: Empowering the Transformation of Cultural Digital Communication

3.3.1. Integration of Digital Technology and Cultural Heritage

(1) Introducing advanced digital technologies. In the process of promoting the digital dissemination of Silk Road culture, introducing advanced digital technologies is a crucial step. Cutting-edge technologies such as big data, AI, AR, XR, and VR can provide strong support for the protection and inheritance of Silk Road culture. Cutting-edge technologies such as big data, AI, AR, XR, and VR can provide strong support for the protection and inheritance of Silk Road culture.

(2) Develop specialized software and tools. While strengthening scientific and technological innovation, it is also necessary to develop specialized software and tools tailored for the digital development of Digital Silk Road culture. Utilize high-precision 3D scanners to comprehensively scan various cultural elements along the Silk Road and establish high-precision three-dimensional models. Develop interactive experience platforms based on Digital Silk Road culture, such as virtual creation tools and online puzzle games, enabling the public to understand and learn about the charm of excellent traditional culture through interaction.

3.3.2. Data Empowerment Enhancement

(1) Standardized collection of cultural heritage data. The data resource repository is the basis for the digital dissemination of Digital Silk Road culture. To ensure the accuracy and completeness of the data, a comprehensive data collection, storage, and management mechanism must be established. Therefore, it is necessary to regularly update the data repository, correct and optimize existing data, and ensure the timeliness and accuracy of the database.

(2) Intelligent management of cultural heritage data. During data collection and processing, privacy and intellectual property rights must be protected in strict compliance with relevant laws and regulations.

When collecting data, the purpose and scope of data use must be clearly communicated to the data subjects, and their consent must be obtained. The digitalization outcomes of Silk Road culture are legally protected and fall under the category of intellectual property rights.

(3) Deep utilization of cultural heritage data. The deep utilization of cultural heritage data is a crucial step in maximizing the value of cultural big data and promoting cultural dissemination and innovation.

3.3.3. Cultivating composite digital heritage talent

(1) Knowledge structure of cultural heritage digitization professionals. Cultural heritage digitization

requires professionals to possess a multidisciplinary knowledge structure. Cultural heritage digitization also involves knowledge from fields such as intellectual property, cultural industries, project management, psychology, and communication studies. The integration of multiple disciplines is a distinctive feature of the knowledge structure of cultural heritage digitization professionals.

(2) The competency requirements for cultural heritage digitization professionals include: Cultural heritage digitization professionals must also possess a range of competencies, including cultural sensitivity, logical thinking ability, innovative design ability, teamwork ability, and self-directed learning ability.

(3) The pathways for cultivating cultural heritage digitization professionals. Efforts can be made through higher education, on-the-job training, and industry-academia collaboration, among other approaches, to cultivate cultural heritage digitization professionals.

4. Conclusion

This study aims to explore the dissemination mechanism of homogeneous information based on cultural content homogeneity in cross-border e-commerce networks, revealing the process by which homogenized digital Silk Road cross-border e-commerce cross-cultural communication information is disseminated and evolves online.

(1) The cultural communication network established in this study exhibits small-world characteristics compared to random networks. The degree distribution curve of the network is approximately linear in a double-logarithmic coordinate system, indicating that the cross-border cultural communication network is a small-world network with scale-free properties.

(2) Under certain conditions, increases in market size, infection rate, and information survival time can enhance the effectiveness of cross-border cultural communication marketing. However, under certain conditions, direct immunity rate, recovery rate, self-isolation rate, and the number of competitors can weaken the effectiveness of cross-border cultural communication marketing, with recovery rate and the number of competitors having a more pronounced weakening effect.

(3) This paper proposes mechanisms such as strengthening scientific and technological innovation, optimizing data collection, management, and application, and improving talent cultivation mechanisms to promote the sustainability of cross-border cultural transmission under the Digital Silk Road.

Acknowledgements

This research was funded by Fujian Social Science Fund Project: Research on Fujian's International Communication Strategy Based on the Belt and Road Initiative (grant number: FJ2024BF033). This research was funded by Xiamen Social Science Research Project funded by Xiamen Federation of Social Sciences and Xiamen Academy of Social Sciences (grant number: XM2025QND09).

References

1. Ebabu, E. A., Yu, H., & Weikang, Z. (2025). Opportunities and challenges in cross-border e-commerce: strategic management within the legal context of BRI countries-A systematic literature synthesis and future research directions. Technology Analysis & Strategic Management, 1-20.
2. Cui, Y., Shi, Y., Gu, M., & Li, J. (2025). Exploring the knowledge mapping and research trends of cross-border e-commerce. South African Journal of Economic and Management Sciences, 28(1), 5909.
3. Wang, F., & Zhou, Y. (2025). Cross-border E-commerce, platform economy, and export product quality. International Business Review, 102466.
4. Gao, D., Tan, L., & Chen, Y. (2025). Unlocking carbon reduction potential of digital trade: Evidence from China’s comprehensive cross-border e-commerce pilot zones. Sage Open, 15(1), 21582440251319966.
5. Liu, C., & Luo, Y. (2019, May). Cross-cultural examination of Chinese cross-border e-commerce web sites design and contents. In 2019 International Conference on Management, Education Technology and Economics (ICMETE 2019) (pp. 443-446). Atlantis Press.
6. Qi, M. (2021). APPLICATION OF CROSS-CULTURAL PSYCHOLOGY IN CROSS-BORDER E-COMMERCE COMMUNICATION. Psychiatria Danubina, 33(suppl 8), 79-80.
7. Tang, W., & Li, G. (2024). Enhancing competitiveness in cross-border e-commerce through knowledge-based consumer perception theory: an exploration of translation ability. Journal of the Knowledge Economy, 15(3), 14935-14968.
8. Yao, G., Dato’Mansor, Z., Ghazali, H. B., & Yan, Z. (2024). A comprehensive mixed-methods study on cross-border e-commerce SMEs, digital transformation and dynamic managerial capabilities. Environment and Social Psychology, 9(4), 2255.
9. Sun, X., Huang, Q., Zhang, H., & Zhao, X. (2024). Comprehensive pilot zones for cross-border E-commerce propel the digital transformation of manufacturing enterprises: new evidence from China. Electronic Commerce Research, 1-32.
10. Ma, Y. (2024). Exploring innovative business models in cross-border e-commerce under digital economy.

Frontiers in Business, Economics and Management, 13(1), 205-209.
11. Cai, Y., & Liu, X. (2024). AI-Driven Social Media E-commerce Advertising: A Cross-Cultural Communication Study from the Perspective of Yiwu's Trade and Commerce. Sociology, Philosophy and Psychology, 1(2), 20-32.
12. Majcherczyk, M., & Shuqiang, B. (2019). Digital Silk Road-The role of cross-border e-commerce in facilitating trade. J. WTO & China, 9, 106.
13. Sharma, R., Srivastva, S., & Fatima, S. (2023). E-commerce and digital transformation: Trends, challenges, and implications. Int. J. Multidiscip. Res.(IJFMR), 5, 1-9.
14. She, B., Ramasamy, S. S., Chakpitak, N., & Laohavilai, P. O. (2021). IMPROVING DIGITAL PLATFORMS AND B2B2C STRATEGIES FOR CROSS-BORDER E-COMMERCE. Turkish Online Journal of Qualitative Inquiry, 12(6).
15. Wang, C., Liu, T., Wang, J., Li, D., Wen, D., Ziomkovskaya, P., & Zhao, Y. (2022). Cross-border e-commerce trade and industrial clusters: evidence from China. Sustainability, 14(6), 3576.
16. Chiang, C. H., Chen, L. B., Kuo, S. Y., Chen, T. Y., & Chen, X. C. (2022, July). Risk management in cross-border E-commerce by AIoT technology. In 2022 IEEE International Conference on Consumer Electronics-Taiwan (pp. 317-318). IEEE.
17. Feng, L. (2025). Analysis of Product Selection Strategy for Cross-Border E-Commerce with Assistance of Artificial Intelligence. Journal of Internet Technology, 26(1), 111-122.
18. Li, L., Du, K., Zhang, W., & Mao, J. Y. (2024). Empowering digital transformation: The roles of platforms. Journal of Information Technology, 39(4), 650-667.
19. Borojo, D. G., & Weimin, H. (2025). From Click to Cargo: The Role of Digitalization, Cross-Border E-Commerce, and Logistics in Deepening the China–Africa Trade. Economies, 13(6), 171.
20. Tan, Y. (2024). Leadership Training in the Era of Digital Transformation: Case Study of Amazon. Advances in Economics, Management and Political Sciences, 119, 22-28.
21. Knösel, C. T., Cheng, C. C., & Shiu, E. C. (2025). Exploring Social Media Use in Cross-Border E-Commerce and the Internationalization Process: A Comparative Study of Cross-Country and Firm Size. Thunderbird International Business Review, 67(2), 257-283.
22. Guo'e, X., & Xueping, L. (2020). China's Cross-Border E-Commerce: Evolution Pattern and Influencing Factors. China Economist, 15(2), 64-76.
23. Chan, S. T. (2021). Digital transformation of family small-to-medium-sized enterprises. Succession and Innovation in Asia’s Small-and-Medium-Sized Enterprises, 289-305.
24. Renxiang Guan,Hao Quan,Deliang Li & Dayu Hu. (2025). An effective global structure-aware feature aggregation network for multi-modal medical clustering. Expert Systems With Applications,277,126835-126835.
25. Wang Yan,Lu Guichen & Du Jiang. (2022). Calibration and prediction for the inexact SIR model.. Mathematical biosciences and engineering: MBE,19(3),2800-2818.