Data Science Research Project

Agent-based Modelling for Market Diffusion Research

September 04, 2024

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Abstract

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2.1 Diffusion of Innovation and Bass Model

2.1.1 Innovation Diffusion Theory

Innovation diffusion theory, proposed by Rogers (Rogers, 1976), the process of people accepting a new product usually follows the product life cycle theory and can be divided into several stages: introduction, growth, maturity and decline. In the introduction stage, only a few innovators (about 2.5% of the population) and early adopters (about 13.5%) will try the new product. As time goes by, the product enters the growth stage and more early majority (about 34%) begin to adopt it. In the maturity stage, most potential users (late majority about 34%) have adopted the product and the market tends to be saturated. Finally, it enters the decline stage, with only a few laggards (about 16%) still adopting it (Chesbrough & Crowther, 2006). The adoption process at the individual level includes stages such as cognition, interest, evaluation, trial and final adoption (Everett M. Rogers, 2003). Different types of consumers have different adoption times and can be divided into groups such as innovators, early adopters, early majority, late majority and laggards (Diederen et al., 2003).

2.1.2 Bass Diffusion Model

Innovation diffusion models are used to describe and predict the process by which new products or technologies are gradually accepted and popularized in society. The most famous and widely used model is the Bass diffusion model (Bass, 2004). Since Frank Bass proposed the new product diffusion model in 1969, the Bass model has had a profound impact on the research of new product adoption and technology diffusion. The model describes the diffusion process of new products through a simple differential equation:

$$\frac{\mathrm{dF}(t)}{\mathrm{dt}} = (p + qF(t))(1 - F(t))$$

where F(t) represents the cumulative adopter ratio, and p and q represent the innovation and imitation coefficients, respectively.

The solutuion of the Bass model is: $F(t) = 1 - \frac{\exp(-(p+q)t)}{1+\frac{q}{p}\exp(-(p+q)t)}$

The sales volume S(t) can be expressed as: $S(t) = m\frac{\mathrm{dF}(t)}{\mathrm{dt}}$

The core assumption of the Bass model is that the adoption of new products is the result of innovation and imitation, and the adoption probability is linearly related to the number of adopters (Boswijk & Franses, 2005).

The literature shows that the main advantage of the Bass model is that it can accurately predict the S-shaped curve and sales peak of new product sales, and the model parameters have a clear market interpretation. Although originally developed for durable consumer goods, subsequent studies have confirmed that the model is applicable to a wide range of product and service categories, including technology products and B2B market (Massiani & Gohs, 2015).

The following figure uses pure Python to simulate the acceptance process of a product by 1000 potential users (p = 0.03, q = 0.38) and visualize the results using Matplotlib (Figure 1):

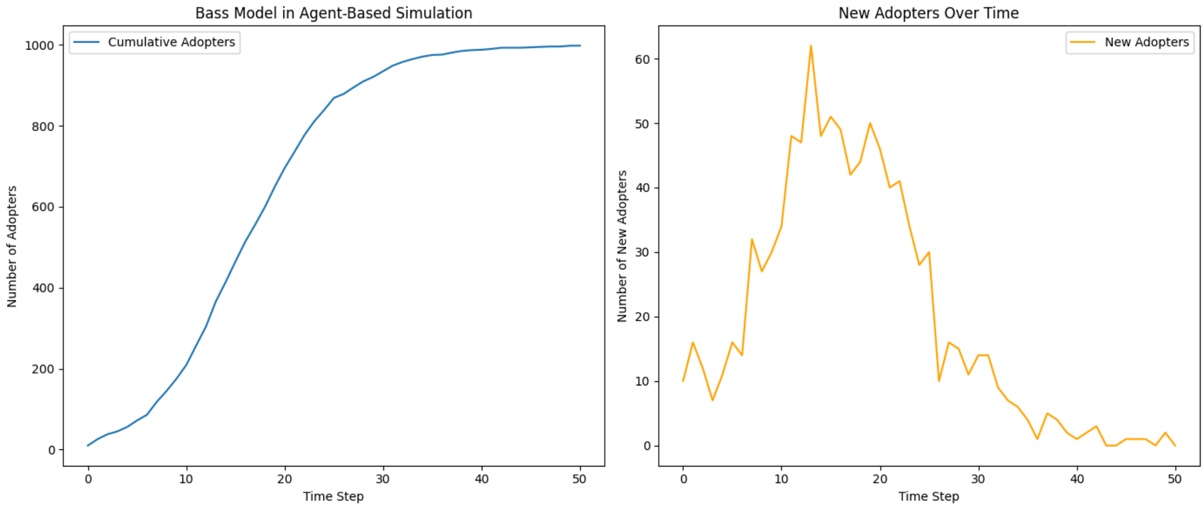

Figure 1: Bass Model Simulation with Python NumPy and Matplotlib [Code]

The influence of the Bass model is reflected in the fact that it has become the basis of many extended models. For example, the intergenerational diffusion model and the generalized Bass model developed by Bass are important developments based on the original model. These extensions further improve the scope of application and predictive power of the model.

2.2 Agent-based Modelling and Simulation

2.2.1 Definition and Concept of Agent-Based Modelling

Agent-Based Modeling (ABM) is an innovative and powerful modeling and simulation approach used to study and understand the dynamic behavior of complex systems (Macal & North, 2005). The core concept of ABM is to evaluate the impact on an entire system by simulating the behavior and interactions of numerous autonomous individuals within it, known as agents. The fundamental premise of ABM is that even complex phenomena can be understood and simulated through a series of autonomous agents following specific interaction rules (Zheng et al., 2013).

Unlike traditional equation-based modeling methods, ABM employs a rule-based approach to construct models (Dorri et al., 2018), making it particularly suitable for simulating complex dynamic systems. In ABM, each agent is endowed with the ability to make autonomous decisions (Macal & North, 2009), acting based on its own state, surrounding environment, and interactions with other agents (Macal, 2016). These agents not only influence their physical and social environment but are also influenced by it, forming an intricate network of interactions.

A key feature of ABM is its capacity to capture heterogeneity within a system, allowing for the simulation of agents with diverse characteristics and behaviors, thus more accurately reflecting the diversity of the real world. Through ABM, researchers can observe and analyze how complex behaviors and patterns at the system level emerge from simple rules at the individual level. This “bottom-up” modeling approach makes ABM a powerful tool for studying emergent phenomena, adaptive behaviors, and the evolution of complex systems.

In ABM, agents are core elements with multiple characteristics, including autonomy, heterogeneity, proactivity, and reactivity. They can make independent decisions, interact with each other, learn and adapt, perceive their environment, and act according to specific rules (Davidsson, 2000). Agents typically possess bounded rationality, goal-oriented behavior, and variable internal states. These features enable ABM to effectively simulate individual behaviors and overall dynamics in complex systems.

The ABM models contains three main components: agents, environment, and interaction rules.

ABM Components	Description
Agents	Autonomous individuals with specific attributes and behavioral rules
Environment	The context in which agents operate
Interaction Rules	Governing agent-to-agent and agent-environment interactions

Table 1: Main Components of ABM

Refer to (Badham et al., 2018) and Gilbert's ABM specification sheet (Gilbert, n.d.) for summarizing the ABM modeling process:

1. Define model purpose and scope.
2. Identify and characterize agents.
3. Determine agent behavior theories and decision rules.
4. Establish agent relationships and interaction theories.
5. Design the environment.
6. Choose an ABMS platform and development strategy.
7. Implement learning and evolution strategies.
8. Incorporate security mechanisms (Ramchurn et al., 2004).
9. Develop interaction protocols.
10. Collect relevant agent data.
11. Validate agent behavior models.
12. Run simulations and analyze output results.
13. Link micro-level agent behaviors to macro-level system behaviors.

The setting of interaction rules, the selection of key parameters and the verification of results of ABM are the core links in the modeling process. The interaction rules are usually implemented by setting the behavior and topological structure of the agent, including the "Soup" model, cellular automata, Euclidean space, GIS and network topology (Macal & North, 2009). The key parameters cover the personal characteristics and environmental factors of the agent (Conte & Paolucci, 2014), and may also include specific belief parameters (Ramchurn, Huynh, & Jennings, 2004). The result verification methods include comparing the ABM simulation results with classical models or empirical data, adopting multi-level verification methods (calibrating parameters at the micro level and observing the reality of macro behavior) (Conte & Paolucci, 2014), and using social network analysis and participatory simulation to obtain information about agent behavior and interaction. However, due to the complexity of ABM models, verification and calibration remain one of the main challenges, and the lack of standardized methods makes it difficult to interpret and analyze the results.

2.2.2 Pros and Cons of ABM and its Applications

The main advantage of ABM is its powerful ability to simulate complex systems. It can capture complex interactions between heterogeneous agents, observe macro-emergent phenomena generated by micro-behavior (Conte & Paolucci, 2014), and provide an intuitive and realistic description of the system. The flexibility of ABM enables it to easily adapt to different scenarios and simulate the learning and adaptive behavior of agents (Dorri, Kanhere, & Jurdak, 2018). It supports multi-level modeling that simultaneously considers dynamics at the individual, organizational and system levels. ABM is also spatially explicit, able to simulate the movement and interaction of agents in specific environments (Davidsson, 2000). In addition, it provides generative explanations, can improve efficiency through parallel computing, and can be integrated with other modeling methods to enhance overall modeling capabilities.

However, ABM also faces some significant challenges and limitations. The most prominent one is the difficulty of verification (Zheng, Son, Chiu, Head, Feng, Xi, Kim, Hickman, & University of Arizona, 2013). Due to the complexity of the model, it is difficult to fully verify the accuracy of the results. ABM often requires powerful computing resources, especially for large-scale or complex models (Conte & Paolucci, 2014). It also requires large amounts of detailed process data for calibration and validation, which increases the difficulty of data collection. The complexity of parameter calibration and the highly technical requirements of the model are also important constraints. In addition, the complex interactions and emergent behaviors generated by ABM can be difficult to interpret, running the risk of producing arbitrary and inconsistent models. High computational cost, lack of unified modeling standards, and the possibility of overfitting are important issues to consider when using ABM. Despite these challenges, ABM remains a powerful tool for studying complex systems, but its use requires careful weighing of these advantages and disadvantages.

ABM has been widely used in multiple disciplines, demonstrating its strong potential as an interdisciplinary research tool and its applicability in systems of different scales and complexities, providing researchers with a powerful tool to understand and predict complex social, economic, and natural phenomena (Macal & North, 2005).

2.2.3 Application of ABM in complex systems and social science research

ABM has demonstrated its unique advantages in the study of complex systems and can effectively reflect the complexity and adaptability of the system (Zheng, Son, Chiu, Head, Feng, Xi, Kim, Hickman, & University of Arizona, 2013). Through simple local rules, ABM can generate complex system behaviors, such as the collective behaviors exhibited by the "Life" and "Boids" models (Macal & North, 2009). It can simulate multi-level systems, capture complex interactions between individuals and between individuals and the environment, and allow agents to adapt and change decisions over time (Badham, Chattoe-Brown, Gilbert, Chalabi, Kee, & Hunter, 2018). ABM can also simulate the properties of complex adaptive systems (CAS), including nonlinearity, fluidity and diversity, as well as feedback mechanisms in the system, which together constitute the complexity and adaptability of the system (Macal & North, 2005).

In social science research, ABM provides an innovative way to integrate social science theory and computational methods. It applies decision theory in social science (such as the BDI model) to the decision rules of agents (Zheng, Son, Chiu, Head, Feng, Xi, Kim, Hickman, & University of Arizona, 2013), and combines data mining and complex system modeling to create the emerging field of computational social science. ABM can transform behavioral theories into computable models and calibrate them using multiple data sources. It integrates the theoretical foundations of multiple disciplines, including complexity science, system science, and management science. Through models such as SugarScape, ABM successfully simulates complex social processes (Macal & North, 2009). In addition, the application of ABM in trust models and other fields demonstrates its ability to combine sociological concepts with computational models. This interdisciplinary approach not only promotes the development of social science theories, but also provides new perspectives and tools for the study of complex social systems.

2.3 Platforms and Building Philosophy of ABM

2.3.1 Platforms for ABM Development

ABM tools encompass a diverse range, including specialized platforms (e.g., NetLogo, GAMA), large-scale development environments (e.g., Repast, MASON), commercial software (e.g., AnyLogic), and frameworks based on general-purpose programming languages (e.g., Mesa for Python). The choice of tool depends on the user's programming experience, project complexity, and specific requirements. Pure ABM builders might find intuitive specialized tools like NetLogo more suitable, while experienced programmers may prefer tools integrated with their familiar languages. For projects requiring GIS integration or large-scale simulations, tools such as GAMA or MASON might be more appropriate. If scientific computing and graph theory related content are needed in the modeling process, it is more appropriate to use the MESA package (Team, n.d.).

2.3.2 Building Philosophy of ABM

Modeling plays a crucial role in scientific research, with diverse purposes including prediction, explanation, and description. Edmonds emphasize the importance of clarifying model purposes, as this influences modeling and validation strategies (Edmonds et al., 2019). In terms of modeling strategies, KISS (Keep It Simple, Stupid) and KIDS (Keep It Descriptive, Stupid) represent two distinct approaches. KISS aims for simplicity, while KIDS emphasizes descriptiveness and extensive evidence. Both strategies have their advantages and disadvantages, and the choice depends on factors such as research objectives and phenomenon complexity. As computational power increases and complex systems research advances, KIDS may gain favor in certain fields (Edmonds & Moss, 2005). However, regardless of the chosen strategy, it is crucial to clearly define the model's purpose and demonstrate its applicability. Researchers should flexibly select strategies based on specific circumstances to construct the most effective models.

Bottom-up ABM starts from the micro-level, defining agents' attributes, behavioral rules, and interactions to simulate complex system dynamics (Rixon et al., 2005). This approach allows macro-level phenomena to emerge naturally from micro-level interactions, capturing the heterogeneity and adaptivity of the system (Nägeli et al., 2020). By constructing models from the individual level, ABM provides a unique perspective for understanding and explaining complex systems, demonstrating the advantages of bottom-up modeling approaches.

With the improvement of computing power, ABM may play an increasingly important role in social sciences. Rand proposed a guiding framework for rigorous use of agent-based modeling (ABM) in research, including using some existing model frameworks, determining the applicability of ABM, designing and building models, and model verification and validation (Rand & Rust, 2011).

UML also enhances Agent-Based Modeling by providing higher abstraction, improved readability, and better modularity. It facilitates communication, documentation, and design pattern application while being language-independent. UML captures dynamic behaviors, promotes efficient modeling, and encourages professional practices, ultimately improving ABM quality and maintainability (Bersini, 2012).

2.3.3 Apply ABM methods into the Bass model

ABMs offer significant advantages for modeling innovation diffusion compared to traditional aggregate approaches. As illustrated in the reviewed papers, ABMs can capture heterogeneity among agents, such as different consumer types in electric vehicle adoption models (Mehdizadeh et al., 2022) or varying farmer characteristics in agricultural innovation studies (Kiesling et al., 2012). They explicitly model interactions and social networks, like word-of-mouth effects in movie-going behavior (Ratna, n.d.) or peer influence in solar panel adoption (Rand & Stummer, 2021). ABMs reveal emergent phenomena from micro-level behaviors, as seen in the diffusion of organic farming practices. They provide flexibility to incorporate various decision rules, spatial effects, and qualitative factors, exemplified by models integrating psychological theories like the Theory of Planned Behavior. By enabling analysis at both individual and aggregate levels, ABMs facilitate policy experimentation, as demonstrated in studies on energy technology adoption (Nägeli, Jakob, Catenazzi, & Ostermeyer, 2020) and electric vehicle diffusion (Zhang & Vorobeychik, 2016). This approach allows for more realistic representation of complex social dynamics in innovation diffusion, providing valuable insights for both theoretical understanding and practical decision support.

2.4 Influencers and Opinion Leaders in Diffusion

Influencers or opinion leaders are nodes in social networks that have a particularly important influence on the spread of information. They usually account for about 10% of network users, have a high degree of connectivity in the network, and play a key role in the widespread dissemination of information (Turnbull & Meenaghan, 1980). Studies have found that the probability of dissemination (p_op) of opinion leaders is often a key factor in successfully simulating the spread of real-world information (Feder & Savastano, 2006). Ideally, early adopters are also opinion leaders, so that information can be spread most effectively. In general, influencers are widely connected and influential nodes in social networks, and play a disproportionately important role in the widespread dissemination of information (Li et al., 2021).

2.5 Network Structure and Diffusion

2.5.1 Network topological structure

Several studies have shown that different network topologies have a significant impact on information dissemination. By comparing the information diffusion effect of priority connection network, random network, small world network and lattice network in ABM simulation. It was found that structural characteristics such as average degree, clustering coefficient and average path length of the network are closely related to the speed and scope of information propagation. For example, small-world networks tend to exhibit faster information propagation speeds due to their high clustering and short average path lengths (Bohlmann et al., 2010).

Chen further explored the selection strategies of early adopters (seed nodes) under different network structures (Chen, 2019). The study found that the most effective early adopter identification methods may be different in different network structures. For example, the degree discount algorithm performs well in most networks, while the greedy algorithm works better in grid networks.

2.5.2 Node Heterogeneity and Opinion Leaders

Smith and Burow emphasize the importance of considering node heterogeneity for accurately modeling information propagation. They proposed an extended Bass diffusion model that divided nodes into different connectivity categories and took into account the correlation between nodes (Smith & Burow, 2020). Research shows that highly connected nodes (so-called "opinion leaders") play a key role in information dissemination, especially in the early stages of information dissemination.

Xue used ABM to study the spread of immunization policies in social networks. Their model considered the influence of opinion leaders and found that targeted publicity targeting opinion leaders can significantly improve the efficiency of information dissemination (Xue et al., 2016).

2.6 Conclusion of Literature Review

By collating the literature review, the following ideas inspired my research report:

- ABM is a powerful tool for simulating complex systems and social phenomena, providing a bottom-up approach to understanding emergent behaviors.
- The Bass diffusion model is widely used in innovation diffusion research, and ABMs offer advantages for modeling innovation diffusion compared to traditional aggregate approaches.
- KISS and UML enhance ABM modeling by emphasizing simplicity and abstraction, respectively.
- Influencers and opinion leaders play a key role in information dissemination, and network structure and node heterogeneity significantly impact diffusion processes. Influencers mean they have more connections in the social network.
- Network topological structure, node heterogeneity, and opinion leaders are important factors in information diffusion, and ABMs can capture these dynamics effectively.

2.7 Statement of research objectives

This study is based on the theoretical foundation of the Bass diffusion model and combines the Agent-Based Modeling method to simulate the market diffusion process. The Bass model provides us with a theoretical framework to describe the diffusion process of innovative products in the market, which takes into account the role of external influences (such as advertising) and internal influences (such as word of mouth) on potential adopters. ABM allows us to simulate the behavior and interaction of individual consumers at the micro level, thereby exploring the various factors that affect the diffusion process at a more detailed scale.

By combining the macro-forecasting capabilities of the Bass model with the micro-simulation advantages of ABM, this study aims to gain a more comprehensive and in-depth understanding of the diffusion dynamics of new products in the market. This approach allows us to consider factors such as individual differences, social network structure, and market heterogeneity while maintaining a grasp of overall market trends.

The following are my research proposals:

1. Study on the relationship between the probability distribution of individual acceptance of new products in the market and the product diffusion rate: Explore the impact of different acceptance probability distributions on the overall market diffusion process.
2. Analysis of the role of innovators and opinion leaders in product diffusion: Study how the proportion of innovators and influential opinion leaders who spontaneously accept new products affects the market penetration and diffusion speed of products.
3. Research on the impact of consumer group heterogeneity on product diffusion: Analyze the impact of the proportion of different types of consumer groups in the market on the diffusion of product acceptance, and explore the potential impact of the absence of a specific type of consumer group on the diffusion process.
4. Investigation of the interactive effects of multiple factors on product diffusion: Explore the combined impact on the product diffusion process when multiple key parameters - such as innovation coefficient, imitation coefficient, proportion of innovators, or proportion of influencers - vary simultaneously. Analyze potential synergistic or counteracting effects among these factors and how they collectively shape diffusion dynamics.
5. Analysis of the impact of social network structure on product diffusion dynamics: Study how different types of social network structures (such as small-world networks, random networks, etc.) affect the spread and adoption speed of product information, as well as the relationship between

these network characteristics and key indicators of the diffusion process (such as diffusion rate, peak time, saturation level, etc.).

3 Methodology

In this section, I will introduce the model framework (Section 3.1), agent attributes (Section 3.2), social network structure (Section 3.3), and diffusion mechanism of the ABM model for market diffusion research (Section 3.2.2). The model is designed to simulate the diffusion process of new products in the market, taking into account the influence of individual characteristics, social network structure, and market composition on the diffusion dynamics. After that, I designed simulation experiments for the research questions (Section 3.4.2) and ran ABM using the Mesa framework (Section 3.5).

3.1 Model framework introduction

3.1.1 Model Assumption

To address the research questions raised in Section 2.7, I built a model framework for ABM market diffusion research. It is based on the following key assumptions:

- Agent heterogeneity: Agents are divided into two main types: innovators and imitators, which are further divided into influential and non-influential individuals. Each agent has unique attributes, including consumer type and whether it is influenced. The transition from "non-adopted" to "adopted" for the adoption status of a new product is irreversible.
- Social network structure: Product information is spread through network connections, and the relationship between agents is constructed through small-world networks and random networks. On this basis, influential agents will add more connections to simulate the role of opinion leaders or key nodes in the diffusion process.
- Diffusion mechanism: The adoption of new products is affected by two main factors: external influence (innovation effect) and internal influence (imitation effect). Innovators adopt products independently, while imitators are influenced by the adoption behavior of other consumers in the social network. The adoption probability of each agent is determined by the parameters of the innovator and imitator.
- Market composition: Assuming a closed market, a fixed number of potential adopters (N), the total potential market size remains constant during the diffusion process, and the market consists of four types of agents: influential innovators, influential imitators, non-influential innovators, and non-influential imitators.

The market diffusion research model established based on these assumptions becomes a powerful platform for simulating and analyzing complex product diffusion processes by integrating agent heterogeneity, social network dynamics and market structure.

3.1.2 Model structure

Regarding the many ABM modeling frameworks mentioned in Section 2.3.1, considering that my model requires some support for complex networks and statistics on the agent status at each moment, I finally chose to develope with MESA[1], using object-oriented programming, and consists of two main classes: BassModel and BassAgent. The BassModel class defines the overall model structure, including the network environment, agent creation, and data collection. The BassAgent class defines the properties and behaviors of individual agents.

[1]Mesa allows users to quickly create agent-based models using built-in core components (such as spatial grids and agent schedulers) or customized implementations; visualize them using a browser-based interface; and analyze their results using Python's data analysis tools. Website: https://mesa.readthedocs.io/en/stable/

The following UML shows the overview class diagram of the ABM model (Figure 2):

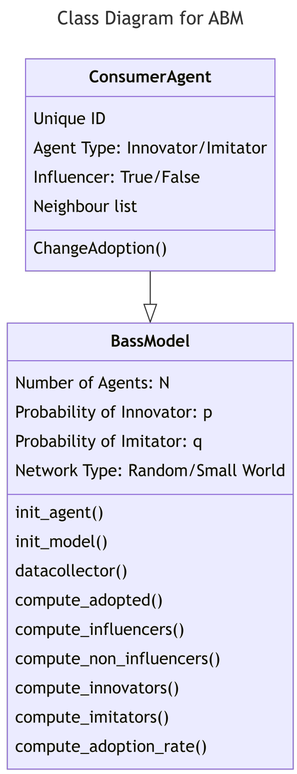

Figure 2: Class Diagram of the ABM Model

I used a top-down modeling approach to design the customer (agent) and the market environment (BassModel). The characteristics (such as the type of the consumers, the probability of accepting the product, etc.) of the user will be introduced in detail in Section 3.2, and the simulation of the market environment (like the social network type, the market scale and the proportion of different kinds of consumer, etc.) will be presented in Section 3.3.

3.2 Agent Attributes

3.2.1 Parameters for Agent Level

Each agent represents a potential consumer in the market and has the following key attributes:

- Basic attributes:
  - Unique identifier (unique_id): used to distinguish different agents.
  - Adoption status (adopted): Boolean value, indicating whether the agent has adopted the product
- Type Attributes:
  - Consumer type (agent_type): divided into "Innovator" or "Imitator"
    - Innovators: tend to adopt new products independently, and the adoption probability is determined by parameter p
    - Imitator: The adoption decision is influenced by others in the social network, and the adoption probability is determined by the parameter q and the proportion of neighbors that have adopted.
  - Influencer: Boolean value, divided into influential (influencer) and non-influencer (non-influencer)
    - Influential agents have more connections in the network, representing opinion leaders or key nodes in the diffusion process.
    - Non-influential agents represent ordinary consumers.

- Social network characteristics: Neighbors: A list of other agents that an agent is directly connected to in the social network.

3.2.2 Diffusion mechanism

We hypothesize that new product adoption is influenced by two main factors:
- External influence (innovation effect): from external information sources such as advertising and media.
- Internal influence (imitation effect): from the adoption behavior of other consumers in the social network.

So in each time step, the adoption probability of an agent is determined by:
- For innovators p: Agents independently adopt products with fixed probability p.
- For imitators q: Agents are influenced by the adoption behavior of their neighbors, and the adoption probability is determined by the proportion of neighbors who have adopted the product. The equation is (N means neighbors):

$$p_{\text{adopt}} = q \times \frac{N_{\text{Adopted}}}{N_{\text{Total}}}$$

3.3 Social Network Structure

The network structure in my ABM model is based on small-world networks and random networks. On top of these two basic network structures, I further introduced the key attribute of influencers. Influencers have more connections in the network. This design is intended to simulate the role of opinion leaders or key nodes in real society. There are three steps to build such a network:

Initialize a base network (Section 3.3.1 and Section 3.3.2) → Put agents on the network → Add connections for influencers (Section 3.3.3)

As shown in the Figure 3 below:

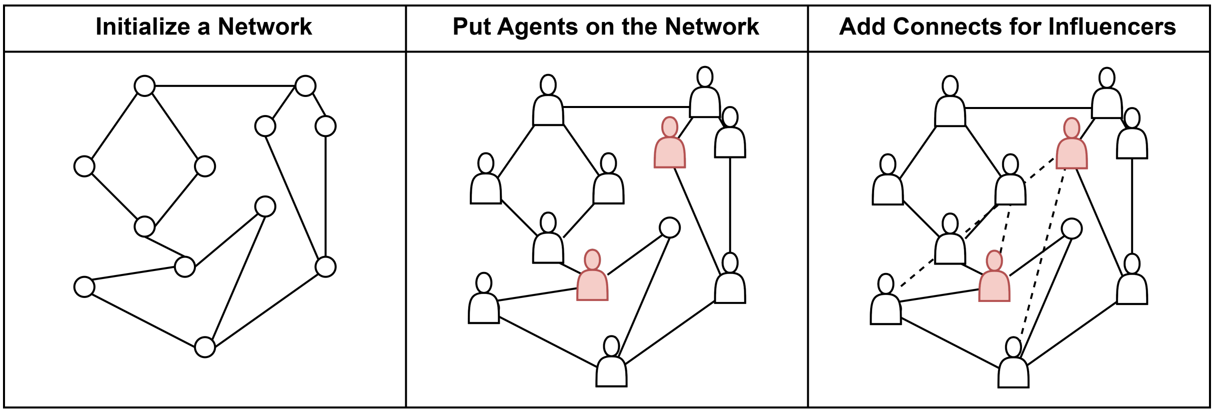

Figure 3: Initialization of the ABM Model Network

3.3.1 Base Network Structure

This model simulates the interconnection and influence between consumers through different social network structures. The network structure has an important impact on the information dissemination and product adoption process. The model supports 2 typical network types (small world and random network). The use the Python NetworkX library[2] to create the initial network structure.

[2]NetworkX is a package for complex networks. Official website: https://networkx.org/

The following table summarizes the key characteristics of the two network:

Characteristics	Random Network	Small-World Network
Implementation Method	Erdős-Rényi model	Watts-Strogatz model
Function	nx.erdos_renyi_graph	nx.watts_strogatz_graph
Features	Fixed probability p of connection between each pair of nodes	High clustering coefficient and low average path length, simulating "six degrees of separation"
Parameters	• n: number of nodes • p: connection probability (0.05 in this model)	• n: number of nodes • k: number of neighbors for each node (4 in this model) • p: rewiring probability (0.1 in this model)
Potential Impact	Simulates completely random social relationships, may lead to relatively uniform information diffusion	May result in rapid local diffusion and relatively fast global information spread
Mathematical Expression	• P(edge) = p for any two nodes • Average degree = $p(n-1)$ • Graph is almost certainly connected when $p > \frac{\ln(n)}{n}$	• $C \approx \frac{3(k-2)}{4(k-1)}$ • $L \propto \frac{\log(n)}{\log(k)}$ • Maintains high clustering coefficient while reducing average path length through long-distance connections

Table 2: Comparison of Random and Small-World Network Models

The figure shows the network structure of a small-world network with 100 nodes (agents), we can see that the random network has a higher clustering coefficient and a shorter average path length compared to the small world network:

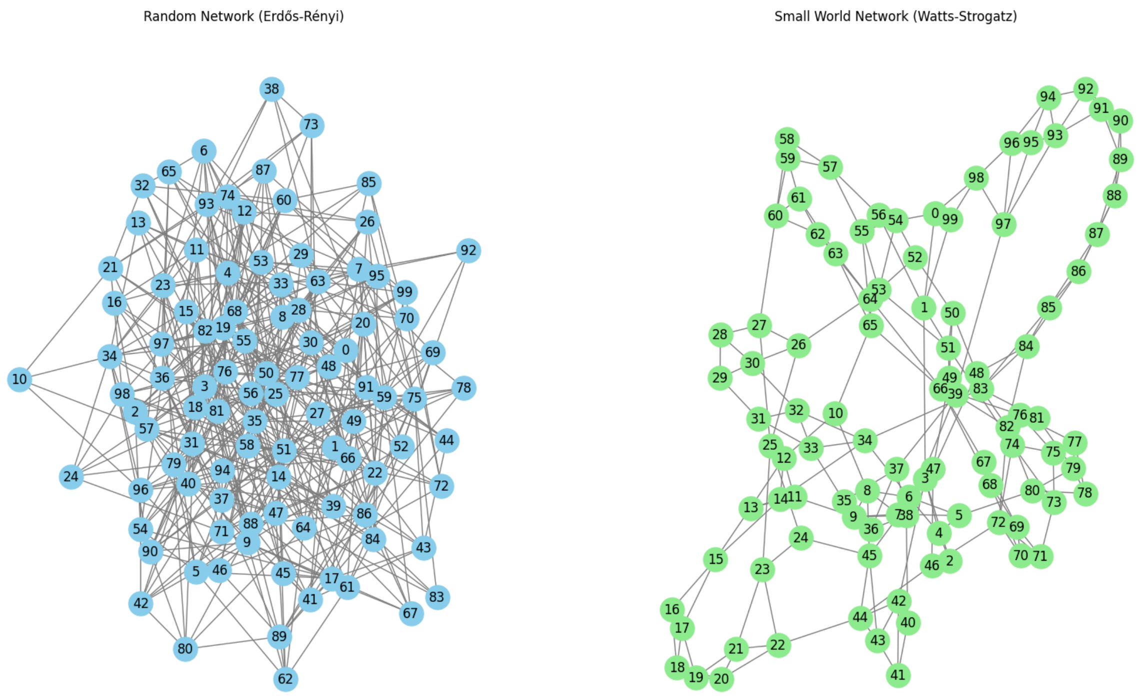

Figure 4: Random and Small-World Network Structures [Code]

3.3.2 Network Edge Equalization

We hope to compare market diffusion in Erdős-Rényi random graphs and Watts-Strogatz small-world networks. To ensure comparability, I use a controlled variable approach, maintaining identical node counts (N) and total edge numbers across both network types.

I achieve two different networks in which each node has the same number of connections with other nodes by adjusting the connection probability p in the random network model and the initial neighbor count k in the small world model to achieve the same number of edges:

- For Erdős-Rényi graphs, the expected number of edges is:

$$E(\text{edges}) = \frac{1}{2} \times p \times N(N-1)$$

- For Watts-Strogatz graphs, the number of edges is fixed at:

$$\text{edges} = \frac{1}{2} \times N \times k$$

By setting these two values equal, we can derive:

$$p = \frac{k}{N-1}$$

For example, in my simulation, I set $N = 1000$, $k = 4$ in the small world network, so we can calculate $p \approx 0.004004$ for random network.

This approach constructs network models with identical node counts and edge numbers but differing topological structures, providing an ideal platform for studying the impact of network structure on information diffusion. This way, each agent can have a similar number of neighbors before adding more links to the Influencial agent. This can be demonstrated in Section 4.1.

3.3.3 Add More Edges for Influencers

In social network structure research, influencers are usually defined as nodes with more connections. Here we add additional connections to influencers. This can simulate the influencer's extensive influence in the social network.

Here is the logic to implement adding more neighbors to an influencer (G means the network graph, achieved by Section 3.3.2):

Algorithm 1: Rules for adding more neighbors to Influencer

```
function ENHANCE-INFLUENCERS-CONNECTIONS(G, agents)
    for each agent in agents do
        if agent is influencer then
            Get current neighbors of agent
            Identify potential new neighbors (nodes not currently connected and not self)
            Additional Edges = min(int(25*random.random())+30, len(potential_neighbors)))
            Calculate number of additional edges (random between 30 to 54 ↑)
            Randomly select new neighbors from potential neighbors
            for each new neighbor do
                if edge doesn't exist between agent and new neighbor then
                    Add edge between agent and new neighbor
```

Table 3: Algorithm for Enhancing Influencers' Connections

3.4 Model Input and Simulation Design

3.4.1 Model Parameters

This Model contains several key parameters that together define the behavior and characteristics of the model. The following is a detailed description of these parameters:

Parameter	Description	Impact
Basic Parameters		
N	Total number of agents (consumers)	Determines market size, affects network complexity and computation time
p	Innovation coefficient (0.01 to 0.03)	Higher values accelerate innovators adoption
q	Imitation coefficient (0.3 to 0.5)	Higher values accelerate imitators adoption
Agent Type Distribution		
agent_proportion	List of four values representing proportions of: 1. Influential innovators 2. Influential imitators 3. Non-influential innovators 4. Non-influential imitators	Determines market composition, affecting overall diffusion dynamics

Parameter	Description	Impact
Network Structure		
network_type	Options: "random", "small_world"	Different structures lead to varied information spread patterns
p_random	Connection probability for random networks (default: 0.05)	Affects connectivity in random networks
k	Number of neighbors per node for small-world networks (default: 4)	Influences local clustering in small-world networks
p_rewire	Rewiring probability for small-world networks (default: 0.1)	Affects "small-world-ness" of the network
Influence Parameter		
Extra connections	Additional connections for influential agents	Simulates the broad influence of opinion leaders

Table 4: Model Parameters for Agent-Based Bass Diffusion Model

3.4.2 Design of the Simulation Experiment

Experimental design is a core component of methodology, which directly determines how to test research hypotheses and answer research questions. My experimental design systematically covers changes in multiple key parameters (such as innovation coefficient p, imitation coefficient q, network type, influencer ratio, etc.) and considers their interactions to ensure the comprehensiveness and rigor of the research. Each set of experiments is iterated 5 or 25 times, and such a design captures the randomness of the model and the stability of the results. Through this systematic and comprehensive experimental design, the foundation for the analysis and discussion of the results is laid.

I designed a series of simulation experiments to explore the impact of different parameters on the product diffusion process. These experiments are divided into two categories, each containing 6 sets of experiments, conducted in small-world networks and random networks respectively. All experiments are based on a network of 1,000 agents with multiple iterations to eliminate the randomness of the simulation. Each set of experiments uses the same parameter settings in both network structures in order to directly compare the impact of the network structure. The following is a detailed description of the experimental design:

- Network Type: Small-world network experiments (simulations 1-6) and random network experiments (simulations 7-12)
- Effect of the innovation coefficient (p) on diffusion:
  - Simulations 1 and 7: Adjust the p coefficient (0.01 to 0.03), keeping other parameters unchanged.
  - Purpose: To understand how the innovator adoption probability affects the diffusion speed and pattern in different network structures.
- Effect of imitation coefficient (q) on diffusion:
  - Simulations 2 and 8: Adjust the q coefficient (0.3 to 0.5) and keep other parameters unchanged.
  - Purpose: To explore the effect of imitator adoption probability on the diffusion process in different network structures.
- Effect of influencer ratio on innovator diffusion:
  - Simulations 3, 4 and 9, 10: Adjust the ratio of influencers to innovators (0 to 0.01), keeping the total innovator ratio constant.

  - Purpose: To study how the proportion of influencers in the innovator group affects the diffusion dynamics of different network structures.
- Effect of the ratio of influencers to innovators on diffusion:
  - Simulations 3 and 9: Adjust the ratio of influential innovators (0 to 0.01), keeping the ratio of total innovators constant (0.01).
  - Simulations 4 and 10: Adjust the ratio of influential innovators (0 to 0.01), keeping the ratio of total influencers constant.
  - Purpose: To study how the ratio of influencers in the group of innovators affects the diffusion dynamics of different network structures. In particular, we want to study what happens when the number of influential innovators is zero.
- Interaction between innovation coefficient and proportion of innovators:
  - Simulations 5 and 11: Adjust p coefficient (0.01 to 0.05) and proportion of innovators (0.01 to 0.07) simultaneously.
  - Purpose: To explore how the interaction between innovation coefficient and proportion of innovators affects the diffusion process in different network structures.
- Interaction of innovator and influencer proportions:
  - Simulations 6 and 12: Simultaneously adjust the innovator proportion (0.01 to 0.07) and the influencer proportion (0 to 0.6).
  - Purpose: To investigate how the distribution of innovators and influencers in different network structures jointly influences diffusion dynamics.

3.5 Run the ABM Model

3.5.1 Initialize the Model

The following pseudocode outlines the core initialization process for our Agent-Based Model (ABM) of product diffusion. This initialization sets up the fundamental structures and parameters necessary for simulating the Bass diffusion model in a network context. The code demonstrates how we establish the agent population, create the social network, and prepare the model for simulation runs.

Algorithm 2: Final Initialization for Market Diffusion Simulation Model

```
function INITIALIZE-MODEL(N, p, q, agent_proportion, network_type)
    ▷ Initialize core parameters and structures
    total_agents ← N
    innovation_coefficient ← p
    imitation_coefficient ← q
    Create social network based on network_type
    Generate agent distribution list

    ▷ Create and place agents
    for i = 0, N − 1 do
        Create new BassAgent with properties from distribution list
        Add agent to network and scheduler

    ▷ Enhance network for influential agents
    for each influential agent do
        Add extra connections

```

```
▷ Initialize tracking variables
steps_to_key_percentages ← None
running ← True

return Initialized model
```

Table 5: Summary of the Model Initialization Process

3.5.2 Scheduler and Barch Running with MESA

Schedulers play a key role in Agent-Based Models. I chose to use the RandomActivation scheduler provided by Mesa. The main reason for using a scheduler is to manage and control the order in which agents in the model are activated. At each simulation step, the RandomActivation scheduler randomly decides the order in which to activate agents. This randomness is important because it helps avoid systematic biases that may be introduced by a fixed activation order. The Table 6 shows the difference between the five agents at each time step when using random activation and when not using random activation. In the real-world product diffusion process, the order in which consumers make decisions is often not fixed, and using random activations can better simulate this uncertainty. In addition, the scheduler simplifies the time management of the model, allowing us to easily iterate over all agents at each time step, update their states, and collect relevant data. By creating a scheduler instance at model initialization and calling `self.schedule.step()` to activate all agents at each time step, we ensure that the model runs consistently and controllably. This approach is particularly suitable for simulating social processes that do not have a fixed order, such as our product diffusion model, allowing us to more accurately capture complex market dynamics.

Time Step	Without Random Activation	With Random Activation
0	$1 \to 2 \to 3 \to 4 \to 5$	$1 \to 2 \to 3 \to 4 \to 5$
1	$1 \to 2 \to 3 \to 4 \to 5$	$3 \to 1 \to 5 \to 2 \to 4$
2	$1 \to 2 \to 3 \to 4 \to 5$	$5 \to 4 \to 2 \to 1 \to 3$
…	$1 \to 2 \to 3 \to 4 \to 5$	$2 \to 3 \to 1 \to 5 \to 4$
n	$1 \to 2 \to 3 \to 4 \to 5$	$4 \to 1 \to 3 \to 5 \to 2$

Table 6: Comparison of Agent Activation Order with and without Random Activation Scheduler

Batch running is an efficient way to run different parameter combinations in a single simulation script. Using Mesa's BatchRunner, we can systematically explore the impact of different parameter combinations on product diffusion. This method allows us to define parameter ranges (such as innovation coefficients and imitation coefficients), perform multiple repeated simulations, and automatically collect data. Through batch running, we can perform sensitivity analysis, understand how different market conditions affect product adoption, identify key parameters and critical points, and predict diffusion trends under various scenarios. At the same time, repeating the experiment for the same parameter combination takes a lot of time. CPU multiprocessors can solve this problem in the batch running function implementation to speed up the simulation process.

3.5.3 Data Collection

Data collection is essential for analyzing both individual agent behaviors and overall system dynamics. We employ Mesa's `DataCollector()`, a tool that enables systematic gathering of both agent-level and model-level data. This dual-level approach allows us to track individual agent decisions and characteristics while also monitoring system-wide trends. The DataCollector efficiently gathers time-series data throughout the simulation, providing insights into the temporal dynamics of the diffusion process. This comprehensive data collection facilitates model validation, sensitivity analysis, and the exploration of emergent phenomena in product adoption patterns, enhancing our understanding of the complex diffusion process.

Level	Data Collected	Description
Agent-level	Adopted	Whether each agent has adopted the product
	Influencer	Whether each agent is an influential individual
	Agent_Type	Innovator or Imitator
	Neighbors	List of neighbors for each agent
	Neighbors_number	Number of neighbors for each agent
Model-level	Adopted_Count	Total number of agents who have adopted the product
	Influencer_Count	Number of influential agents who have adopted the product
	Non_Influencer_Count	Number of non-influential agents who have adopted the product
	Innovator_Count	Number of innovators who have adopted the product
	Imitator_Count	Number of imitators who have adopted the product
	Steps_to_X_percent	Time steps required to reach 25%, 50%, and 75% adoption rates

Table 7: Data Collection in the Agent-Based Bass Diffusion Model

4 Simulation and Results Analysis

4.1 Table of Neighbors between Influencers and Non-Influencers

Before doing any ABM analysis, I first need to verify the similarity of the number of connections between different networks mentioned and add more neighbors to the influencers in Section 3.3. Statistically analyze whether the influencers and non-influencers are the same in different networks. This is the premise for the following series of comparisons.

The tables below shows the average, maximum, and minimum values of the number of influencer and non-influencer neighbors in the first five simulations. The number of neighbors of an influencer is approximately 4 to 6 times that of a flying influencer (Table 8).

RunId	Inf Mean	INF Max	Inf Min	Non-inf Mean	Non-inf Max	Non-inf Min
0	49.09	62	37	8.132222	17	3
1	49.83	69	36	8.152222	15	3
2	50.24	65	35	8.215556	16	3
3	50.83	64	36	8.283333	17	3
4	49.87	65	37	8.11	17	3

Table 8: Run Data for Agent-Based Model [Code]

The Figure 5 is a statistical analysis of the number of neighbors of all agents in simulation 1 (visualizations of simulations 2-16 are similar). The gray-green points in the figure represent influencers and he brown points represent non-influencers. From Figure 5, we can see that the number of non-influencer neighbors in the small-world network (8.205) and the random network (8.208), as well as the mean number of influencer neighbors (50.044 in random network and 50.077 in small world network), are basically the same. We can also see that the number of influencer neighbors is much higher than that of non-influencers.

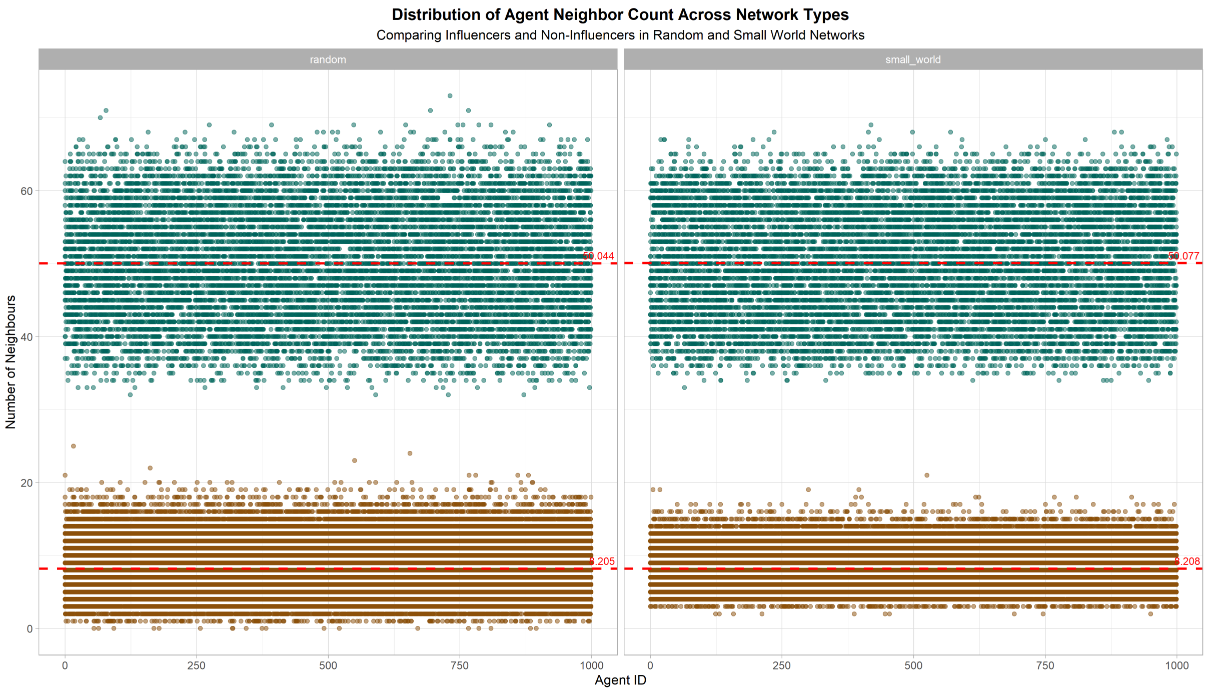

Figure 5: Neighbor statistics for Influencers and Non-Influencers [Code]

In summary, the statistics in this section verify that the number of neighbors of influencers is much higher than that of non-influencers. It also proves that the network equilibrium achieved in Section 3.3.2 makes the two networks comparable.

4.2 Single Run Simulation Results Statistics

4.2.1 Statistics of Consumer's Adoption for single simulation

This Figure 6 shows one of the market diffusion simulations, showing a classic S-shaped adoption curve. The simulation set 1% innovators and 10% influencers, with an innovation coefficient p of 0.01 and an imitation coefficient q of 0.3. The results show that a small number of innovators took the lead in adopting the product in the early stage (0-25 steps), followed by rapid diffusion between 25-50 steps, which may be due to the network effect driven by influencers. Influential agents showed higher adoption rates, but overall imitators constituted the vast majority of adopters. The whole process reached market saturation after about 50 steps, and the final adoption rate was close to 100%.

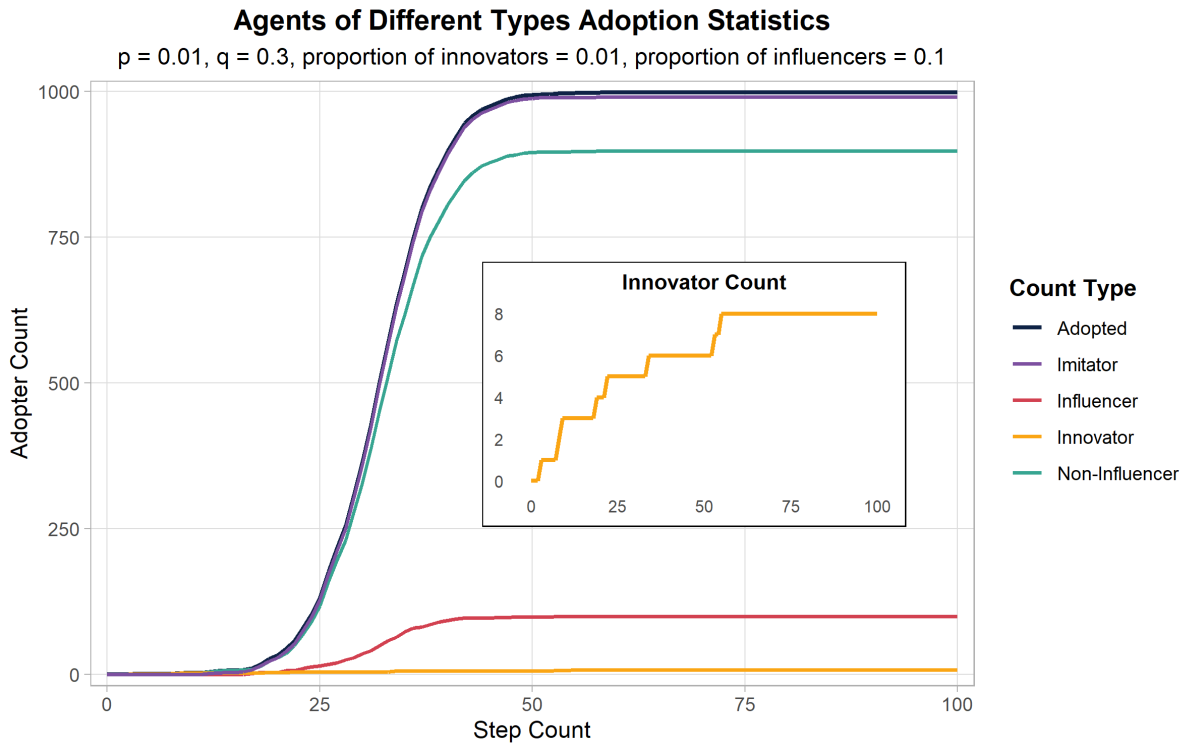

Figure 6: Adoption Statistics for a Single Simulation Run [Code]

It is worth noting that this simulation result (simulating the decision of every potential consumer in the market at the micro level) is highly consistent with the pattern predicted by the traditional Bass diffusion model (describing the entire market at the macro level). This consistency can be regarded as a pattern matching, which provides strong support for the effectiveness of the ABM model test. Among them, due to the relatively small number of innovators, the observation is not obvious, but in the statistics of the three groups of influencers, non-influencers and imitators, an obvious S-shaped growth curve can also be observed.

4.2.2 Visualization of Network Evolution

To gain a more intuitive understanding of the process of product adoption spreading in social networks, I created a series of network graphs to visualize the time evolution of agent activations. These networks (Figure 7) were generated by the NetworkX library and visualized with igraph. In these graphs, nodes represent individual agents and edges represent social connections between them. Red nodes represent agents that have adopted the product, while blue nodes represent agents that have not yet adopted. The size of the node represents the influence of the agent, with larger nodes representing influential individuals.

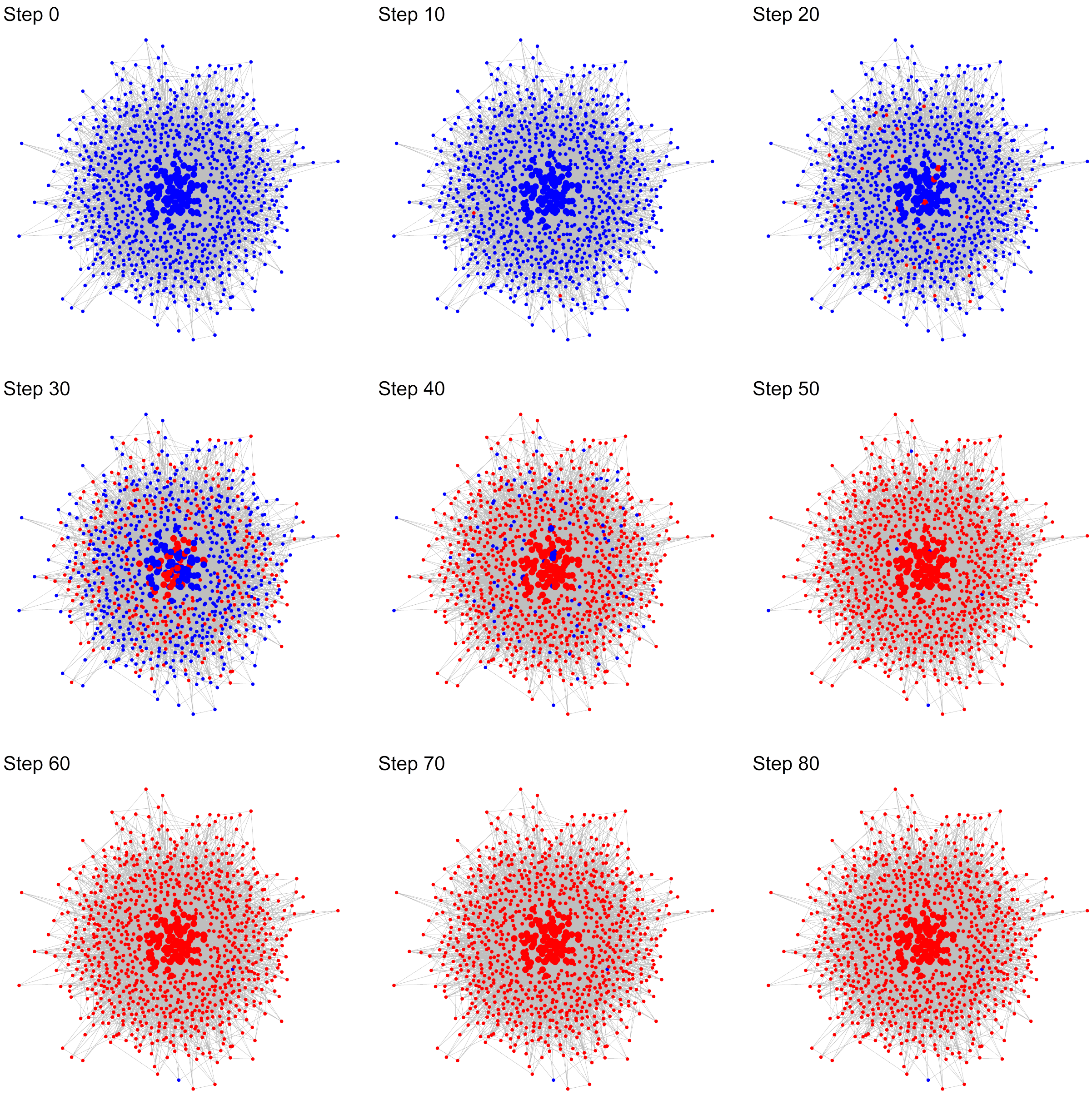

Figure 7: Network Evolution over Time from Step 0 to Step 80 [Code]

Market diffusion shows obvious characteristics of evolution over time. In the initial stage (Step 0-20), the network is predominantly blue, and only a few nodes (most likely innovators) begin to adopt the product. As time goes by to Step 30-40, we observe a significant increase in the number of red nodes, especially in the core area of the network, indicating that the product begins to spread widely among influential agents. Entering Step 50-60, the red nodes quickly spread throughout the network, marking the rapid growth stage of product adoption. Finally, at Step 70-80, the network is almost completely covered by red nodes, indicating that product adoption is close to saturation.

4.3 Research on Different Probability of Adoption

4.3.1 Research on Innovation Coefficient (p)

The innovation coefficient represents the tendency of consumers to independently adopt new products. In simulation 1 and 7, I used the control variable method to change only the value of the innovation coefficient p (ranging from 0.01 to 0.03), while keeping all other parameters unchanged, including the imitation coefficient (q), network structure (q=0.3, proportion of innovators=0.01, proportion of influencers=0.1, N=1000), overall market size, etc. For each p coefficient, multiple simulations were performed to ensure the stability and reliability of the results.

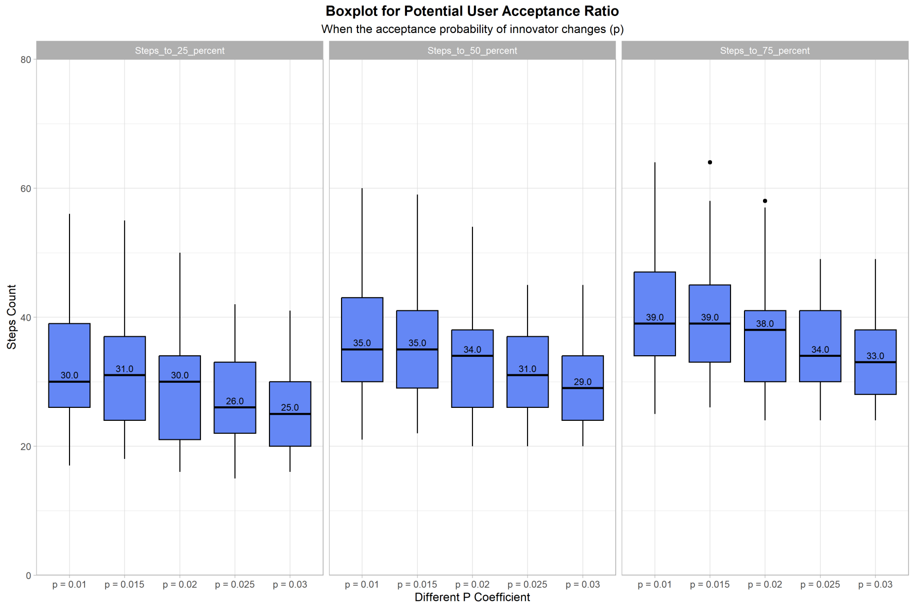

Figure 8: Boxplot of Different Innovator Adoption Probabilities in Small World Network [Code]

This box plot (Figure 8) is made by adjusting the p coefficient from 0.01 to 0.03 while keeping other parameters unchanged in small world network. In general, as the p coefficient increases, the time required to reach 25%, 50%, and 75% adoption rates is significantly shortened, like in the early stages. For example, the median number of steps to reach a 25% adoption rate dropped from about 30 to 25. This effect weakened but still existed in the later stages (75% adoption rate). At the same time, the increase in p coefficient also led to a decrease in the variability of the results, indicating that the adoption process under high innovation coefficients is more stable and predictable. These findings emphasize the importance of increasing the innovation coefficient (such as through effective marketing) to accelerate product adoption, especially in the early stages of market penetration.

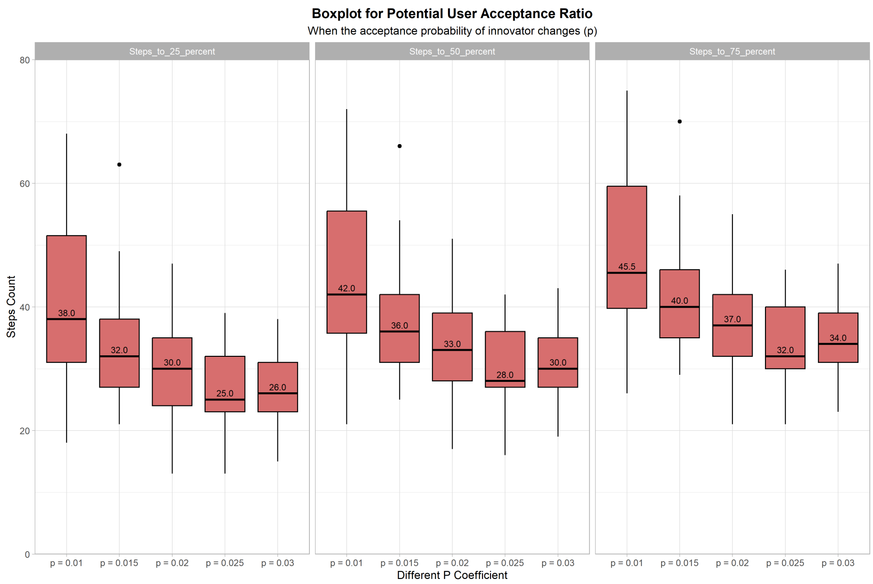

Figure 9: Boxplot of Different Innovator Adoption Probabilities in Random Network [Code]

When comparing the product adoption process in random networks and small-world networks, we can observe an interesting phenomenon: when the innovation coefficient (p) is small, the adoption process in the random network (Figure 9) exhibits greater variability, especially when p = 0.01, the whiskers and outliers of its box plot are wider.

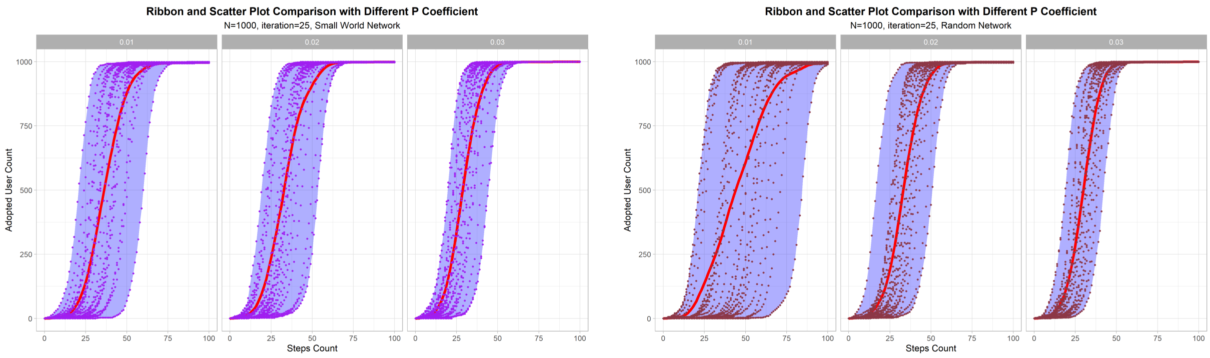

Figure 10: A comparison about Line Plot of Different Innovator Adoption Probabilities [Code]

The left side of the Figure 10 shows what different p look like in a small-world network, and the right side shows what it looks like in a random network. Each data point represents a specific simulation result, the blue shaded area indicates the distribution range of the simulation results, and the red line represents the average number of steps at each p coefficient.

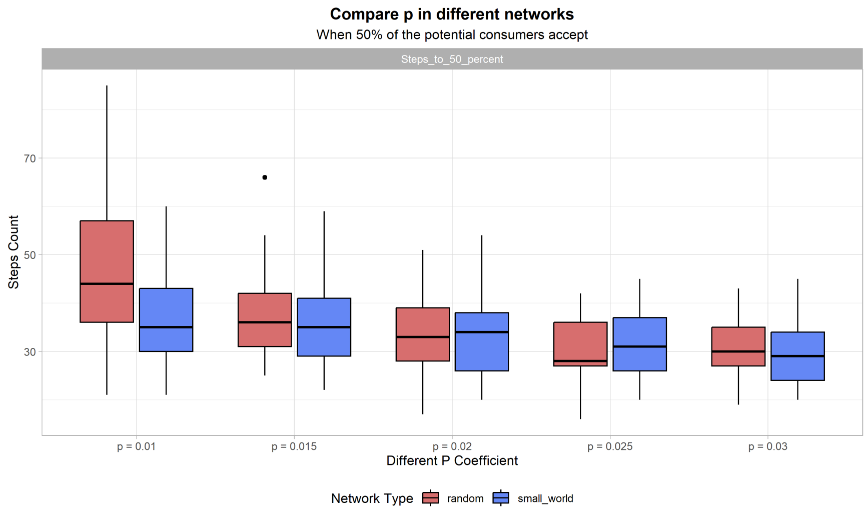

Figure 11: Comparison of different p coefficient in two networks when 50% reaches [Code]

It can be seen that when p coefficient is relatively large (Figure 11), the results of the two networks are more similar. However, when P is relatively small, the coverage interval after random network simulation is larger.

I think this result may be caused by the fact that small-world networks have the characteristics of high clustering coefficient and short average path length, which may lead to rapid local propagation of information and rapid reach to other parts of the network. In contrast, the connections of random networks are more evenly distributed, but lack strong local clustering. At the same time, when the p coefficient is small, product adoption mainly depends on social propagation in the network (imitation effect) rather than independent adoption by individuals. In this case, the characteristics of the network structure become more important.

4.3.2 Research on Imitation Coefficient (q)

Similar to the method of studying the innovation coefficient, in the study of the imitation coefficient q (simulation 2 and 8), other parameters are fixed (p=0.02, proportion of innovators=0.01, proportion of influencers=0.1, N=1000), only the value of q is changed (0.3 to 0.5), and the simulation is repeated many times. This study selects p=0.02 as the baseline innovation coefficient instead of 0.01, which is based on the observation in previous experiments that the two network types showed huge differences at p=0.01 (in Section 4.3.1 when p=0.01 in random network, the box plot shows the results varied more than the small world network). This choice aims to reduce the interference of differences in network structure on the analysis of the impact of imitation coefficients, thereby obtaining a purer q coefficient effect. The following (Figure 12) are the simulation results when 25%, 50%, and 75% of the users are accepted in two different networks:

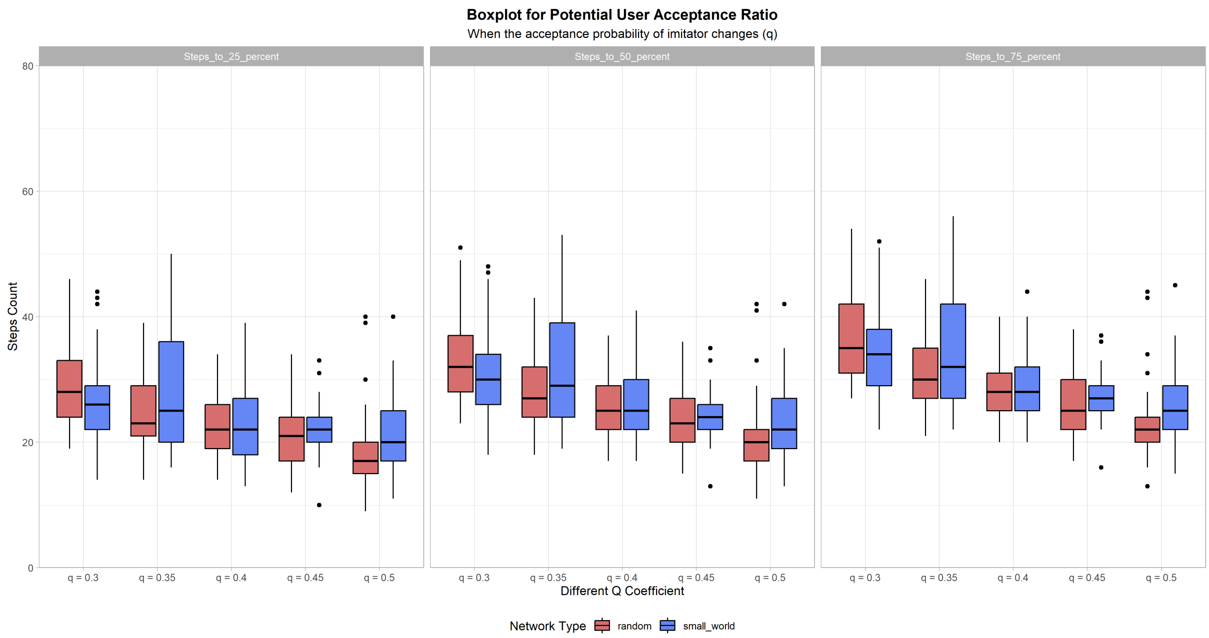

Figure 12: The impact of imitation coefficient on product adoption rate in different network structures

The results show that as the imitation coefficient q increases from 0.3 to 0.5, the speed of product diffusion generally shows an accelerated trend. Especially in random networks, the variability of results is significantly reduced, indicating that the propagation process under high imitation coefficients becomes more stable and predictable in random networks. However, small-world networks do not show the same clear trend of decreasing variability. Although small-world networks still exhibit slightly faster propagation speeds at lower q values, the performance gap between the two network types gradually narrows as q values increase.

It is worth noting that compared with the growth effect of the innovation coefficient p (from 0.01 to 0.02), the growth of the imitation coefficient q has a relatively limited impact on accelerating network diffusion. This finding highlights that in the product adoption process, increasing the imitation coefficient may not be as effective as increasing the innovation coefficient, especially when pursuing significantly accelerated diffusion.

4.4 Research on the proportion of Influential Innovators

This section will focus on the impact of the proportion of influential innovators on the product diffusion process. We will study this issue through two different experimental settings: First, we will study how the change in the proportion of influential innovators affects the product diffusion process when the total influencer proportion is fixed (simulation 3 and 9). Second, we will study how the change in the proportion of influential innovators affects the product diffusion process when the innovator proportion is fixed (simulation 4 and 10).

4.4.1 Fixed proportion of Innovators

The Figure 13 analyzes the impact of changes in the proportion of influential innovators on the product diffusion process when the total proportion of innovators is fixed at 1% (p=0.01, q=0.03, N=1000):

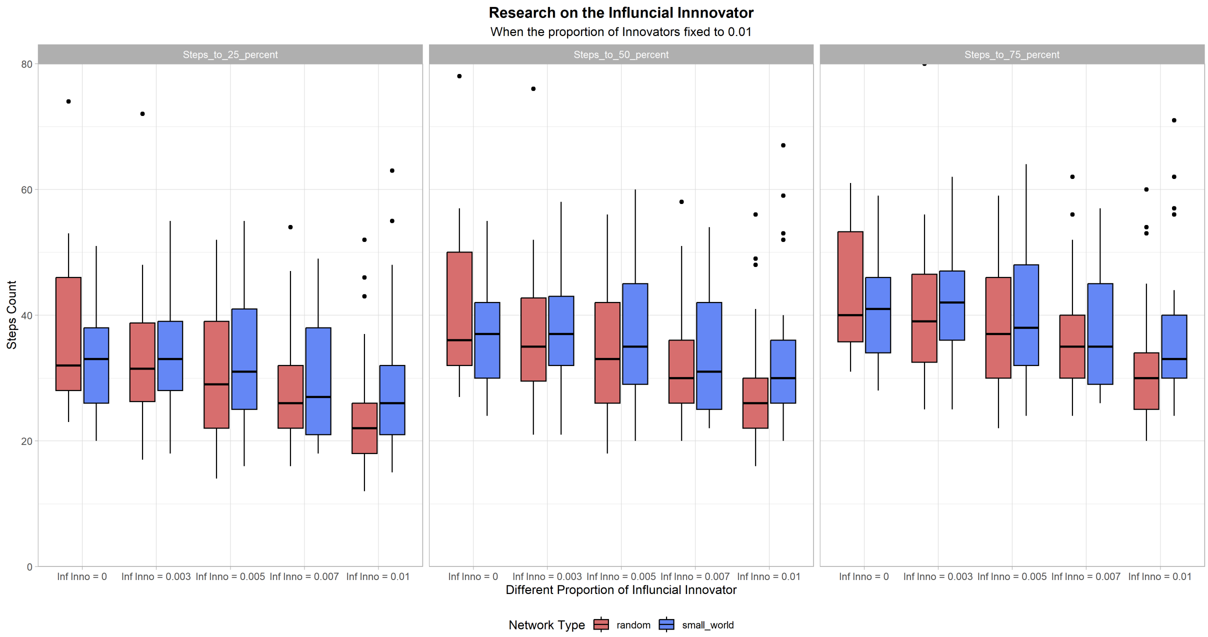

Figure 13: Keep the innovators' proportion changed when the influential proportion is fixed

From the figure, we can analyze that when the total proportion of innovators is fixed, increasing the proportion of influential innovators can only slightly accelerate the product diffusion process. Random networks and small-world networks show similar characteristics at different stages, and the overall propagation speed of random networks is slightly faster than that of small-world networks. This shows that increasing the proportion of influential innovators has limited effect on accelerating product diffusion, especially when the total proportion of innovators is low. At the same time, similar to the simulation results of the lower innovation coefficient p, a low proportion of innovators will cause greater variability in results.

4.4.2 Fixed proportion of Influencers

The Figure 14 shows the effect of changing the proportion of influential innovators on the product diffusion process, while fixing the total proportion of influencers at 10% (p=0.01, q=0.03, N=1000):

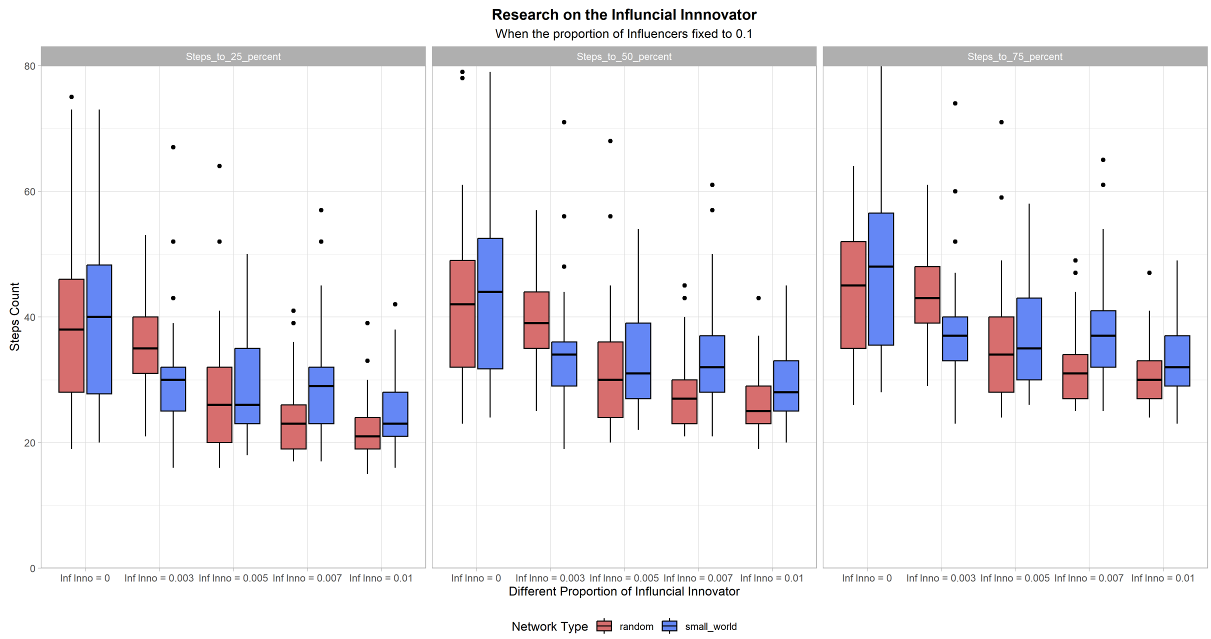

Figure 14: Keep the influential innovators' proportion changed when the innovator proportion is fixed

It can be clearly seen from this figure that compared with the scenario where the proportion of total innovators remains constant, when the proportion of total influencers is fixed, increasing the proportion of influential innovators can significantly accelerate the product diffusion process. At the same time, as the proportion of influential innovators increases (from 0 to 0.003), the variability of the results significantly decreases.

Compared with the previous figure (Figure 13), it can be concluded that the diffusion rate of random networks is slightly higher than that of small-world networks. With the proportion of total influencers fixed, increasing the proportion of influential innovators has a more significant positive impact on product diffusion speed, while significantly reducing the variability of results, making the diffusion process more predictable. In this case, continuously increasing the proportion of influential innovators seems to continuously improve the diffusion effect. In contrast, when the total proportion of innovators is fixed, increasing the proportion of influential innovators has a small impact on the diffusion speed, the reduction in the variability of the results is not obvious, and the improvement effect is more limited. This suggests that overall market structure (especially the overall proportion of influencers) has an important impact on product diffusion dynamics when considering the role of influential innovators.

4.5 Change on the Innovation Coefficient and Innovator proportion

In market diffusion research, we often need to consider the impact of multiple factors on the product adoption process at the same time. In order to intuitively show how the two key variables, the innovation coefficient (p) and the proportion of innovators, jointly affect the product diffusion rate, I designed this set of heat maps (Figure 15). Heat maps can effectively show the interaction between two variables and their impact on the outcome variable. In this study, each cell in the heat map represents the average number of time steps required for the product to reach a specific adoption rate (25%, 50% and 75%) under a specific combination of innovation coefficient and innovator proportion. Each value shown in the figure is the average result of five independent simulations with the same parameter settings.

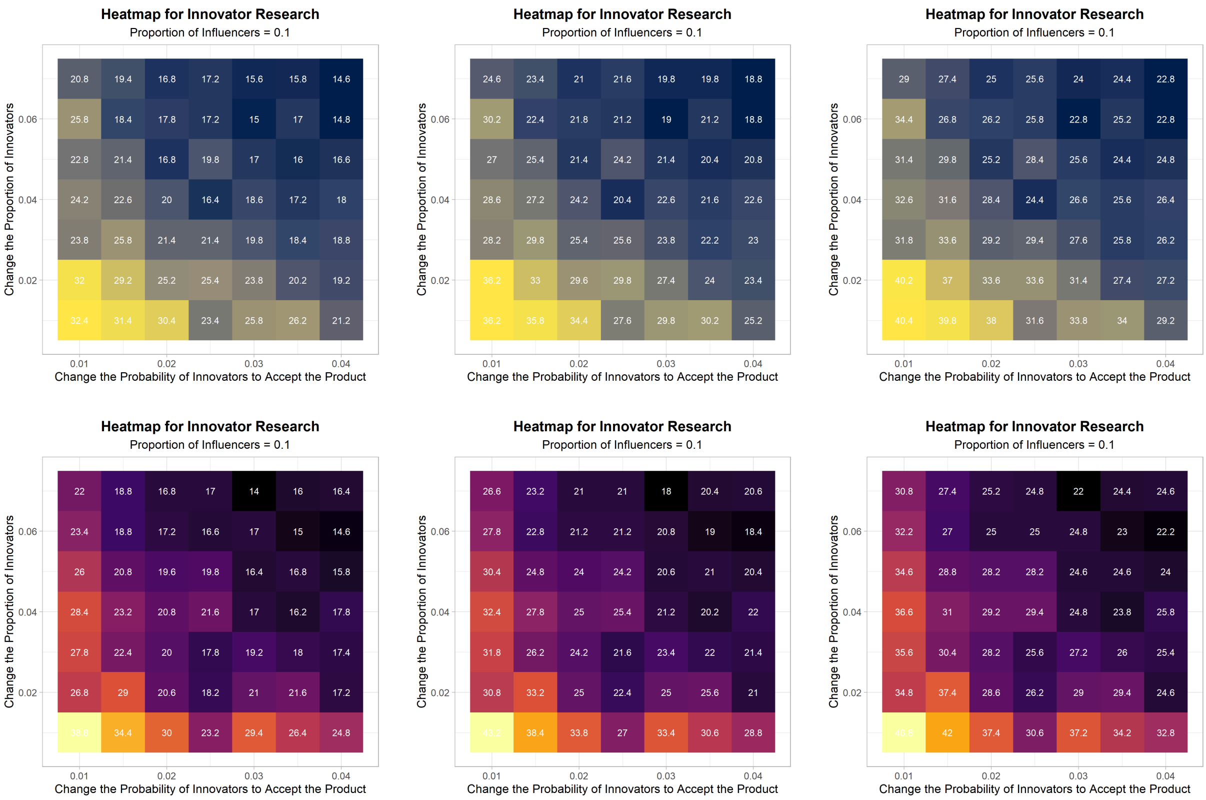

Figure 15: Research on Innovators of Small World Network (up) and Random Network (down)

These heat maps (Figure 15) illustrate how the probability of product acceptance by an innovator and the proportion of innovators jointly affect the rate of product diffusion. The overall trend shows that as these two factors increase, diffusion speeds up (the heat map becomes darker and the values decrease). However, this relationship is nonlinear, the changes are more significant in low-value areas, and there are obvious interactive effects.

The two network structures (possibly small-world and random networks) exhibit similar overall patterns but differ in details, especially in regions of low innovation parameters. It is worth noting that a saturation effect appears in the high-value area, indicating that there is an optimal point beyond which the marginal benefits of continuing to increase innovation input are diminishing.

These findings have important implications for formulating market strategies: when resources are limited, a trade-off needs to be made between increasing the probability of innovator acceptance and increasing the proportion of innovators; in the early stage, more emphasis may be placed on increasing the probability of acceptance; different network structures may require different Optimization strategy.

4.6 Change on Proportion of Influencers and Innovators

In order to gain a deeper understanding of the interaction between these two key factors, a heat map is also used here, as in Section 4.5. The Figure 16 shows how the proportion of innovators and the proportion of influencers jointly affect the speed of product diffusion under a fixed innovation coefficient (p=0.01) and imitation coefficient (q=0.3). Each cell in these heat maps represents the average number of time steps required for a product to reach a specific adoption rate under a specific combination of parameters.

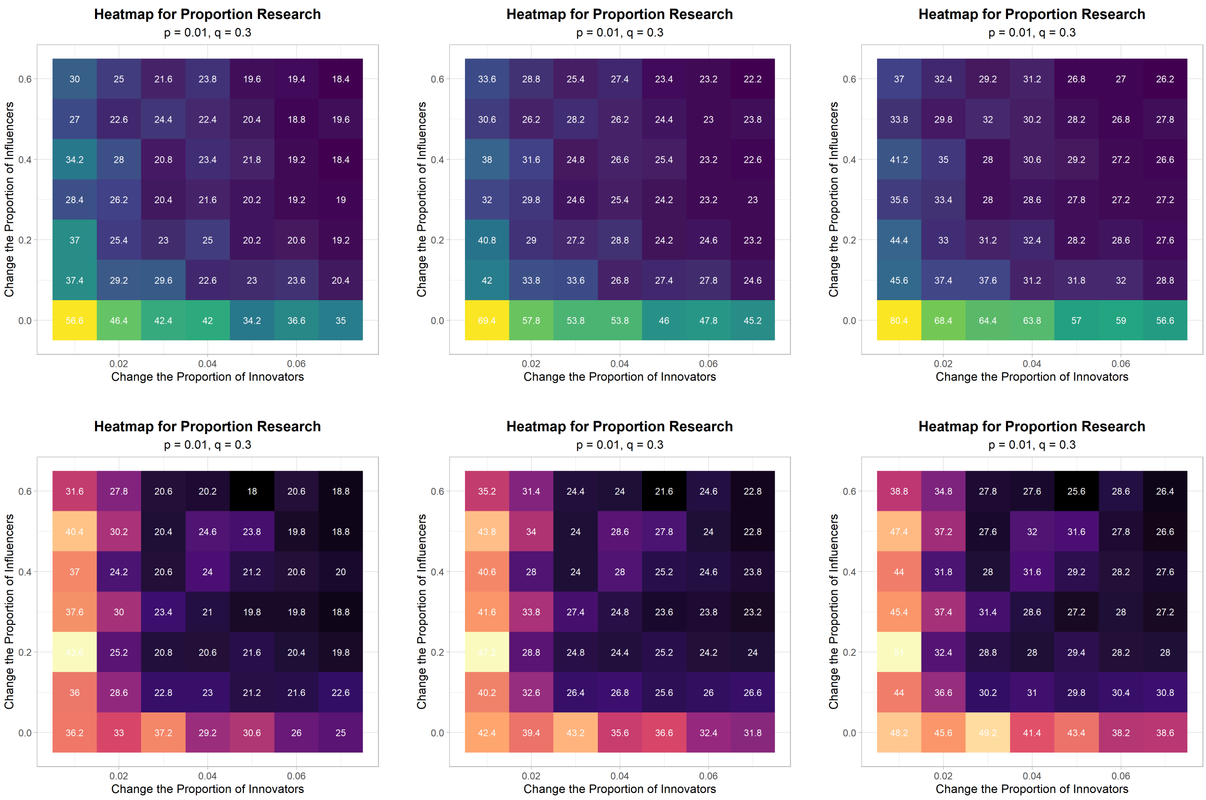

Figure 16: Steps to Reach 25%, 50%, and 75% Adoption Rates with Different Innovator's Proportion and Influencer's Proportion (small world network ↑, random network ↓)

It can be analyzed from the figure that as the proportion of innovators increases from 0.02 to 0.07, and the proportion of influencers increases from 0 to 0.6, we observe an overall acceleration of the diffusion speed, but this effect is not linear. The impact of the innovator ratio is more significant at low values, while the marginal benefit of the influencer ratio shows a decreasing trend. The interactive effect between the two is most obvious in the lower left corner (both ratios are low) and the upper right corner (both ratios are high), which correspond to the slowest and fastest diffusion speeds respectively.

Comparing the heat maps of small-world networks and random networks, we find that although the overall trends are similar, random networks exhibit slower diffusion speeds at low innovator and low influencer ratios, again indicating that network structure has an important impact on innovation diffusion. In addition, color "jumps" in the heat map suggest possible critical points beyond which the marginal benefit of increased diffusion speed decreases.

5 Discussion

5.1 Summary of Findings

5.2 Contributions and Implications

5.3 Limitations and Future Research

6 Conclusion

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Appendix A: Model Code

Appendix B: Words Count

In this document, there are 8826 words all up.