Data Science Research Project

Agent-based Modelling for Market Diffusion Research

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Abstract

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1.1 Introduction

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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):

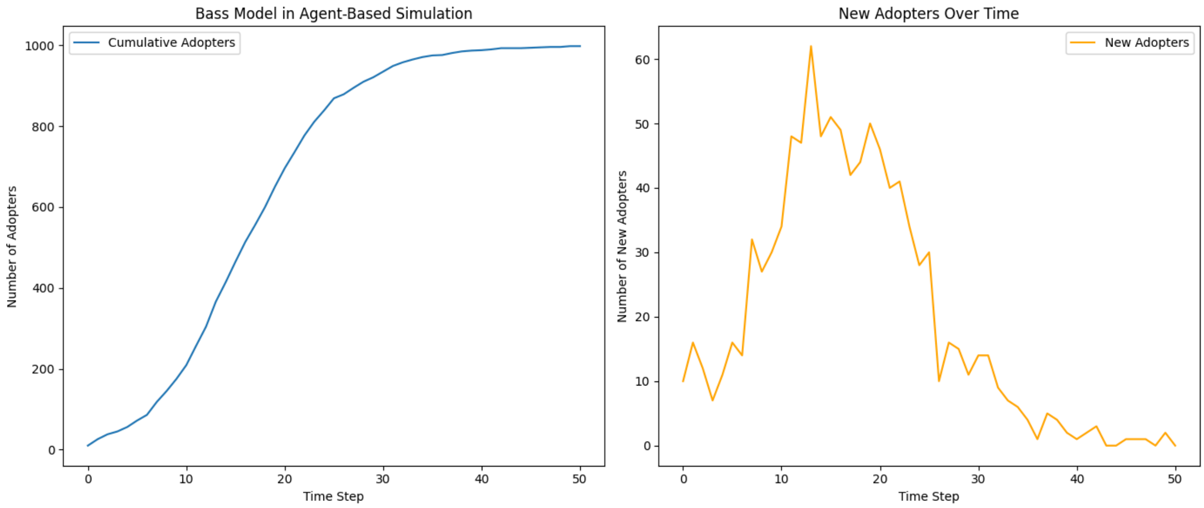

Figure 1: Bass Model Simulation with Python NumPy and Matplotlib [Code]

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.

2.2.4 Theoretical contributions and future development of ABM

ABM's contribution to social science theory lies in its unique modeling and analysis capabilities. It can directly simulate individual behaviors and interactions, generate overall system behaviors, and provide a platform for verifying theoretical hypotheses (Conte & Paolucci, 2014). ABM reveals the multi-level nature of social phenomena, demonstrates the dynamic process from micro-behavior to macro-structure, and provides a new perspective on long-standing problems. By introducing computational models, such as computable trust measures, ABM improves traditional research methods and provides new analytical tools and frameworks for social science theory (Macal & North, 2009).

The cutting-edge and interdisciplinary potential of ABM research is reflected in many aspects. Its application in complex system research is constantly expanding, especially in the study of self-organizing systems. ABM is being integrated with methods such as data mining and machine learning to promote the development of computational social science (Davidsson, 2000). At the theoretical level, ABM promotes in-depth research on rational agents and system strategic structures. In the future, ABM is expected to make important contributions in the formalization of social selection processes and the standardization of intelligent agent systems, promote the deep integration of social sciences with natural sciences and computational sciences, and open up new prospects for complex system research (Macal & North, 2009).

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. Evaluating the impact of market size on product diffusion dynamics: Studying how different sizes of potential user groups affect the final diffusion rate and saturation level of a product.
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, scale-free 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

3.1 Model framework introduction

3.1.1 Model Assumption

3.1.2 Model structure

My ABM model is developed with MESA, 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.

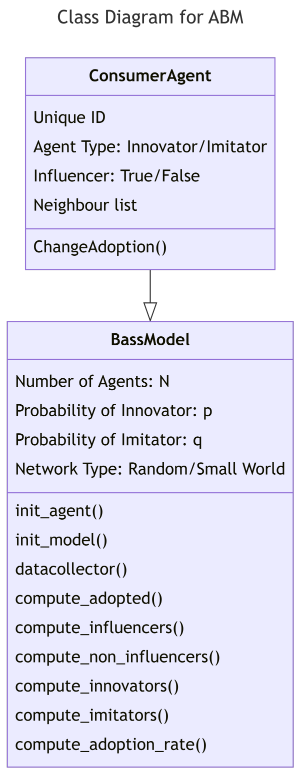

Figure 2: Class Diagram of the ABM Model

3.1.3 Agent Attributes

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.

3.1.4 Social 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 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:

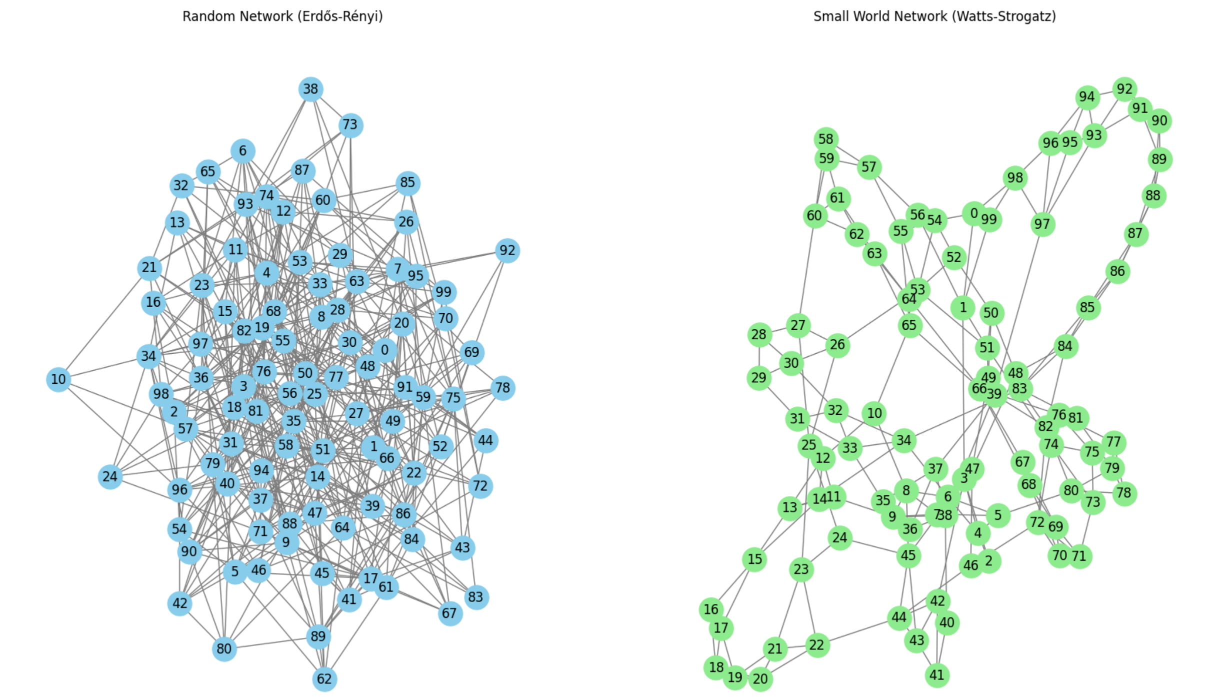

Figure 3: Random and Small-World Network Structures

3.1.5 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):

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

3.1.6 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

Parameter	Description	Impact
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
Network Structure		
network_type	Options: "random", "small_world", "scale_free"	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
m	Number of edges added per new node in scale-free networks (default: 2)	Influences hub formation in scale-free networks
Influence Parameter		
Extra connections	30 to 55 additional connections for influential agents	Simulates the broad influence of opinion leaders

Table 3: Model Parameters for Agent-Based Bass Diffusion Model

3.2 Design of the Simulation Experiment

3.3 Run the ABM Model

3.3.1 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.

```
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
```

Here is the detialed network initialization process of the ABM model:

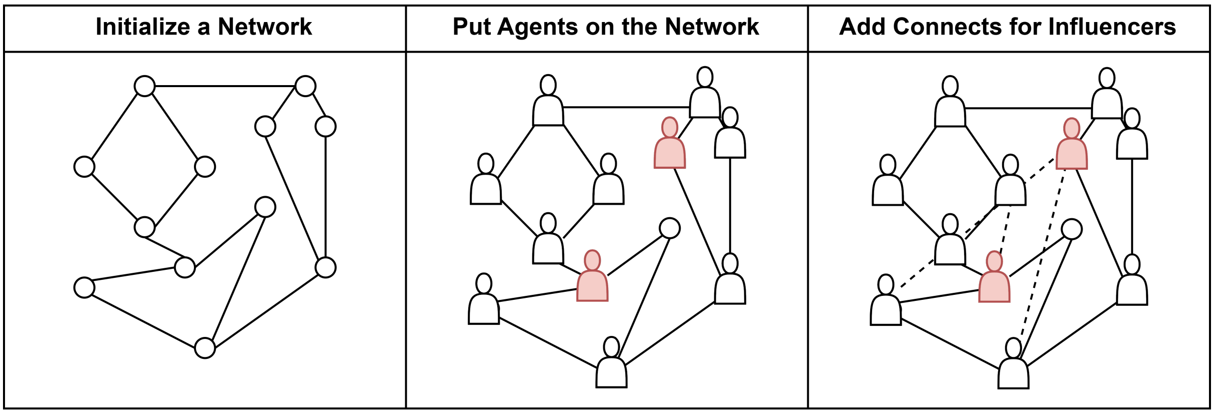

Figure 4: Initialization of the ABM Model Network

3.3.2 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. 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.

Batch Running is the core method of model analysis. Using Mesa's BatchRunner, we are able to systematically explore the impact of different parameter combinations on product diffusion. This method allows us to define parameter ranges (such as innovation coefficient, and imitation coefficient), perform multiple repeated simulations, and automatically collect data. Through batch running, we can conduct sensitivity analysis, understand how different market conditions affect product adoption, identify key parameters and critical points, and predict diffusion trends under various scenarios. This method greatly enhances our understanding and prediction capabilities of the product diffusion process and provides strong empirical support for market strategies.

3.3.3 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 4: Data Collection in the Agent-Based Bass Diffusion Model

4 Simulation and Results Analysis

这个是结果分析部分，测试一下中文看看可不可以。

4.1 Design of the Experiment

Split the experiment into different groups, each with specific parameters changed, and run batch simulations.

4.2 Visualization of Network Evolution

Use the network graph to visually track whether an agent is activated at any time.

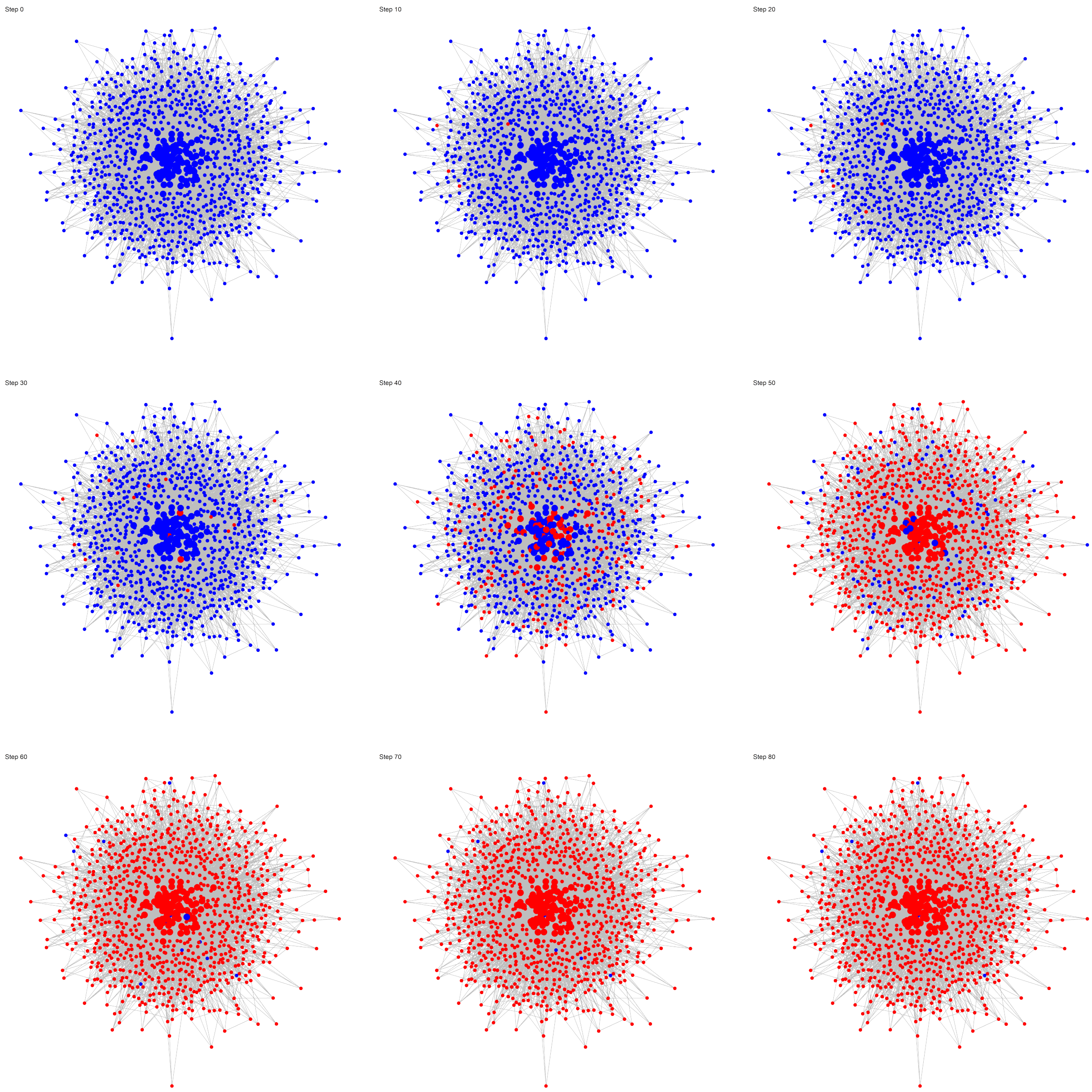

Figure 5: Network Evolution over Time from Step 0 to Step 80

4.3 Table of Neighbors between Influencers and Non-Influencers

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 four to six times that of a flying influencer.

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 5: Run Data for Agent-Based Model

4.4 Research on Different Probability of Innovators Adoption

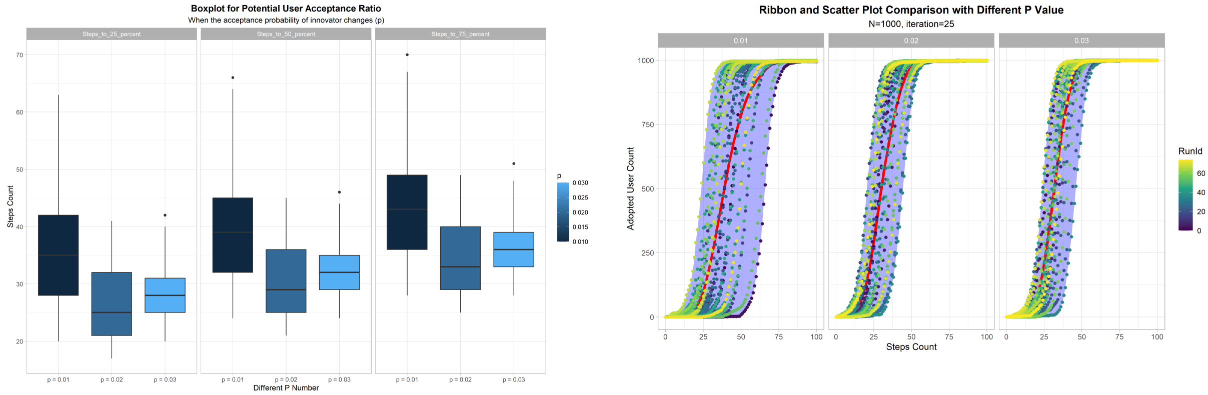

Figure 6: Boxplot and Line Plot of Different Innovator Adoption Probabilities

4.5 Research on Different Probability of Imitators Adoption

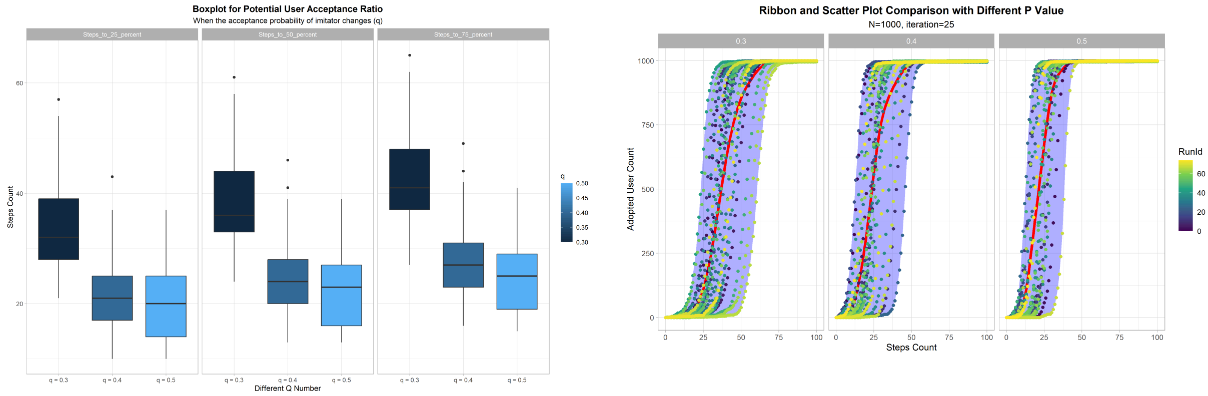

Figure 7: Boxplot and Line Plot of Different Imitator Adoption Probabilities

4.6 Research on the Impact of Fixed Influencial proportion

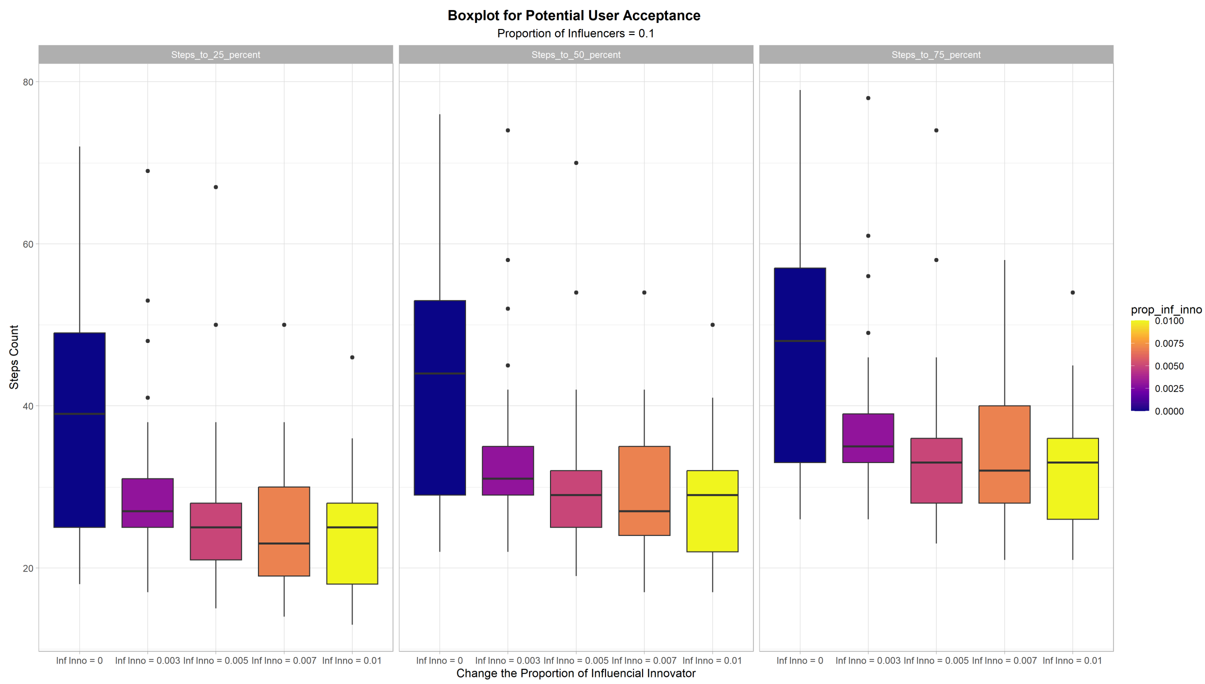

Figure 8: Keep the influential innovators' proportion changed when the innovator proportion is fixed

4.7 Research on the Impact of Fixed Innovator's proportion

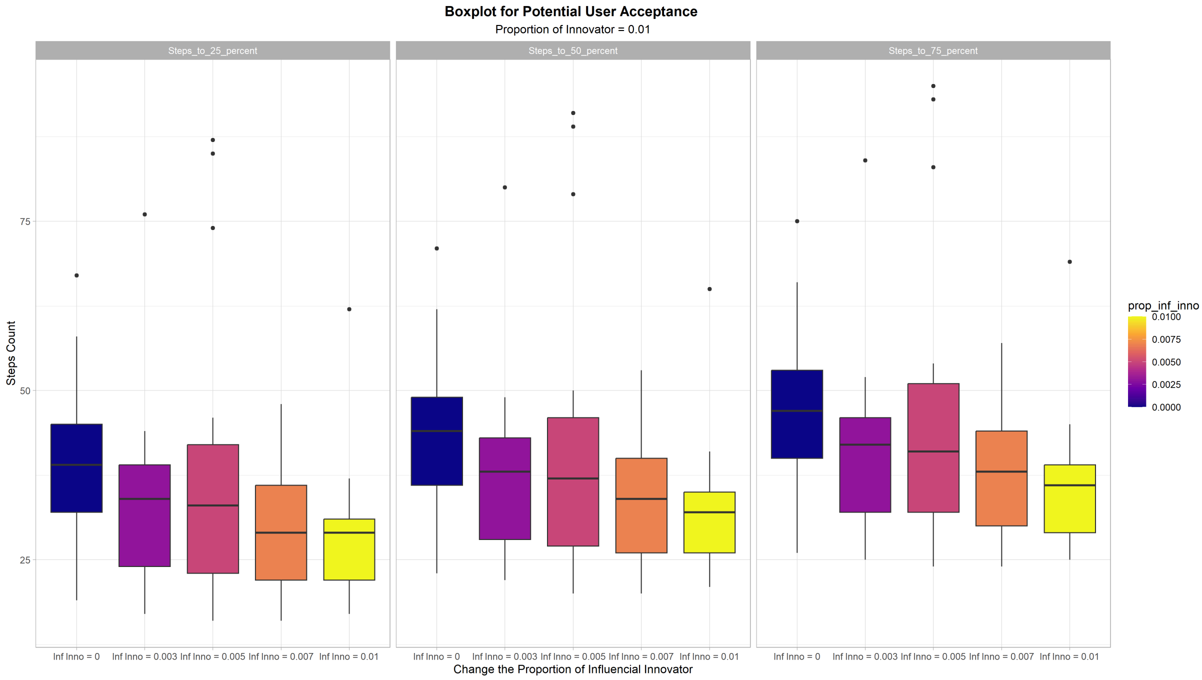

Figure 9: Keep the influential innovators' proportion changed when the influential proportion is fixed

4.8 Change on the Innovators and Innovator proportion

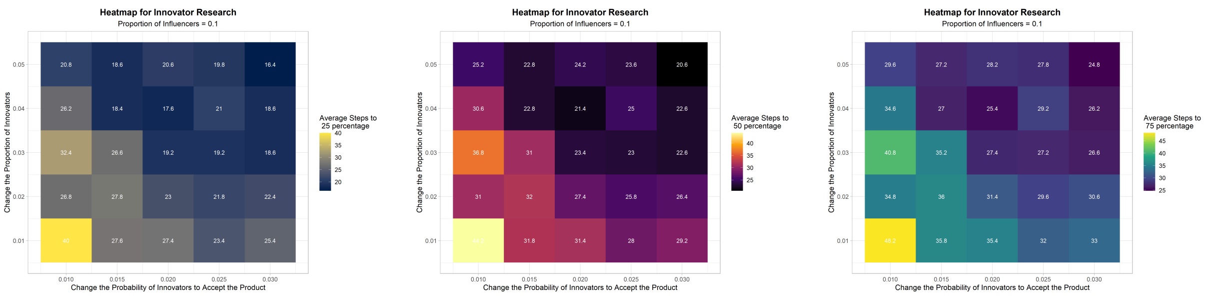

Figure 10: Steps to Reach 25%, 50%, and 75% Adoption Rates with Different Innovator's P and Innovator's Proportion

4.9 Change on Proportion of Influencers and Innovators

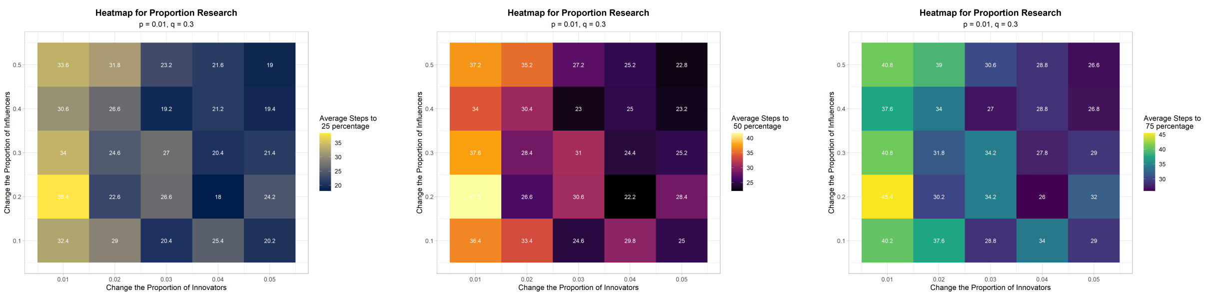

Figure 11: Steps to Reach 25%, 50%, and 75% Adoption Rates with Different Innovator's Proportion and Influencer's Proportion

5 Conclusion

5.1 Summary of Findings

5.2 Contributions and Implications

5.3 Limitations and Future Research

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Appendix A: Model Code