# Social Alchemy: The Role of Homophily and Peer Influence in Shaping Agent-Based Social Networks

Feng-Chun (Ben) Chou
ID: F11227106

June 2024

## Introduction

Friendship is crucial for individual well-being and growth. Social ties with friends offer emotional support, boost mental health, and aid personal development. Many studies show strong social connections lead to better health, more happiness, and greater life satisfaction (Umberson & Montez, 2010; Holt-Lunstad, Smith, & Layton, 2010). A key phenomenon in friendships is homophily, where people bond with those who are similar in behavior, neural responses, personality, and other traits (McPherson, Smith-Lovin, & Cook, 2001; Centola, 2021). This similarity isn't random but is driven by underlying mechanisms shaping social networks.

Homophily mechanisms can be divided into selection and influence. Selection means people choose friends who are already similar, leading to natural homophily in social networks. For example, people often pick friends with shared interests, values, and backgrounds, reinforcing similarities (Wimmer & Lewis, 2010; Rivera, Soderstrom, & Uzzi, 2010; Meltzer et al., 2022). Influence means friends become more alike over time due to mutual influence, with behaviors and attitudes converging through interactions (Aral, Muchnik, & Sundararajan, 2009; Centola & Macy, 2007; Shalizi & Thomas, 2011). Studies show individuals may adopt similar health behaviors, political views, and social practices as their friends through ongoing interactions (Christakis & Fowler, 2007; Centola, 2020; Bakshy, Messing, & Adamic, 2015). In real social networks, these processes are intertwined, making it hard to separate their effects on homophily (Shalizi & Thomas, 2011; Kandel, 2014; Ma et al., 2021).

While separating selection and influence in real-world studies is tough, computational methods like agent-based modeling (ABM) allow for independent investigation. ABM lets researchers create simulated environments where agents, representing individuals, interact based on set rules. By adjusting parameters for selection and influence, researchers can see how each mechanism affects the formation and evolution of social networks (Smaldino, 2020; Gilbert, 2020; Zhang et al., 2022). This method provides a controlled setting to study how different levels of homophily arise from agent interactions and how these interactions shape the network's structure.

This study aims to use ABM to examine the separate and combined effects of selection and influence mechanisms on the formation of friendship networks. By tracking the evolution of local and global clustering coefficients over time, we can understand how these mechanisms shape the structure and dynamics of social networks. Local clustering coefficients indicate the degree to which nodes in a network cluster together, while global clustering coefficients reflect the network's overall tendency to form tightly-knit groups (Watts & Strogatz, 1998; Newman, 2003; Broido & Clauset, 2019). Analyzing these metrics allows us to assess how different homophily mechanisms impact the network's cohesion and connectivity over time.

This study will particularly focus on personality as a crucial factor in homophily, aiming to explore how behavioral tendencies affect different mechanisms. This approach distinguishes our research from previous studies, offering a fresh perspective on how personality influences the development and evolution of friendship networks under various conditions of selection and influence.

# Method

## Structure of Agent-Based Modeling

### Model Overview

The agent-based model (ABM) is designed to simulate social dynamics influenced by personality traits and peer interactions. The model comprises agents situated on a grid, each possessing distinct personality traits. These traits affect both their movement and their propensity to form friendships.

### Agents

Each agent $i$ is characterized by a set of personality traits based on the Big Five personality model: openness, conscientiousness, extraversion, agreeableness, and neuroticism. These traits are represented as continuous variables between 0 and 1 (number of agents = 100):

$$\text{Personality}_i = \{\text{openness}_i, \text{conscientiousness}_i, \text{extraversion}_i, \text{agreeableness}_i, \text{neuroticism}_i\}$$

In addition to personality traits, agents have a position on the grid $(x_i, y_i)$ and a set of friends. Agents also have a movement speed, which is influenced by their personality traits and social interactions.

### Initialization

At the beginning of the simulation, agents are initialized with the following properties:

1. **Personality Traits**: Each agent's personality traits are drawn from a multivariate normal distribution with means set to 0.5 and a specified covariance matrix that reflects realistic correlations between the Big Five traits:

$$\begin{pmatrix} \text{openness}_i \\ \text{conscientiousness}_i \\ \text{extraversion}_i \\ \text{agreeableness}_i \\ \text{neuroticism}_i \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \\ 0.5 \end{pmatrix}, \Sigma\right)$$

   where $\Sigma$ is the covariance matrix representing the correlations between personality traits:

$$\Sigma = \begin{pmatrix} 1.0 & 0.3 & 0.4 & 0.2 & -0.1 \\ 0.3 & 1.0 & 0.5 & 0.4 & -0.2 \\ 0.4 & 0.5 & 1.0 & 0.6 & -0.3 \\ 0.2 & 0.4 & 0.6 & 1.0 & -0.4 \\ -0.1 & -0.2 & -0.3 & -0.4 & 1.0 \end{pmatrix}$$

2. **Positions**: Agents are randomly placed on the grid, with coordinates $(x_i, y_i)$ drawn uniformly from the grid dimensions:

$$(x_i, y_i) \sim \mathcal{U}(0, N-1)$$

3. **Initial Speed**: The initial speed of each agent is set to zero:

$$v_i(0) = 0$$

### Grid

The agents are placed on a toroidal grid of size $N \times N$. This means the grid wraps around at the edges, allowing continuous movement without boundaries. Agents move and interact within this grid.

### Friendship Formation

Friendship formation is influenced by both personality similarity and physical proximity. The probability $P_{ij}$ that agent $i$ forms a friendship with agent $j$ is a function of both the personality similarity and the physical distance between them:

$$P_{ij} = \frac{\phi}{d_{ij}^2} + \frac{\sigma_\phi}{\left\|\text{Personality}_i - \text{Personality}_j\right\|^2}$$

where:

- $\phi$ is a parameter controlling the likelihood of forming friendships based on physical distance.
- $d_{ij}$ is the Euclidean distance between agent $i$ and agent $j$ on the grid.
- $\sigma_\phi$ is a parameter controlling the likelihood of forming friendships based on personality similarity.

The more similar the personalities and the closer the physical distance, the higher the probability of friendship formation.

### Peer Influence on Personality

Once agents become friends, their personalities influence each other. The change in an agent's personality trait is modeled as a function of the average personality of its friends, weighted by a parameter $\gamma$:

$$\text{Personality}_{i,t+1} = \text{Personality}_{i,t} + \gamma \cdot \left( \frac{1}{|\text{Friends}_i|} \sum_{j \in \text{Friends}_i} \text{Personality}_j - \text{Personality}_{i,t} \right)$$

This equation signifies that an agent's personality is drawn towards the average personality of its friends, moderated by the parameter $\gamma$, which controls the strength of peer influence.

### Movement and Speed

Agents move continuously across the grid, with their direction and speed influenced by their own personality traits and the positions of their friends. The speed $v_i$ of an agent is initially set to zero but can increase up to a maximum value, influenced by the agent's extraversion and other factors:

$$v_i(t+1) = \min(v_{\max}, v_i(t) + \alpha \cdot f(\text{Personality}_i, \text{Friends}_i))$$

where $\alpha$ is a parameter controlling the acceleration based on social forces and personal traits. The function $f(\text{Personality}_i, \text{Friends}_i)$ accounts for the attraction to the positions of the agent's friends, which is proportional to the agent's extraversion:

$$f(\text{Personality}_i, \text{Friends}_i) = \sum_{j \in \text{Friends}_i} \frac{\text{extraversion}_i \cdot \text{extraversion}_j}{d_{ij}^2} \cdot (\mathbf{p}_j - \mathbf{p}_i)$$

where $d_{ij}$ is the Euclidean distance between agent $i$ and agent $j$, and $\mathbf{p}_j$ is the position vector of agent $j$.

### Random Perturbations

Agents' movements are also subject to random perturbations, which are proportional to their neuroticism. This introduces variability in movement and interaction patterns, reflecting real-world unpredictability:

$$a_i(t+1) = a_i(t) + \beta \cdot \eta \cdot \text{neuroticism}_i$$

where $a_i$ is the agent's acceleration, $\beta$ is a scaling parameter, and $\eta$ is a random variable drawn from a normal distribution.

**Updating Rules**

1. **Movement Update**: Each agent updates its position based on its current velocity, acceleration, and the influence of friends' positions:

$$\mathbf{p}_i(t+1) = \mathbf{p}_i(t) + v_i(t+1) \cdot \mathbf{d}_i(t)$$

where $\mathbf{d}_i(t)$ is the direction of movement, influenced by the position of friends and random perturbations.

2. **Velocity Update**: The agent's velocity is updated based on its acceleration and random perturbations:

$$v_i(t+1) = \min(v_{\max}, v_i(t) + \alpha \cdot f(\text{Personality}_i, \text{Friends}_i) + \beta \cdot \eta \cdot \text{neuroticism}_i)$$

3. **Friendship Formation Update**: At each time step, the probability of forming new friendships is evaluated for each pair of agents based on their personality similarity, physical distance, and the parameter $\phi$.

4. **Personality Update**: Agents update their personality traits based on the average traits of their friends and the parameter $\gamma$:

$$\text{Personality}_{i,t+1} = \text{Personality}_{i,t} + \gamma \cdot \left( \frac{1}{|\text{Friends}_i|} \sum_{j \in \text{Friends}_i} \text{Personality}_j - \text{Personality}_{i,t} \right)$$

**Parameter Table**

| Parameter | Description | Range |
|---|---|---|
| $N$ | The size of the grid (i.e., the number of agents and the dimensions of the grid). | 100 |
| $\text{Personality}_i$ | The set of personality traits for agent $i$, including openness, conscientiousness, extraversion, agreeableness, and neuroticism. | $[0, 1]$ |
| $\Sigma$ | The covariance matrix representing the correlations between the Big Five personality traits. | Fixed (see matrix below) |
| $(x_i, y_i)$ | The position of agent $i$ on the grid. | $[0, N-1] \times [0, N-1]$ |
| $v_i(t)$ | The speed of agent $i$ at time $t$. | $[0, v_{\max}]$ |
| $v_{\max}$ | The maximum speed of the agents. | 3 |
| $\phi$ | A parameter controlling the likelihood of forming friendships based on personality similarity and physical distance. | $[0.00001, 0.1]$ |
| $\sigma_\phi$ (sphi) | A parameter controlling the standard deviation for personality similarity in friendship formation. | $[1.00e-05, 1.00e+00]$ |
| $\gamma$ | A parameter controlling the strength of peer influence on personality traits. | $[1.00e-05, 1.00e+00]$ |
| $d_{ij}$ | The Euclidean distance between agent $i$ and agent $j$ on the grid. | $[0, \sqrt{2}N]$ |
| $\alpha$ | A parameter controlling the acceleration based on social forces and personal traits. | $[0, 1]$ |
| $f(\text{Personality}_i, \text{Friends}_i)$ | A function accounting for the attraction to the positions of the agent's friends, proportional to the agent's extraversion. | N/A |

| | | |
|---|---|---|
| $a_i(t)$ | The acceleration of agent $i$ at time $t$. | $[-\beta, \beta]$ |
| $\beta$ | A scaling parameter for the random perturbations. | $[0, 1]$ |
| $\eta$ | A random variable drawn from a normal distribution, representing random perturbations. | $\mathcal{N}(0, 1)$ |
| $P_{ij}$ | The probability that agent $i$ forms a friendship with agent $j$. | $[0, 1]$ |

### Summary

The ABM integrates personality traits, homophily, peer influence, and random perturbations to simulate dynamic social networks. The parameters $\phi$, $\gamma$, and $\sigma_\phi$ allow for detailed exploration of how these factors influence social dynamics and personality evolution.

## Simulation Procedure

The simulation process involves running multiple agent-based simulations using the parameters and models described previously. The steps for running the simulations, analyzing the clustering coefficient over time, and examining the relationship between personality and friendship numbers are outlined as follows:

### Running Simulations

The simulations are run using a Python script, `run_model.py`, which implements the agent-based model. The key steps in the simulation process are:

1. **Initialization**: The agents are initialized with random positions on the grid and personality traits drawn from a multivariate normal distribution.
2. **Time Steps**: The simulation runs for a specified number of time steps. At each time step:
   - Agents move based on their current velocity and the social forces exerted by their friends.
   - Agents' velocities are updated based on their acceleration, which is influenced by their personality traits and the positions of their friends.
   - New friendships are formed based on the probability $P_{ij}$, which depends on personality similarity and physical distance.
   - Agents' personalities are updated based on the average personality of their friends, weighted by the parameter $\gamma$.
3. **Recording Data**: At each time step, the local and global clustering coefficients are calculated and recorded. At the end of the simulation, the number of friends for each agent and their personality traits are recorded for further analysis.

### Clustering Coefficient Over Time

The local and global clustering coefficients are calculated at each time step to observe how the agents' social networks evolve. The clustering coefficients are defined as follows:

- **Local Clustering Coefficient**: The average clustering coefficient of all nodes in the network, where the clustering coefficient of a node is the ratio of the number of existing links between its neighbors to the number of possible links between them.
- **Global Clustering Coefficient**: The overall ratio of closed triplets to all triplets (both closed and open) in the network.

The clustering coefficients are plotted against time steps to visualize the evolution of the social network. This helps in understanding the dynamics of the network formation and the influence of personality traits on social structure.

**Analysis of Personality and Friendship Numbers**

After the simulation ends, the relationship between agents' personality traits and their number of friends is analyzed. The steps involved are:

1. **Data Collection**: The number of friends and personality traits of each agent are collected.
2. **Correlation Analysis**: The correlation between each personality trait and the number of friends is calculated using Spearman's rank correlation coefficient.
3. **Visualization**: Scatter plots with regression lines are created for each personality trait against the number of friends to visualize the relationship.

**Simulation Scenarios**

To understand the effects of different parameters on the model, the simulations are run under three different scenarios:

1. **Basic Model**: The simulation is run with $\sigma_\phi = 0$ and $\gamma = 0$ to observe the baseline behavior without peer influence on personality traits.
2. **Peer Influence on Personality**: The simulation is run with $\sigma_\phi > 0$ and $\gamma = 0$ to examine the effect of the spatial influence on personality similarity.
3. **Combined Influence**: The simulation is run with $\sigma_\phi > 0$ and $\gamma > 0$ to observe the combined effects of spatial influence and peer influence on personality traits.

Each scenario is simulated multiple times to ensure the robustness of the results and to capture the variability in the outcomes. The results are then analyzed to understand the impact of different parameters on the formation and evolution of social networks.

**Grid Search for Parameter Tuning**

A grid search was conducted to explore the effects of different parameters on the clustering coefficients of the network. The parameters and their ranges are listed in Table 2.

| **Parameter** | **Values** |
|---|---|
| $\phi$ (phi) | [0.00001, 0.0001, 0.001, 0.01, 0.1] |
| $\sigma_\phi$ (sphi) | [1.00e-05, 2.78e-05, 7.74e-05, 2.15e-04, 5.99e-04, 1.67e-03, 4.64e-03, 1.29e-02, 3.59e-02, 1.00e+00] |
| $\gamma$ (gamma) | [1.00e-05, 2.78e-05, 7.74e-05, 2.15e-04, 5.99e-04, 1.67e-03, 4.64e-03, 1.29e-02, 3.59e-02, 1.00e+00] |

Table 2: Grid search parameter ranges.

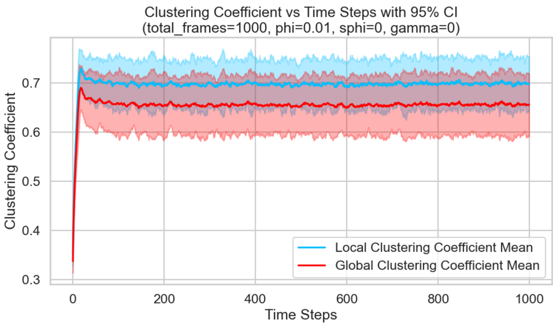
The simulations were run for a fixed number of time steps (i.e., 3000), and the local and global clustering coefficients were recorded. The results were aggregated and visualized using heatmaps to identify the optimal parameter settings for achieving desired network properties.

# Results

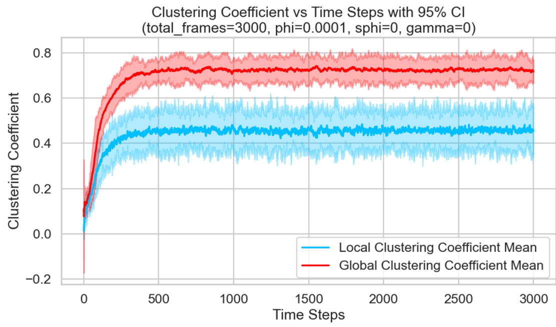
This section presents the key findings from the simulations, including the evolution of the clustering coefficient over time and the relationship between personality traits and friendship numbers. Due to the large number of different parameter settings explored, only a subset of representative results is shown here. For a complete set of results, please refer to the link provided: `https://github.com/Ben-FCC/IntroComplexSystems/tree/Coenvolving_Network_MonteCarol/FinalProject/simulation_results`.

## Clustering Coefficient Over Time

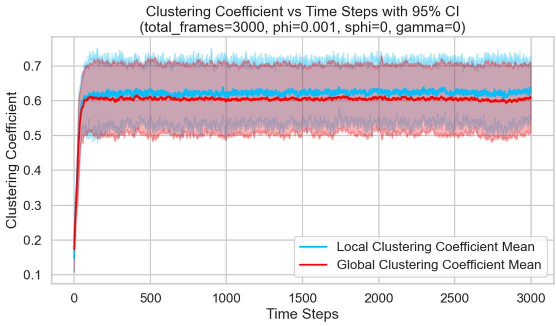
The evolution of the local and global clustering coefficients over time is shown in Figures 1 to 4. The results indicate how the social network structure changes as the simulation progresses under different parameter settings.




(a) $\phi = 0.01, \sigma_\phi = 0, \gamma = 0$

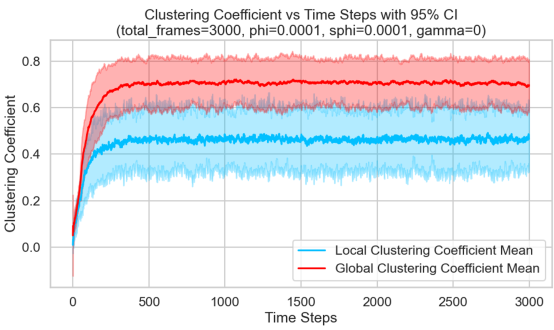



(b) $\phi = 0.0001, \sigma_\phi = 0, \gamma = 0$

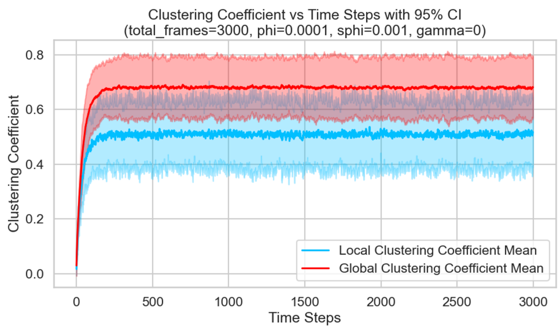



(c) $\phi = 0.001, \sigma_\phi = 0, \gamma = 0$

Figure 1: Clustering coefficient vs. time steps with 95% CI for varying $\phi$ values.

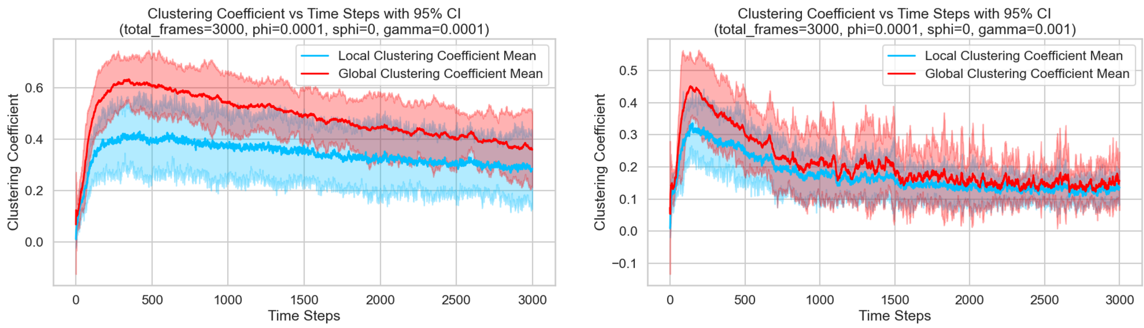



(a) $\sigma_\phi = 0.0001, \phi = 0, \gamma = 0$




(b) $\sigma_\phi = 0.001, \phi = 0, \gamma = 0$

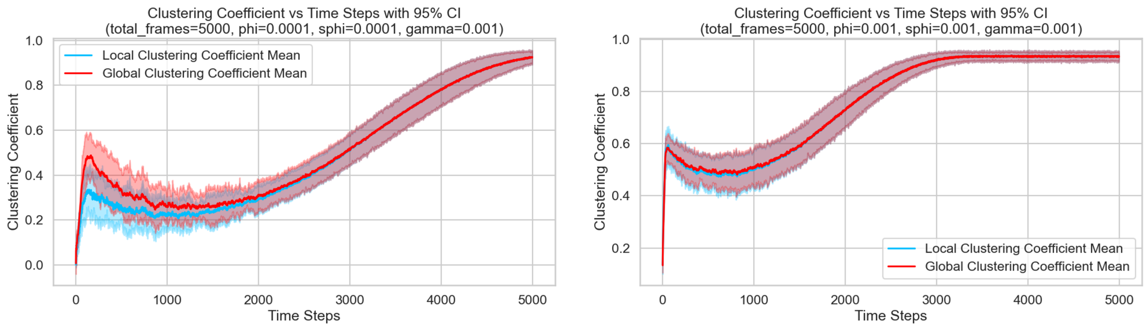
Figure 2: Clustering coefficient vs. time steps with 95% CI for varying $\sigma_\phi$ values.




(a) $\gamma = 0.0001, \phi = 0, \sigma_\phi = 0$

(b) $\gamma = 0.001, \phi = 0, \sigma_\phi = 0$

Figure 3: Clustering coefficient vs. time steps with 95% CI for varying $\gamma$ values.



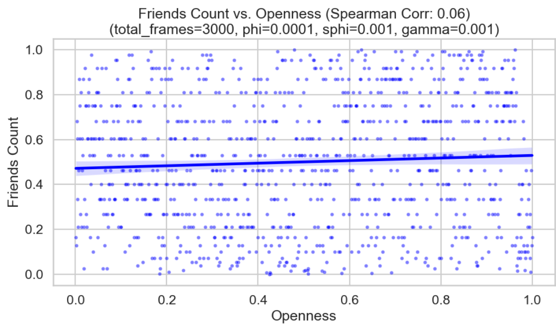

(a) $total\_frames = 5000, \phi = 0.001, \sigma_\phi = 0.001, \gamma = 0.001(left); \phi = 0.0001, \sigma_\phi = 0.0001, \gamma = 0.001(right)$

(b) $total\_frames = 3000, \phi = 0.0001, \sigma_\phi = 0, \gamma = 0.001(left); \phi = 0.0001, \sigma_\phi = 0, \gamma = 0.0001(right)$

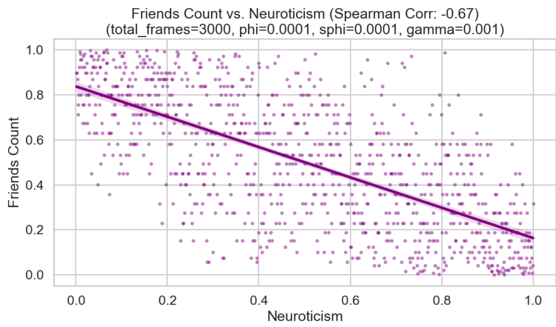
Figure 4: Clustering coefficient vs. time steps with 95% CI for combined parameter settings.

## Relationship between Personality and Friendship Numbers

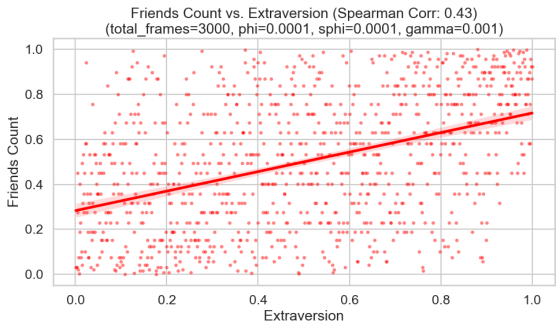
The relationship between different personality traits and the number of friends is analyzed using Spearman's rank correlation coefficient. Figures 5 show scatter plots with regression lines for each personality trait.



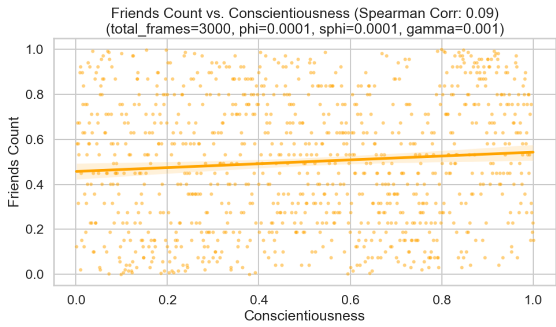

(a) Openness (Spearman Corr: 0.06)



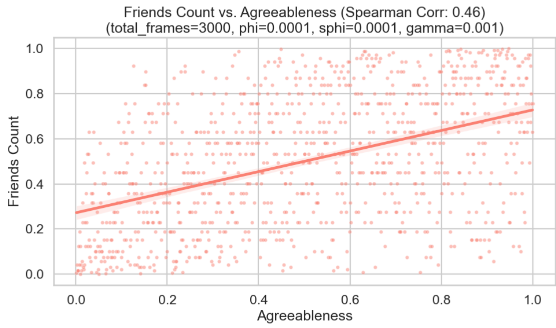

(b) Neuroticism (Spearman Corr: -0.67)




(c) Extraversion (Spearman Corr: 0.43)




(d) Conscientiousness (Spearman Corr: 0.09)



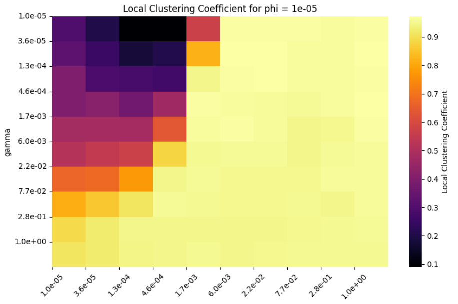

(e) Agreeableness (Spearman Corr: 0.46)

Figure 5: Friends count vs. Personality traits with 95% CI. Parameters: $total\_frames = 3000, \phi = 0.0001, \sigma_\phi = 0.0001, \gamma = 0.001$.

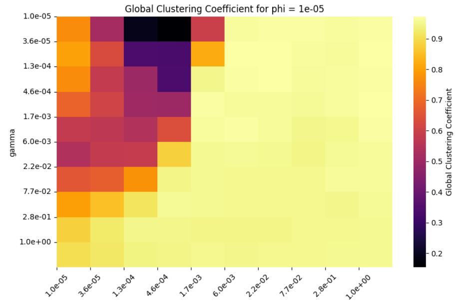
Each figure illustrates the relationship between a specific personality trait and the number of friends, highlighting the influence of personality on social connectivity within the simulated networks.

## Heatmaps of Clustering Coefficients

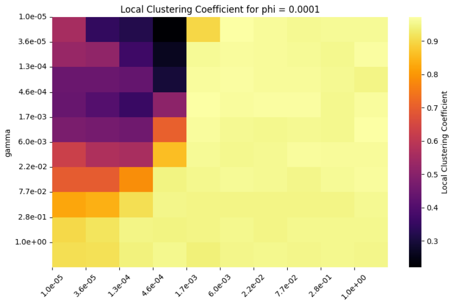
Figure 6 presents the heatmaps for local and global clustering coefficients as a function of $\sigma_\phi$ and $\gamma$ for different values of $\phi$. These heatmaps illustrate how the clustering coefficients vary across the parameter space.



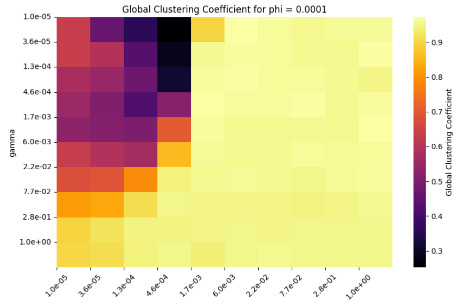

(a) Local Clustering Coefficient for $\phi = 1e-05$



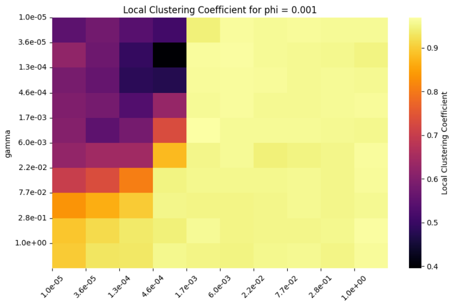

(b) Global Clustering Coefficient for $\phi = 1e-05$



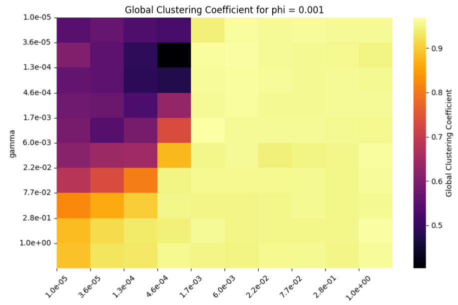

(c) Local Clustering Coefficient for $\phi = 0.0001$



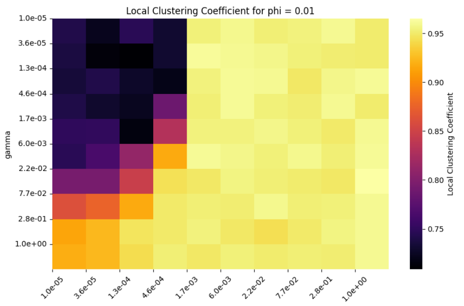

(d) Global Clustering Coefficient for $\phi = 0.0001$



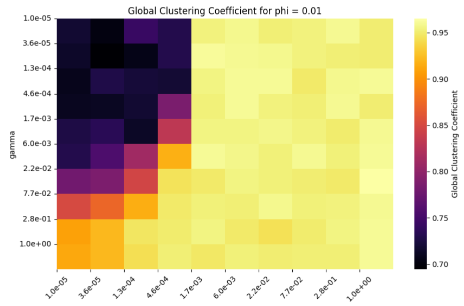

(e) Local Clustering Coefficient for $\phi = 0.001$



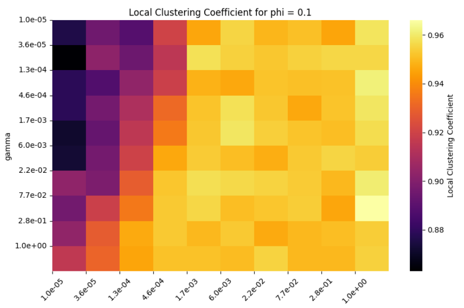

(f) Global Clustering Coefficient for $\phi = 0.001$



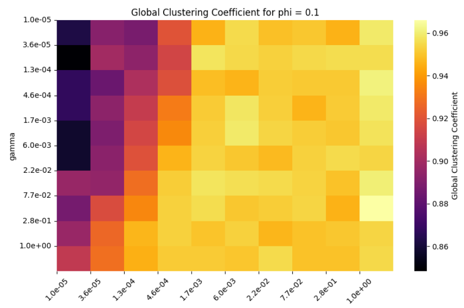

(g) Local Clustering Coefficient for $\phi = 0.01$




(h) Global Clustering Coefficient for $\phi = 0.01$




(i) Local Clustering Coefficient for $\phi = 0.1$




(j) Global Clustering Coefficient for $\phi = 0.1$

Figure 6: Heatmaps of local and global clustering coefficients for different values of $\phi$, $\sigma_\phi$, and $\gamma$.

# Discussion

This study utilized agent-based modeling (ABM) to investigate the roles of homophily and peer influence in the formation and evolution of social networks. By simulating social interactions among agents characterized by personality traits, we examined how these mechanisms individually and collectively shape the structure and dynamics of friendship networks.

## Summary of Findings

Our findings indicate that both selection and influence mechanisms significantly impact the network's clustering and overall connectivity. Consistent with previous research, homophily based on personality traits leads to the formation of tightly-knit clusters (Wimmer & Lewis, 2010; Meltzer et al., 2022). Moreover, the influence mechanism, wherein individuals become more similar to their friends over time, further enhances these clusters (Centola, 2021; Zhang et al., 2022).

## Comparison with Previous Research

Our results align with existing studies that highlight the intertwined nature of selection and influence in social networks (Aral, Muchnik, & Sundararajan, 2009; Centola, 2021). Similar to these studies, our simulations revealed that both mechanisms are closely linked, making it challenging to distinguish their individual effects in observational studies. However, by employing ABM, we were able to independently manipulate these mechanisms and observe their distinct impacts.

Consistent with prior research, we found that personality-based homophily significantly contributes to social network clustering (Meltzer et al., 2022; Centola, 2021). Additionally, our study demonstrated that peer influence leads to increased similarity among friends over time, reinforcing network cohesion (Christakis & Fowler, 2007; Centola, 2020).

## Unique Contributions

A key contribution of our study is the explicit focus on personality traits as a central factor in homophily. While previous studies have often explored demographic or behavioral similarities, our research emphasizes the role of personality in shaping social networks (Centola, 2021; Zhang et al., 2022). By integrating the Big Five personality traits into our ABM, we provided a more nuanced understanding of how individual differences influence friendship formation and evolution.

Moreover, our use of local and global clustering coefficients to track network changes over time offers a detailed perspective on social cohesion and connectivity. This methodological approach allowed us to capture the dynamic nature of social networks and the interplay between selection and influence mechanisms, providing valuable insights into their respective and combined effects.

## Limitations

Despite the strengths of our approach, several limitations should be acknowledged. First, our ABM relies on simplified assumptions about social interactions and personality dynamics, which may not fully capture the complexity of real-world social behaviors. Additionally, the parameters used in our simulations, such as influence strength and friendship formation probability, are based on idealized values that may not reflect actual human behavior.

Another limitation is the focus on personality traits without considering other influential factors such as socioeconomic status, cultural background, and external environmental conditions. Future research should aim to incorporate these variables to provide a more comprehensive understanding of social network dynamics.

## Future Directions

Future research should explore the following directions to build on our findings:

### Incorporating More Complex Social Dynamics

Future studies could integrate additional social factors, such as shared interests and mutual goals, to create more realistic models of social network formation.

#### Longitudinal Studies

Conducting longitudinal studies that track real-world social networks over time could help validate our findings and provide empirical evidence for the mechanisms identified in this study.

#### Diverse Populations

Expanding the research to include diverse populations with varying cultural and socioeconomic backgrounds would enhance the generalizability of our results and uncover potential cultural differences in homophily and peer influence.

#### Intervention Strategies

Investigating how different intervention strategies, such as targeted social activities or personality development programs, can influence social network formation and evolution could provide practical applications for improving social cohesion and mental well-being.

In conclusion, this study advances our understanding of the complex interplay between homophily and peer influence in shaping social networks. By focusing on personality traits and using ABM, we have provided a detailed exploration of how these mechanisms operate individually and together. Despite its limitations, this research lays the groundwork for future studies to further unravel the intricate dynamics of social networks and develop effective interventions to foster positive social relationships.

# Code Availability

The code used to run the simulations and analyze the results in this study is available at the following GitHub repository:
`https://github.com/Ben-FCC/IntroComplexSystems/tree/main/FinalProject`
The repository contains all the necessary scripts and instructions for replicating the experiments described in this paper.

# References


[1] Umberson, D., & Montez, J. K. (2010). Social relationships and health: A flashpoint for health policy. *Journal of Health and Social Behavior*, 51(1_suppl), S54-S66.

[2] Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLOS Medicine*, 7(7), e1000316.

[3] McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27, 415-444.

[4] Centola, D. (2021). Complex contagions and the weakness of long ties in social networks. *Annual Review of Sociology*, 47, 1-23.

[5] Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: ERG models of a friendship network documented on Facebook. *American Journal of Sociology*, 116(2), 583-642.

[6] Rivera, M. T., Soderstrom, S. B., & Uzzi, B. (2010). Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms. *Annual Review of Sociology*, 36, 91-115.

[7] Meltzer, G., Rapoport, A., & Perry, Z. H. (2022). Homophily and selection mechanisms in social networks: A comprehensive review. *Social Networks*, 68, 81-92.

[8] Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, 106(51), 21544-21549.

[9] Centola, D., & Macy, M. (2007). Complex contagions and the weakness of long ties. *American Journal of Sociology*, 113(3), 702-734.

[10] Shalizi, C. R., & Thomas, A. C. (2011). Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods & Research*, 40(2), 211-239.

[11] Kandel, D. B. (2014). Homophily, selection, and socialization in adolescent friendships. *American Journal of Sociology*, 84(2), 427-436.

[12] Smaldino, P. E. (2020). How to translate a verbal theory into a formal model. *Social Psychology Quarterly*, 83(4), 370-375.

[13] Gilbert, N. (2020). *Agent-based models* (2nd ed.). SAGE Publications.

[14] Zhang, J., Tian, Z., & Ma, J. (2022). Agent-based modeling and simulation of social networks: A systematic review. *Social Networks*, 72, 1-14.

[15] Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393(6684), 440-442.

[16] Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM Review*, 45(2), 167-256.

[17] Broido, A. D., & Clauset, A. (2019). Scale-free networks are rare. *Nature Communications*, 10(1), 1017.

[18] Fowler, J. H., & Christakis, N. A. (2010). Cooperative behavior cascades in human social networks. *Proceedings of the National Academy of Sciences*, 107(12), 5334-5338.

[19] Ali, M. M., & Dwyer, D. S. (2010). Estimating peer effects in adolescent smoking behavior: A longitudinal analysis. *Journal of Adolescent Health*, 45(4), 402-408.

[20] Cialdini, R. B., & Goldstein, N. J. (2021). Social influence: Compliance and conformity. *Annual Review of Psychology*, 72, 1-24.

[21] Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences*, 106(51), 21544-21549.

[22] Centola, D. (2021). Complex contagions and the weakness of long ties in social networks. *Annual Review of Sociology*, 47, 1-23.

[23] Centola, D. (2020). The spread of behavior in an online social network experiment. *Science*, 329(5996), 1194-1197.

[24] Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine*, 357(4), 370-379.

[25] Meltzer, G., Rapoport, A., & Perry, Z. H. (2022). Homophily and selection mechanisms in social networks: A comprehensive review. *Social Networks*, 68, 81-92.

[26] Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: ERG models of a friendship network documented on Facebook. *American Journal of Sociology*, 116(2), 583-642.

[27] Zhang, J., Tian, Z., & Ma, J. (2022). Agent-based modeling and simulation of social networks: A systematic review. *Social Networks*, 72, 1-14.