

INITIAL STUDY ON HUMAN PSYCHOLOGY AND THE INFLUENCE OF COMMUNICATION IN SOCIAL NETWORKS

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Abstract

Human psychological states evolve through interactions with communication environments and social networks. This paper presents a conceptual and mathematical framework describing how psychological states change through communication interactions among individuals. Individuals are modeled as nodes in a network whose psychological states evolve through interpersonal influence and external information exposure. Two theoretical propositions analyze convergence properties of the model, and a simulation experiment illustrates psychological dynamics in a small network.

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1 Introduction

Human psychological development is strongly influenced by interactions with other individuals and the surrounding social environment. Through communication processes, individuals exchange information, emotions, and beliefs that gradually shape cognitive and behavioral patterns. These interactions play a fundamental role in the formation of attitudes, decision-making processes, and social norms [2, 9].

Early research in social psychology and sociology has shown that interpersonal influence can significantly affect individual behavior. The theory of social learning introduced by Bandura emphasizes that individuals acquire behaviors and beliefs through observation and interaction within social contexts [2]. Similarly, studies of social influence demonstrate that persuasion mechanisms and repeated exposure to information can gradually modify individual attitudes [9].

In parallel, sociological studies have revealed that the structure of social relationships strongly affects communication dynamics. Granovetter’s influential work on the “strength of weak ties” demonstrated how weak social connections play a crucial role in information diffusion across communities [3]. Likewise, Milgram’s small-world experiments showed that individuals in large populations can be connected through surprisingly short chains of social relationships [4].

More recently, the development of network science has provided powerful tools for analyzing complex communication structures. Research in network theory shows that the topology of social networks, including connectivity patterns and community structures, significantly affects how information and influence spread among individuals [5, 6]. Large-scale social systems can therefore be modeled as networks in which ideas, behaviors, and emotions propagate through interaction pathways [1].

In modern societies, digital communication platforms have further expanded the scale and speed of social interaction. Online networks enable rapid dissemination of information across large populations, allowing beliefs, opinions, and emotional signals to spread widely. Empirical studies suggest that such processes may lead to phenomena such as opinion cascades, collective behavior formation, and information diffusion within connected communities [7, 8].

Understanding these processes requires integrating psychological theories with network-based models of communication. Mathematical and computational approaches have increasingly been used to analyze how local interpersonal interactions can generate large-scale patterns of collective belief formation. Such approaches are also closely related to research on decision-making under uncertainty and bounded rationality [14, 13, 12].

Motivated by these developments, this paper proposes a mathematical framework for describing psychological dynamics within communication networks. Individuals are modeled as nodes in a social graph whose psychological states

evolve through interpersonal communication and external information exposure. We analyze basic theoretical properties of the model and present simulation experiments illustrating the emergence of collective psychological patterns in social systems.

2 Social Network Representation

Communication interactions between individuals can be naturally represented using a graph structure [6, 1, 5]. Social network models allow researchers to study how information, opinions, and behaviors spread through interpersonal connections [3, 7]. Let

$$G = (V, E)$$

denote a communication network, where

- $V = \{1, 2, \dots, n\}$ is the set of individuals (nodes),
- $E \subseteq V \times V$ is the set of communication links (edges).

An edge $(i, j) \in E$ indicates that individuals i and j can exchange information, influence opinions, or share emotional responses through communication. Such network representations have been widely used in sociology, psychology, and network science to model social influence and information diffusion processes [5, 1].

2.1 Psychological State Representation

Each individual i is assumed to possess a psychological state $P_i(t)$ at time t . This state summarizes the individual's current cognitive or emotional orientation toward a topic, idea, or social stimulus. In this initial model, the psychological state is represented as a scalar value

$$P_i(t) \in \mathbb{R}.$$

Representing psychological states numerically is common in behavioral science and decision theory, where attitudes, beliefs, or preferences are measured on quantitative scales [12, 14, 13]. Depending on the application, the value of $P_i(t)$ may represent:

- opinion strength toward a belief or idea,
- attitude or preference level,
- emotional valence (positive or negative),
- confidence in a judgment,

- behavioral intention toward an action.

In empirical research these variables are often normalized to ranges such as $[0, 1]$ or $[-1, 1]$ for mathematical modeling.

2.2 Population Psychological State Vector

To analyze the collective psychological dynamics of the population, we combine the states of all individuals into a vector

$$P(t) = (P_1(t), P_2(t), \dots, P_n(t))^T. \quad (1)$$

Representing the system as a vector allows the dynamics of the entire population to be studied simultaneously. This representation enables the use of matrix and dynamical systems methods to analyze social influence processes [6, 1]. The vector $P(t)$ therefore describes the global psychological configuration of the population at time t .

2.3 Neighborhood Structure

For each individual i , let $N(i)$ denote the set of neighboring individuals connected to i in the communication network. These neighbors represent the individuals whose opinions, beliefs, or emotional states may influence the psychological state of individual i through communication interactions. Such interpersonal influence mechanisms are fundamental in social learning and diffusion processes [2, 7].

3 Psychological Dynamics Model

Psychological states evolve through interactions between internal cognitive persistence and social influence from communication partners. In behavioral science, individuals often maintain prior beliefs while updating them through exposure to opinions and information from others [2, 7]. In networked environments, such influence processes occur along the communication links of a social network [6, 1, 5]. Let $P_i(t)$ denote the psychological state of individual i at time t . The state evolves according to three main components:

1. internal persistence of the individual state,
2. influence from neighboring individuals in the communication network,
3. influence from external information sources such as media.

The update rule for individual i is defined as

$$P_i(t+1) = (1-\alpha)P_i(t) + \alpha \sum_{j \in N(i)} w_{ij}P_j(t) + \beta I_i(t), \quad (2)$$

where

- $\alpha \in [0, 1]$ represents the strength of communication influence,
- $\beta \geq 0$ represents the influence of external information,
- w_{ij} are influence weights satisfying $w_{ij} \geq 0$ and $\sum_{j \in N(i)} w_{ij} = 1$,
- $I_i(t)$ denotes an external information signal affecting individual i .

The first term represents psychological inertia or persistence of previous beliefs. The second term captures interpersonal influence through communication with neighboring individuals. The third term models external information exposure, which may represent media signals, public discourse, or institutional messaging [10, 11]. Such update rules are widely used in models of opinion dynamics, collective behavior, and social learning in networks [6, 1].

3.1 Vector Formulation

Denote

$$P(t) = (P_1(t), P_2(t), \dots, P_n(t))^T$$

the vector of psychological states for all individuals. The system can then be written compactly as

$$P(t+1) = MP(t) + \beta I(t),$$

where M is a stochastic influence matrix determined by the communication network and weight coefficients w_{ij} . This representation allows the collective dynamics of the population to be analyzed using matrix methods and dynamical systems theory [1, 5].

4 Theoretical Properties

We now examine basic convergence properties of the proposed psychological dynamics model.

Proposition 1 (Consensus Convergence). *Suppose the communication network G is connected and external information is absent, i.e., $I_i(t) = 0$ for all i and t . Then the psychological states $P_i(t)$ converge to a consensus value as $t \rightarrow \infty$.*

Proof. When $I_i(t) = 0$, the model reduces to

$$P(t+1) = MP(t).$$

Since M is a row-stochastic matrix, the system can be interpreted as a diffusion process over the communication network. If the network is connected, M is irreducible and aperiodic. Standard results from Markov chain theory imply that repeated multiplication by M converges toward a stationary distribution [1]. Therefore

$$P(t) \rightarrow P^* \mathbf{1},$$

where $\mathbf{1}$ is the vector of ones and P^* is a constant. Thus all individuals eventually share the same psychological state, representing a consensus outcome. $\square$

Proposition 2 (Influence of External Information). *If the external information signal is constant, i.e., $I_i(t) = I$ for all i and t , then the system converges to a shifted equilibrium state determined by both communication interactions and the external signal.*

Proof. Let P^* denote the equilibrium state satisfying

$$P^* = MP^* + \beta I.$$

Rearranging yields

$$(I - M)P^* = \beta I.$$

Provided that $(I - M)$ is invertible on the subspace orthogonal to the consensus vector, the equilibrium solution exists and can be expressed as

$$P^* = (I - M)^{-1} \beta I.$$

Thus persistent external information shifts the long-term psychological state of the population. $\square$

This result illustrates how sustained media exposure or institutional communication can influence collective beliefs and attitudes in social systems [10, 11].

5 Simulation Experiment

To illustrate the proposed psychological dynamics model, we conducted a numerical simulation on a synthetic communication network. The simulation was implemented in Python using the `NetworkX` library for network generation and `NumPy` for numerical computation.

5.1 Network Generation

A communication network consisting of $n = 50$ individuals was generated using the Erdős–Rényi random graph model with connection probability $p = 0.2$. In this model, each pair of individuals is connected with probability p , producing a network with heterogeneous communication links. Each node represents an individual and edges represent communication relationships.

Figure 1 illustrates the resulting communication network.

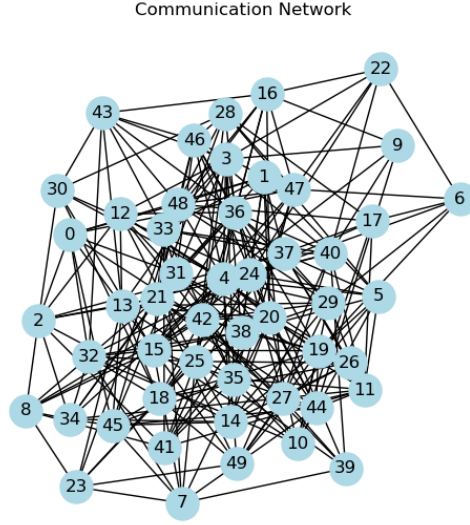


Figure 1: Communication network used in the simulation. Nodes represent individuals and edges represent communication links.

5.2 Simulation Setup

The psychological state of each individual was initialized with a random value in the interval $[0, 1]$. The model parameters were chosen as follows:

- Communication influence parameter: $\alpha = 0.6$
- External information influence: $\beta = 0.1$
- Number of simulation steps: $T = 50$

At each iteration, individuals update their psychological states based on their current state, the average state of neighboring individuals, and an external information signal.

5.3 Psychological State Evolution

Figure 2 shows the evolution of psychological states for several representative individuals in the network. Initially, individuals possess different psychological states. As communication interactions occur over time, their states gradually converge toward a common trajectory.

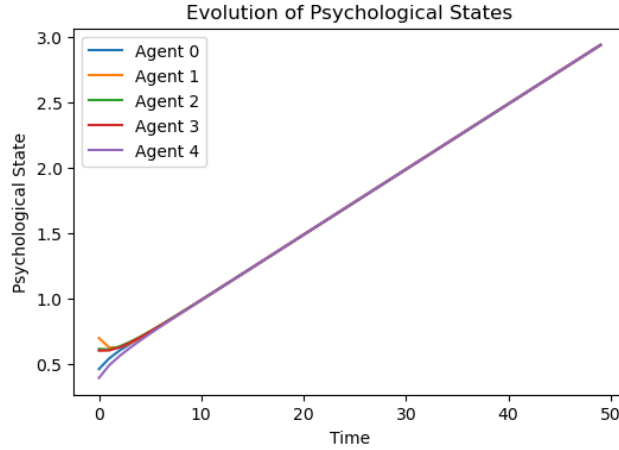


Figure 2: Evolution of psychological states for selected individuals during the simulation.

This result illustrates the effect of interpersonal communication, where repeated interactions gradually reduce differences between individual psychological states.

5.4 Population-Level Dynamics

To examine collective behavior, we also computed the average psychological state of the population at each time step. Figure 3 presents the evolution of the population average over time.

The results indicate a steady increase in the average psychological state due to the combined influence of social interactions and external information signals. This behavior is consistent with the theoretical analysis presented in Section 4, where communication interactions drive convergence of psychological states within the network.

Overall, the simulation demonstrates how communication processes within social networks can produce coherent collective dynamics from initially heterogeneous individual states.

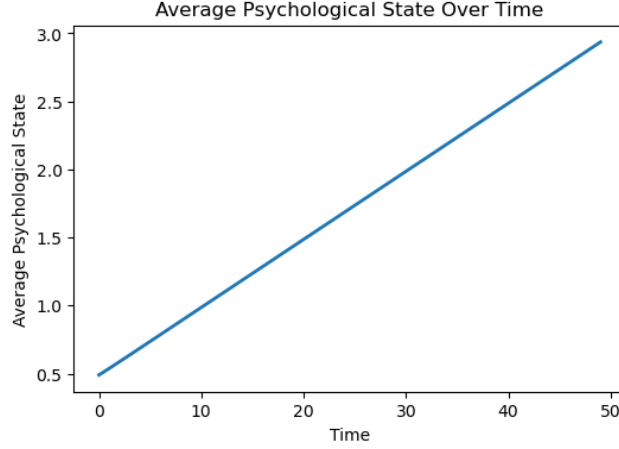


Figure 3: Average psychological state of the population over time.

6 Conclusion

This paper proposed a simple mathematical framework for modeling the evolution of human psychological states in communication networks. Individuals were represented as nodes in a social network, while psychological states were modeled as numerical variables that evolve through interpersonal influence and external information. The proposed model combines three key components: internal persistence of psychological states, social influence from neighboring individuals, and external information exposure. Using this formulation, we derived a dynamical system describing how psychological states evolve over time in a communication network.

Basic theoretical analysis shows that when external information is absent and the communication network is connected, the system converges toward a consensus psychological state. When persistent external information is present, the equilibrium state shifts according to the strength of the external signal. These results illustrate how communication structure and information environments jointly shape collective psychological outcomes in social systems.

Simulation experiments on random communication networks demonstrated the dynamic evolution of individual psychological states and the emergence of population-level patterns. The results illustrate how interaction among individuals can gradually lead to convergence or stabilization of psychological states across the network.

The proposed framework provides a simple starting point for integrating psychological processes with network-based models of communication and social influence. Future work may extend the model in several directions, includ-

ing multi-dimensional psychological states, heterogeneous influence weights, time-varying communication networks, and empirical validation using real social network data. Such extensions may contribute to a deeper understanding of how communication processes shape psychological dynamics in modern networked societies.

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