# Epidemic-Behavior Interaction Model: Understanding Oscillatory Dynamics in Pandemic Response


**王聖夫[1]　李宣緯[2]**

[1]Department of Sociology
National Taiwan University

[2]Department of Community and Population Health
Lehigh University



**Nov 23, 2024 臺灣社會學年會**

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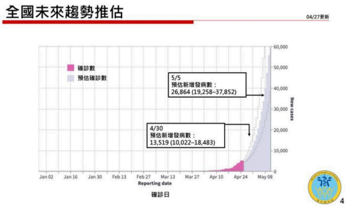
# Some Intuitions and Real-World Examples

台視新聞網 | 6.3k 人追蹤 | ☆ 追蹤

## 預測疫情曲線圖曝光！衛福部預估5/5「單日確診數達2.6萬」

台視新聞網
2022年4月28日




**3月20日起配合防疫鬆綁新制**

## 校園師生 0+n 適用假別

| 對象 | 0+n適用假別 |
| --- | --- |
| 學生 | **學校多爲近距離且群聚型活動，建議篩檢陽性學生0日及次日起5日內，在家進行自主健康管理。**<br>■學生持有證明，可請病假，0日及次日起5日內不列入出缺席紀錄<br>■家長可請防疫照顧假 |
| 教職員工 | **學校多爲近距離且群聚型活動，建議篩檢陽性教職員工0日及次日起5日內，在家進行自主健康管理。**<br>■教師如無法居家辦公或線上教學，持證明可請病假，0日及次日起5日內不列入學年度病假日數計算及成績考核之考量，教師所遺留課務由學校協助排代並支付鐘點費 |

＊ 篩檢陽性者，自主健康管理期間快篩陰性可提早解除。
＊ 請假依據：採認快篩陽性證明(如照片)即可。

2023.03.09

# Some Intuitions and Real-World Examples


## 新冠疫情再回溫！疾管署籲接種疫苗增強保護力

**記者邱怡芳** 2024-06-19 17:05

疾病管制署表示，國內疫情上升且處流行期，6月11日至6月17日新增623例COVID-19本土確定病例（併發症），較前一週新增329例上升，累積併發症中65歲以上長者占79%；另上週新增38例死亡病例，較前一週新增20例上升，累積死亡個案中65歲以上長者占90%。

*疾病管制署表示，國內疫情上升且處流行期。圖：截自freepik*

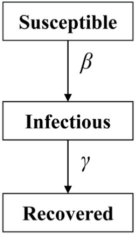
# Overview and Research Questions

- How can sociological perspectives shed light on the application of mathematical disease models?
- How can observed disease phenomena—here, we focus on **oscillatory** patterns—be explained by **underlying social behavior mechanisms**?
  - Other reasons for oscillation: seasons and climatic conditions, immune response cycles, pathogen evolution
- In this study, we draw upon **social network research** and studies on the **diffusion of social behaviors** (simple & complex contagion) to explain this.

# Mathematical Epidemiology

Epidemiologists have long been using mathematical methodologies to comprehend the complexities of disease transmission dynamics to effectively predict and respond to outbreaks.

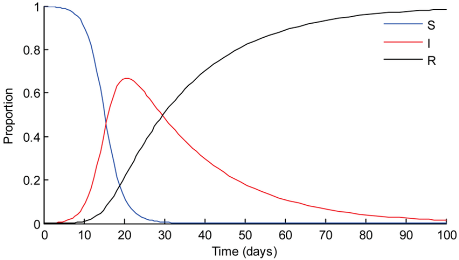
- **Compartmental Models**: Equation-based methods that typically use differential equations to represent transitions between compartments.
  - Examples: Susceptible-Infected-Recovered (SIR) model, SEIR Model, SIS Model...
- **Agent-Based Models**




$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$




**Source:** Luz et al. (2010)

# Mathematical Epidemiology

Epidemiologists have long been using mathematical methodologies to comprehend the complexities of disease transmission dynamics to effectively predict and respond to outbreaks.

- **Compartmental Models**
- **Agent-Based Models**: Computational approach in which agents with a specified set of characteristics interact with each other and with their environment according to predefined rules (See Tracy et al., 2018 for a review of ABM in public health). It strengths include:
  - providing insight into the underlying causal mechanisms;
  - conducting virtual experiments of interventions and policies.

# How Sociology Can Contribute to This:

- **Social networks studies.** Examples:
  - Obesity spread through *social ties* (Christakis and Fowler, 2007).
  - *Homophily* and *transitivity* in social networks formation.
- Sociological insights regarding **social influence on behavioral change.**
  - Social norms, imitation, group pressure, and obedience...
  - Diffusion of behavior: *simplex contagion* & *complex contagion*

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# Health Behavior in the Presence of Infectious Diseases

- **Avoidant behaviors**
  - Quarantine and *social distancing* (avoiding potentially infectious social contact through either choosing not to form a tie to or breaking an existing tie from an infectious other)
  - Therefore, social network structures are not static but rather adaptive to the transmission of diseases.
  - Previous studies have examined this co-evolution (e.g., Gross et al., 2006; Lee et al., 2019; Nunner et al., 2021).
- **Preventive behaviors**
  - Examples: frequent hand washing, mask-wearing, vaccinations...

# Complex Contagion in Preventive Behaviors

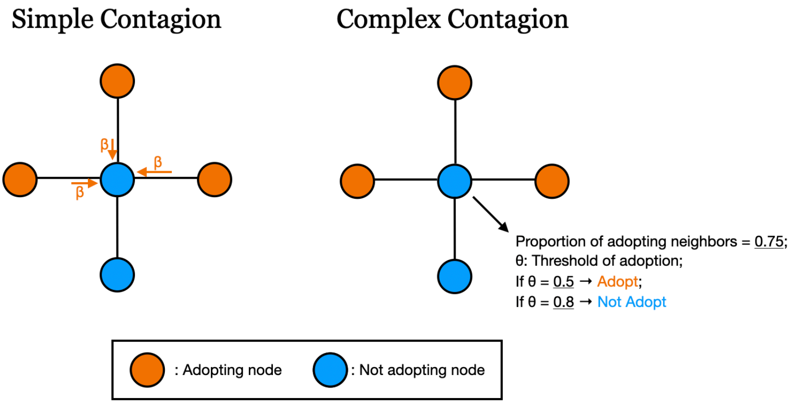
**Preventive behaviors:**

- **Factors affecting adopting preventive behaviors or not**
  1. Goal infection rate and risk perception.
  2. Awareness and difussion of *information* $\rightarrow$ *simple* contagion (e.g., Funk et al., 2009; Zou et al., 2021).
  3. Local social interactions and diffusion of *behavior* $\rightarrow$ *complex* contagion
- **Simple verse. complex contagion**

# Complex contagion in Preventive Behaviors

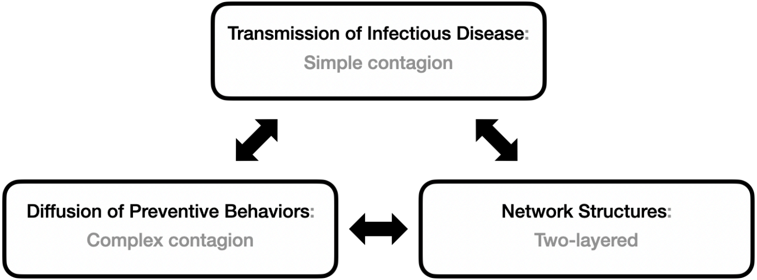
- **Simple contagion**
  - Diffusion of information, knowledge, viruses...
  - *Multiple exposures*: transitive ties tend to be redundant
  - Some network principles: the "strength of weak (long/bridging) ties" and "six degrees of separation"
- **Complex contagion** (Centola and Macy, 2007, *AJS*)
  - Diffusion of innovation, high-risk, high-cost behaviors...
  - *Threshold*-based adoption: social affirmation
  - *Exposure to multiple sources*: transitive structure now becomes an essential

# Simple Verse. Complex Contagion



# Epidemic-Behavior Interaction Model

Our Epidemic-Behavior Interaction Model (EBIM) integrates the above-mentioned sociological insights into traditional epidemic modeling of disease transmission, employing an agent-based approach to simulate the complex interactions among social networks, health behaviors, and infectious disease dynamics.



# Outline

# Model Settings: A Two-Layer Network

- **Physical contact network**: SIS model
  - **Susceptible (S)**: Can contract the disease.
  - **Infectious (I)**: Currently infected and can spread the disease.
- **Virtual behavior network**: NAN Model
  - **Adopting (A)**: Taking preventive actions, such as mask-wearing, to mitigate the disease.
  - **Not Adopting (N)**: Not engaging in preventive actions or behaviors related to the disease.
- **Network structure**: Erdős–Rényi model (ERM) with $N = 1,000$ nodes and $<k> = 5$ average degree.

## Simulation Process

1. Update **health states** in the physical layer
   - **Disease transmission (S $\rightarrow$ I)**: Each infected neighbor has $\beta$ probability of transmission. Thus, a susceptible agent becomes infected with probability $1-(1-\beta)^n$, where $n$ equals the number of infected neighbors.
   - **Recovery (I $\rightarrow$ S)**: All infected agent recovers with a probability of $\gamma$ after $T_{inf}$ days.
2. Update **adoption states** in the virtual layer
3. Update **network structure**

# Simulation Process

1. Update **health states** in the physical layer
2. Update **adoption states** in the virtual layer
   - **Adopting behaviors (N → A)**: The agent adopts preventive behaviors if the proportion of her adopting neighbors exceeds the threshold of $\theta'_{it} = \theta_i * (1 - \pi_t * \lambda) * \rho$, where $\pi_t$ is the global infection rate, and $\theta_i$ follows a beta distribution, i.e., $\theta_i \sim \beta(\alpha, \beta)$.
   - **Not Adopting (A → N)**: If the proportion does not exceed the threshold, then the agent will not adopt.
3. Update **network structure**

# Simulation Process

1. Update **health states** in the physical layer
2. Update **adoption states** in the virtual layer
3. Update **network structure**
   - Each susceptible individual breaks each edge it has with an infected neighbor at rate $\gamma$, rewiring this link to a susceptible node. The new link created during rewiring is made with probability $\eta$ to a susceptible node at a distance 2, that is, a neighbor of a neighbor. Otherwise (i.e., with probability $1 - \eta$), the rewiring is made to another susceptible node selected uniformly at random.

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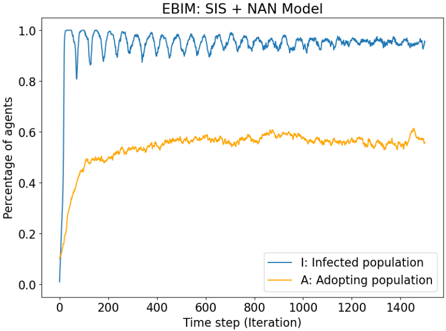
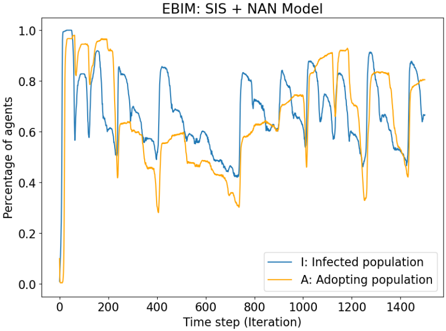
# Prevalence Over Time

## When preventive behaviors reduce disease transmission by a factor of 6:

### Simple contagion



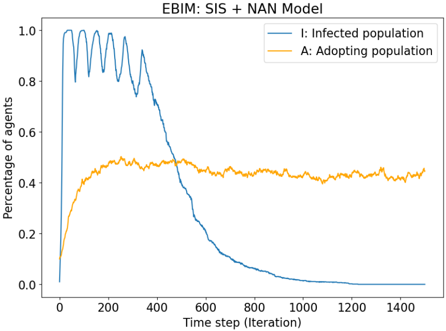

### Complex contagion



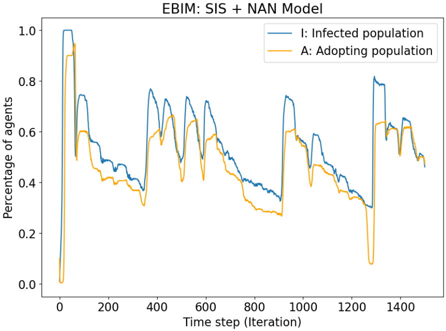
# Prevalence Over Time

## When preventive behaviors reduce disease transmission by a factor of 12:

### Simple contagion

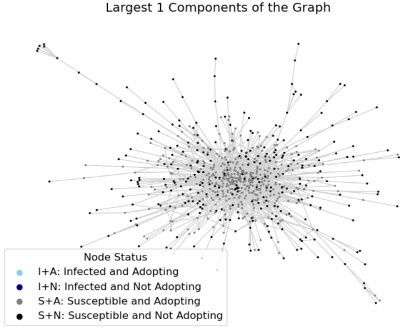



### Complex contagion

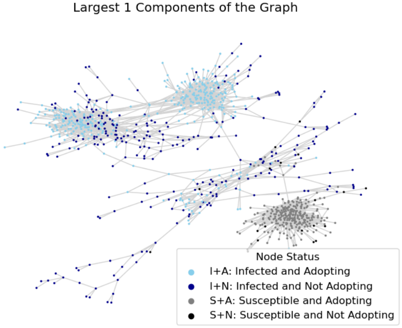


# Network Structure

## Simple contagion




## Complex contagion



# Outline

# Implications

- This study aligns with the call for "social epidemiology" (Hollm-Delgado, 2009) or "epidemiological sociology," (Link, 2008) using sociological concepts and theories to explore the social determinants of health and disease.
- Our agent-based model demonstrates how **multiple contagions** interact (Smith and Christakis, 2008, *Annu. Rev. Sociol*) and highlights the interplay between social networks and disease transmission dynamics.
- Results emphasize the critical role of **preventive behaviors** in explaining the cyclical nature of pandemics and designing effective management policies.

# Future Directions

- Analysis results over **parameter spaces**
- Comparison among different **network typology**
- From multi-layered to **multiplex** network: Decouple ties in the two-layered network
- Add **vaccination** into the model: additional feedback mechanisms, such as waning immunity
- Other mechanisms, such as **delayed behavioral responses**
- Validation with **real-world data**

# Appendix: ABM Implemention

Python code can be assessed: here.

| Parameter | Definition | Default |
|---|---|---|
| $N$ | Size of agents (nodes) | 1000 |
| $T$ | The number of the time step (round) | 1500 |
| $M$ | The number of the trial (realization of simulation) | 1 |
| $<k>$ | The average *degree* of the network at t = 0 | 5 |
| p | p in erdos_renyi_graph() | $<k>$/N |
| $r$ | The percentage of overlapped edges between the physical and virtual layer at t = 0 | 1 |
| $\beta_u$ | Transmission probability for an *unaware* susceptible agent (S_u → I) | 0.85 |
| $\beta_a$ | Transmission probability for an *aware* susceptible agent (S_a → I) | $\frac{\beta_u}{6}$ or $\frac{\beta_u}{12}$ |
| $\alpha$ | Recovery probability (I → S) | 0.25 |
| $T_{inf}$ | Being able to recover only after the infected period | 50 |
| $\gamma$ | A susceptible individual will break each edge with an infected neighbor at a probability of $\gamma$ | 0.8 |
| $\eta$ | Rewiring a new link to a susceptible node at *a distance of 2* is made with a probability $\eta$. Selecting susceptible node at random at a probability of 1– η | 0.8 |
| $\lambda$ | Controlling how sensitive the global infection rate affects the awareness threshold (Only in “complex” contagion) | 0.7 |
| $\rho$ | Turning point of the awareness threshold (Only in “complex” contagion) | 0.6 |
| $\psi$ | Transmission probability for unaware nodes (Only in “simple” contagion) | 0.01 |
| (a, b) | Parameters in $Beta(\alpha, \beta)$ | (1.5, 1.25) |
| _ | Initial ratio of adopting nodes | 0.01 |
| _ | Initial ratio of adopting nodes | 0.1 |

Thank you for your listening!

**Contact Info:**

王聖夫 (Shengfu Wang): r11325008@ntu.edu.tw

李宣緯 (Hsuan-Wei "Wayne" Lee): hsl324@lehigh.edu

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