

# 数理モデリングの理路が大事

感染症伝染・情報伝播・行動依存症蔓延の数理モデリング

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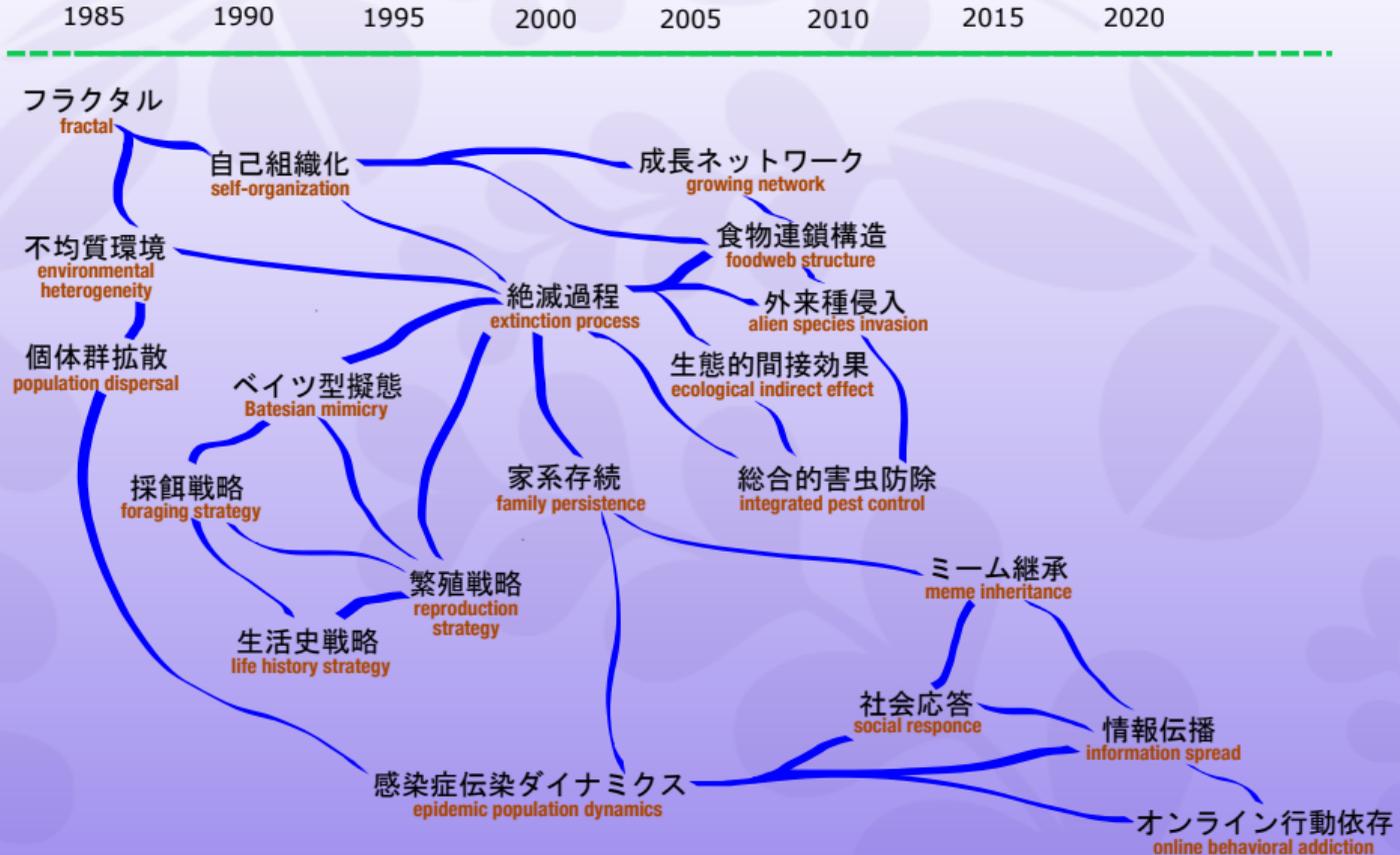
東北大学大学院情報科学研究科

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FOR: 第 25 回学術懇話会@東北大学大学院情報科学研究科, March 6, 2026



# Prologue

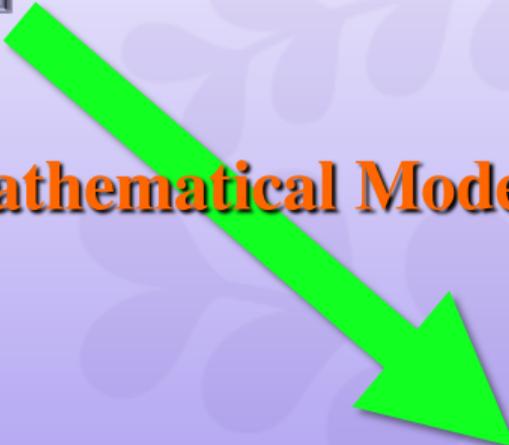


**Population dynamics model**

### Population Dynamics

is the nature of the spatio-temporal variation  
in biological population size (density etc.).

### Mathematical Modelling



繁殖 reproduction  
闘争 fighting  
競争 competition  
共生 mutualism  
捕食 predation  
寄生 parasitism  
etc.

### Mathematical Model

# Prologue

Population  
Dynamics

Interaction  
between individuals

Mathematical Modelling

Mathematical  
Model

繁殖 reproduction  
闘争 fighting  
競争 competition  
捕食 predation  
寄生 parasitism  
etc.

Density Effect

# Prologue

Population  
Dynamics

Interaction  
between individuals

Mathematical Modelling

Mathematical  
Model

繁殖 reproduction  
闘争 fighting  
競争 competition  
捕食 predation  
寄生 parasitism  
etc.

Density Effect

**What mathematical model is  
reasonable  
from the biological viewpoint?**

**What mathematical structure is  
appropriate  
for the reasonable modeling?**

**Distinct four logistic equations**

$$[L-1] \quad \frac{dN(t)}{dt} = \{r_0 - \beta N(t)\} N(t)$$

$$[L-2] \quad \frac{dN(t)}{dt} = r_0 \left\{ 1 - \frac{N(t)}{K} \right\} N(t)$$

$$[L-3] \quad \frac{dN(t)}{dt} = r_0 N(t) - b \{N(t)\}^2$$

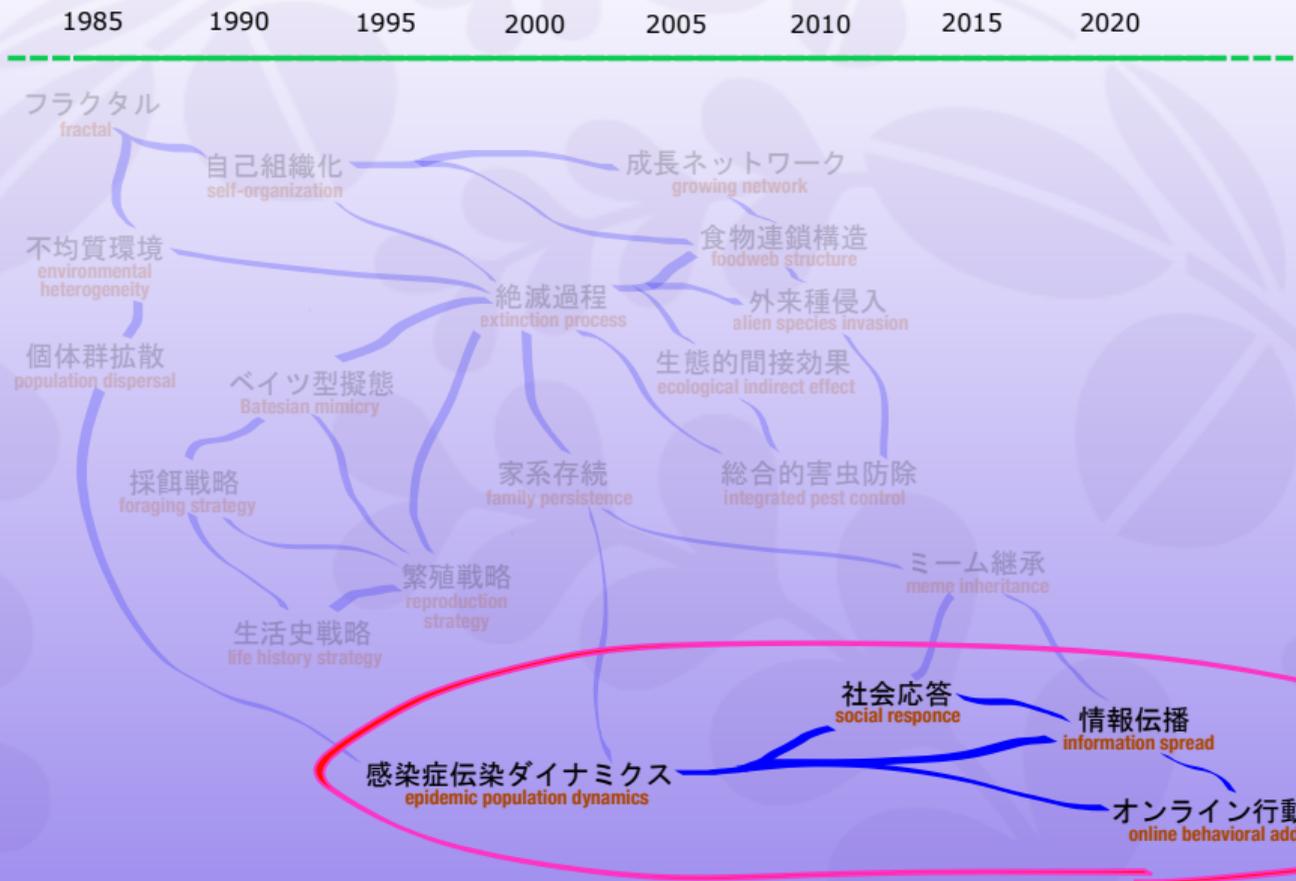
$$[L-4] \quad \frac{dN(t)}{dt} = \{r_0 - \beta N(t)\} N(t) - b \{N(t)\}^2$$

### **Reasonability of modeling depends on**

- i) purpose of theoretical research;**
- ii) available data/knowledge/hypothesis;**
- iii) design of mathematical analysis.**



# Prologue



# Outline

Prologue

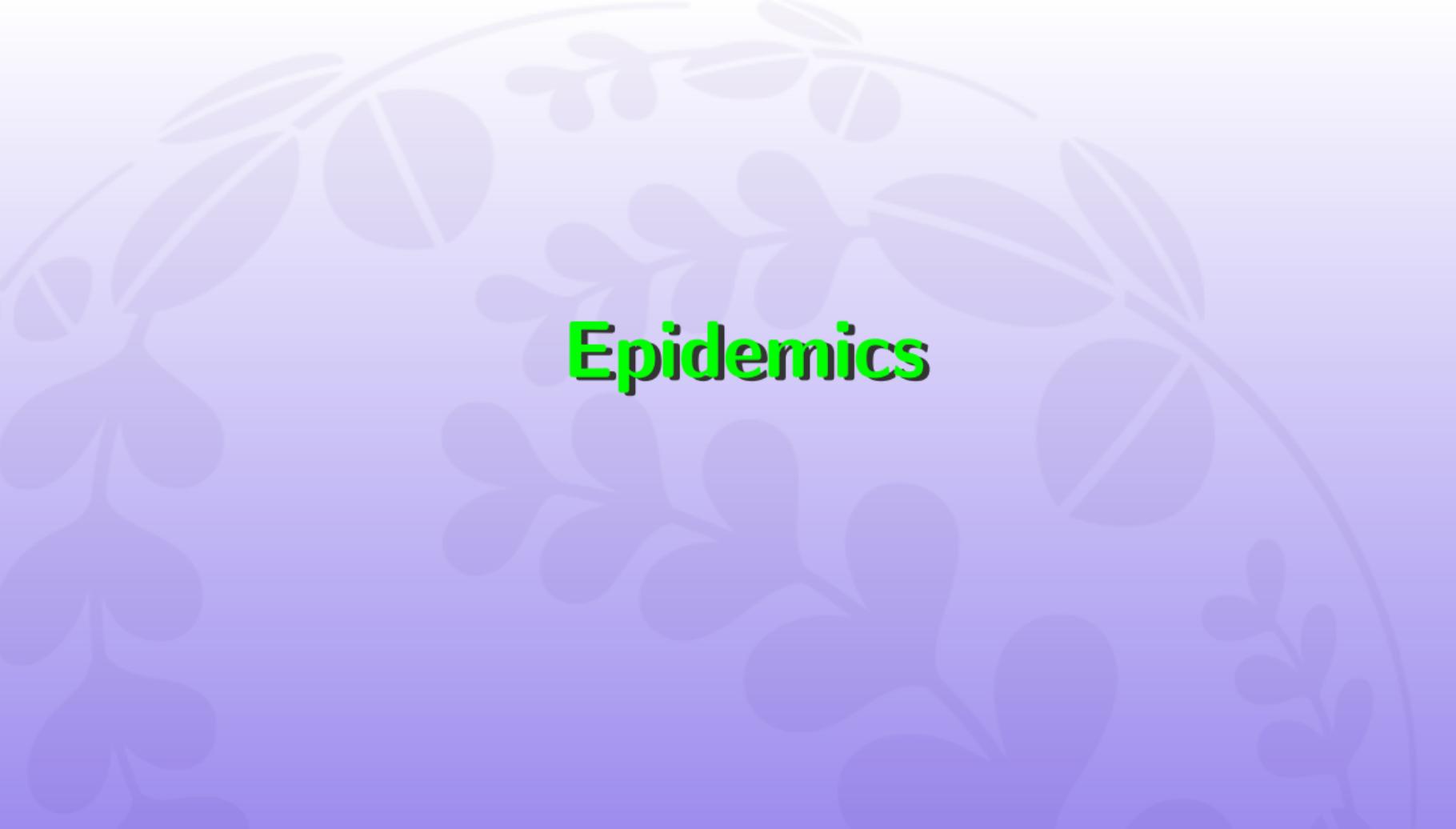
Population dynamics modeling for epidemics

Population dynamics modeling for information spread

Population dynamics modeling for online behavioral addiction

Epilogue

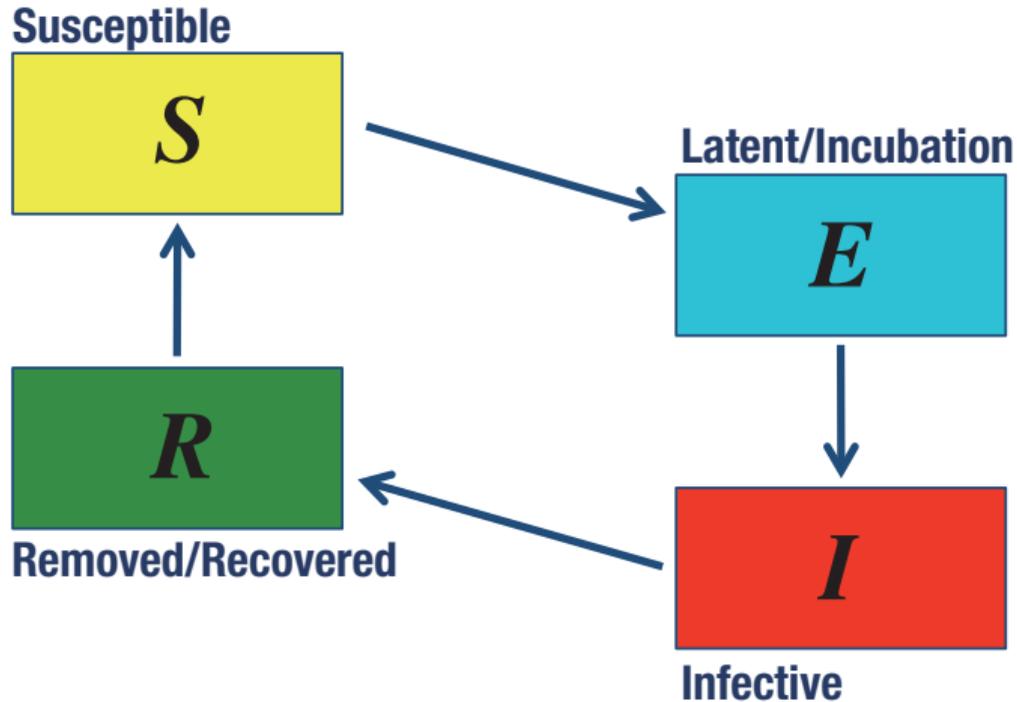




# **Epidemics**

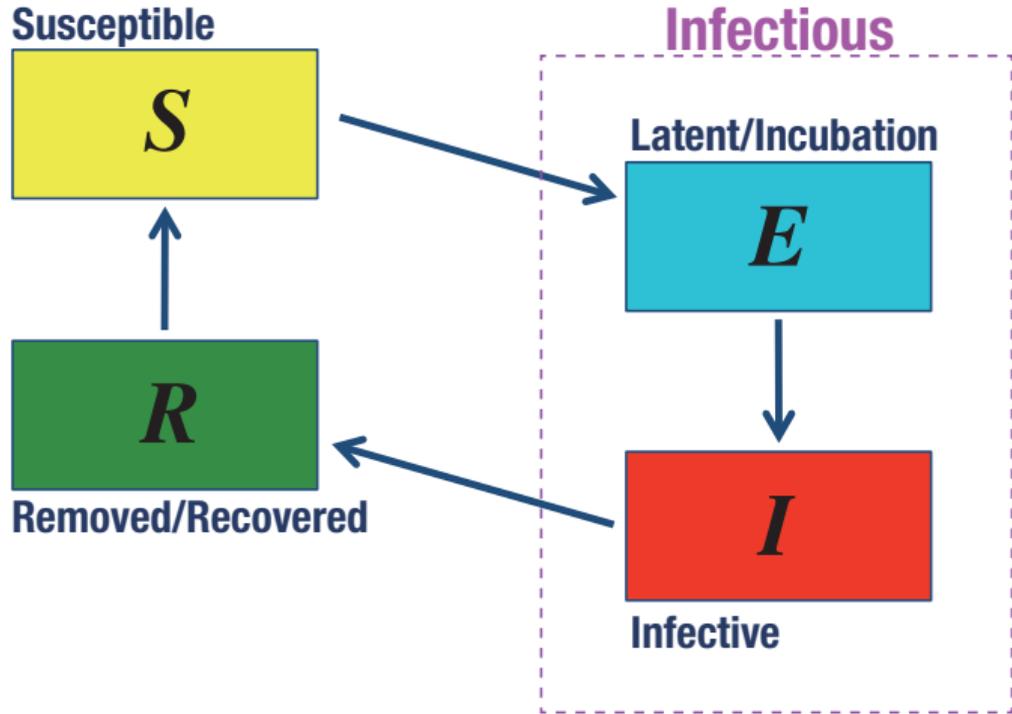
# Epidemic dynamics of infectious disease

$S \rightarrow E \rightarrow I \rightarrow R \rightarrow S$



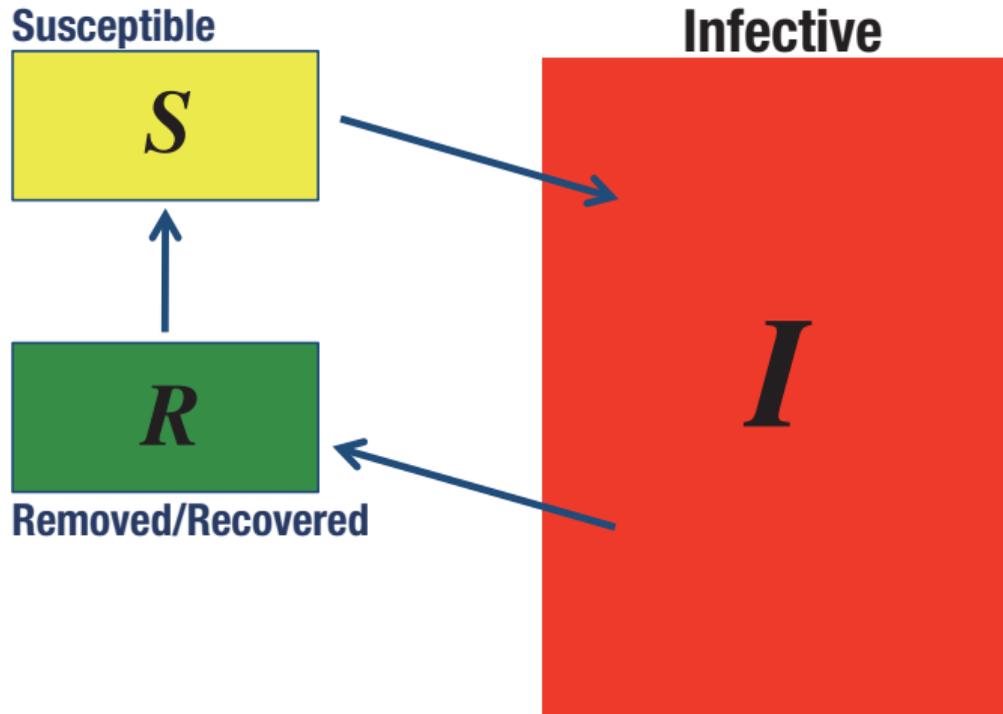
# Epidemic dynamics of infectious disease

$S \rightarrow E \rightarrow I \rightarrow R \rightarrow S$



# Epidemic dynamics of infectious disease

$S \rightarrow I \rightarrow R \rightarrow S$



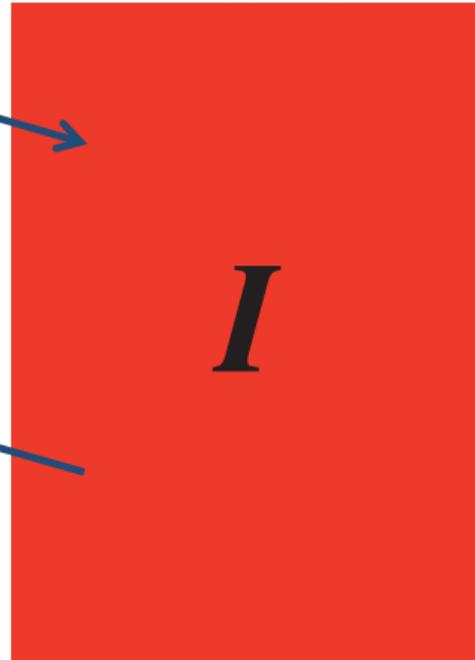
# Epidemic dynamics of infectious disease

$S \rightarrow I \rightarrow R$

Susceptible



Infective



Removed/Recovered



### Generic SIR model

$$\frac{dS(t)}{dt} = B - \Lambda S(t) - \mu_S S(t)$$

$$\frac{dI(t)}{dt} = \Lambda S(t) - qI(t) - \mu_I I(t)$$

$$\frac{dR(t)}{dt} = qI(t) - \mu_R R(t)$$

$\Lambda = \Lambda(S, I, R)$ : Force of infection

## Epidemic dynamics model

Generic SIR model **without demographic change**

$$\frac{dS(t)}{dt} = B - \Lambda S(t) - \mu_S S(t)$$

$$\frac{dI(t)}{dt} = \Lambda S(t) - qI(t) - \mu_I I(t)$$

$$\frac{dR(t)}{dt} = qI(t) - \mu_R R(t)$$

$$\frac{d}{dt} \{S(t) + I(t) + R(t)\} = 0; \quad S(t) + I(t) + R(t) = N$$

(time-independent constant total population size)

## Kermack-McKendrick SIR model

$$\Lambda \propto I$$

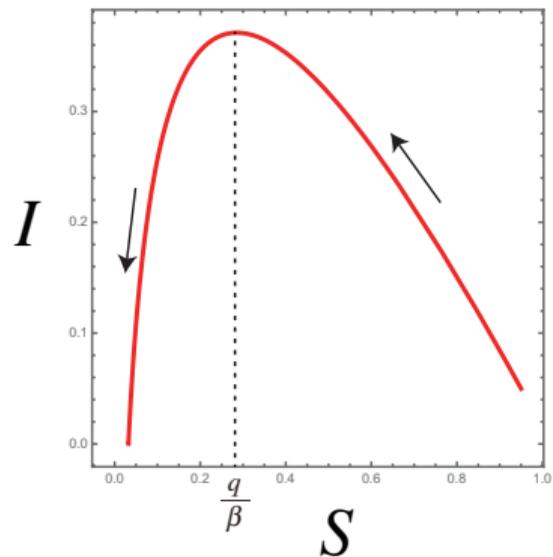
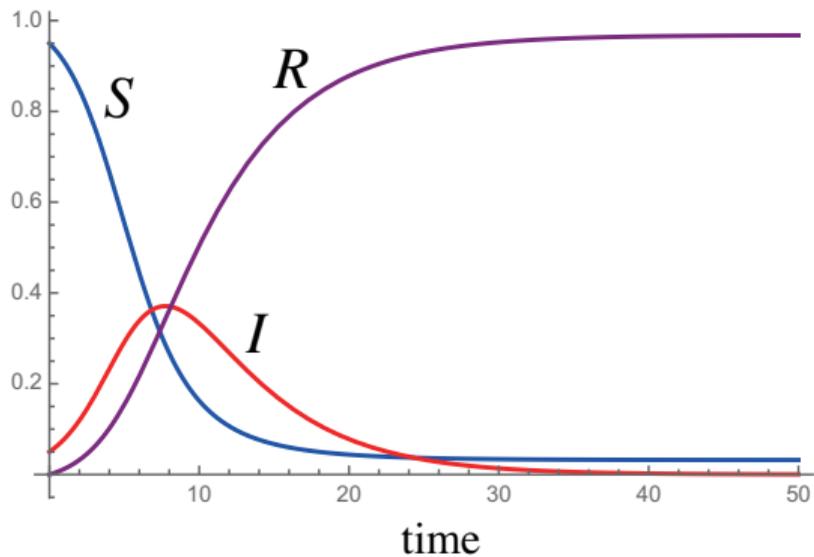
$$\frac{dS(t)}{dt} = -\beta I(t)S(t)$$

$$\frac{dI(t)}{dt} = \beta I(t)S(t) - qI(t)$$

$$\frac{dR(t)}{dt} = qI(t)$$

# Epidemic dynamics model

## Kermack-McKendrick SIR model



### Essential factors for epidemic dynamics

- **Route of disease transmission;**
- **Public health condition;**
- **Availability of medical services;**
- **Cultural/social customs in daily life;**
- **Social responses originated with cultural/political/economic background.**

## Epidemic dynamics model

Seno, H., *A Primer on Population Dynamics Modeling: Basic Ideas for Mathematical Formulation*, Springer Nature Singapore, Singapore, 2022.

Inaba, H., *Age-Structured Population Dynamics in Demography and Epidemiology*, Springer, Singapore, 2017.

齋藤保久・佐藤一憲・瀬野裕美, 数理生物学講義【展開編】— 数理モデル解析の講究 —, 共立出版, 東京, 2017.

Martcheva, M., *An Introduction to Mathematical Epidemiology*, Texts in Applied Mathematics 61, Springer, New York, 2015.

Diekmann, O., Heesterbeek, H., Britton, T., *Mathematical Tools for Understanding Infectious Disease Dynamics*, Princeton University Press, Princeton, 2013.

日本数理生物学会（編）, 『数』の数理生物学（瀬野裕美 責任編集）, シリーズ数理生物学要論, 第1巻, 共立出版, 東京, 2008.

稲葉寿, 感染症の数理モデル, 培風館, 東京, 2008.



# **Information spread**

## Information spread

**Rumor, Fake news**

**Fashion, Trend, Vogue**

**Thought, Idea, Belief, Fear, Panic**

**Innovation, Culture, Habit, Language, Dialect**

**Parasite, Disease, Gene**

**etc.**

## Mathematical modeling

**Stochastic process**

**Network dynamics**

**Cellular automaton**

**Reaction-diffusion system**

**Game-theoretic approach**

**etc.**

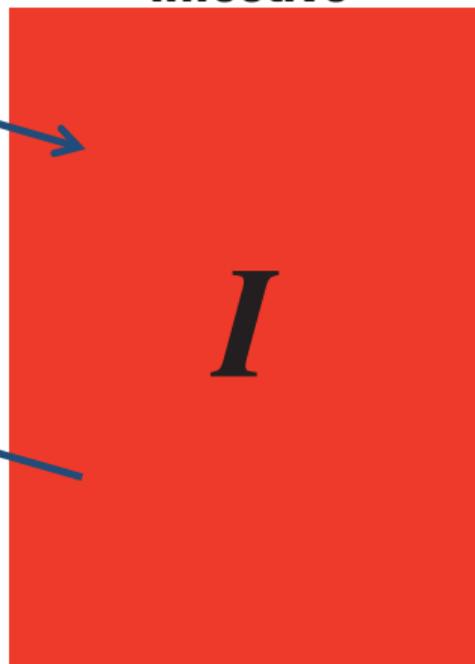
# Information spread dynamics model

$S \rightarrow I \rightarrow R$

Susceptible



Infective



Removed/Recovered



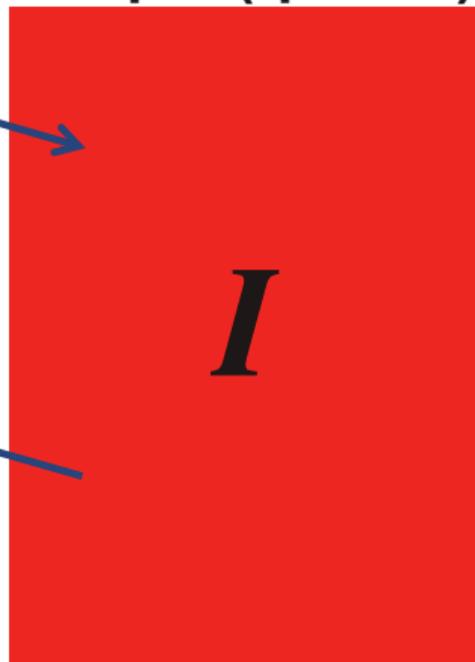
# Information spread dynamics model

$S \rightarrow I \rightarrow R$

non-accepter



accepter (spreader)



unconcerned



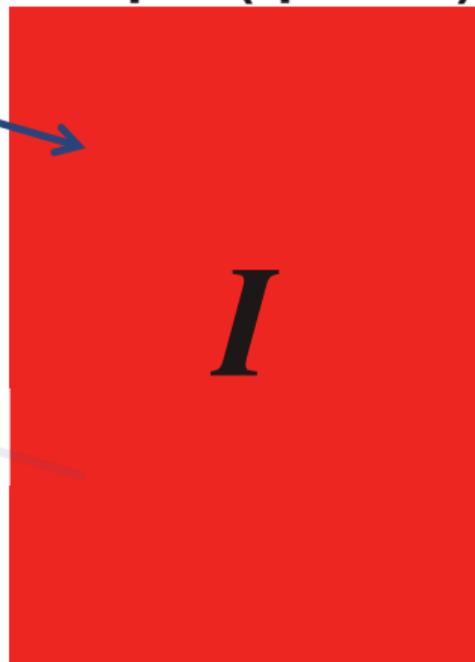
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accepter (spreader)



unconcerned



# **Granovetter's threshold model**

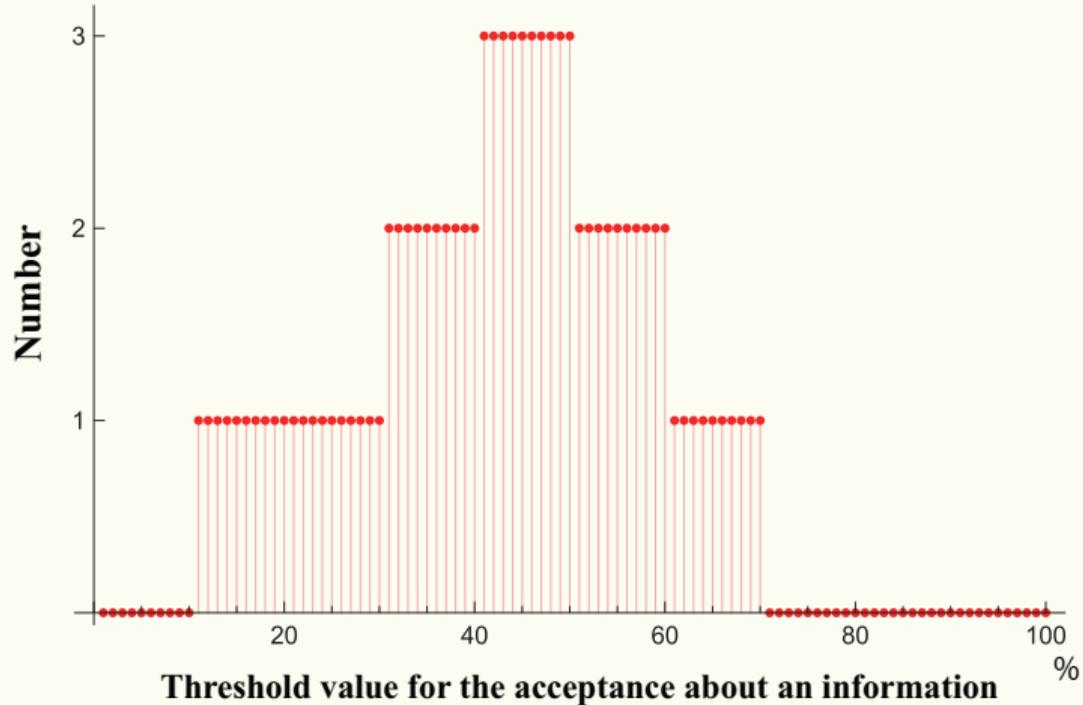
**Granovetter, M. (1978) American Journal of Sociology, 83(6), 1420–1443.**

**Granovetter, M. (1983) Sociological Theory, 1, 201–233.**

**Granovetter, M., Soong, R. (1983) Journal of Mathematical Sociology, 9(3), 165–179.**

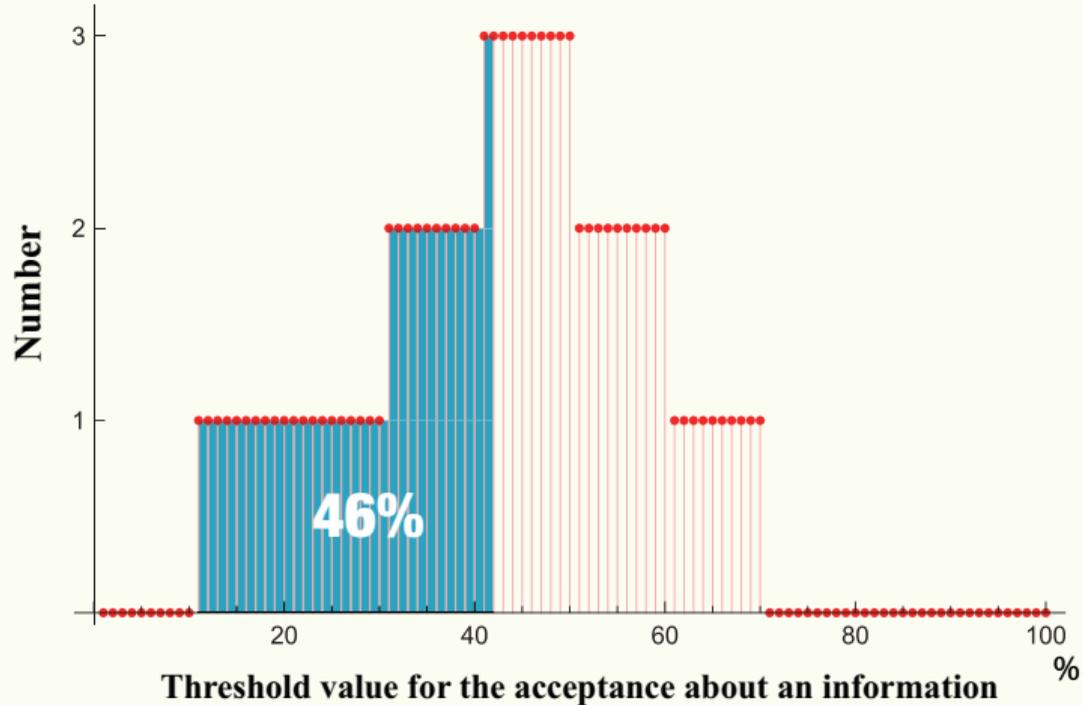
# Granovetter's threshold model

## A threshold distribution



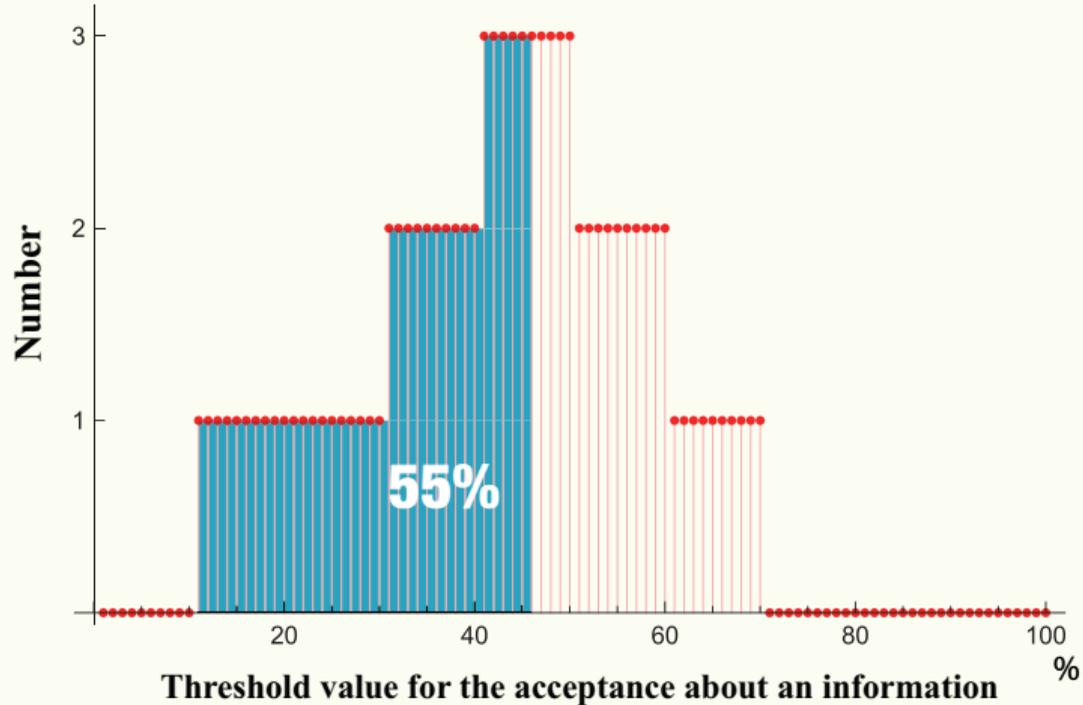
# Granovetter's threshold model

## A threshold distribution



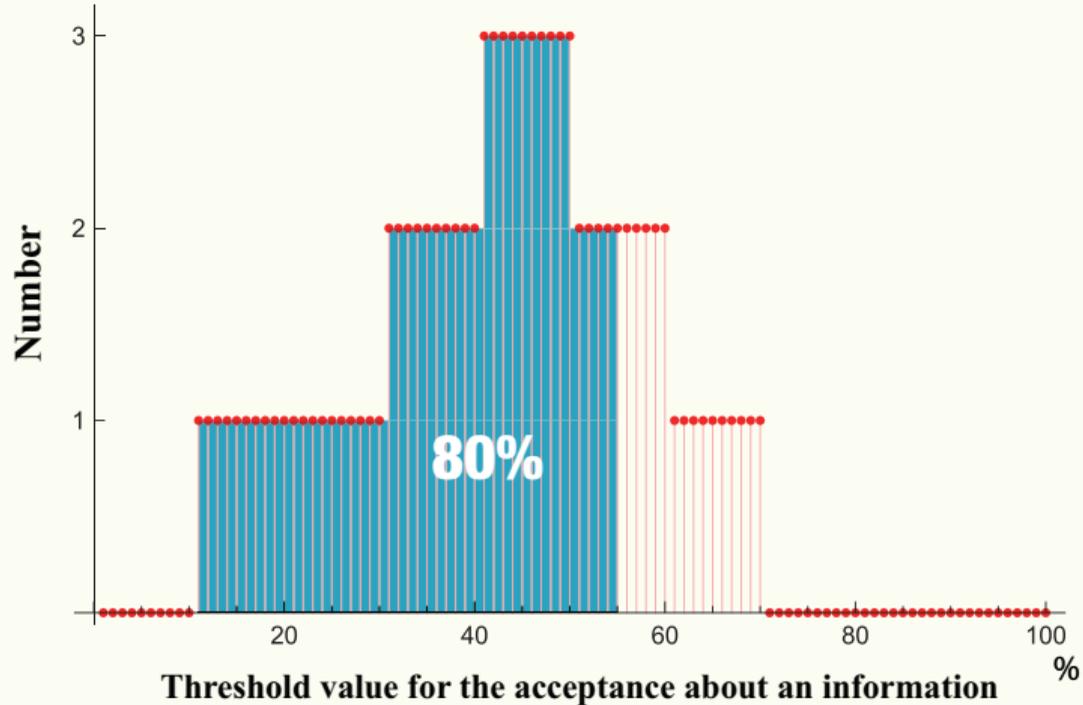
# Granovetter's threshold model

## A threshold distribution



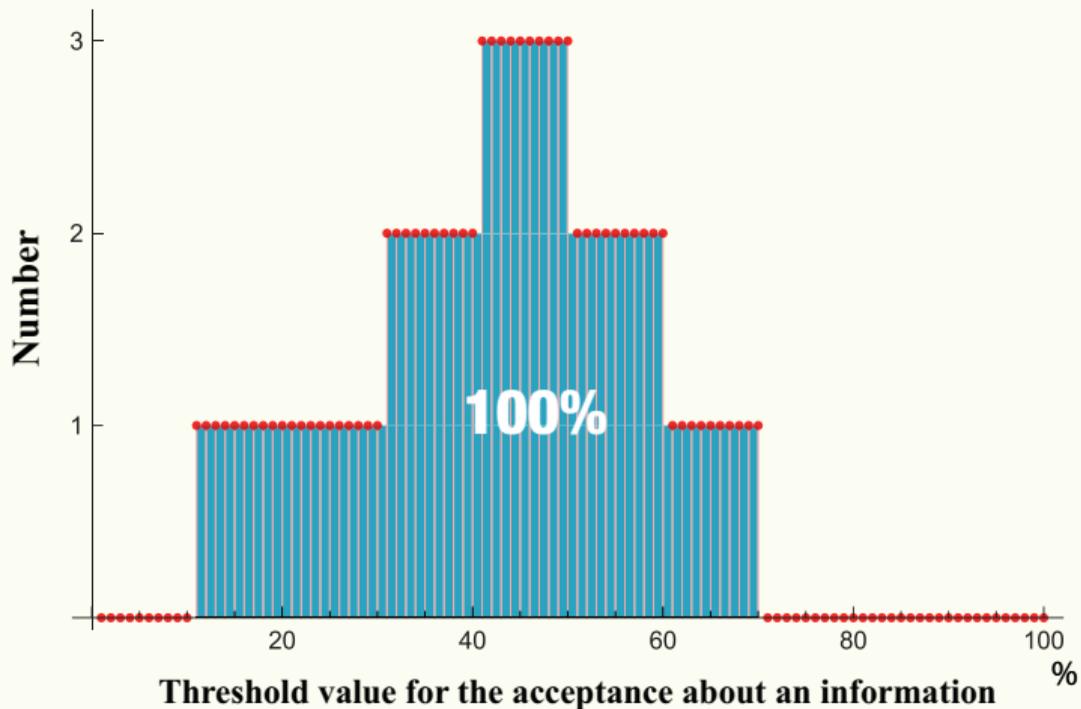
# Granovetter's threshold model

## A threshold distribution



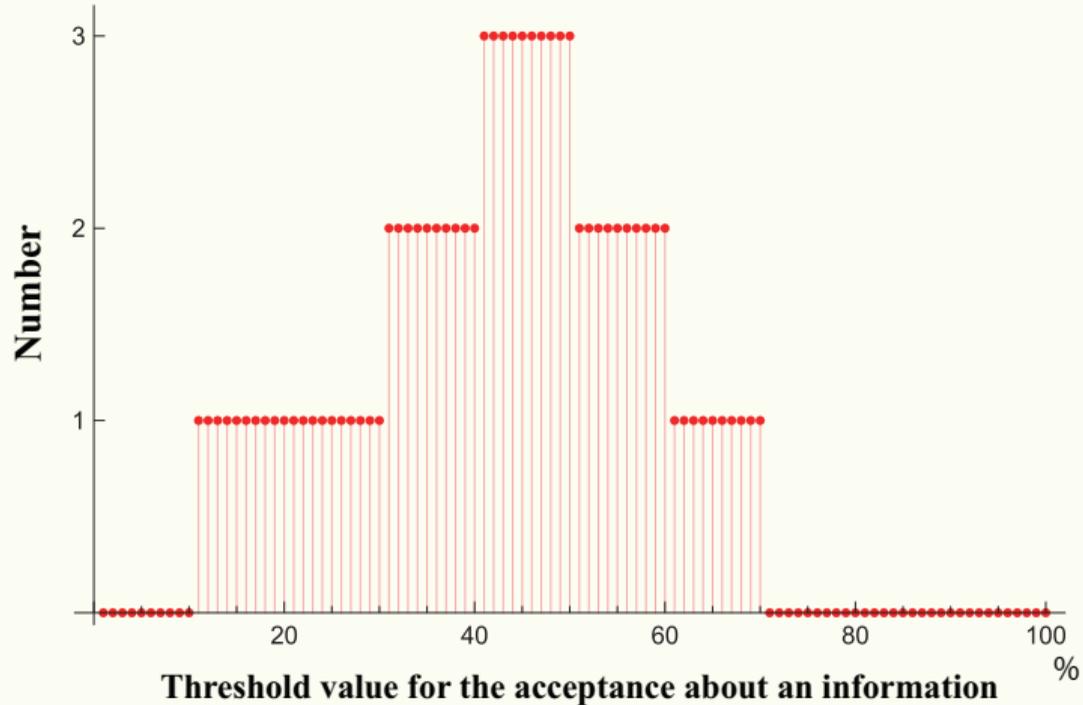
# Granovetter's threshold model

## A threshold distribution



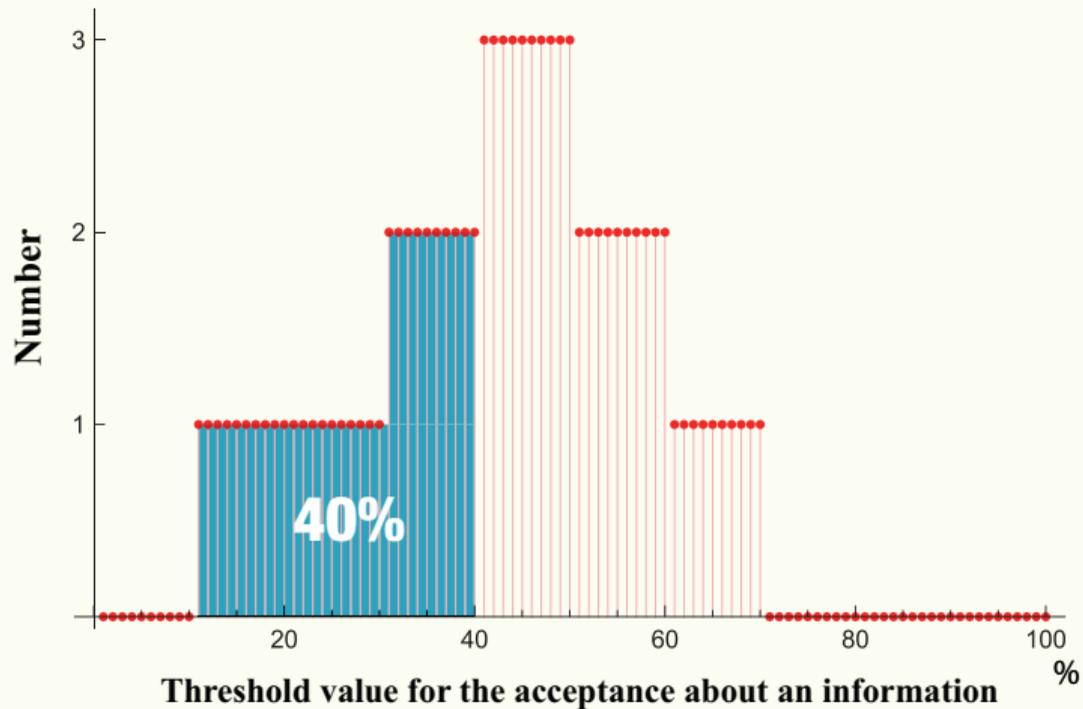
# Granovetter's threshold model

## A threshold distribution



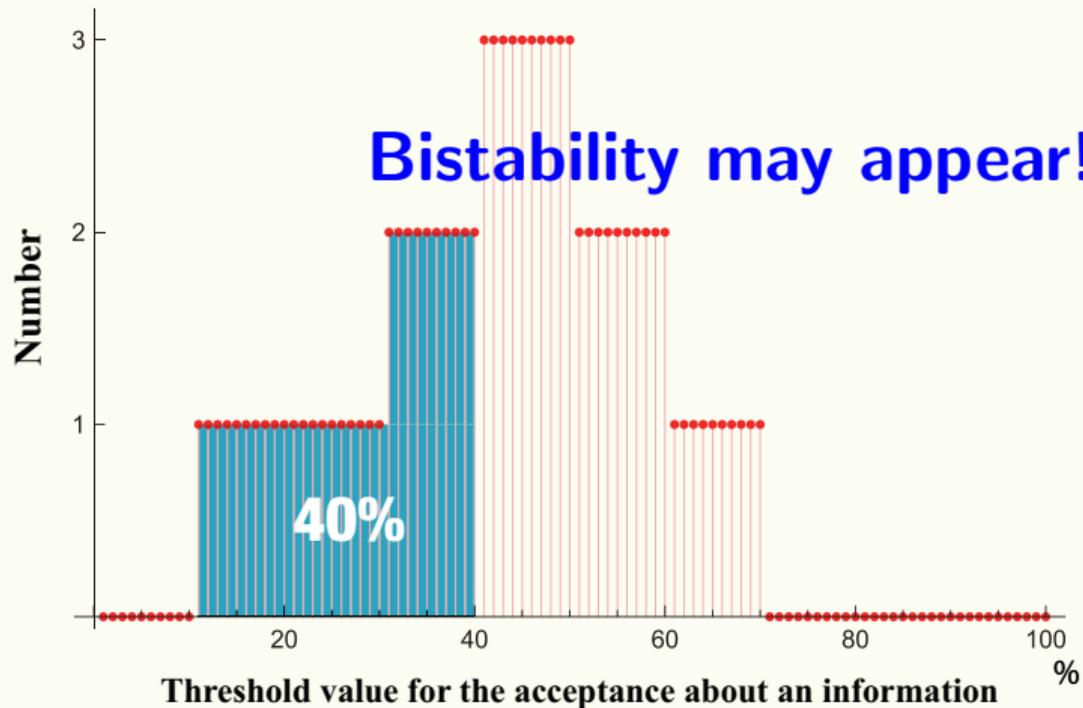
# Granovetter's threshold model

## A threshold distribution



# Granovetter's threshold model

## A threshold distribution

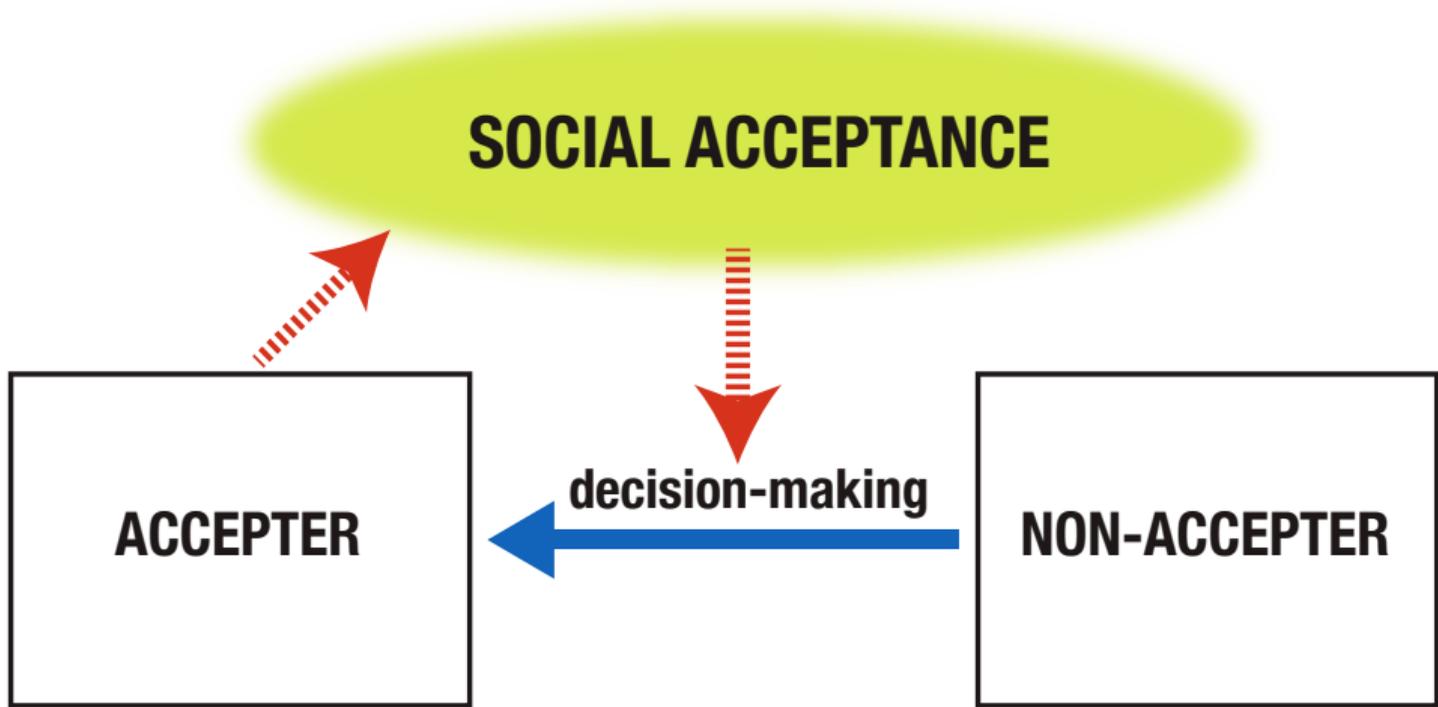


Unclear correspondence to the temporal variation in the number of accepters.



**What population dynamics model is reasonable?**

**How does the heterogeneity of individuality influence the information spread within a population?**



### Rule for the decision-making on accepting the information

$$\begin{cases} \zeta \leq \alpha P \implies \text{The information may be accepted.} \\ \zeta > \alpha P \implies \text{The information is not accepted with} \\ \text{the denial/disregard.} \end{cases}$$

$\zeta$  : **Threshold** value of individual.

$P$  : **Acceptor frequency** within the community.

$\alpha P$  : **Strength of social acceptance** regarding the information, **now assumed to be proportional to the acceptor frequency.**

## Threshold distribution

$$F(x) = \mathbf{Prob}(\zeta \leq x) = \int_{-\infty}^x f(\zeta) d\zeta$$

$$\lim_{x \rightarrow -\infty} F(x) = 0; \quad \lim_{x \rightarrow \infty} F(x) = 1; \quad f(\zeta) \geq 0;$$

$$\bar{\zeta} = \int_{-\infty}^{\infty} \zeta f(\zeta) d\zeta; \quad \sigma^2 = \int_{-\infty}^{\infty} (\zeta - \bar{\zeta})^2 f(\zeta) d\zeta$$

## Threshold distribution

$$F(x) = \mathbf{Prob}(\zeta \leq x) = \int_{-\infty}^x f(\zeta) d\zeta$$

## Mathematical assumption

$$F(x) = \begin{cases} 0 & \text{for } x \leq 0; \\ 1 & \text{for } x \geq \alpha; \end{cases} \quad f(\zeta) = \begin{cases} 0 & \text{for } \zeta \leq 0; \\ \text{non-negative} & \text{for } \zeta \in (0, \alpha); \\ 0 & \text{for } \zeta \geq \alpha. \end{cases}$$

## Initial acceptor frequency

$$P_0 = \int_{-\infty}^{\infty} \varphi_0(\xi) f(\xi) d\xi = \int_0^{\alpha} \varphi_0(\xi) f(\xi) d\xi$$

$$0 \leq \varphi_0(\xi) \leq 1; \quad 0 < P_0 \leq \int_{-\infty}^{\infty} f(\xi) d\xi = \int_0^{\alpha} f(\xi) d\xi = 1$$

**NOTE: They are excepted from the rule of decision-making!**

Initial accepters whose thresholds are BEYOND  $\alpha P_t$  at time  $t$

$$N \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi$$

$N$  : Number of individuals in the community.

$P_t$  : Acceptor frequency at time  $t$ .

$\alpha P_t$  : Strength of social acceptance at time  $t$ .

Initial accepters whose thresholds are BEYOND  $\alpha P_t$  at time  $t$

$$N \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi$$

Individuals with the threshold BELOW  $\alpha P_t$  at time  $t$ , except for the initial accepters

$$N \int_0^{\alpha P_t} \{1 - \varphi_0(\xi)\} f(\xi) d\xi$$

Accepters with the threshold BELOW  $\alpha P_t$  at time  $t$  except for the initial accepters

$$N(P_t - P_0)$$

Non-accepters with the threshold BELOW  $\alpha P_t$  at time  $t$

$$\begin{aligned} N \int_0^{\alpha P_t} \{1 - \varphi_0(\xi)\} f(\xi) d\xi - N(P_t - P_0) \\ = NF(\alpha P_t) + N \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi - NP_t \end{aligned}$$

## Population dynamics modeling for information spread

Non-accepters with the threshold BELOW  $\alpha P_t$  at time  $t$

$$NF(\alpha P_t) + N \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi - NP_t$$

New accepters in unit time step

$$NP_{t+1} - NP_t = \gamma B(P_t) \left\{ NF(\alpha P_t) + N \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi - NP_t \right\}$$

$B(P)$  : **Probability** of having the opportunity to make a decision under the given accepter frequency  $P$ , with  $B(0) = 0$ .

$\gamma$  : **Probability** of making the decision to accept the information per opportunity.

### Recurrence relation for the temporal sequence of accepter frequencies

$$P_{t+1} = \{1 - \gamma B(P_t)\}P_t + \gamma B(P_t) \left\{ F(\alpha P_t) + \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi \right\}$$

$$P_0 := \int_{-\infty}^{\infty} \varphi_0(\xi) f(\xi) d\xi = \int_0^{\alpha} \varphi_0(\xi) f(\xi) d\xi$$

### Recurrence relation for the temporal sequence of accepter frequencies

$$P_{t+1} = \{1 - \gamma B(P_t)\}P_t + \gamma B(P_t) \left\{ F(\alpha P_t) + \int_{\alpha P_t}^{\alpha} \varphi_0(\xi) f(\xi) d\xi \right\}$$

### Theorem

The sequence  $\{P_t\}$  monotonically increases and converges to a value  $P^* \in [P_0, 1]$  for any  $P_0 \in (0, 1)$  as  $t \rightarrow \infty$ .

With

the frequency-proportional probability  $B(P_t) = bP_t$  ( $0 < b \leq 1$ ), and uniformly chosen initial accepters with  $\varphi_0(\xi) = \varphi_0$ ,

**Recurrence relation on the temporal sequence of accepter frequency**

$$P_{t+1} = \left[ 1 + \gamma b \{ \varphi_0 - P_t + (1 - \varphi_0) F(\alpha P_t) \} \right] P_t$$

$$P_0 := \int_{-\infty}^{\infty} \varphi_0(\xi) f(\xi) d\xi = \int_{-\infty}^{\infty} \varphi_0 f(\xi) d\xi = \varphi_0 \int_{-\infty}^{\infty} f(\xi) d\xi = \varphi_0$$

### Recurrence relation on the temporal sequence of accepter frequency

$$P_{t+1} = \left[ 1 + \gamma b \{ \varphi_0 - P_t + (1 - \varphi_0) F(\alpha P_t) \} \right] P_t$$

### Lemma (No spread)

If  $P_0 = \varphi_0 \leq \theta_{\text{inf}} := \zeta_{\text{inf}}/\alpha$ , the accepter frequency remains the initial frequency  $P_0$  with no increase at any time step. Otherwise, it temporally increases.

### Lemma (Complete spread)

If  $P_0 = \varphi_0 \geq \theta_{\text{sup}} := \zeta_{\text{sup}}/\alpha$ , the accepter frequency monotonically increases toward 1.

**How does the heterogeneity of individuality influence the information spread within a population?**

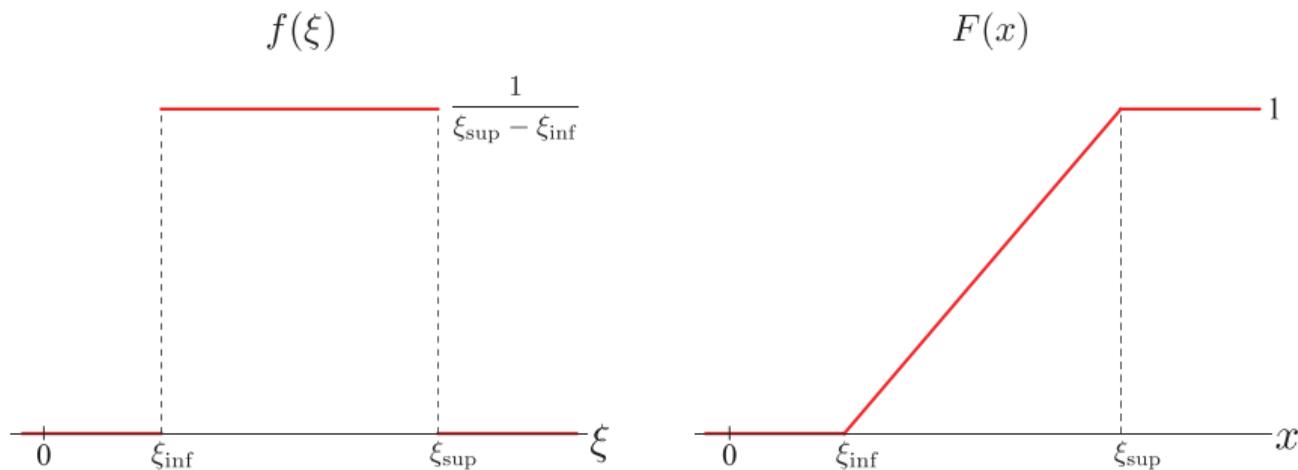
~ How does the dynamical nature of information spread depend on the threshold distribution defined by  $f(\xi)$  ?

## Population dynamics model for information spread

### Recurrence relation on the temporal sequence of accepter frequency

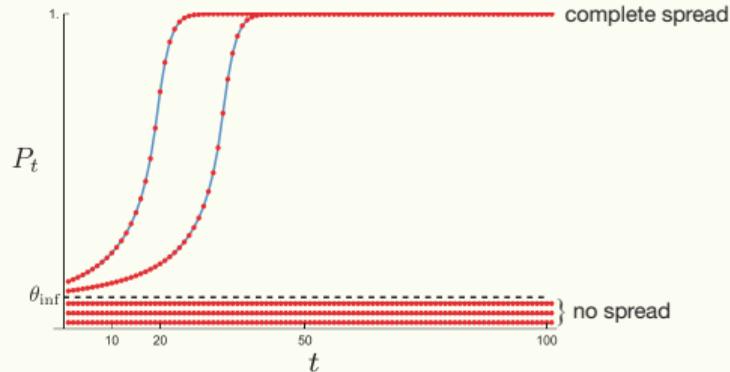
$$P_{t+1} = [1 + \gamma b \{ \varphi_0 - P_t + (1 - \varphi_0) F(\alpha P_t) \}] P_t$$

### Uniform distribution



## Population dynamics model for information spread

For the uniform threshold distribution, the accepter frequency  $P_t$  monotonically approaches 1 as time passes if  $P_0 = \varphi_0 > \theta_{\text{inf}}$ , while it remains the initial frequency,  $P_t \equiv \varphi_0$ , if  $\varphi_0 \leq \theta_{\text{inf}}$ .



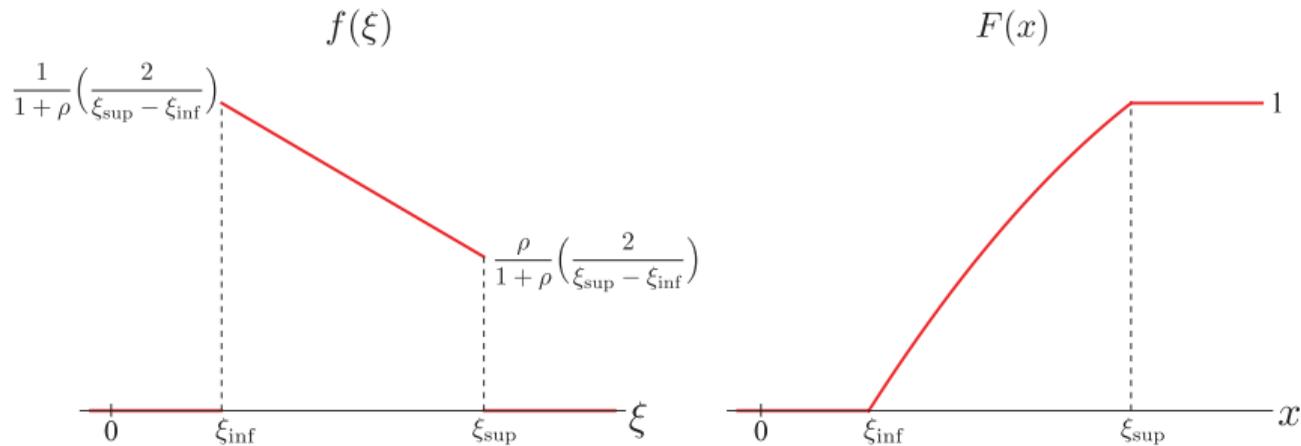
$$P_0 = \varphi_0 = 0.02, 0.05, 0.08, 0.12, 0.15; \alpha = 1.0; \gamma b = 0.5; \zeta_{\text{inf}} = 0.1; \zeta_{\text{sup}} = 0.6; \theta_{\text{inf}} := \zeta_{\text{inf}}/\alpha = 0.1.$$

# Population dynamics model for information spread

Recurrence relation on the temporal sequence of accepter frequency

$$P_{t+1} = [1 + \gamma b \{ \varphi_0 - P_t + (1 - \varphi_0) F(\alpha P_t) \}] P_t$$

A linear example of monotonically decreasing distribution



For the monotonically decreasing threshold distribution, the accepter frequency  $P_t$  monotonically approaches 1 as time passes for the initial accepter frequency such that  $P_0 = \varphi_0 > \theta_{\text{inf}}$ , while it remains the initial frequency,  $P_t \equiv \varphi_0$ , for  $\varphi_0 \leq \theta_{\text{inf}}$ .

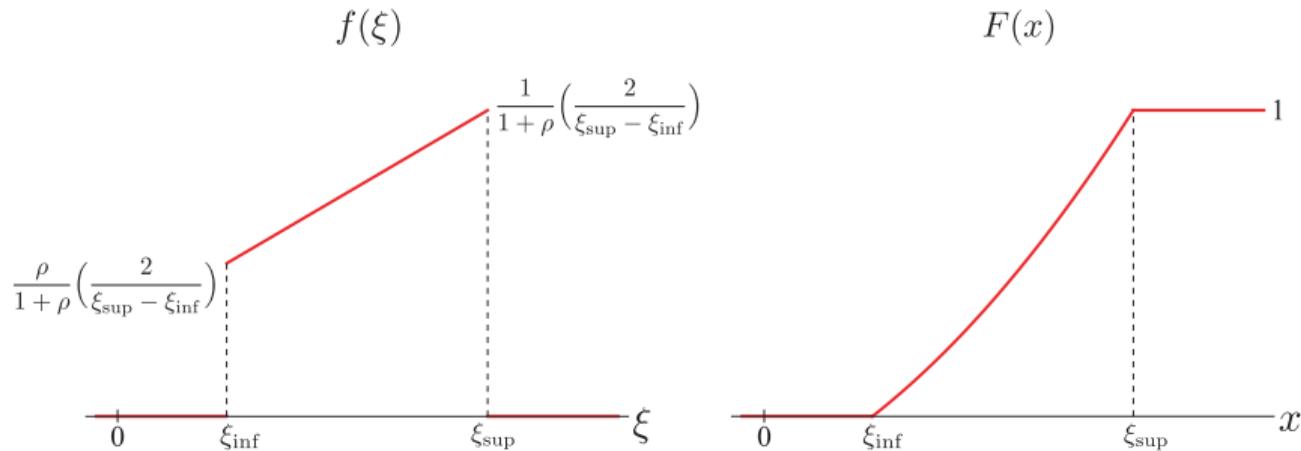
Same as for the uniform threshold distribution!

# Population dynamics model for information spread

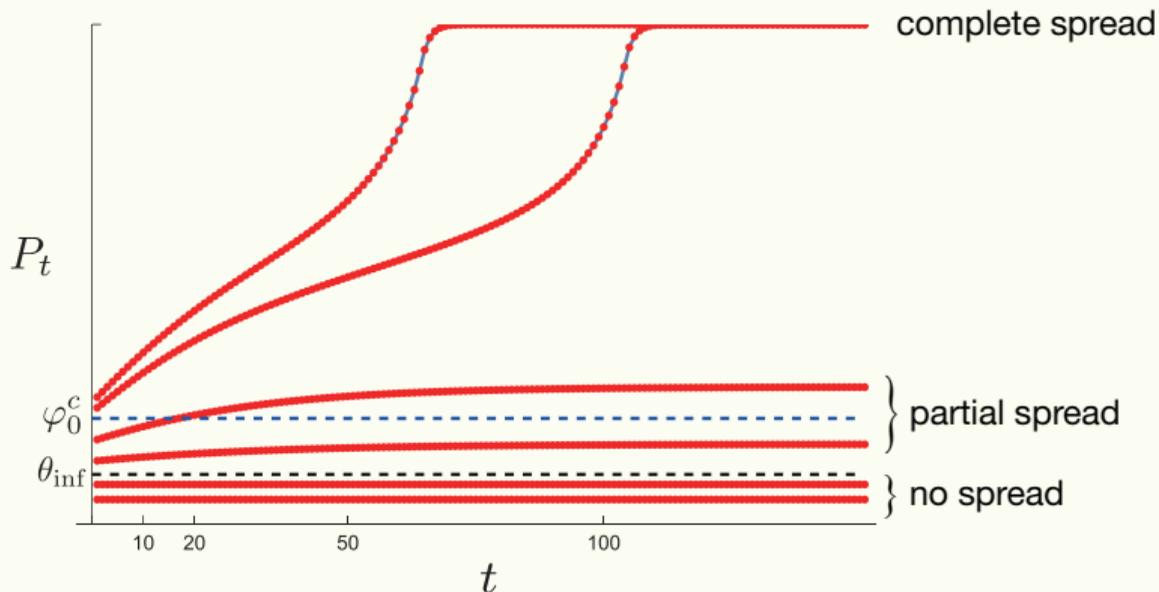
Recurrence relation on the temporal sequence of accepter frequency

$$P_{t+1} = [1 + \gamma b \{ \varphi_0 - P_t + (1 - \varphi_0) F(\alpha P_t) \}] P_t$$

A linear example of monotonically increasing distribution



# Population dynamics model for information spread



$P_0 = \varphi_0 = 0.05, 0.08, 0.127, 0.170, 0.233, 0.255$ ;  $\alpha = 1.0$ ;  $\gamma b = 0.5$ ;  $\zeta_{inf} = \theta_{inf} = 0.1$ ;  $\zeta_{sup} = 0.9$ ;  $\rho = 0.3$ ;  $\varphi_0^c = 0.212$ ;  $\rho_c = 0.8$ .

## Population dynamics model for information spread

**A partial spread of information occurs only when the increasing threshold distribution is sufficiently biased towards the higher value.**

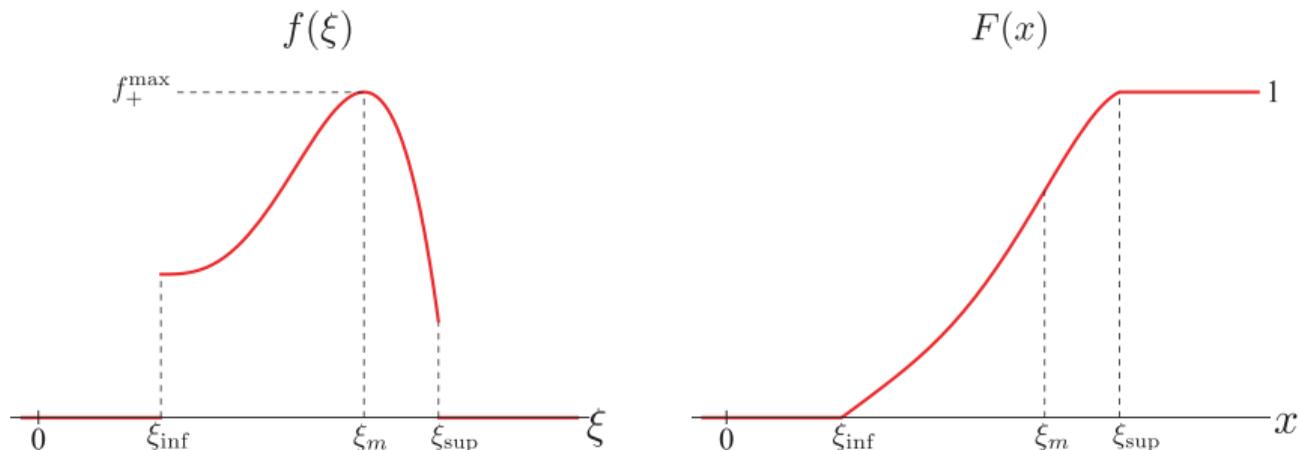
**In a population with a high mean threshold value, and therefore a sufficiently conservative characteristic according to the acceptance of the spreading information, only a partial spread may occur, even if the spread is ongoing.**

## Population dynamics model for information spread

Recurrence relation on the temporal sequence of accepter frequency

$$P_{t+1} = [1 + \gamma b \{ \varphi_0 - P_t + (1 - \varphi_0) F(\alpha P_t) \}] P_t$$

A schematic example of unimodal threshold distribution



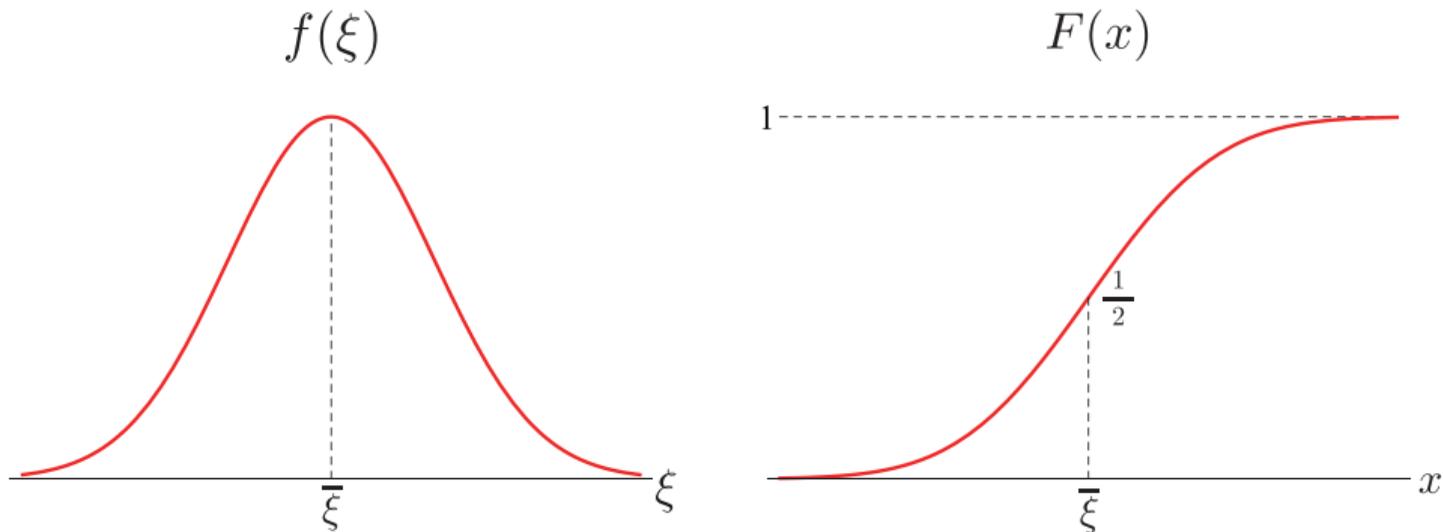
The behavioral characteristics of the acceptor frequency is **qualitatively same** as for the monotonically increasing distribution.

It is implied that the complete spread of an information becomes harder as the unimodal threshold distribution is biased towards the larger value.

For the unimodal threshold distribution that is biased towards the larger value, the complete spread of an information becomes more challenging, while the partial spread becomes relatively more successful when it occurs.

## Population dynamics model for information spread

An extra case: Normal threshold distribution

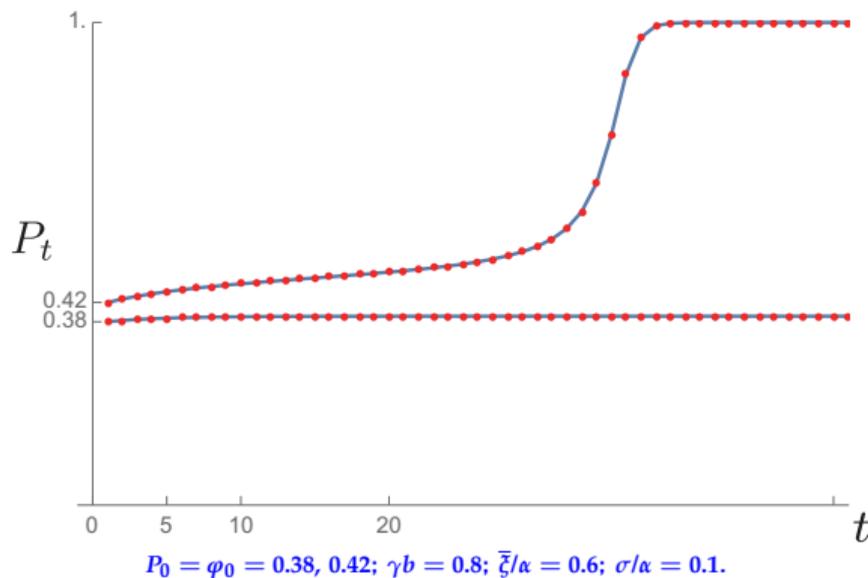


$$f(\xi) := \frac{1}{\sigma\sqrt{2\pi}} e^{-(\xi-\bar{\xi})^2/2\sigma^2};$$

$$F(\alpha P_t) = \int_{-\infty}^{\alpha P_t} f(\xi) d\xi = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{(P_t - \bar{\xi}/\alpha)/(\sigma\sqrt{2}/\alpha)} e^{-x^2} dx$$

## Population dynamics model for information spread

An extra case: Normal threshold distribution



Qualitatively same as the results for the general unimodal threshold distribution.

## Population dynamics model for information spread

For a spreading information to be widely accepted, the threshold distribution must have a sufficiently small mean and a large variance within the community.

Such a community can be considered one that has a high diversity of individuality and readily accepts the information.

In contrast, for a community with a large mean and a small variance in the threshold distribution, meaning many cautious members are hesitant to accept the information, its spread would be unsuccessful.

## Population dynamics model for information spread

Seno, H., Uchioke, R., Dansu, E.J., 2024. A discrete-time population dynamics model for the information spread under the effect of social response, *J. Biol. Syst.* **32**(4): 1379–1426.

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## Negative aspect of information spread

Diffusion of an innovative technology could change people's lifestyle.

May bring problems to our societies,  
like environmental pollution, global warming, drug disasters, etc.

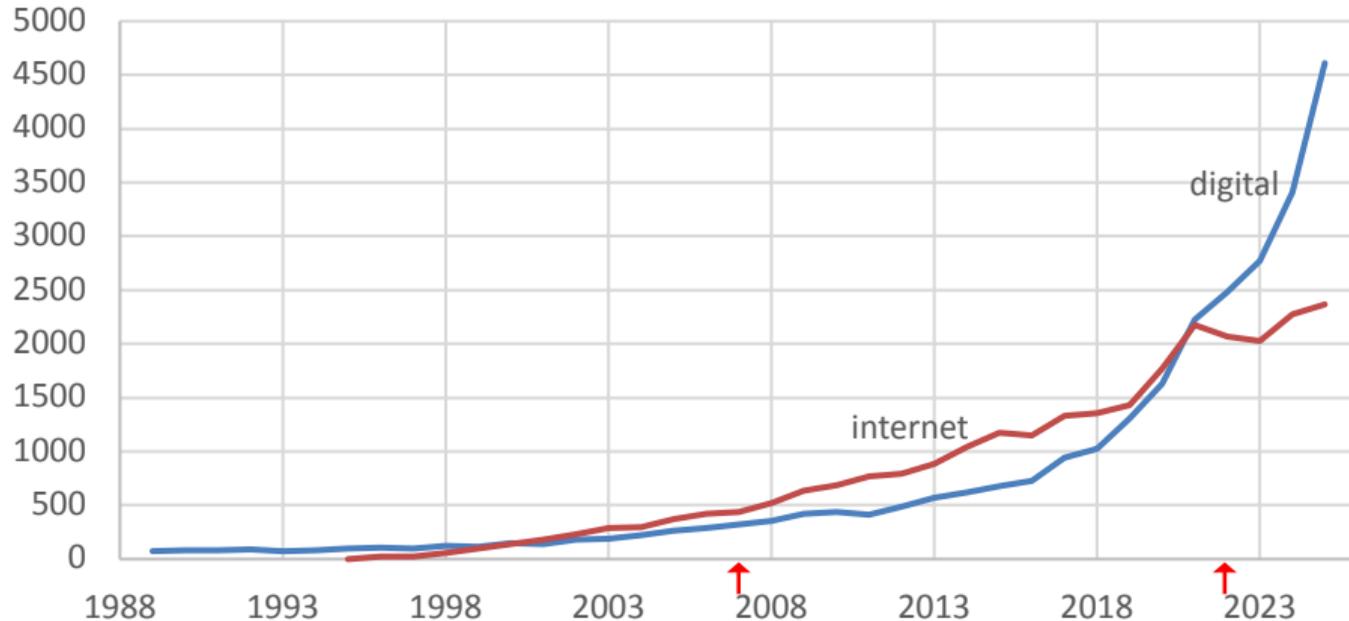
Over the past decade, similar scenarios have emerged and become increasingly serious across various aspects of digital technologies.

e.g., digital dependency, smartphone dependency, internet dependency, internet gaming disorder, SNS dependency, AI dependency.

~ online behavioral addiction

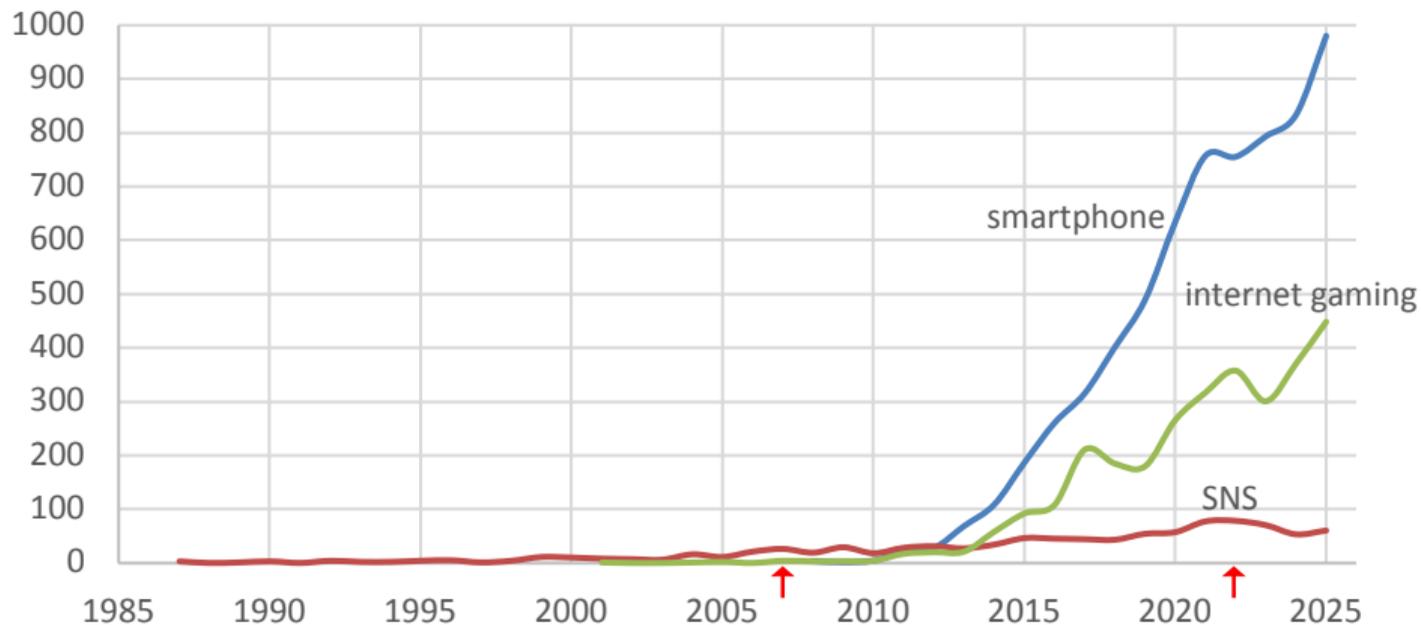
# Online behavioral addiction

Hit counts of Scopus search with “dependency”, “addiction”, or “disorder”

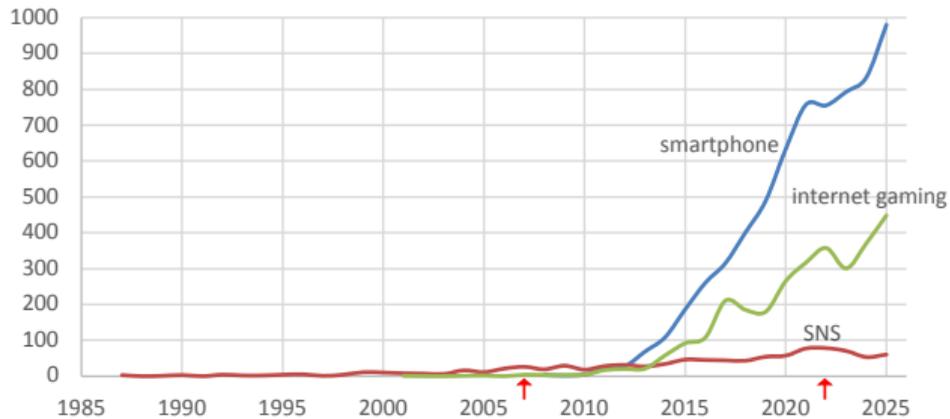


## Online behavioral addiction

Hit counts of Scopus search with “dependency”, “addiction”, or “disorder”



# Internet gaming disorder



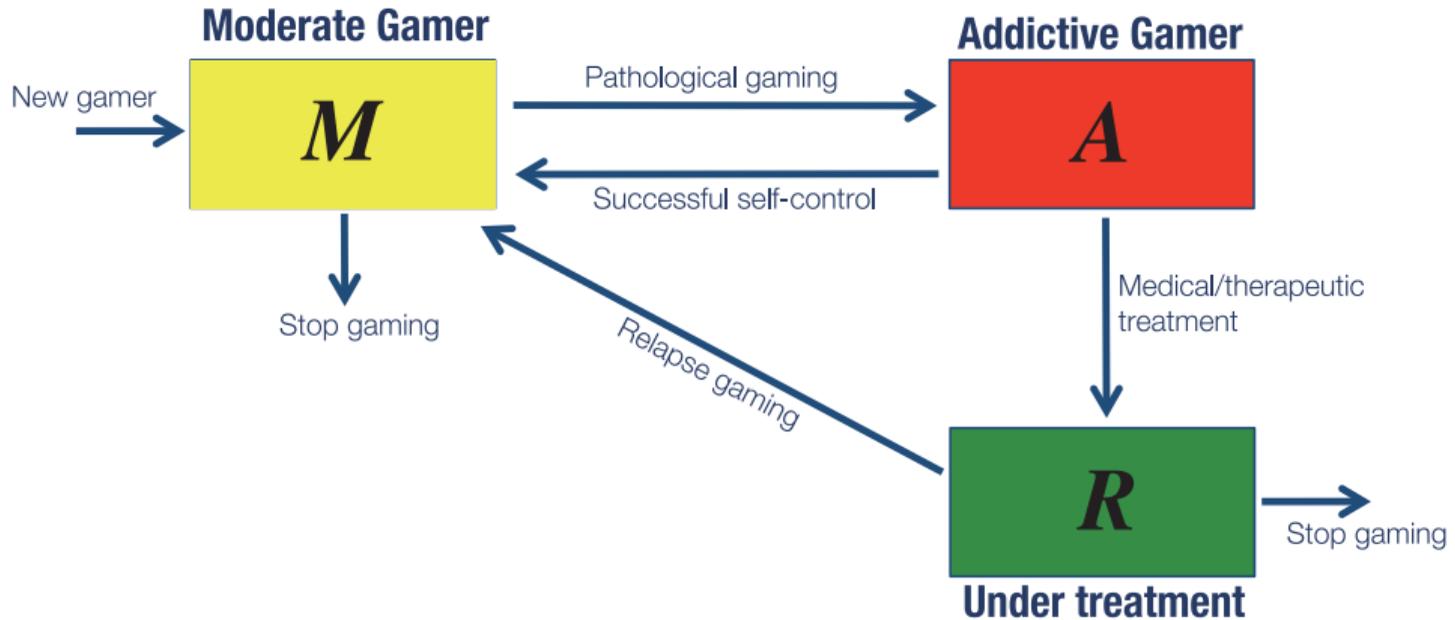
## Online gaming disorder (IGD)

*“Gaming disorder, predominantly online”*

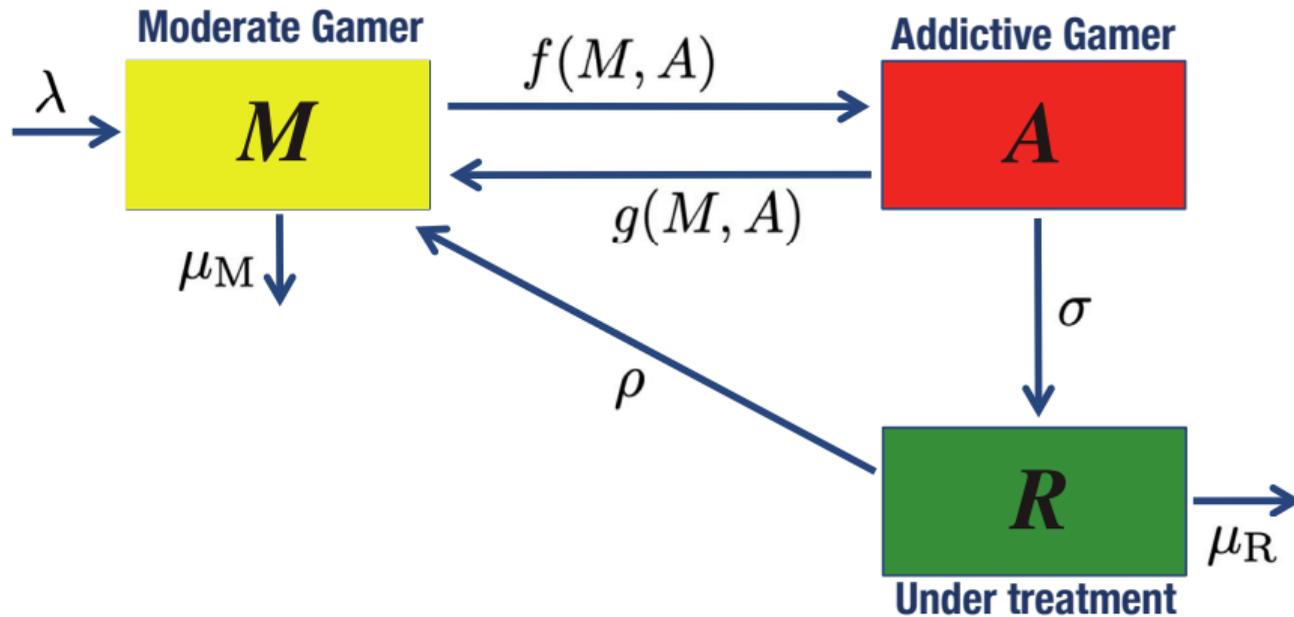
**A pattern of gaming behavior (“digital-gaming” or “video-gaming”) characterized by impaired control over gaming, increasing priority given to gaming over other activities to the extent that gaming takes precedence over other interests and daily activities, and continuation or escalation of gaming despite the occurrence of negative consequences.**

(WHO, ICD-11, 2018. <https://www.who.int/standards/classifications/frequently-asked-questions/gaming-disorder>)

# Population dynamics model for online gaming disorder



## Population dynamics model for online gaming disorder



- Both of  $f(x, y)$  and  $g(x, y)$  are positive and continuous on  $[0, \infty) \times [0, \infty)$ ;
- $f(x, y)$  is increasing in terms of  $x$  and  $y$ ;
- $g(x, y)$  is decreasing in terms of  $x$  and  $y$ .

### Genetic model

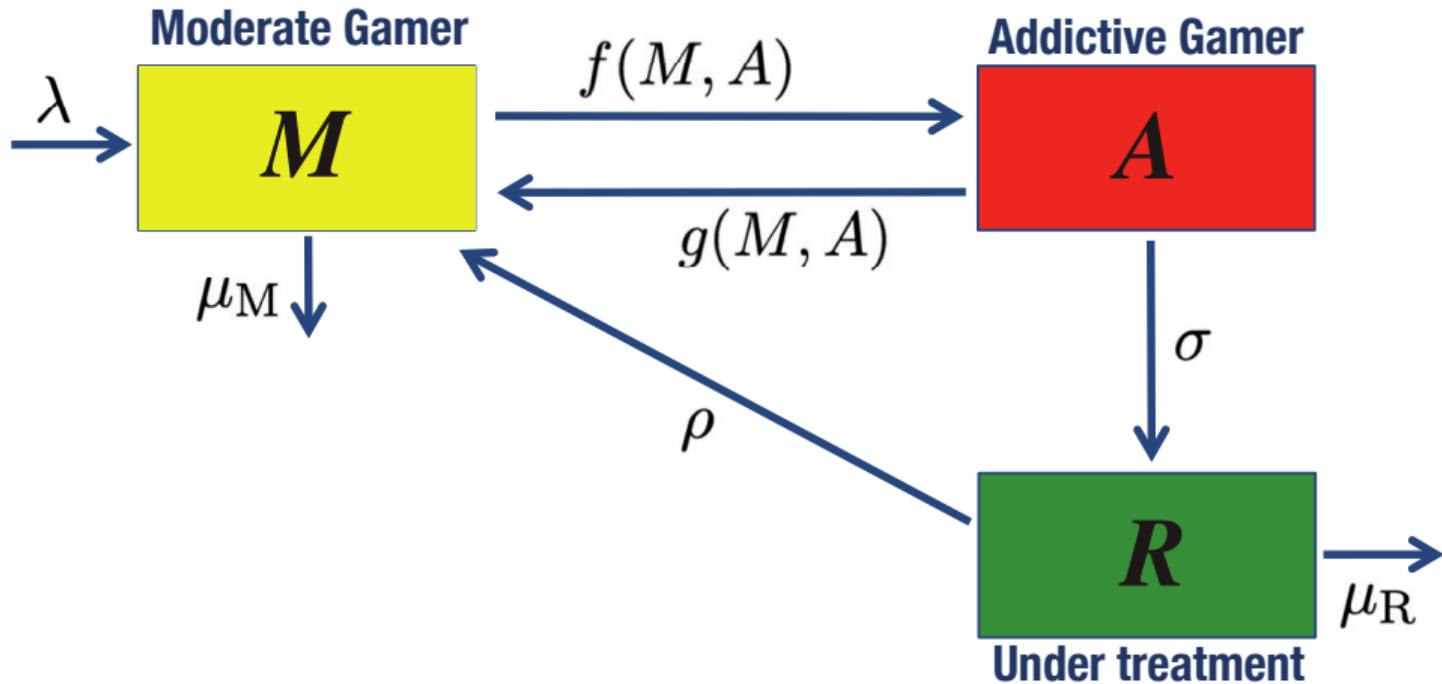
$$\frac{dM}{dt} = \lambda - f(M, A)M + g(M, A)A - \mu_M M + \rho R$$

$$\frac{dA}{dt} = f(M, A)M - g(M, A)A - \sigma A$$

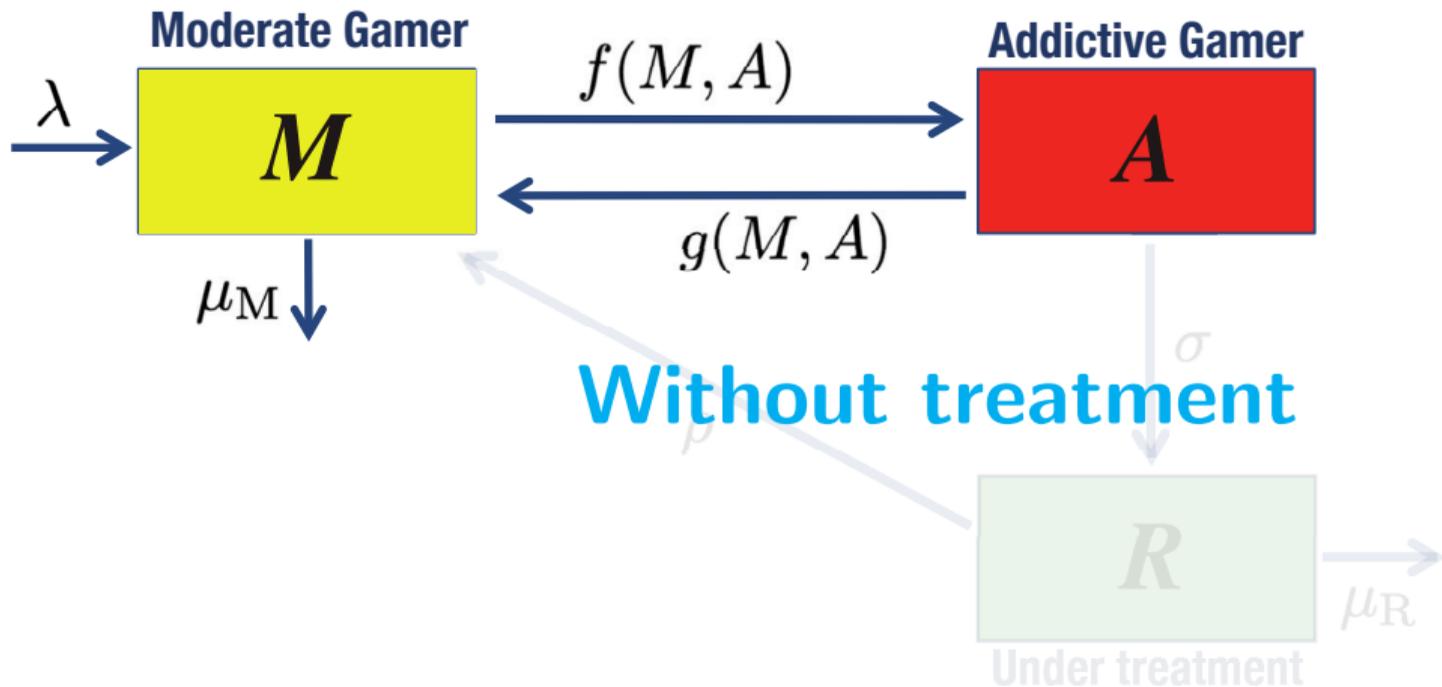
$$\frac{dR}{dt} = \sigma A - \rho R - \mu_R R$$

- Both of  $f(x, y)$  and  $g(x, y)$  are positive and continuous on  $[0, \infty) \times [0, \infty)$ ;
- $f(x, y)$  is increasing in terms of  $x$  and  $y$ ;
- $g(x, y)$  is decreasing in terms of  $x$  and  $y$ .

## Population dynamics model for online gaming disorder



## Population dynamics model for online gaming disorder



### Model without treatment

$$\frac{dM}{dt} = \lambda - f(M, A)M + g(M, A)A - \mu_M M + \rho R$$

$$\frac{dA}{dt} = f(M, A)M - g(M, A)A - \sigma A$$

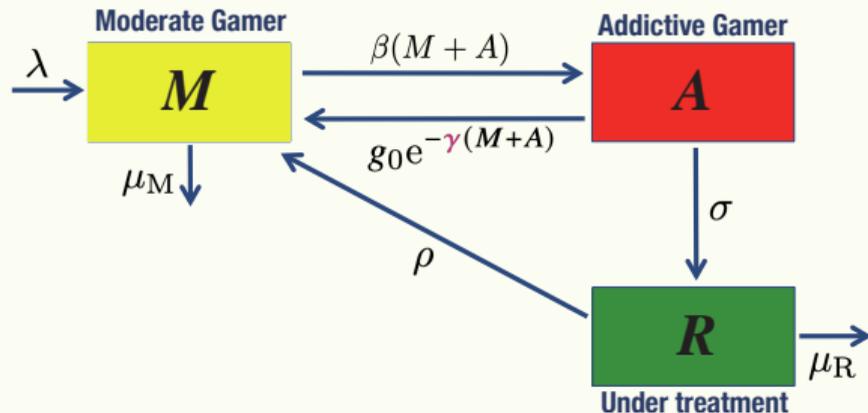
$$\frac{dR}{dt} = \sigma A - \rho R - \mu_R R$$

- Both of  $f(x, y)$  and  $g(x, y)$  are positive and continuous on  $[0, \infty) \times [0, \infty)$ ;
- $f(x, y)$  is increasing in terms of  $x$  and  $y$ ;
- $g(x, y)$  is decreasing in terms of  $x$  and  $y$ .

# Population dynamics model for online gaming disorder

## A simple model

$$f(M, A) = \beta(M + A); \quad g(M, A) = g_0 e^{-\gamma(M+A)}$$



$\beta$ : Coefficient of transition to addiction;

$g_0$ : Intrinsic self-recovery rate from addiction;

$\gamma$ : Coefficient of the bond of online social relationship

### A simple model **WITHOUT** treatment

$$\frac{dM}{dt} = \lambda - \beta(M + A)M + g_0 e^{-\gamma(M+A)} A - \mu_M M + \rho R$$

$$\frac{dA}{dt} = \beta(M + A)M - g_0 e^{-\gamma(M+A)} A - \sigma A$$

$$\frac{dR}{dt} = \sigma A - \rho R - \mu_R R$$

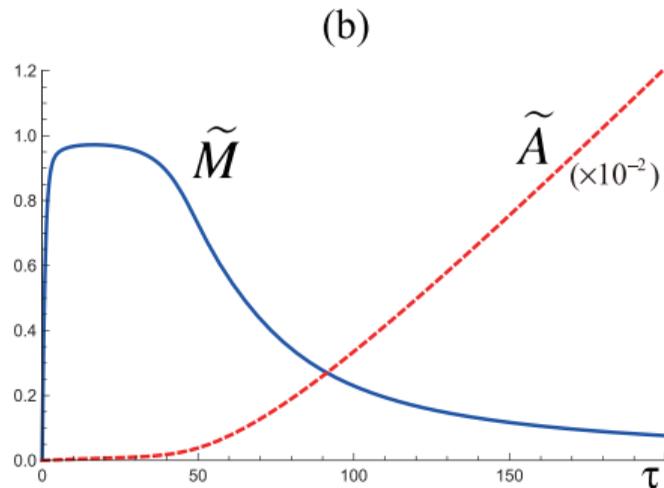
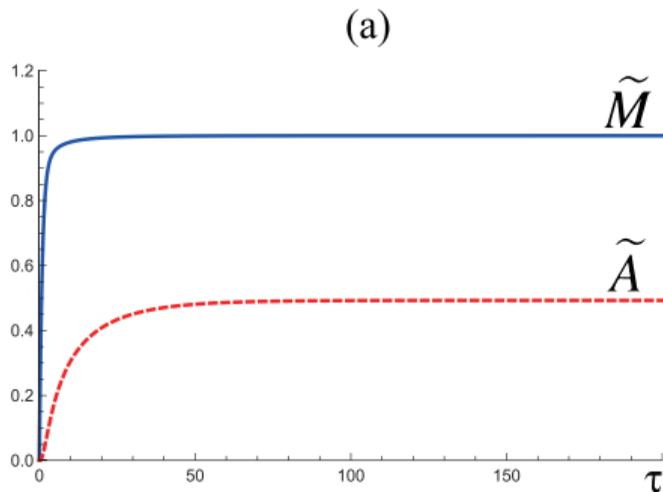
$\beta$ : Coefficient of transition to addiction;

$g_0$ : Intrinsic self-recovery rate from addiction;

$\gamma$ : Coefficient of the bond of online social relationship

# Population dynamics model for online gaming disorder

Temporal variations for the simple model **WITHOUT** treatment



Numerically obtained temporal variations of  $(\tilde{M}, \tilde{A}) = (M/(\lambda\mu_M), A/(\lambda\mu_M))$ : (a)  $\tilde{\gamma} = 0.8$ ; (b)  $\tilde{\gamma} = 1.0$ . Commonly,  $\tau = \mu_M t$ ;  $(\tilde{M}(0), \tilde{A}(0)) = (0.0, 0.0)$ ;  $\tilde{\beta} = 0.1$ ;  $\tilde{g}_0 = 1.0$ ;  $\tilde{\gamma}_c = 0.832529$ .

### A simple model WITH treatment

$$\frac{dM}{dt} = \lambda - \beta(M + A)M + g_0 e^{-\gamma(M+A)} A - \mu_M M + \rho R$$

$$\frac{dA}{dt} = \beta(M + A)M - g_0 e^{-\gamma(M+A)} A - \sigma A$$

$$\frac{dR}{dt} = \sigma A - \rho R - \mu_R R$$

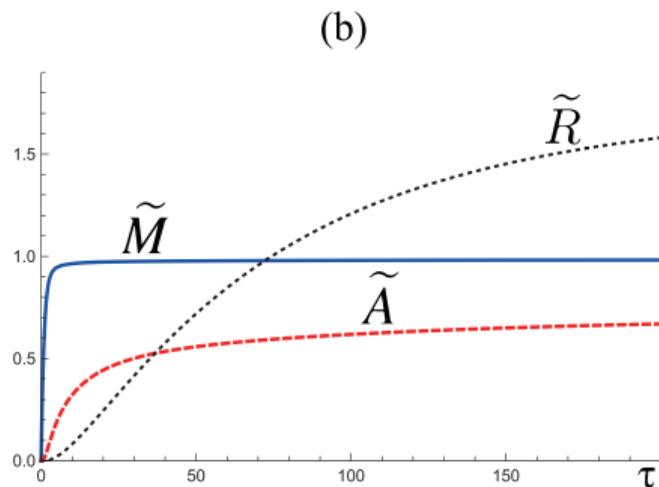
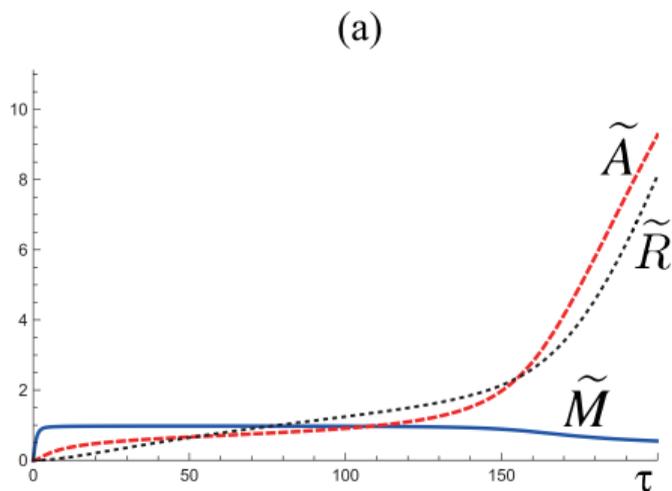
$\beta$ : Coefficient of transition to addiction;

$g_0$ : Intrinsic self-recovery rate from addiction;

$\gamma$ : Coefficient of the bond of online social relationship

# Population dynamics model for online gaming disorder

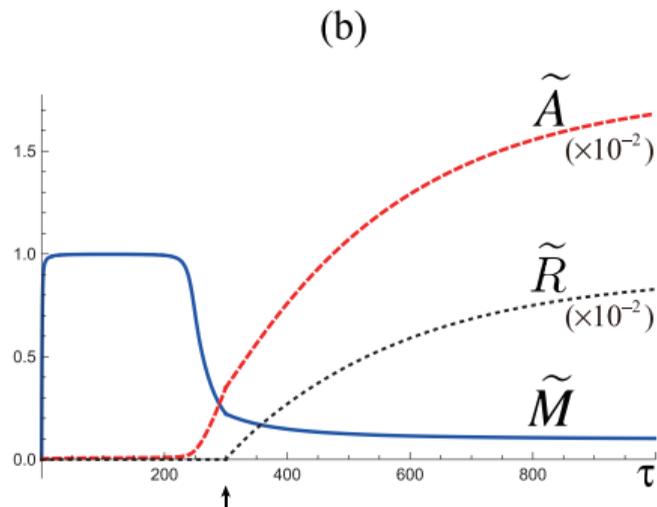
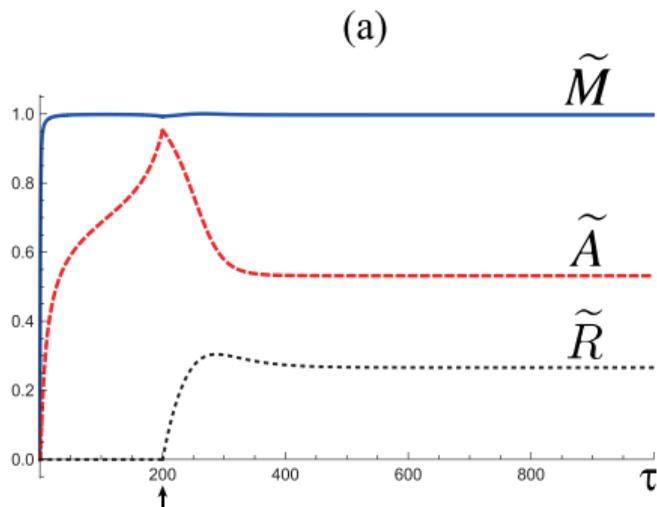
## Temporal variations for the simple model WITH treatment



Numerically obtained temporal variations of  $(\tilde{M}, \tilde{A}, \tilde{R}) = (M/(\lambda/\mu_M), A/(\lambda/\mu_M), R/(\lambda/\mu_M))$ :  
 $\tilde{\sigma} = \sigma/\mu_M =$  (a) 0.04; (b) 0.05. Commonly,  $\tau = \mu_M t$ ;  $(\tilde{M}(0), \tilde{A}(0), \tilde{R}(0)) = (0.0, 0.0, 0.0)$ ;  
 $\tilde{\beta} = (\lambda/\mu_M)\beta/\mu_M = 0.1$ ;  $\tilde{g}_0 = g_0/\mu_M = 1.0$ ;  $\tilde{\gamma} = (\lambda/\mu_M)\gamma = 1.0$ ;  $\tilde{\rho} = \rho/\mu_M = 0.01$ ;  
 $\tilde{\mu} = \mu_R/\mu_M = 0.01$ ;  $\tilde{\gamma}_c = 0.832529$ ;  $\tilde{\sigma}_c = 0.0497871$ .

# Population dynamics model for online gaming disorder

Temporal variations for the simple model "WITHOUT  $\rightarrow$  WITH" treatment



Numerically obtained temporal variations of  $(\tilde{M}, \tilde{A}, \tilde{R}) = (M/(\lambda\mu_M), A/(\lambda\mu_M), R/(\lambda\mu_M))$  with a moment  $\tau = \mu_M t = \tau_1$  before which there is no treatment and at which the treatment starts with  $\tilde{\sigma} = 0.01$ :  $\tau_1 =$  (a) 200; (b) 300. Commonly,  $(\tilde{M}(0), \tilde{A}(0), \tilde{R}(0)) = (0.0, 0.0, 0.0)$ ;  $\tilde{\beta} = (\lambda/\mu_M)\beta/\mu_M = 0.1$ ;  $\tilde{g}_0 = g_0/\mu_M = 1.0$ ;  $\tilde{\gamma} = (\lambda/\mu_M)\gamma = 0.84$ ;  $\tilde{\rho} = \rho/\mu_M = 0.01$ ;  $\tilde{\mu} = \mu_R/\mu_M = 0.01$ ; ;  $\alpha_c = 0.704641$  ;  $\tilde{\gamma}_c = 0.832529$ .

## Population dynamics model for online gaming disorder

When the bond of online social relationships is weak, the population of addictive gamers remains relatively low. However, once the bond becomes sufficiently strong, the number of addictive gamers can show a sudden surge.

Only a treatment operation with a sufficiently high efficiency would be successful in suppressing the population size of addictive gamers at a certain level.

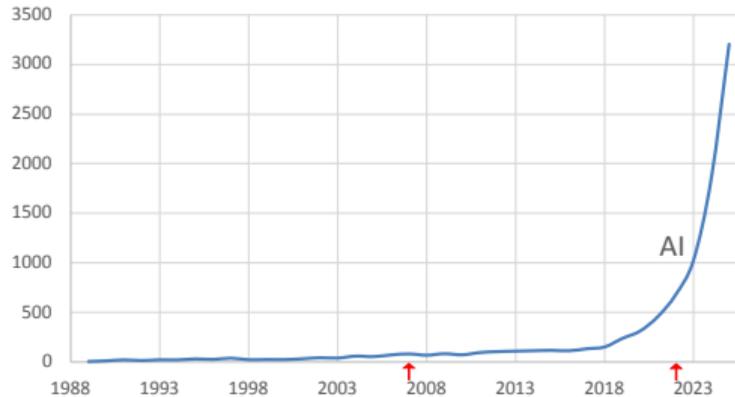
The effectiveness of a treatment operation heavily relies on the inherent social reinforcements provided by online gaming. The stronger social reinforcements make the treatment operation more challenging.

The outcome of a treatment operation could significantly depend on the timing of its commencement.

**REFERENCE:** Seno, H., 2021. A mathematical model of population dynamics about the internet gaming addiction, *Nonlinear Analysis: Modelling and Control* **26**(5): 861–883.

## ON THE OTHER HAND, TODAY

we have already been aware of the emergence of a new type of internet addiction stemming from **the dependency on generative AI**.



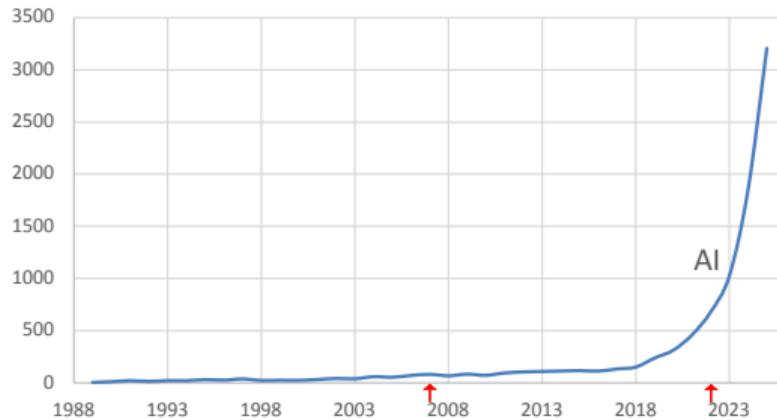
### ON THE OTHER HAND, TODAY

we have already been aware of the emergence of a new type of internet addiction stemming from **the dependency on generative AI**.

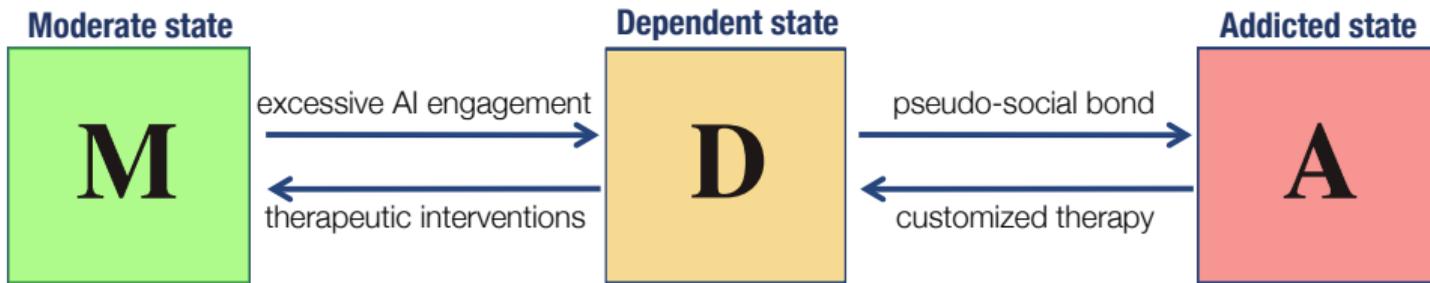
AI dependency has a distinct nature compared to online gaming disorders, especially in terms of its population dynamics. It is triggered by **a pseudo-social bond with a virtual personal relationship created by AI**, which is actually independent of the other users.

**We should recognize its high potential to spread widely across our society, while acknowledging that AI usage is certainly beneficial for a variety of social activities.**

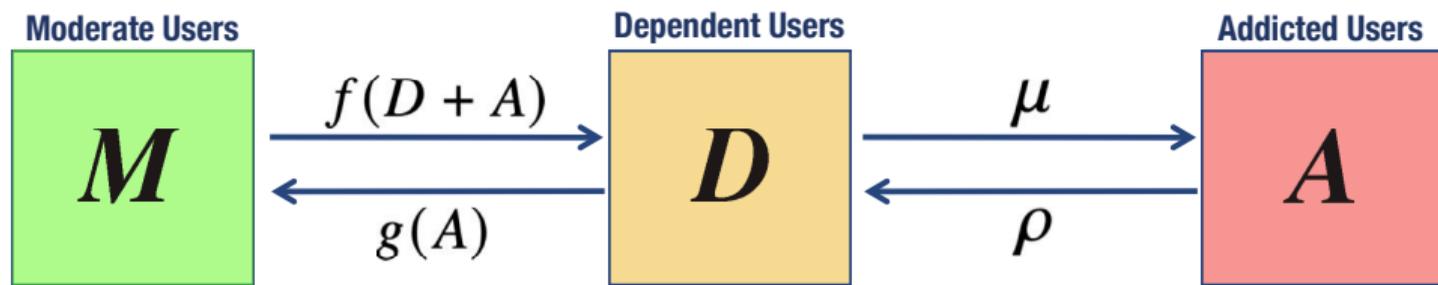
# AI dependency



# Population dynamics model for AI dependency



## Population dynamics model for AI dependency



$f$ : Transition rate from moderate to dependent state;

$g$ : Transition rate from dependent to moderate state;

Both of  $f(x)$  and  $g(x)$  are positive, differentiable, and monotonically increasing for  $x > 0$ , satisfying that  $f(0) = f_0 > 0$  and  $g(0) = g_0 > 0$ .

$\mu$ : Transition rate from dependent to addicted state;

$\rho$ : Transition rate from addicted to dependent state.

$M(t) + D(t) + A(t) = N$  (a positive constant) for any  $t \geq 0$ .

## Population dynamics model for AI dependency

### Genetic model

$$\frac{dM}{dt} = -f(D + A)M + g(A)D$$

$$\frac{dD}{dt} = f(D + A)M - g(A)D - \mu D + \rho A$$

$$\frac{dA}{dt} = \mu D - \rho A$$

**$f$ :** Transition rate from moderate to dependent state;

**$g$ :** Transition rate from dependent to moderate state;

Both of  $f(x)$  and  $g(x)$  are positive, differentiable, and monotonically increasing for  $x > 0$ , satisfying that  $f(0) = f_0 > 0$  and  $g(0) = g_0 > 0$ .

**$\mu$ :** Transition rate from dependent to addicted state;

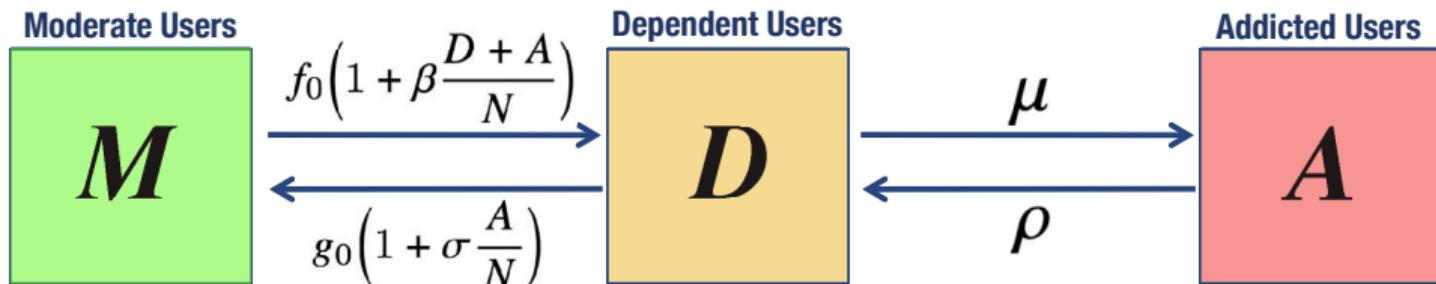
**$\rho$ :** Transition rate from addicted to dependent state.

$M(t) + D(t) + A(t) = N$  (a positive constant) for any  $t \geq 0$ .

## Population dynamics model for AI dependency

### A simple model

$$f(D + A) = f_0 \left( 1 + \beta \frac{D + A}{N} \right); \quad g(A) = g_0 \left( 1 + \sigma \frac{A}{N} \right)$$



- $f_0$ : Intrinsic likelihood to become dependent on AI;
- $\beta$ : Coefficient of enhancement to AI dependency;
- $g_0$ : User's inherent tendency to overcome AI dependency;
- $\sigma$ : Coefficient of enhancement to the recovery from AI dependency.

## Population dynamics model for AI dependency

### A simple model

$$\frac{dM}{dt} = -f_0 \left( 1 + \beta \frac{D + A}{N} \right) M + g_0 \left( 1 + \sigma \frac{A}{N} \right) D$$

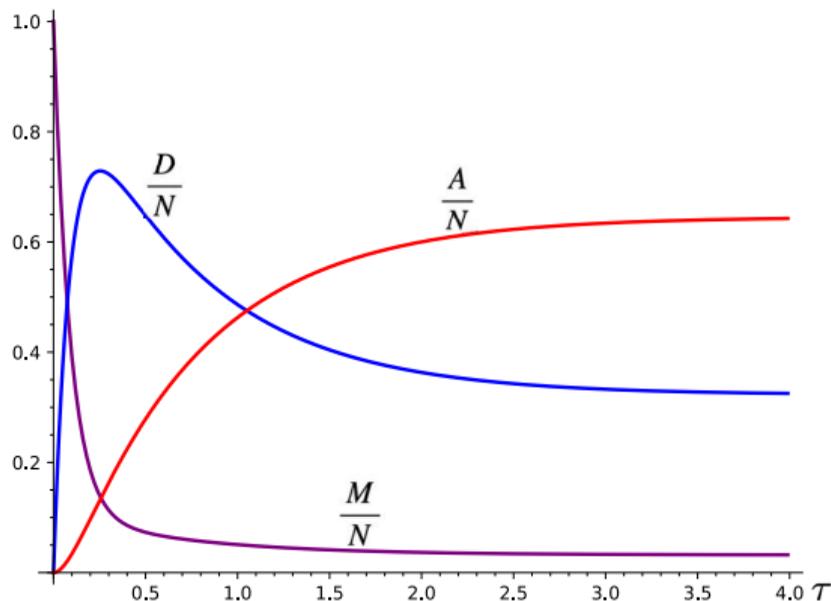
$$\frac{dD}{dt} = f_0 \left( 1 + \beta \frac{D + A}{N} \right) M - g_0 \left( 1 + \sigma \frac{A}{N} \right) D - \mu D + \rho A$$

$$\frac{dA}{dt} = \mu D - \rho A$$

- $f_0$ : Intrinsic likelihood to become dependent on AI;
- $\beta$ : Coefficient of enhancement to AI dependency;
- $g_0$ : User's inherent tendency to overcome AI dependency;
- $\sigma$ : Coefficient of enhancement to the recovery from AI dependency.

## Population dynamics model for AI dependency

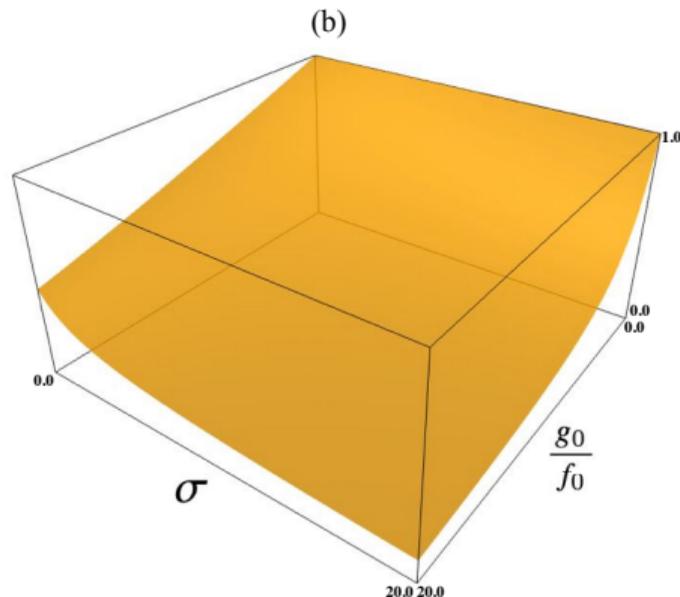
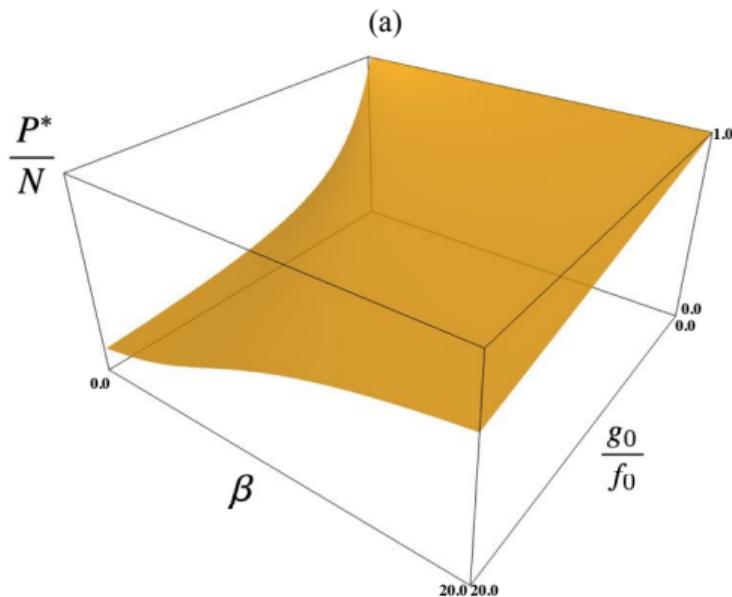
### Temporal variation for the simple model



Temporal variation of  $(\frac{M}{N}, \frac{D}{N}, \frac{A}{N})$ . Numerically drawn with  $\tau = \mu t$ ;  $\phi_0 = f_0/\mu = 10.0$ ;  $\beta = 0.01$ ;  $r = \rho/\mu = 0.5$ ;  $\gamma_0 = g_0/\mu = 1.0$ ;  $\sigma = 0.01$ ;  $(\frac{M(0)}{N}, \frac{D(0)}{N}, \frac{A(0)}{N}) = (1.0, 0.0, 0.0)$ .

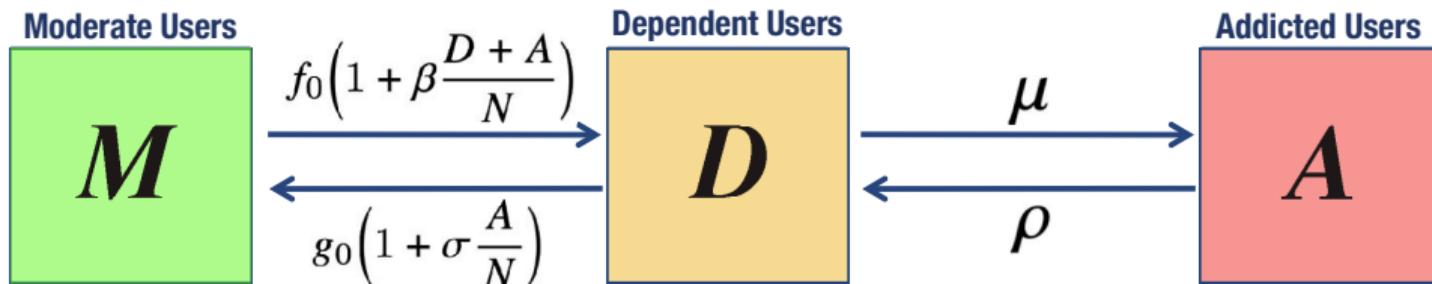
# Population dynamics model for AI dependency

$(\beta, \sigma, \frac{g_0}{f_0})$ -dependence of  $\frac{D^*+A^*}{N}$  for the simple model



Numerically drawn with  $r = \rho/\mu = 0.5$ , and (a)  $\sigma = 0.0$ ; (b)  $\beta = 10.0$ .

## Population dynamics model for AI dependency



Given the strong attraction to AI usage, it is imperative that we conduct researches and make preparations to mitigate the rise in AI dependency.

**REFERENCE:** Seno, H., 2026. A population dynamics model for the rampancy of AI dependency, in preparation.



# Epilogue



## Distinct four logistic equations

$$[L-1] \quad \frac{dN(t)}{dt} = \{r_0 - \beta N(t)\} N(t)$$

$$[L-2] \quad \frac{dN(t)}{dt} = r_0 \left\{ 1 - \frac{N(t)}{K} \right\} N(t)$$

$$[L-3] \quad \frac{dN(t)}{dt} = r_0 N(t) - b \{N(t)\}^2$$

$$[L-4] \quad \frac{dN(t)}{dt} = \{r_0 - \beta N(t)\} N(t) - b \{N(t)\}^2$$

# Epilogue

1985

1990

1995

2000

2005

2010

2015

2020

フラクタル  
fractal

自己組織化  
self-organization

成長ネットワーク  
growing network

不均質環境  
environmental  
heterogeneity

食物連鎖構造  
foodweb structure

Greatly appreciate your collaboration,  
cooperation, and support until today!

絶滅過程  
extinction process

外来種侵入  
alien species invasion

個体群拡散  
population dispersal

ベイツ型擬態  
Batesian mimicry

生態的間接効果  
ecological indirect effect

採餌戦略  
foraging strategy

家系存続  
family persistence

総合的害虫防除  
integrated pest control

繁殖戦略  
reproduction strategy

ミーム継承  
meme inheritance

生活史戦略  
life history strategy

社会応答  
social response

情報伝播  
information spread

感染症伝染ダイナミクス  
epidemic population dynamics

オンライン行動依存  
online behavioral addiction