Modeling Narrative Influences

Team 1085

Ziwen Zhu, Tuyen Truong, Joseph Menzo

Department of Mathematics
University of Florida

March 11, 2025

Definitions

- **The Two Movements:**
- **Positive Messaging** (persuade to get vaccinated)- emphasizes the risks of non-vaccination. Such things can include harm to self and others, exacerbated flu symptoms, less chances of developing flu-like symptoms, less chances of hospitalization, etc.
- **Negative Messaging** (dissuade)- emphasize the side effects of vaccination, question its effectiveness, or highlight rare adverse reactions.
- Mood susceptibility- the degree to which an individual's mood (e.g., positive or negative) influences their receptivity to persuasive messages.
- Decay of influence- in our case it means the reduction in the impact of a message or influence over time if it is not reinforced
- Vaccination uptake- the proportion of individuals in a population who choose to receive a vaccination.

Defining the Problem

- Modeling transitions from undecided individuals to vaccinated or non-vaccinated groups, influenced by positive and negative messaging, mood susceptibility, and decay of influence over time.
- Projecting vaccination rates and potential public health impacts, showing how different messaging strategies can affect long-term trends and economic costs.
- Determine which kind of messaging is more effective to suggest improved public advertising of flu vaccinations to governments and healthcare companies.

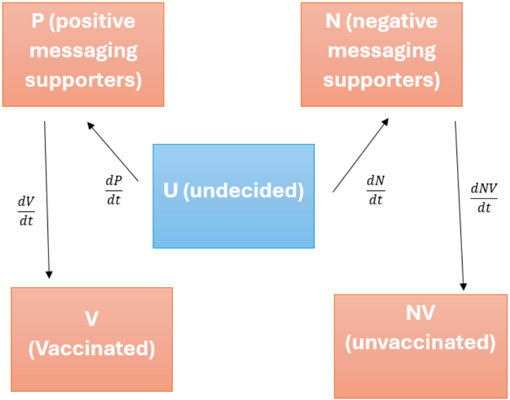
Our Approach

- We will implement the compartmental model typically used in mathematical biology in deriving our model
- We created transition states for each compartment in the form of separate differential models
- Using software, we will plot and solve our model
- To assess for the robustness of our model, we will perform a parameter sensitivity analysis

We will assume that...

- Positive mood increases susceptibility to informational recall
- Influence fades overtime - Assume that the effect of positive and negative messaging decays at a certain rate unless reinforced.
- Assume that the receptivity to messaging across the population follows a normal distribution.
- All data is taken after the COVID-19 outbreak in 2020, as that might limit access to influenza vaccinations.
- The literature review that contained some data we used collected data from 2000 college students in 4 major cities China (See reference 6).

Model Derivation



The Model

Equations

$$\frac{dP}{dt} = \lambda_p * U(1+m) - dP$$
$$\frac{dN}{dt} = \lambda_n * U(1+m) - dN$$
$$\frac{dV}{dt} = \alpha_p * P$$
$$\frac{dNV}{dt} = \alpha_n * N$$

Parameters

Defining the Parameters

- λ=the intensity/strength of the positive/negative messaging.
- U= the number of undecided individuals.
- m=mood susceptibility factor.
- d=decay rate.
- ***P= the number of people who individuals influenced by positive messaging (moving toward vaccination).**
- ***N= the number of individuals influenced by negative messaging (moving away from vaccination).**
- In our code P_0, N_0 are our initial values

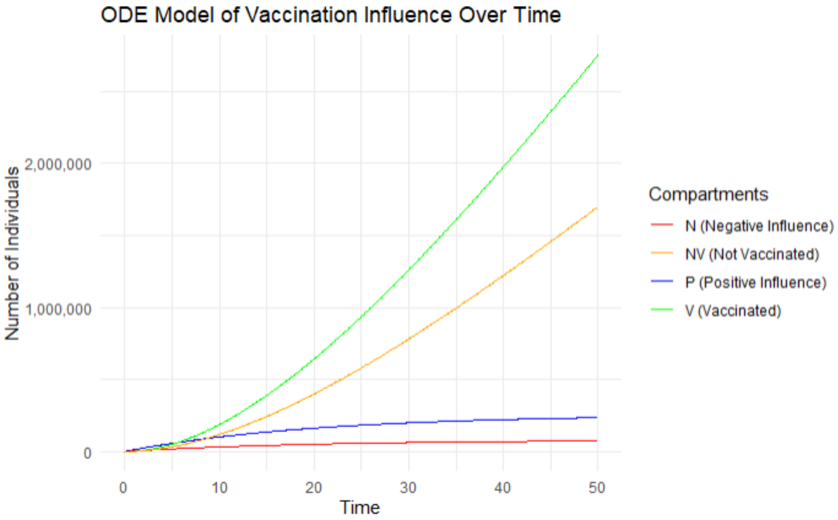
Parameters Cont.

Now we will find the values for our parameters through literature reviews (see references on last slide).

Defining the Parameters

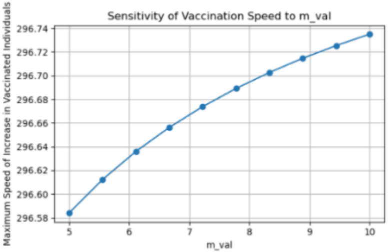
- $\lambda_p = 0.761$ (5)
- $\lambda_n = 0.239$ (5)
- $\alpha_p = 0.338$ (5)
- $\alpha_n = 0.662$ (5)
- $m = 7.43$ (4)
- $d = 0.05$ (4)
- $U = 2000$ (5)

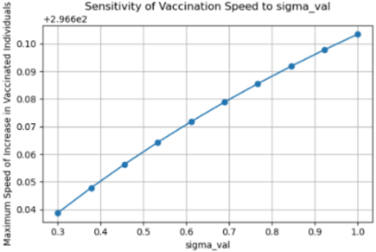
Graphs



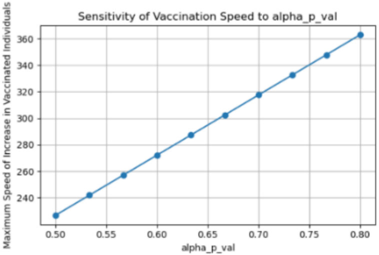
ODE Model of Vaccination Influence Over Time
Number of Individuals
2,000,000
1,000,000
0
0
10
20
30
40
50
Time
Compartments
N (Negative Influence)
NV (Not Vaccinated)
P (Positive Influence)
V (Vaccinated)

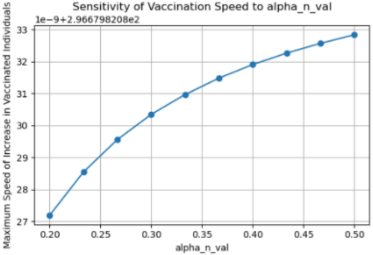
Sensitivity Testing





Above for m and decay rate (denotated as sigma in graph)





Conclusion

- The number of vaccinated individuals (green line) shows exponential growth over time, indicating that positive influence has a strong effect on encouraging flu vaccinations.
- Positive messaging effectively moves individuals into the vaccinated group as time progresses.
- The positive influence compartment (blue line) shows steady growth but at a slower rate than vaccination uptake.
- The steady but lower growth rate of positive influence could imply that those positively influenced are more likely to convert to vaccination rapidly, rather than staying in the positive influence compartment for extended periods.
- The negative influence compartment (red line) remains relatively low and stable throughout the time period.
- This could imply that negative messaging is less effective than positive messaging.

Conclusion Cont.

- The non-vaccinated compartment (orange line) grows at a slower rate compared to the vaccinated population. This indicates that while some people remain unvaccinated, their numbers increase at a lower rate relative to the vaccinated population.
- People in a positive mood are more likely to recall and accept information presented in a narrative format.
- Higher vaccination rates reduce flu transmission, lowering the burden on healthcare systems.
- With fewer people infected, there would be a lower health burden on healthcare systems, leading to better public health outcomes.
- We can recommend to public health officials to use positive messaging when advertising influenza vaccines. While it is important to address common myths or concerns about the flu vaccine, avoid amplifying negative messaging or fear-based framing.

Limitations/Improvements

- Limited demographic
- For the future we could also investigate vaccine messaging on different demographics(age, gender, college-educated/not)
- The model does not account for potential interactions between individuals in different compartments. For example, people exposed to negative messaging might influence those with positive views, leading to more complex interactions.
- External factors like media coverage, healthcare provider recommendations, or peer influence are not explicitly modeled.
- We potentially overlooked economic/social constraints (e.g. access to vaccines, people living in rural areas, etc)

References

- (1) Nehama Lewis Erga Atad (2024) Effects of Message Framing and Narrative Format on Promoting Persuasive Conversations with Others About the Flu Vaccine, Health Communication, 39:10, 2110-2122, DOI: 10.1080/10410236.2023.2257427
- (2) Aguolu, O. G., Willebrand, K., Elharake, J. A., Qureshi, H. M., Kiti, M. C., Liu, C. Y., . . . Omer, S. B. (2022). Factors influencing the decision to receive seasonal influenza vaccination among US corporate non-healthcare workers. Human Vaccines Immunotherapeutics, 18(6). https://doi.org/10.1080/21645515.2022.2122379
- (3) Nan, X., Futerfas, M., Ma, Z. (2016). Role of Narrative Perspective and Modality in the Persuasiveness of Public Service Advertisements Promoting HPV Vaccination. Health Communication, 32(3), 320–328. https://doi.org/10.1080/10410236.2016.1138379
- (4) Wegener DT, Petty RE, Smith SM. Positive mood can increase or decrease message scrutiny: the hedonic contingency view of mood and message processing. J Pers Soc Psychol. 1995 Jul;69(1):5-15. doi: 10.1037//0022-3514.69.1.5. PMID: 7643302.
- (5) Zou, H., Huang, Y., Chen, T., Zhang, L. (2023). Influenza vaccine hesitancy and influencing factors among university students in China: a multicenter cross-sectional survey. Annals of Medicine, 55(1). https://doi.org/10.1080/07853890.2023.2195206

Code

```
  install.packages("deSolve")
}
library(deSolve)

# parameters
lambda_p <- 0.761          # influence rate for positive messaging
lambda_n <- 0.239          # influence rate for negative messaging
U <- 2000                  # initial number of undecided individuals
m <- 7.43                 # mood influence factor
d <- 0.05                 # decay rate
alpha_p <- 0.338          # conversion rate from P to V
alpha_n <- 0.662          # conversion rate from N to NV
P_init <- 1106            # initial number influenced by positive messaging
N_init <- 894             # initial number influenced by negative messaging
V_init <- 0               # initial number vaccinated
NV_init <- 0           # initial number not vaccinated

# ODEs
model <- function(time, state, parameters) {
  with(as.list(c(state, parameters)), {
    dP <- lambda_p * U * (1 + m) - d * P
    dN <- lambda_n * U * (1 + m) - d * N
    dV <- alpha_p * P
    dNV <- alpha_n * N

    # Return the rate of change
    list(c(dP, dN, dV, dNV))
```

Thank you for your time!