The impact of media coverage on the transmission dynamics of human influenza

Robert Smith?

Department of Mathematics and Faculty of Medicine
The University of Ottawa

Outline

- Effects of media

Outline

- Effects of media
- The model


The Daily Telegraph
FREE DVD
NATIONAL GEOGRAPHIC
QUEST FOR THE GRAIL
BRITAIN'S BEST-SELLING QUALITY DAILY
PANIC!

Outline

- Effects of media
- The model
- Analysis

Outline

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- Optimal controls

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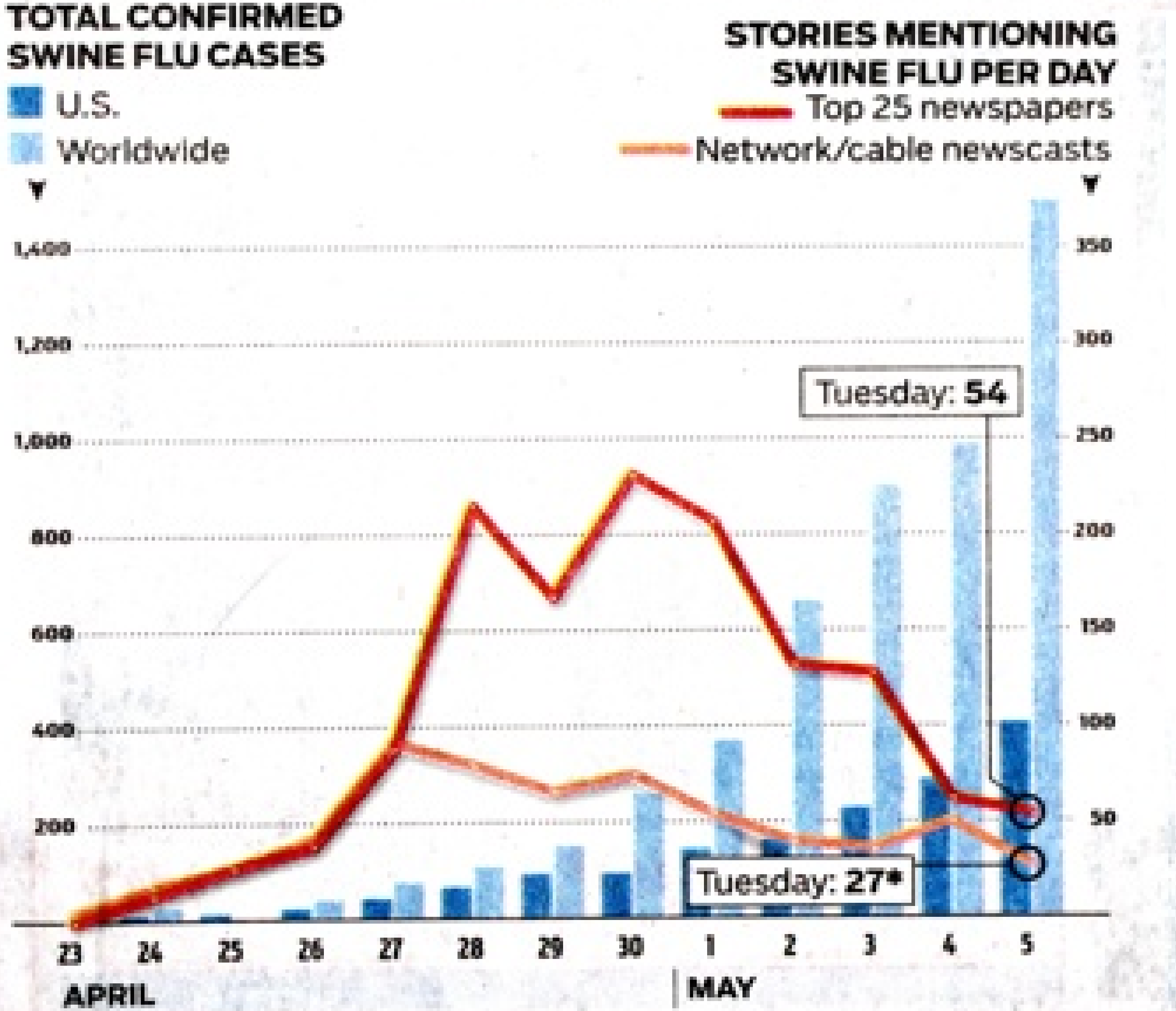
- Implications.

Story arc: Media and swine flu

The swine flu outbreak appears to have peaked, at least in terms of media coverage. While the number of confirmed cases continues to grow, the number of fatalities associated with the virus remains low, especially when compared to typical seasonal flu deaths.



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SOURCES: Centers for Disease Control and Prevention, World Health Organization

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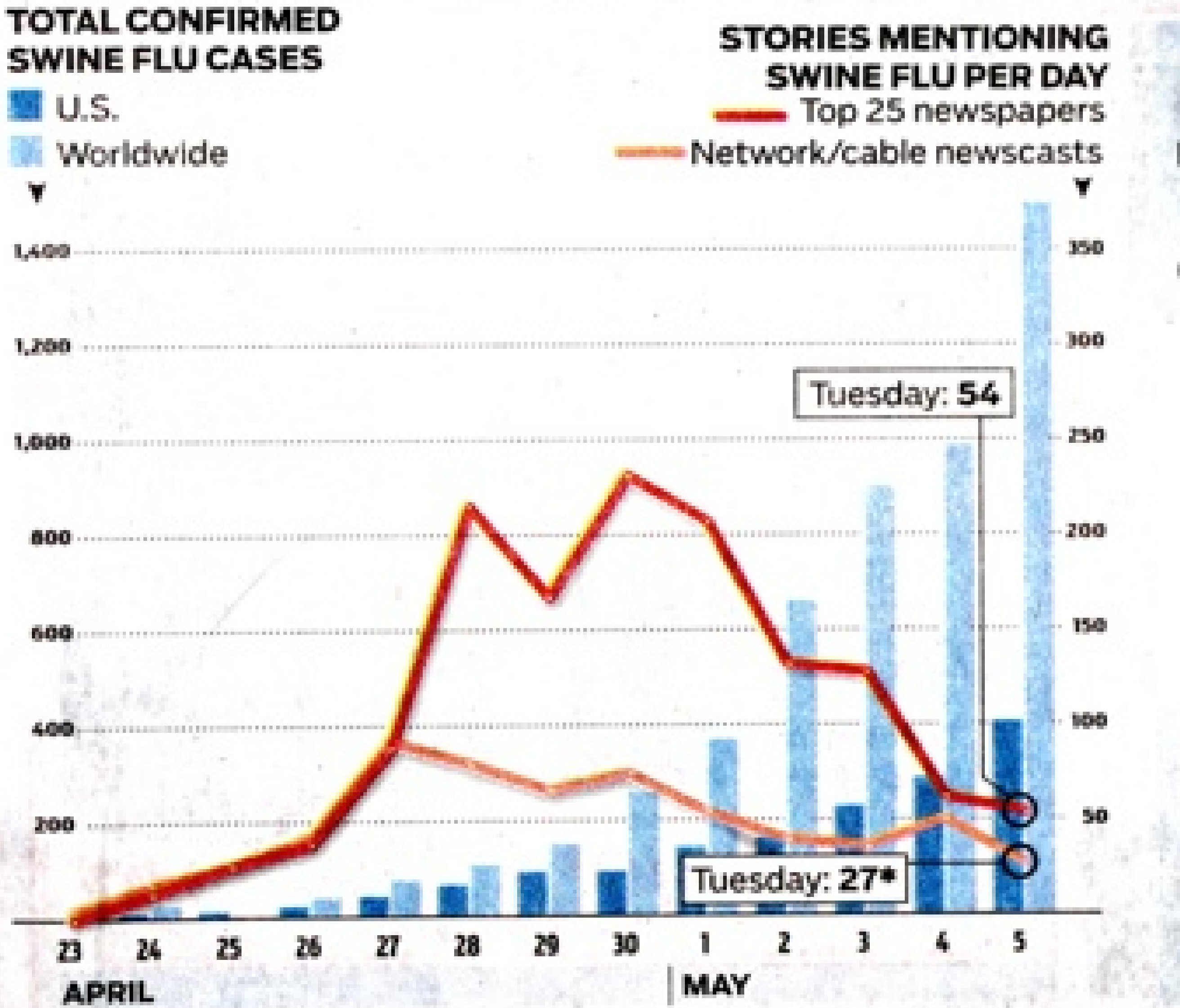

31

Number of swine flu deaths worldwide as of Tuesday (Mexico, **29**; U.S., **2**)

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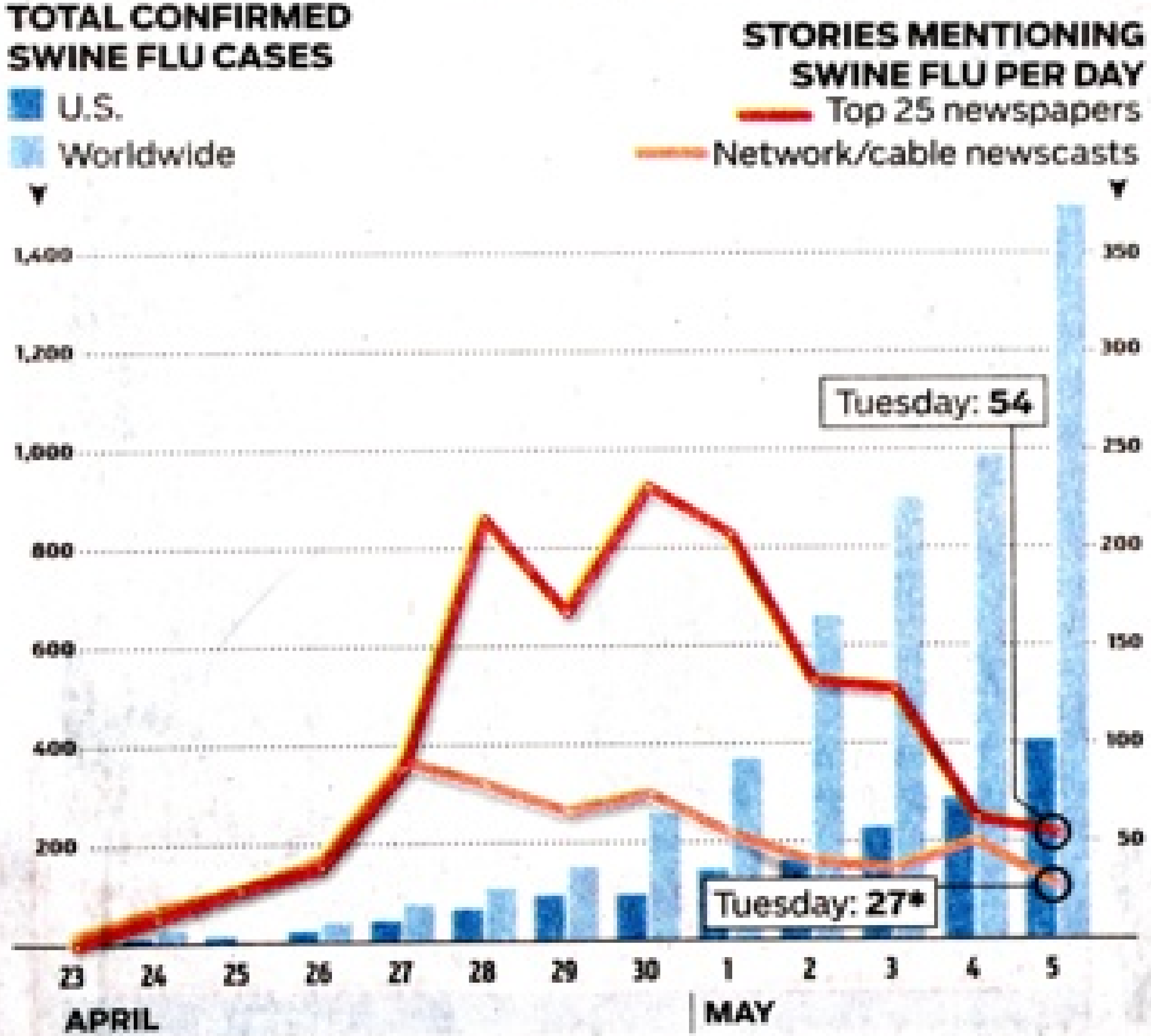

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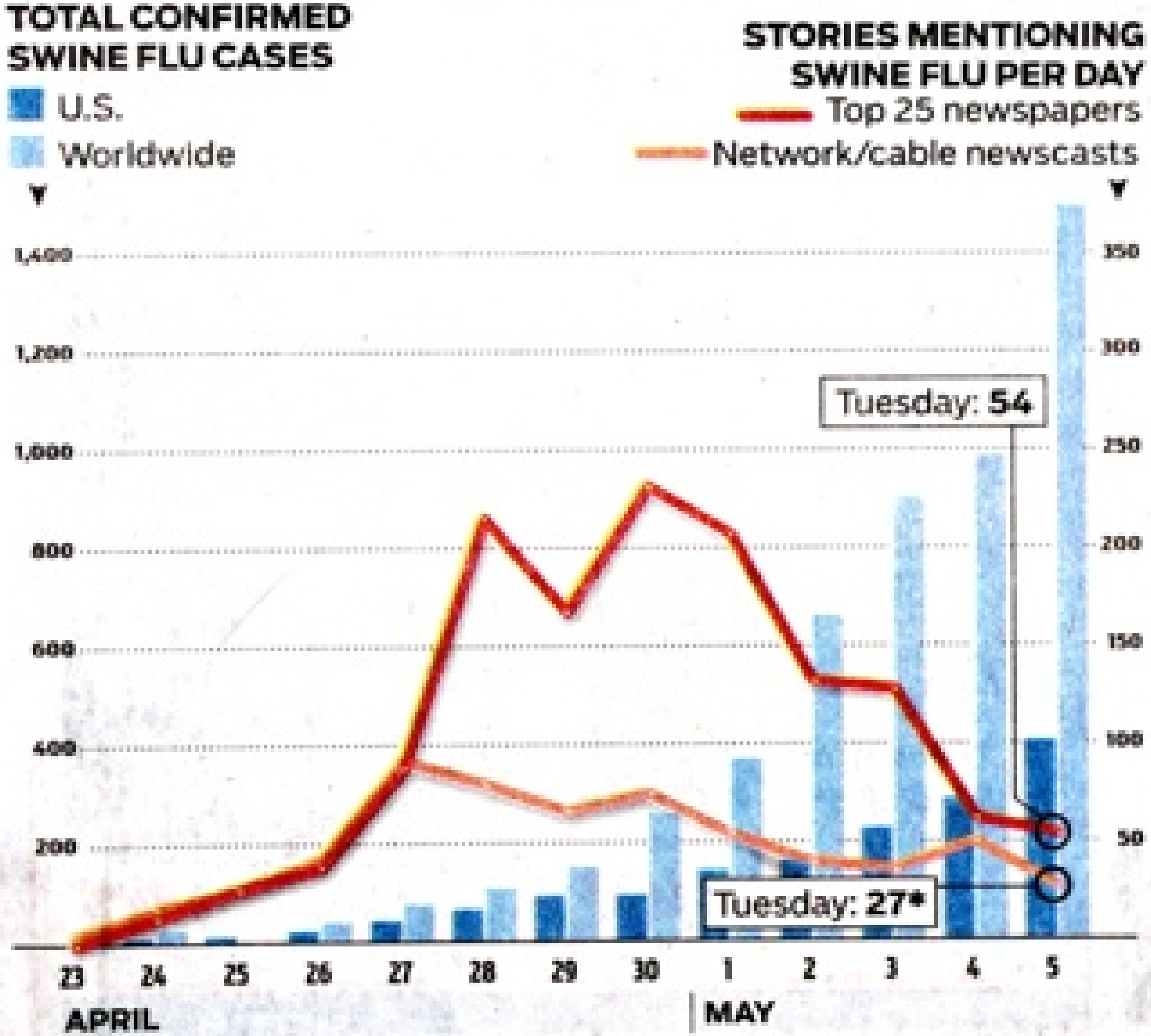

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36,000

Estimated number of Americans who die from the flu each year

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ADAM ZOLL AND PHIL GEIB/TRIBUNE

The media

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- individual behaviour

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  (eg SARS in Chinatown).

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- However, they have been criticised for making risk a spectacle.

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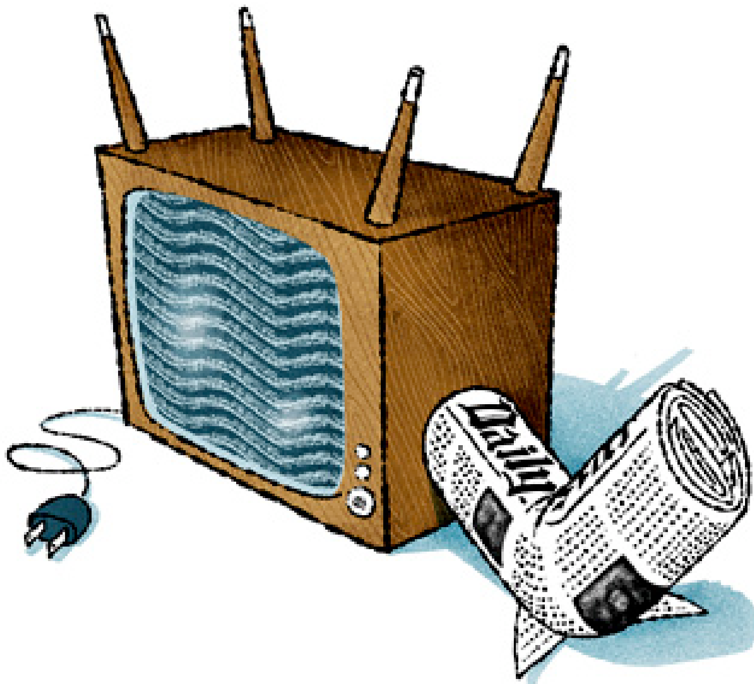
- However, this has been revised in recent years.

Contemporary media theories

- Media is shaped by the dominant cultural norms



Contemporary media theories

- Media is shaped by the dominant cultural norms
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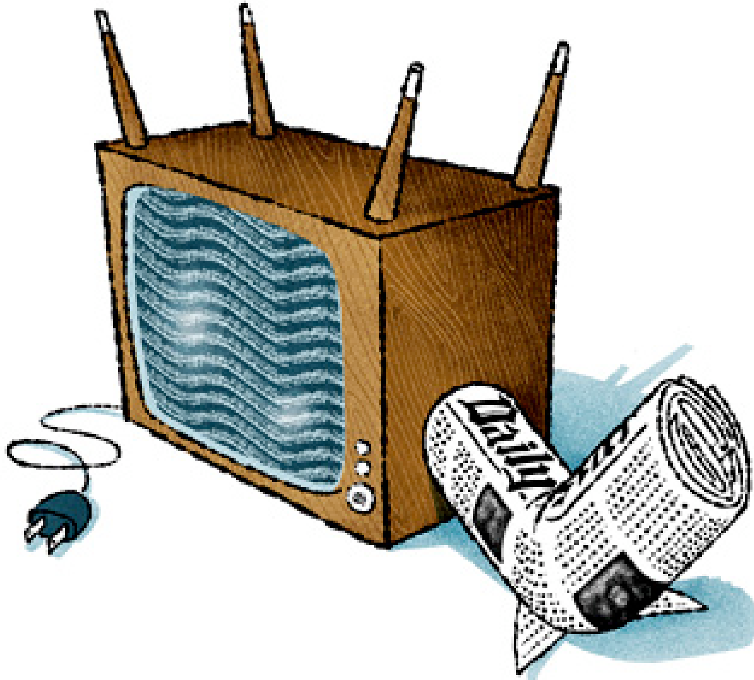

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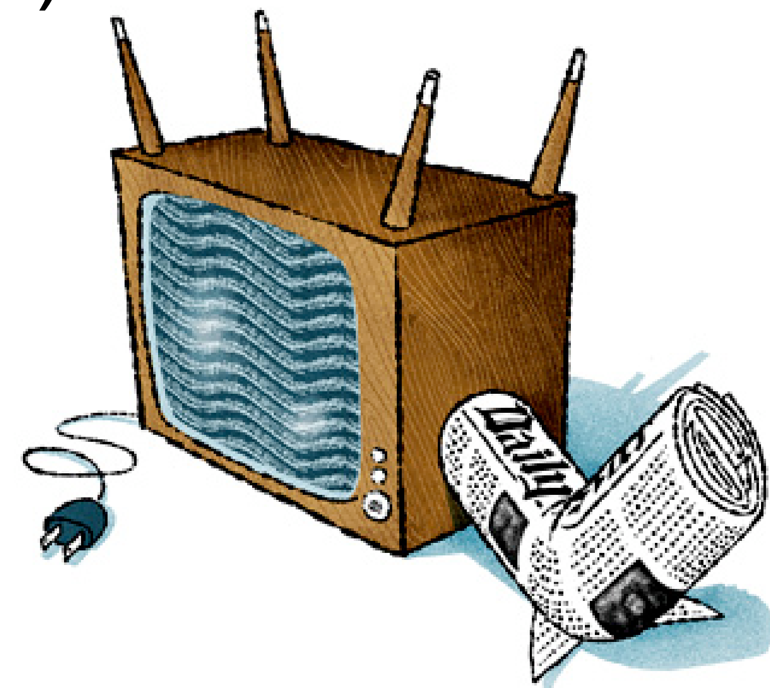

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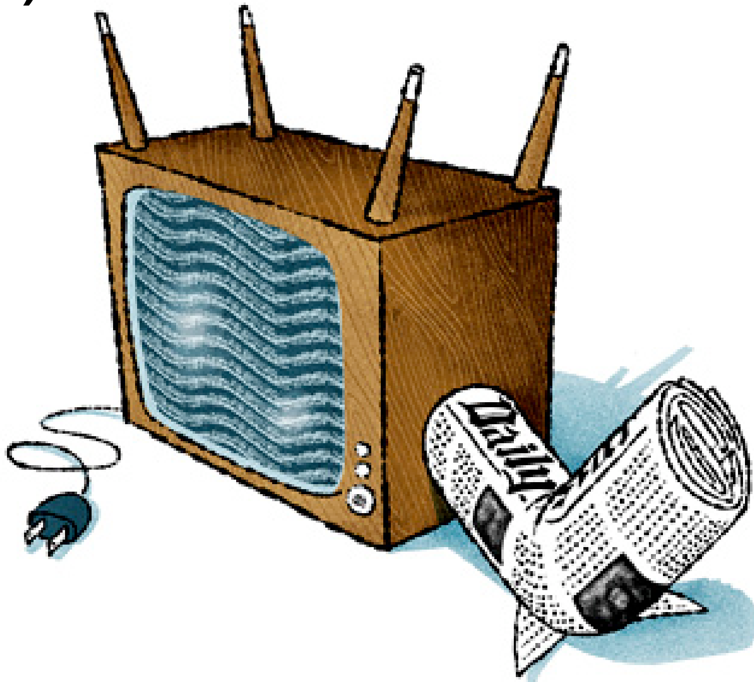

Contemporary media theories

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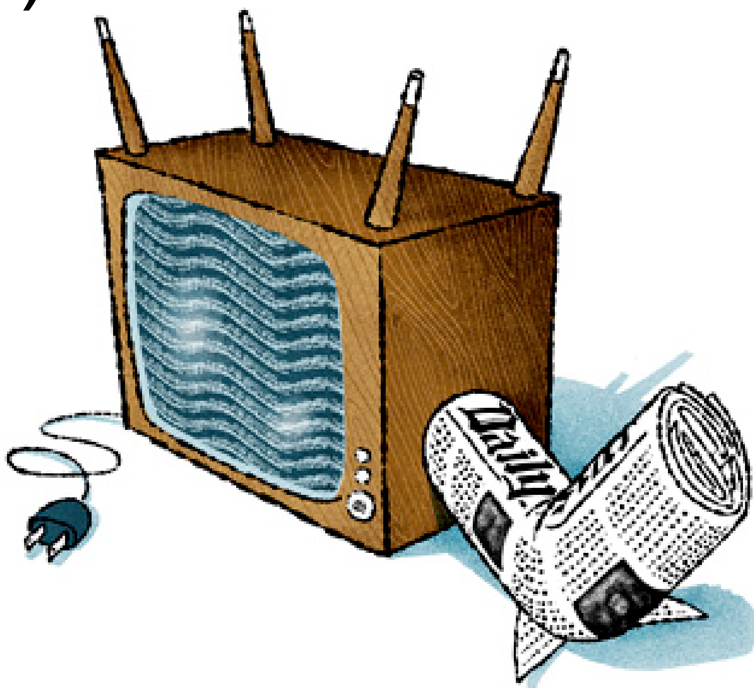
- It is impossible to separate the message from the society from which it originates (eg WNV vs Chagas' Disease)
- Consumers might only partially accept a particular media message
- Or they may resist the dominant media messages altogether.



Implications for a pandemic

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- Conversely, media may have little effect on more familiar diseases

  (eg seasonal influenza).

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- Non-state-controlled media thrive in a crisis (eg Wikileaks)
- However, state-controlled media are rewarded for creating an illusion of normalcy (eg embedded journalists).

An intersubjective anchorage

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  (eg climate change).

Media and risk protection

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- Individuals may overprotect, which may have additional consequences for the disease
- eg, after an announcement of the 1994 outbreak of plague in Surat, India, many people fled to escape the disease, thus carrying it to other parts of the country
- Media influences behaviour, which in turn influences media.

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- Misplaced fears of autism in the developed world have stoked fears of vaccinations against childhood diseases.

Demographic interruption

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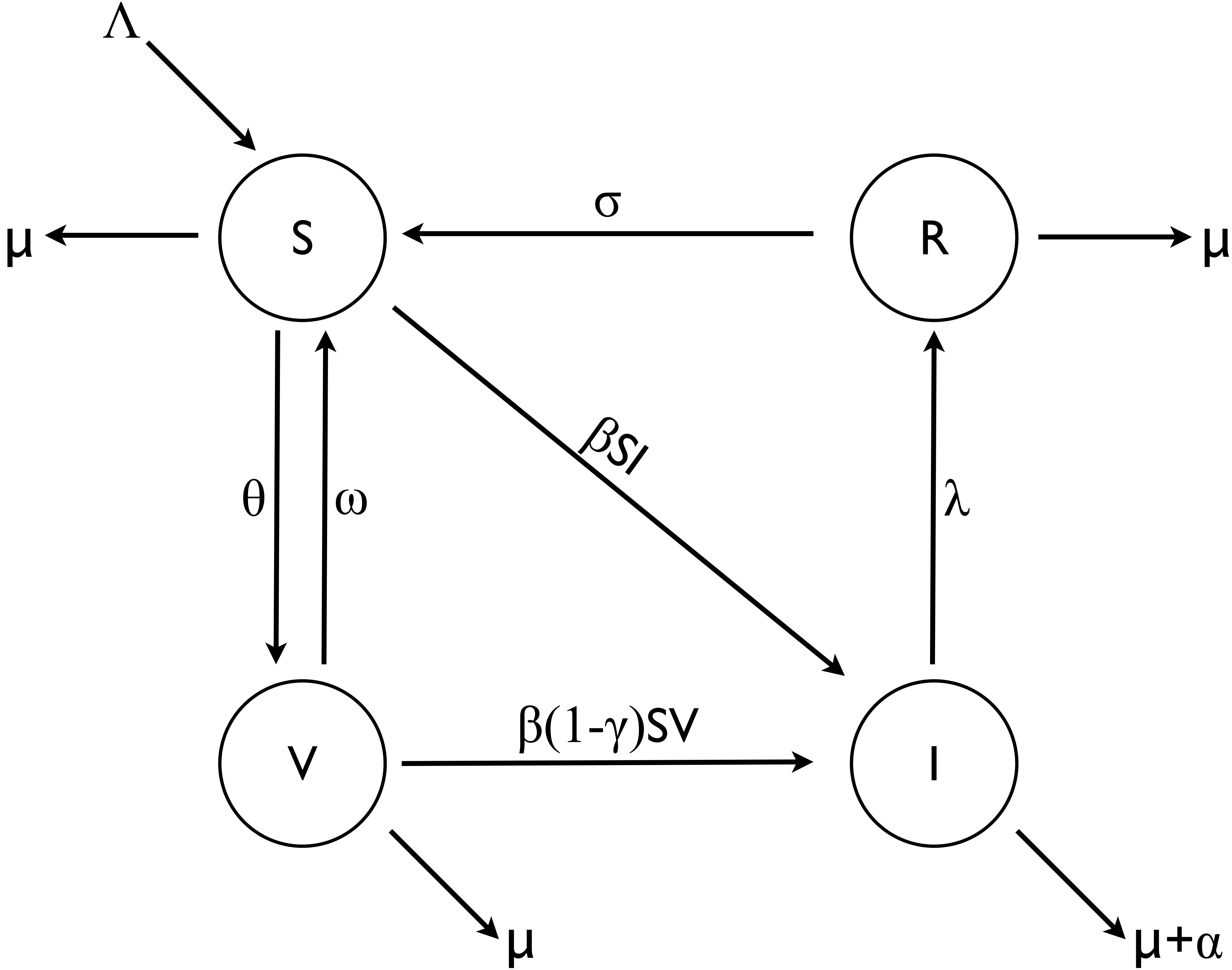
- Media converage is included via a saturated incidence function.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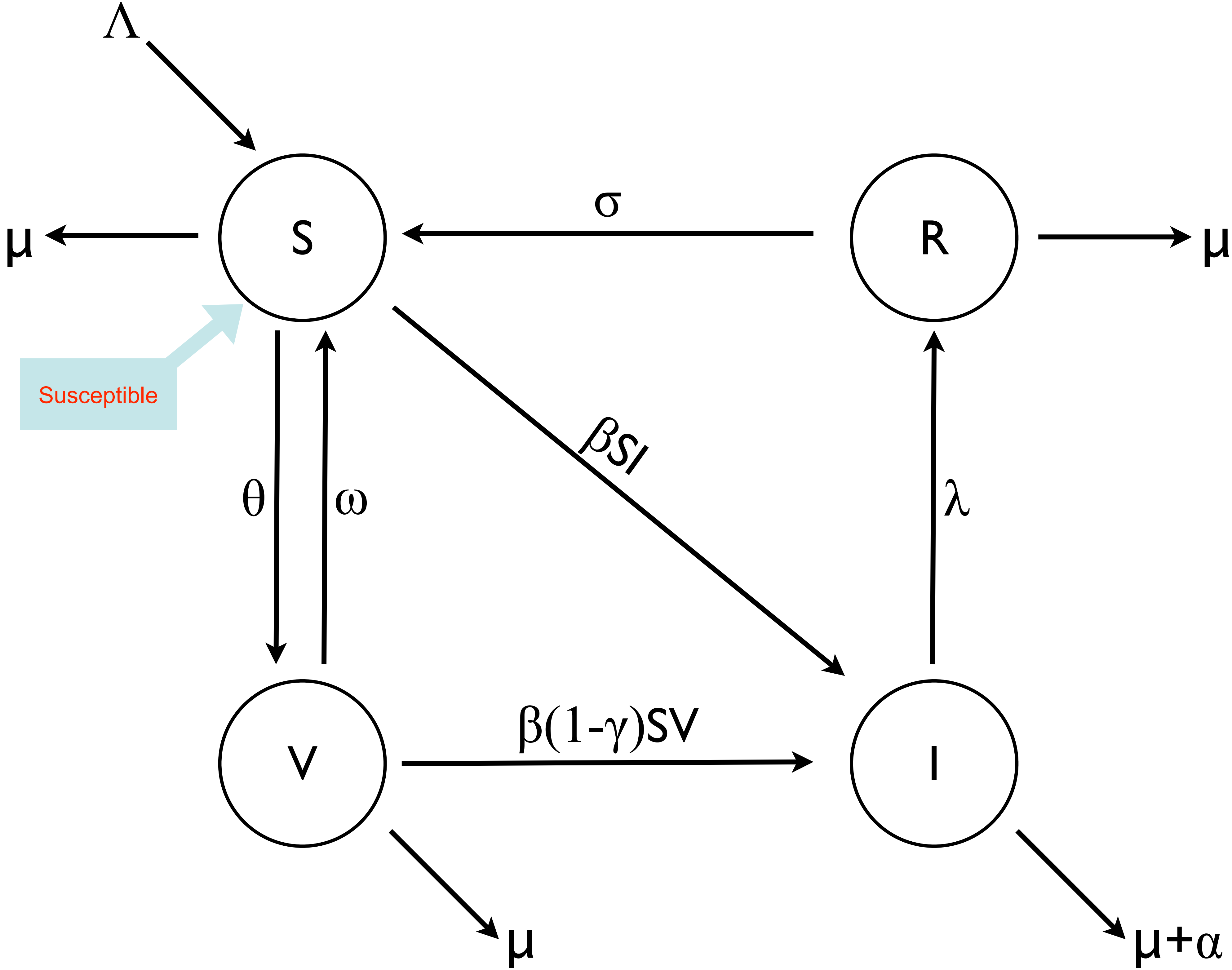

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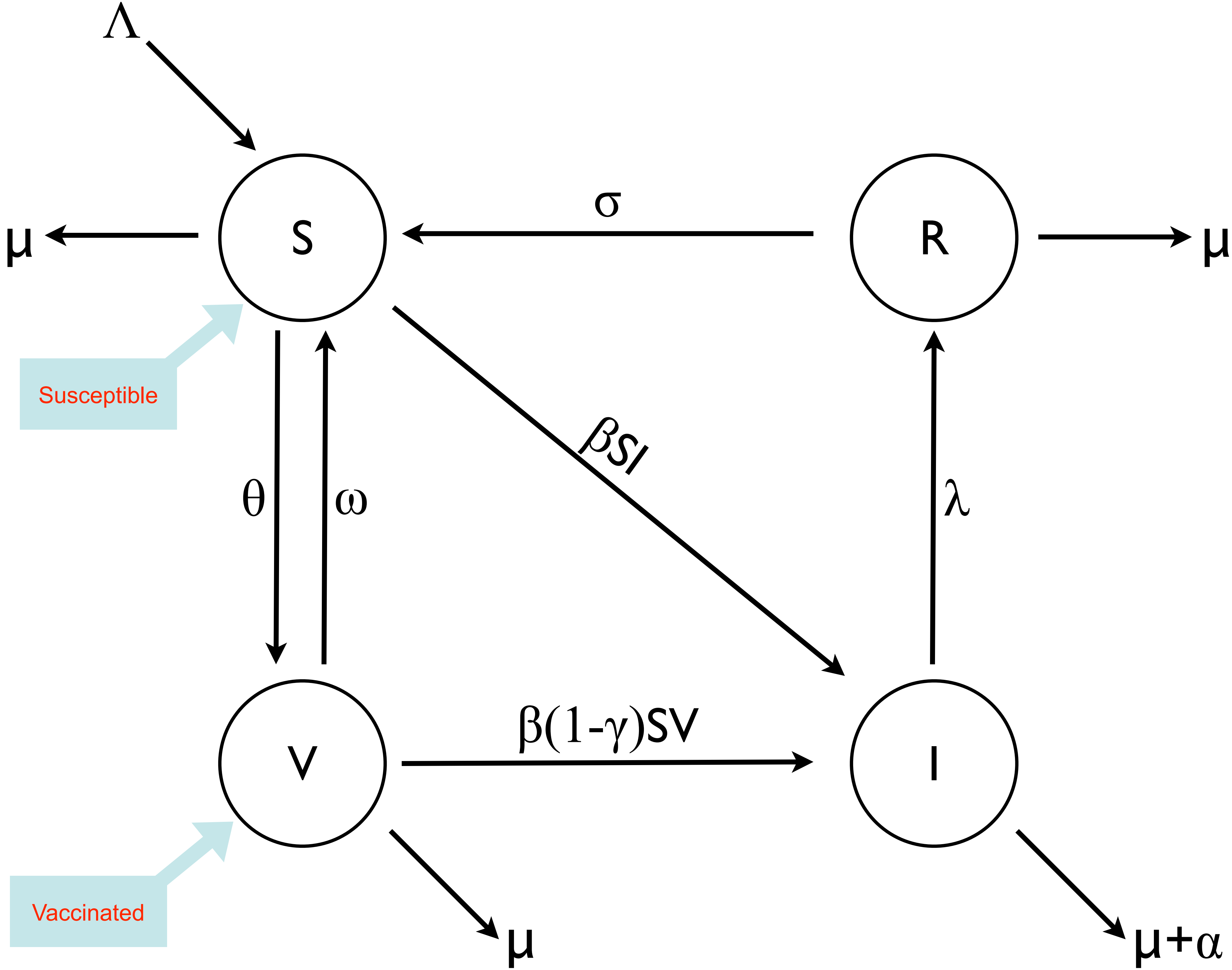
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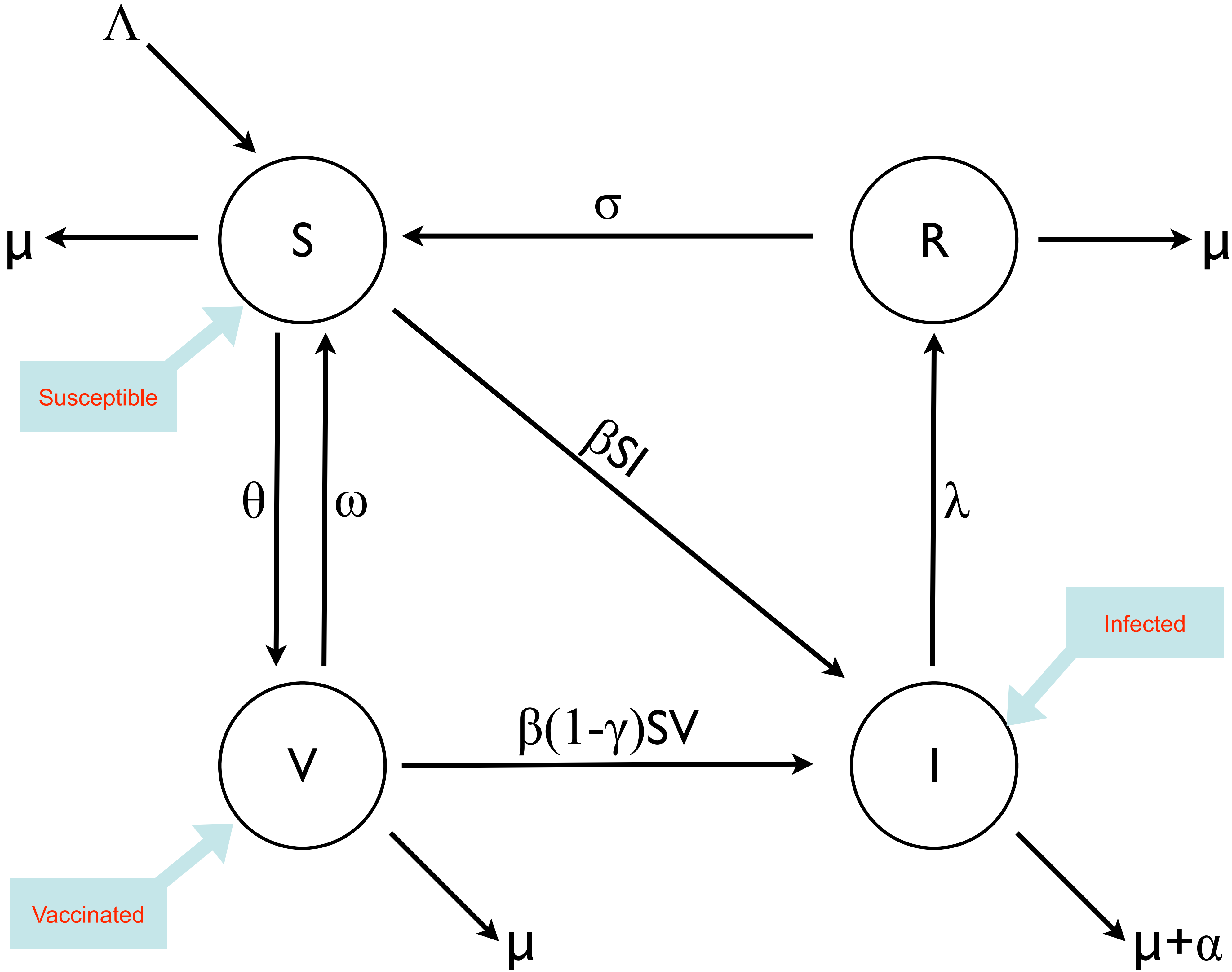

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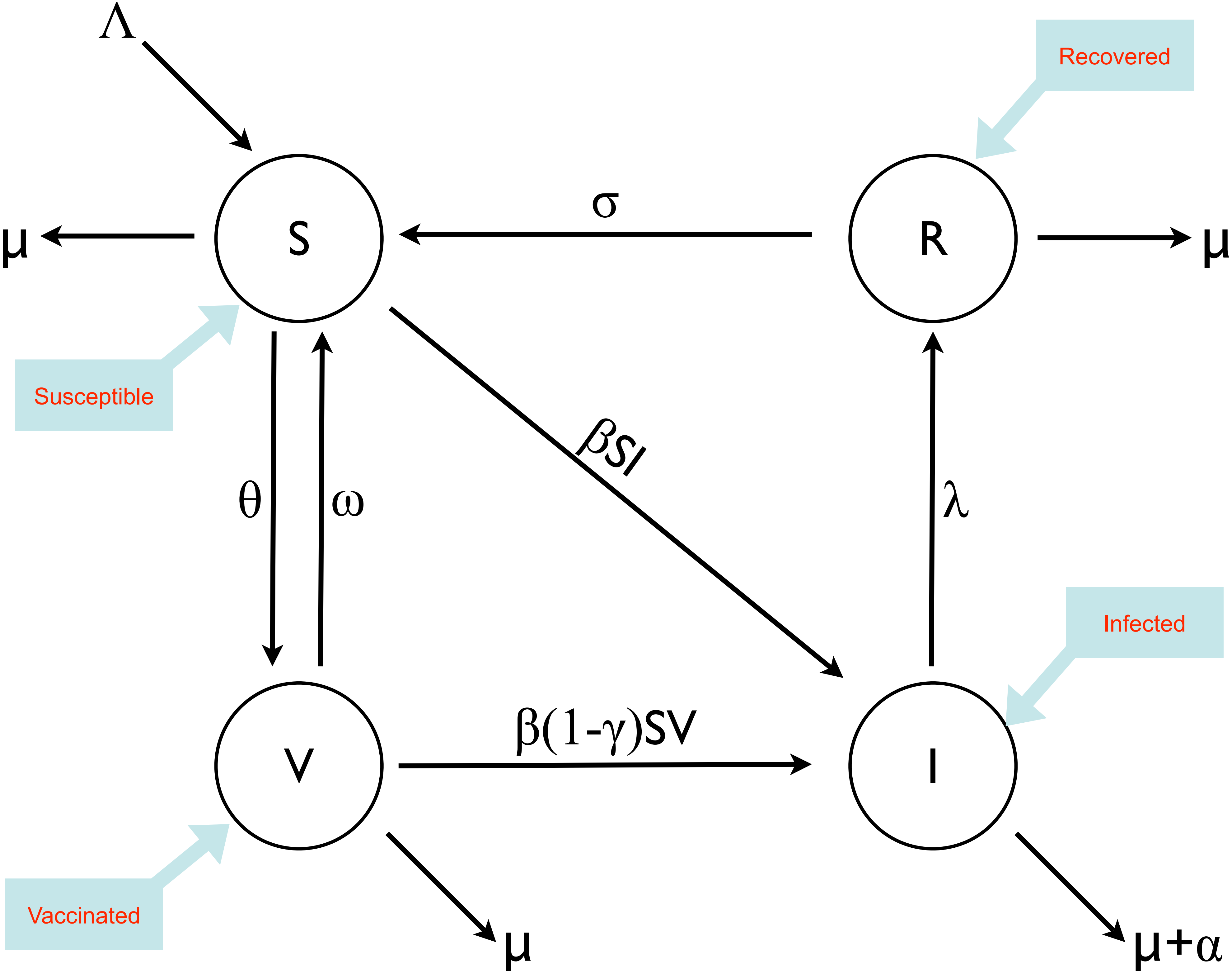
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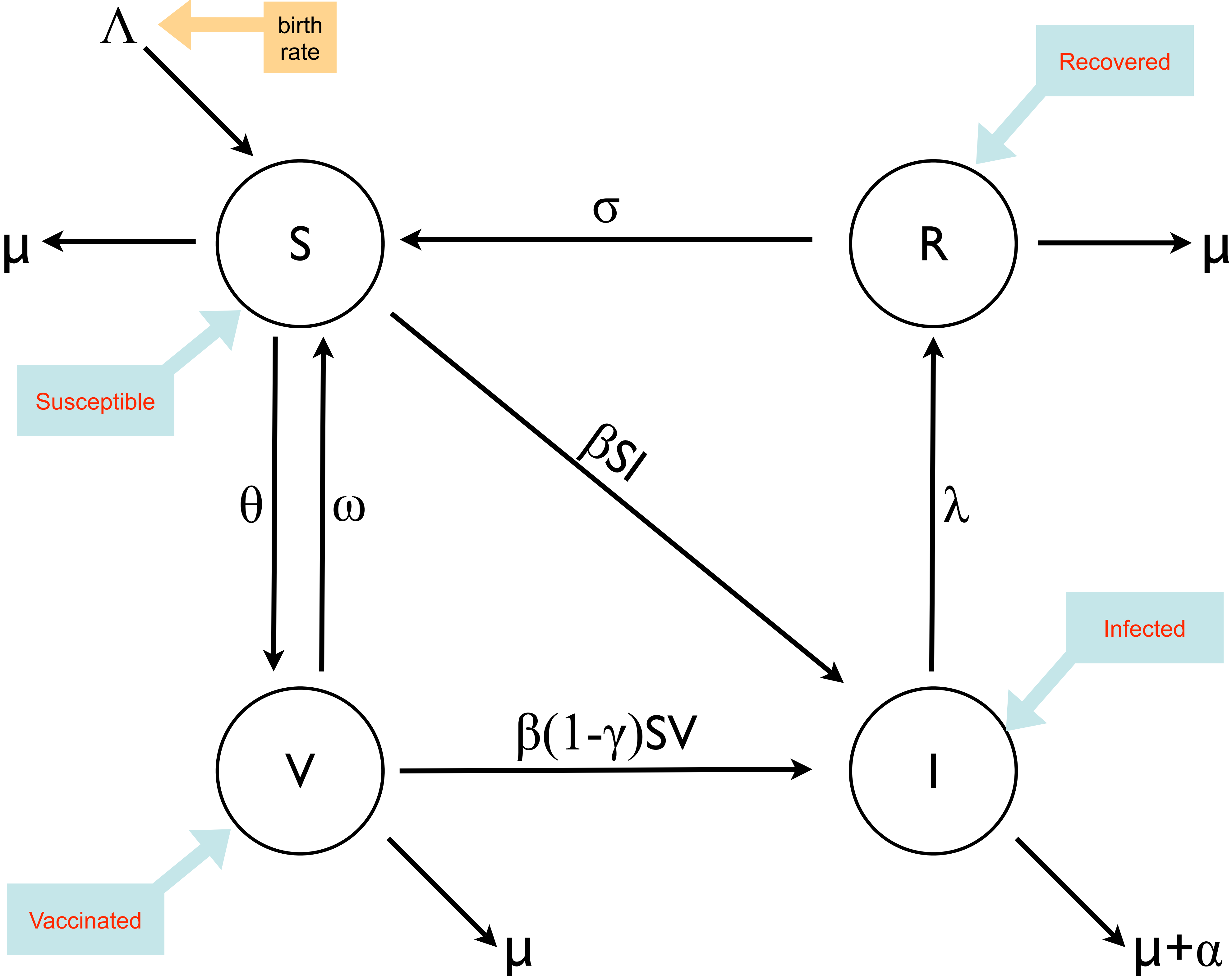
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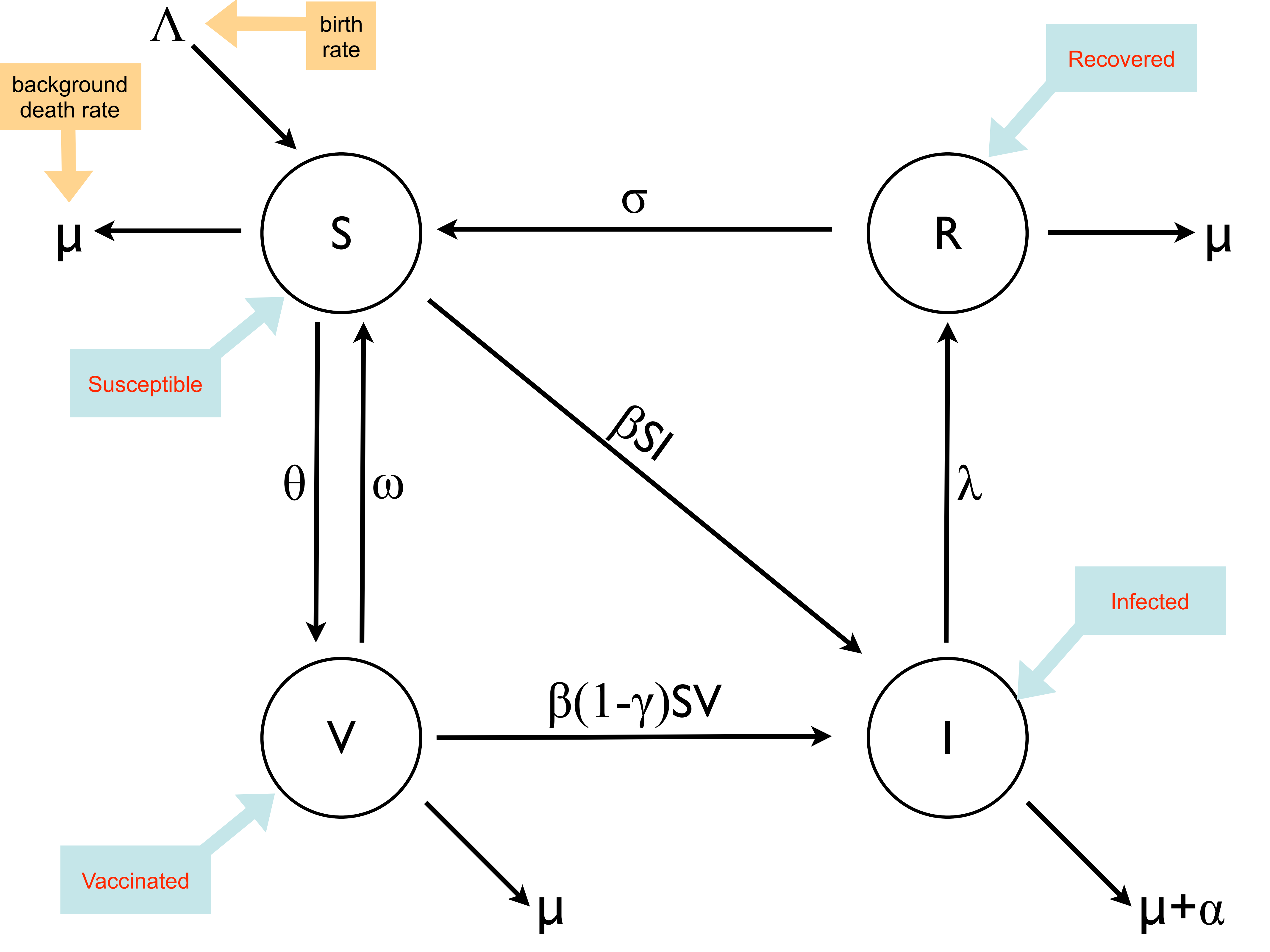

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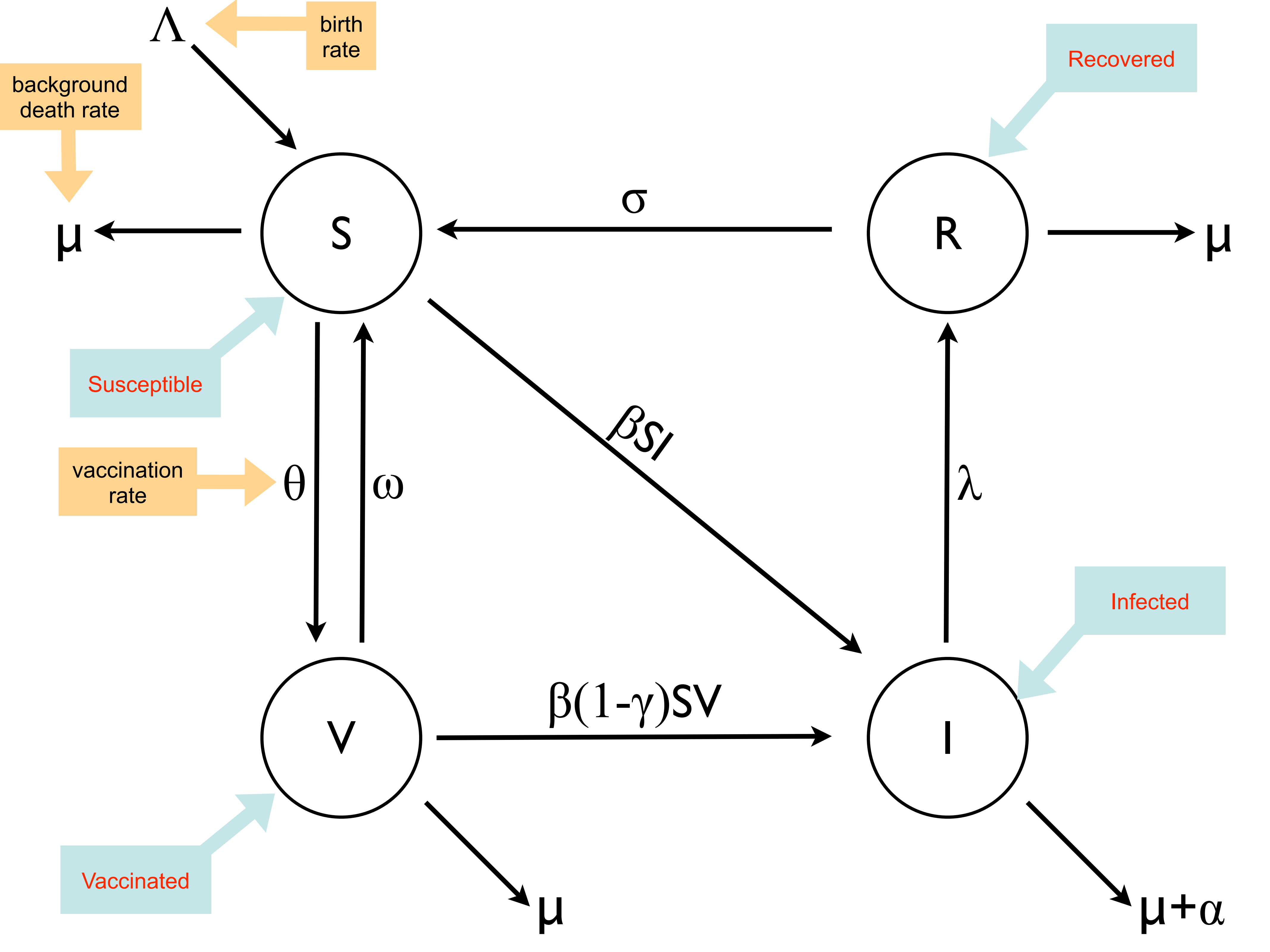

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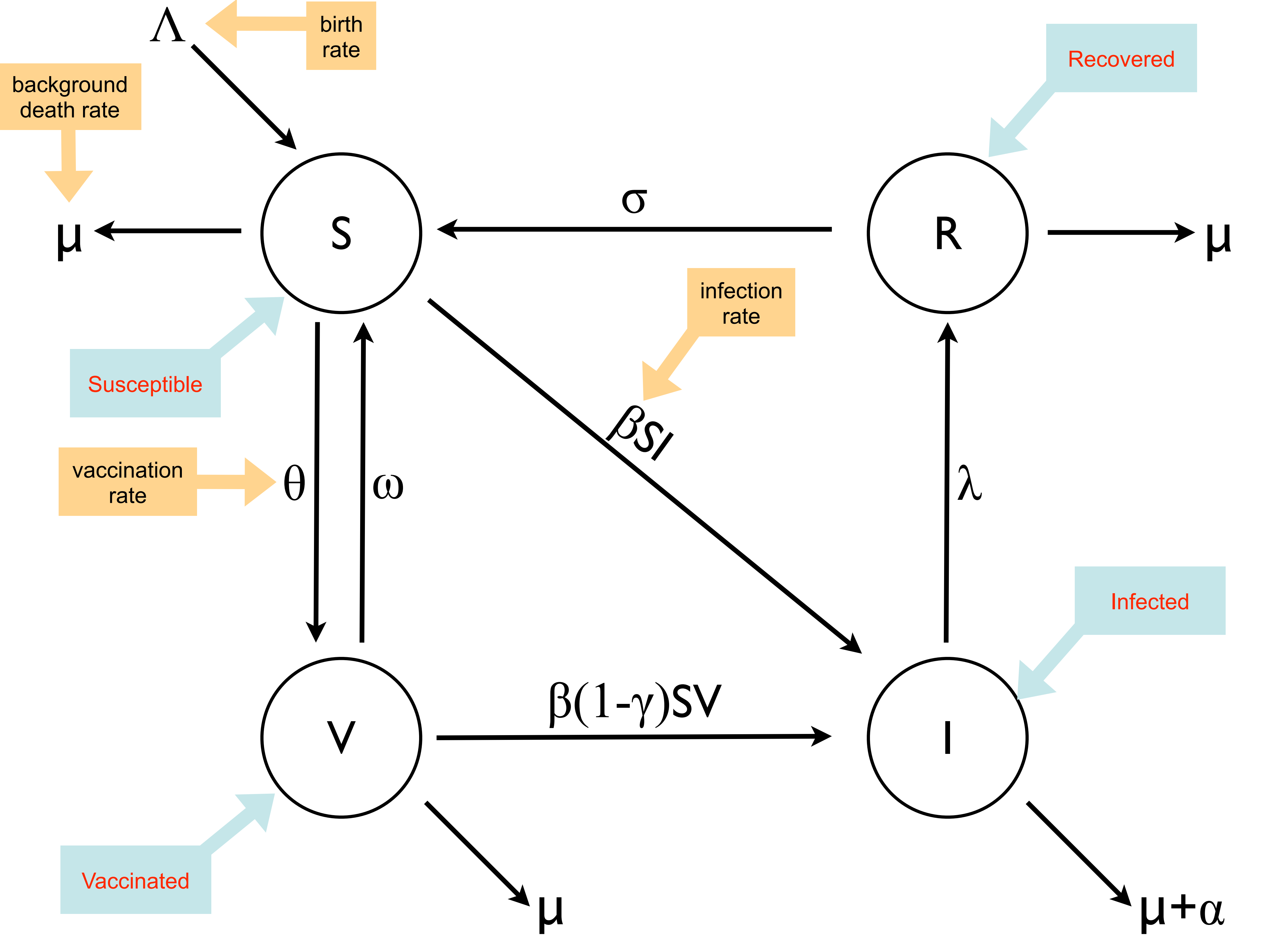

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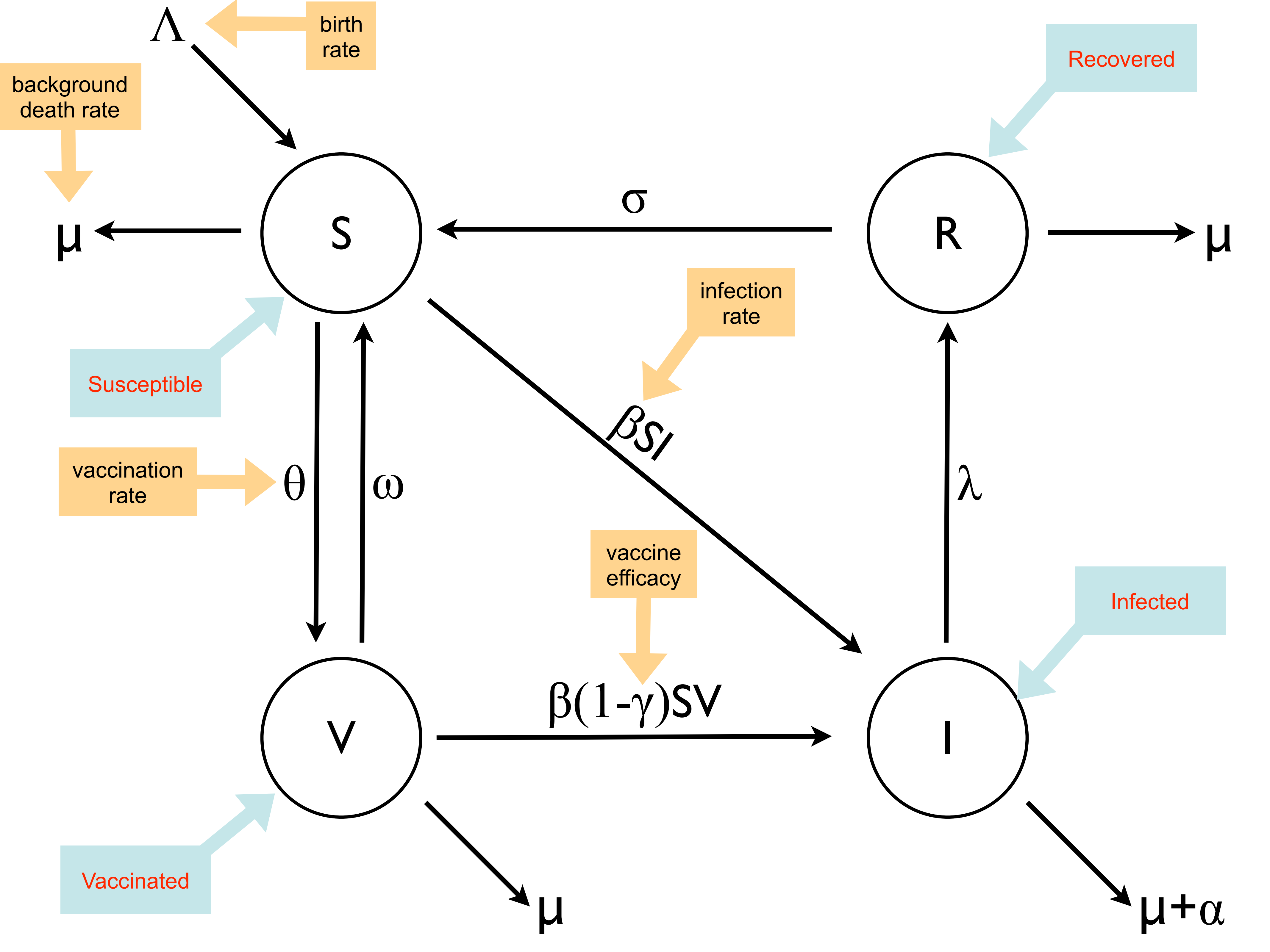

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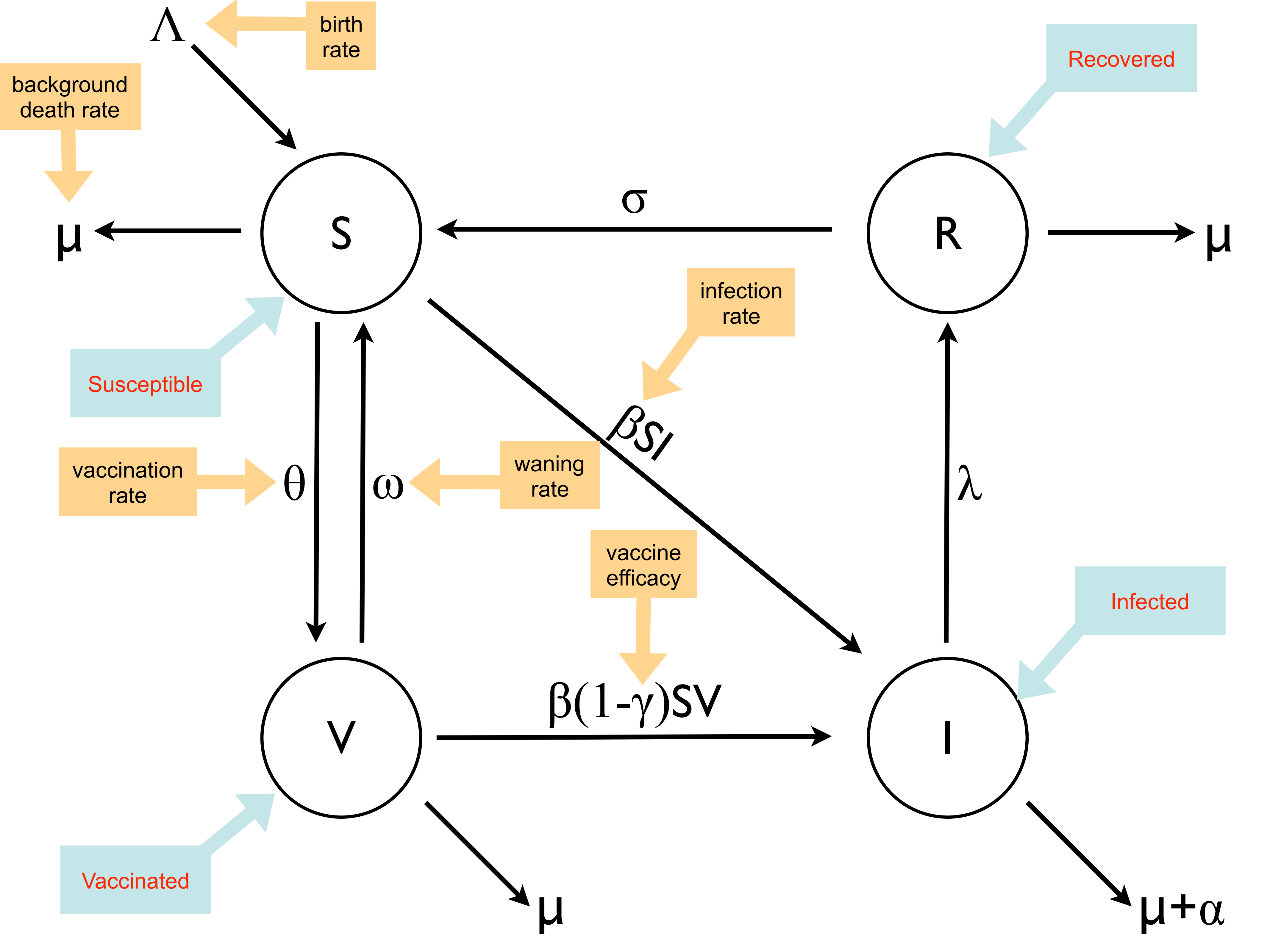

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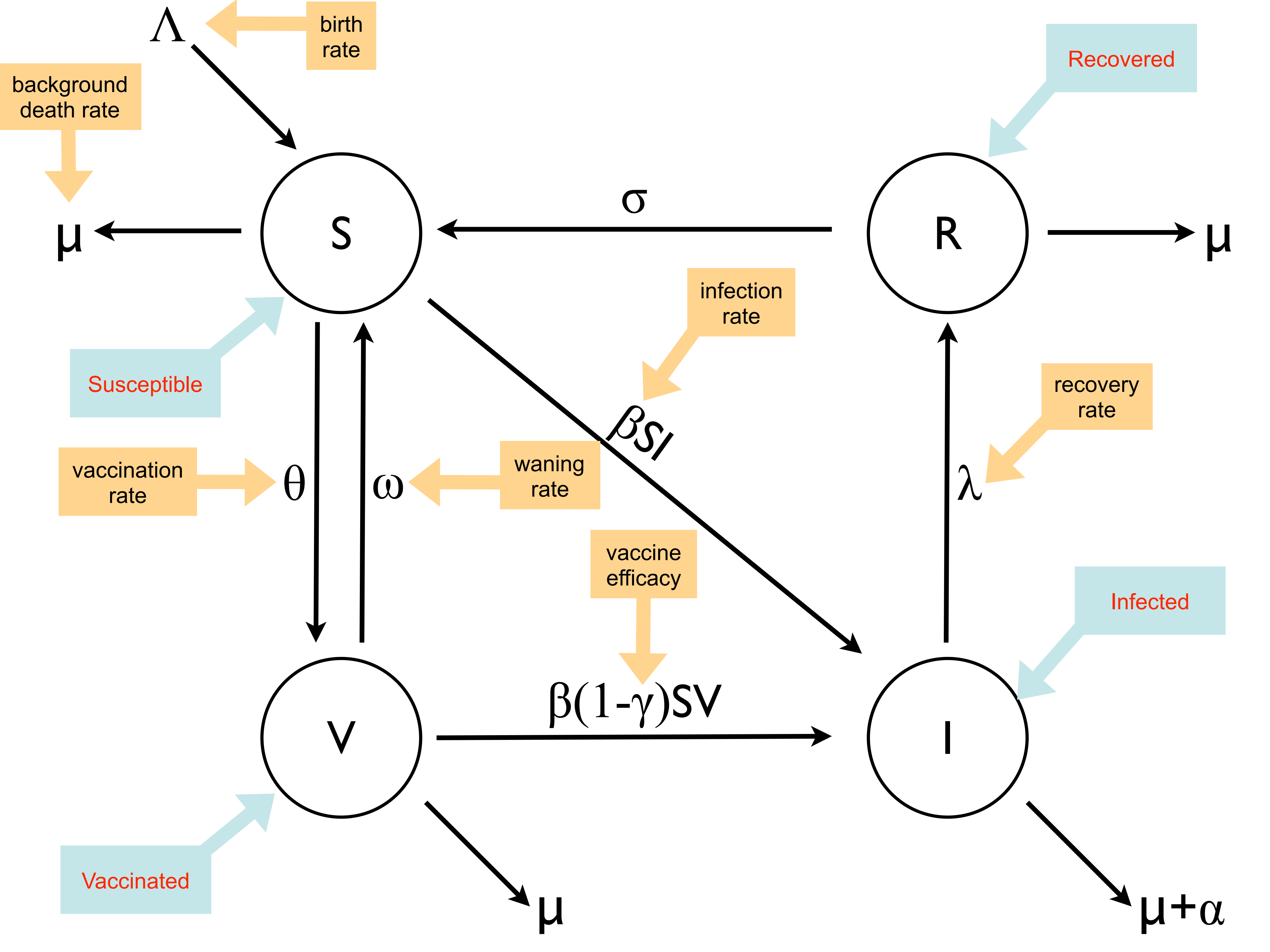
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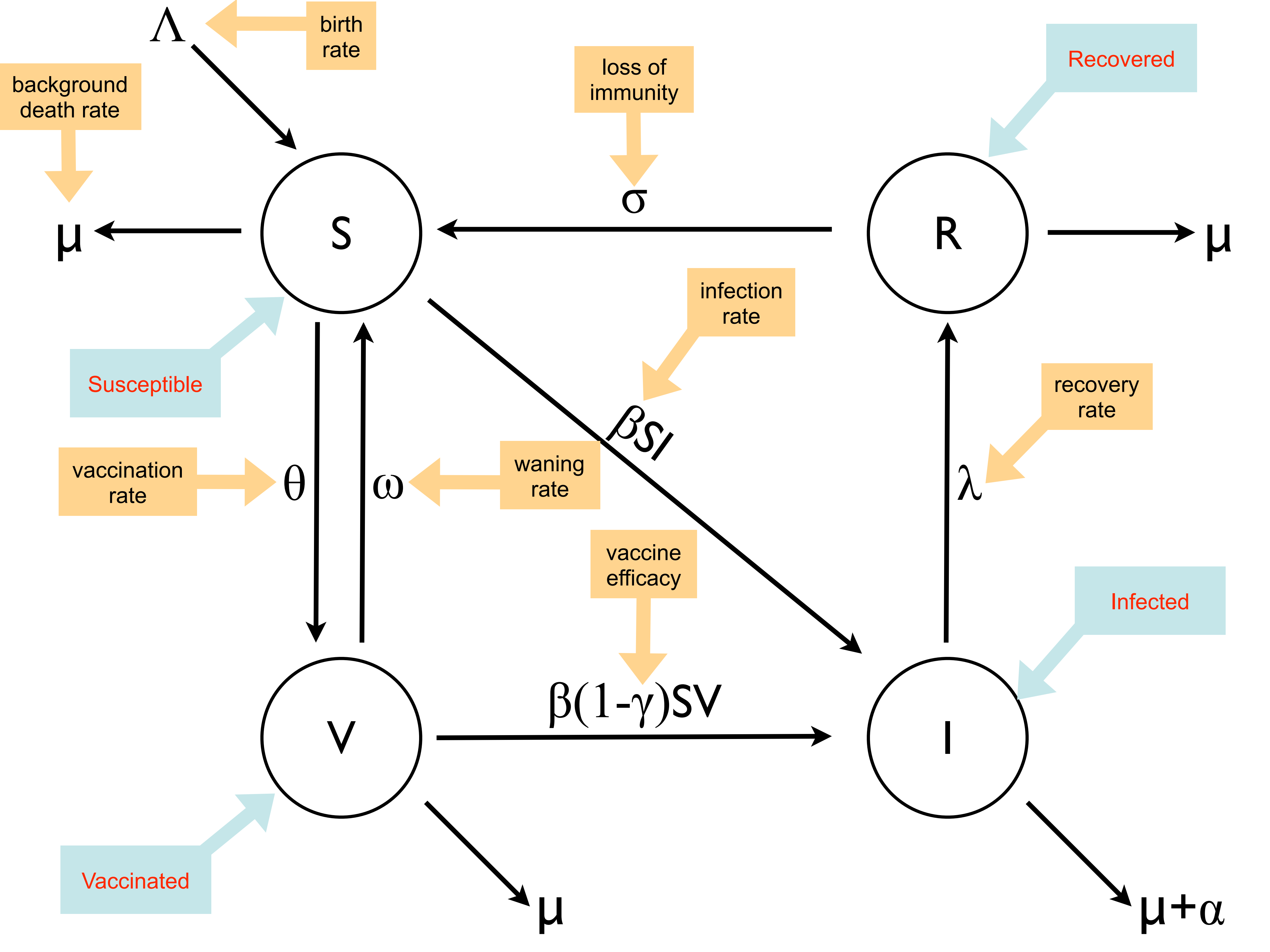

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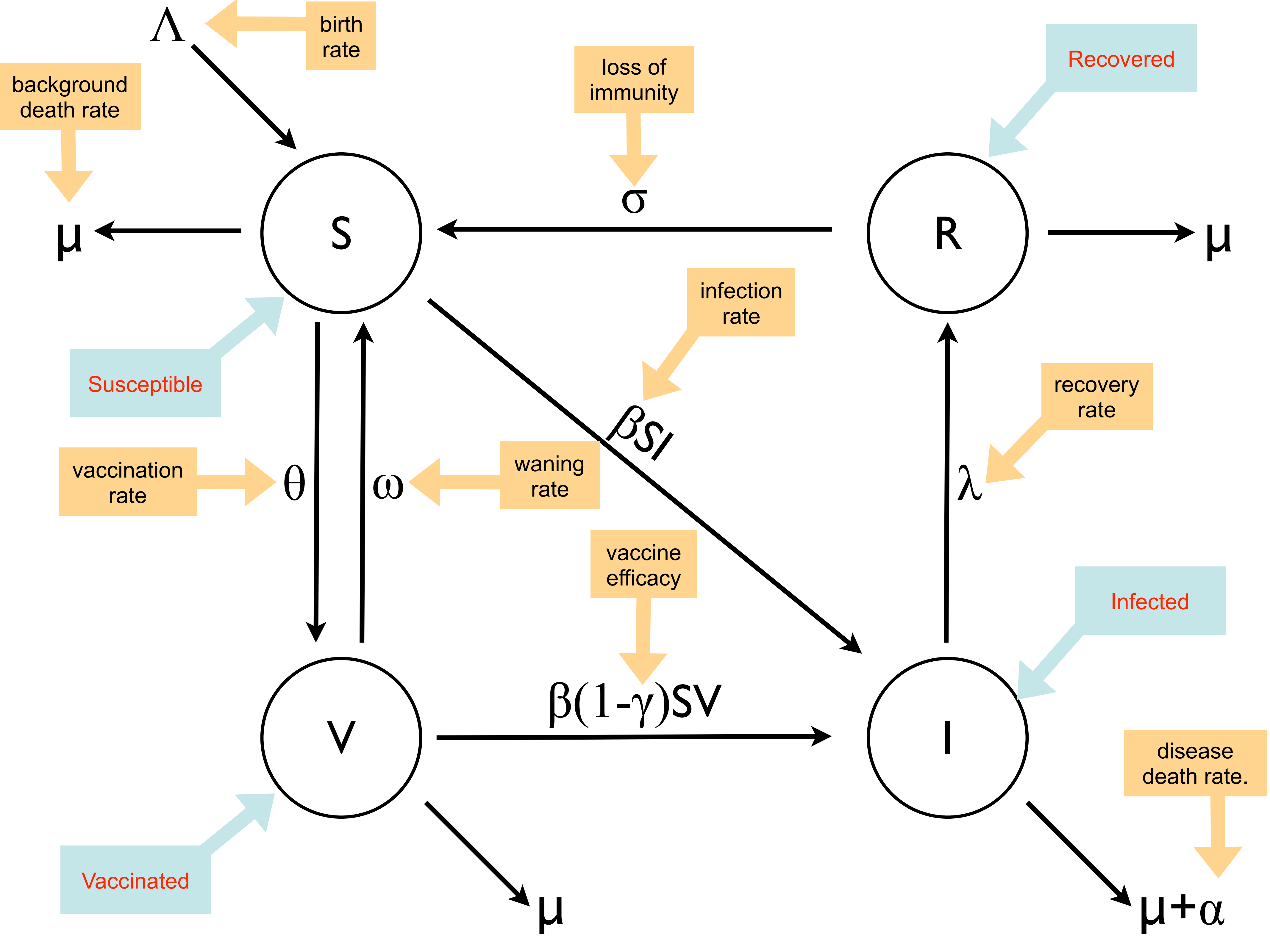

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The model equations

$$\frac{dS}{dt} = \Lambda + \omega V - (\theta + \mu)S - \left(\beta_1 - \beta_2 \frac{I}{m_I + I}\right) SI + \sigma R$$

$$\frac{dI}{dt} = \left(\beta_1 - \beta_2 \frac{I}{m_I + I}\right) SI + \left(\beta_1 - \beta_3 \frac{I}{m_I + I}\right)(1 - \gamma)VI - (\alpha + \mu + \lambda)I$$

$$\frac{dV}{dt} = \theta S - (\mu + \omega)V - \left(\beta_1 - \beta_3 \frac{I}{m_I + I}\right)(1 - \gamma)VI$$

$$\frac{dR}{dt} = \lambda I - (\mu + \sigma)R$$

Λ=birth rate μ=background death rate θ=vaccination rate
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Media affects mixing rates

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- β_i are the relative transmissibilities.

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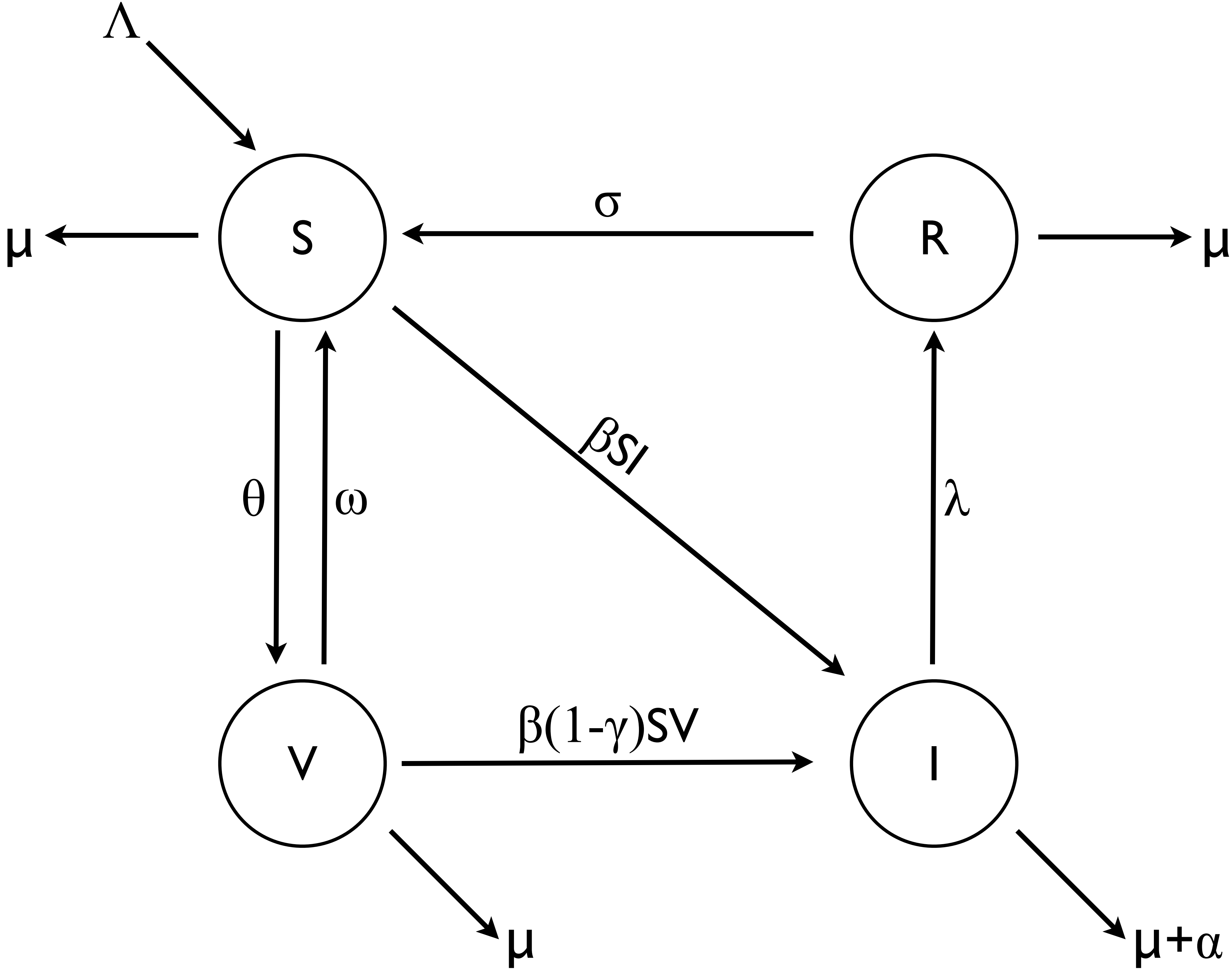
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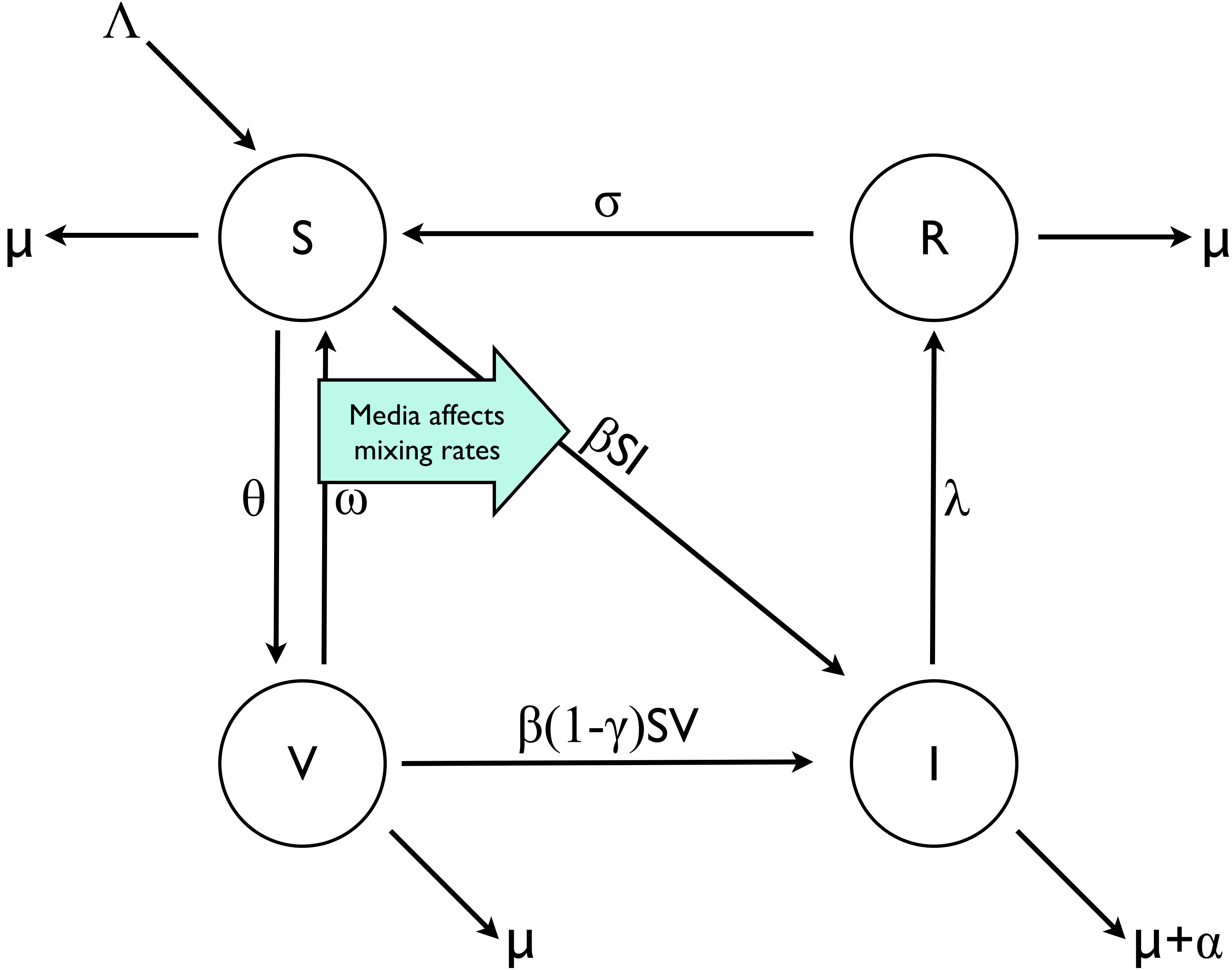

Λ
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Media affects
mixing rates
βSI
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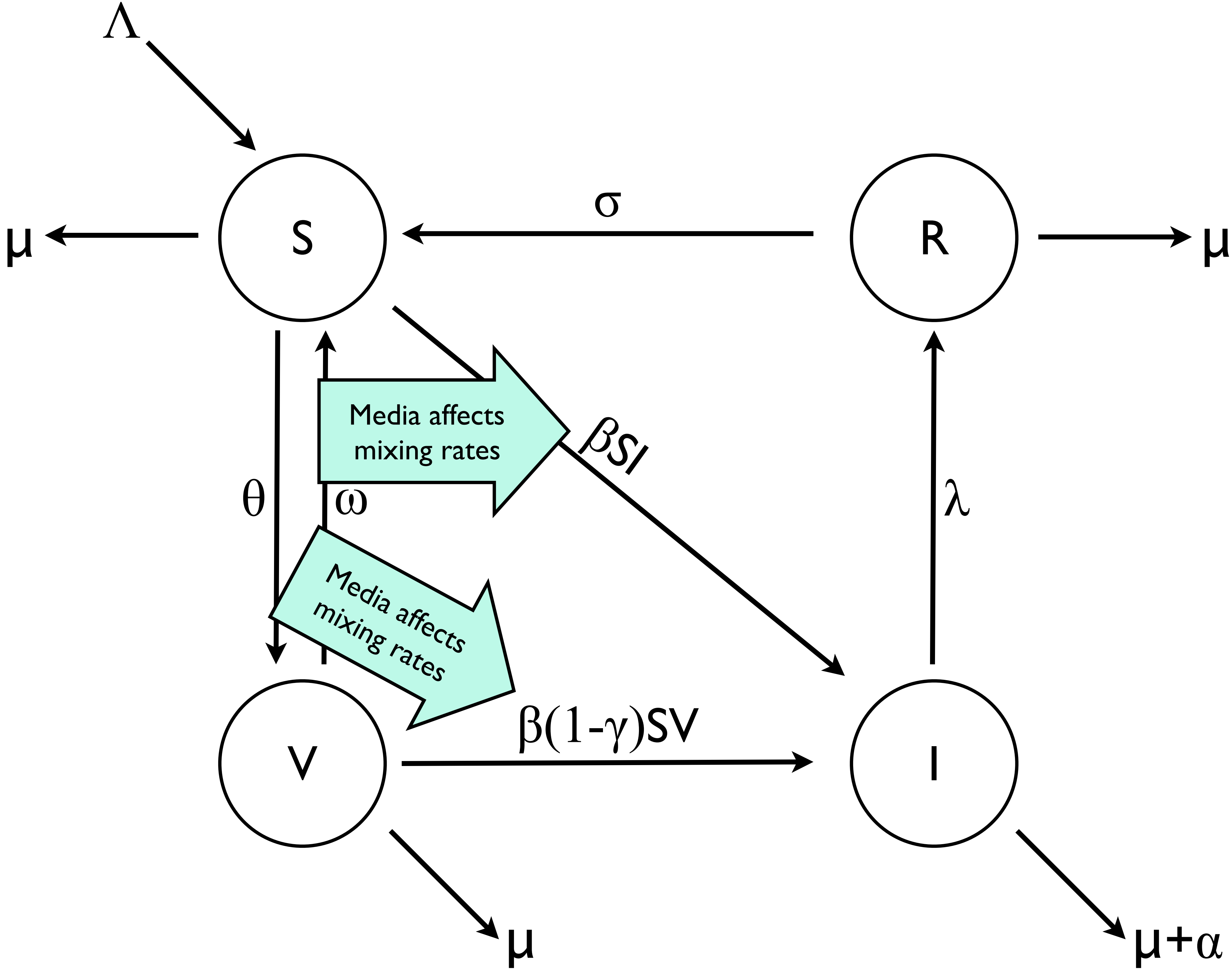

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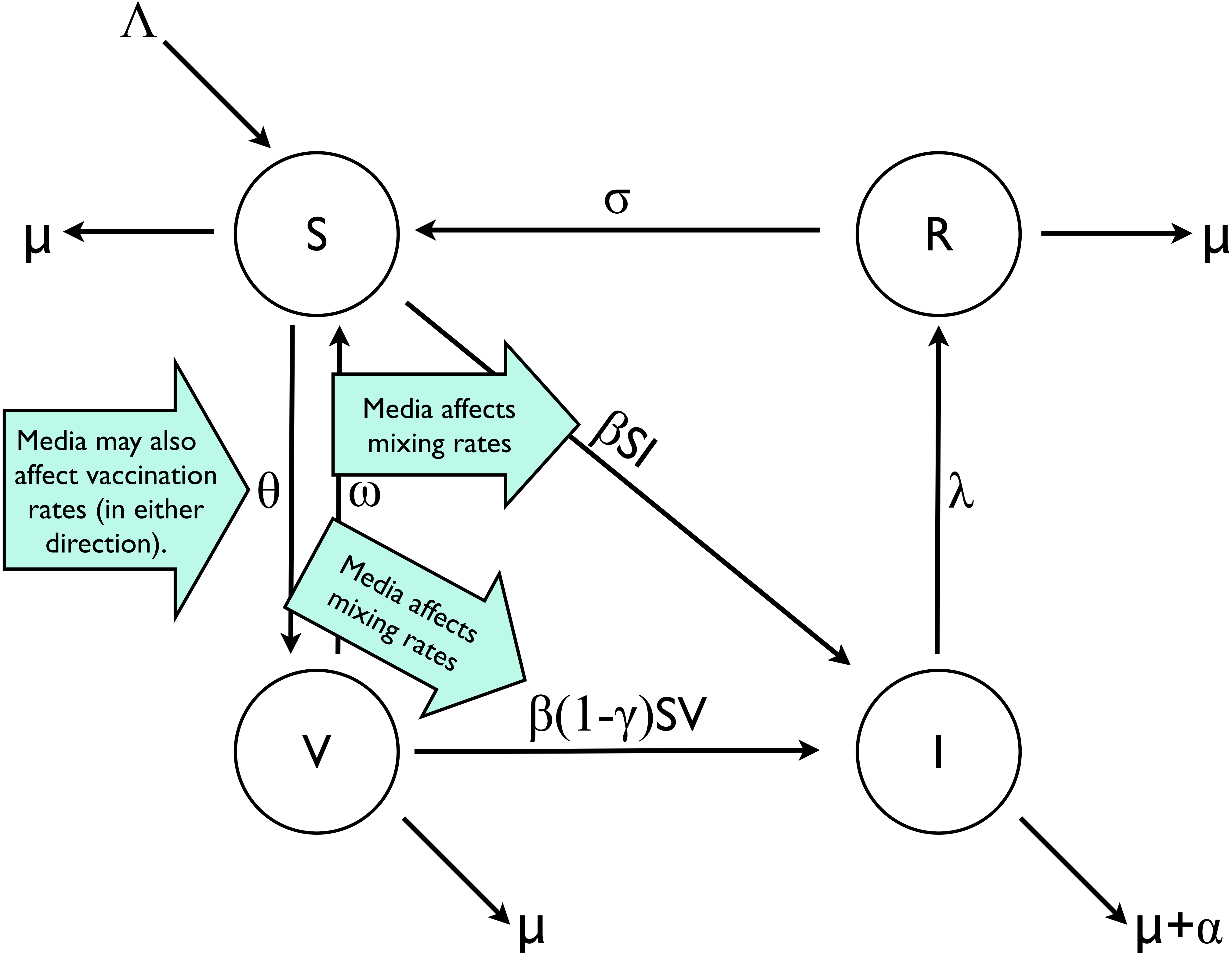
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Media may also affect vaccination rates (in either direction).
Media affects mixing rates
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Media effects

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- ie message reaches a maximum number of people due to information saturation
- This also reflects the fact that the media are less interested in a story once it's established in society.

Equilibria

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- Using the next-generation method, we can calculate

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  - If $R_0 > 1$ the DFE is unstable.

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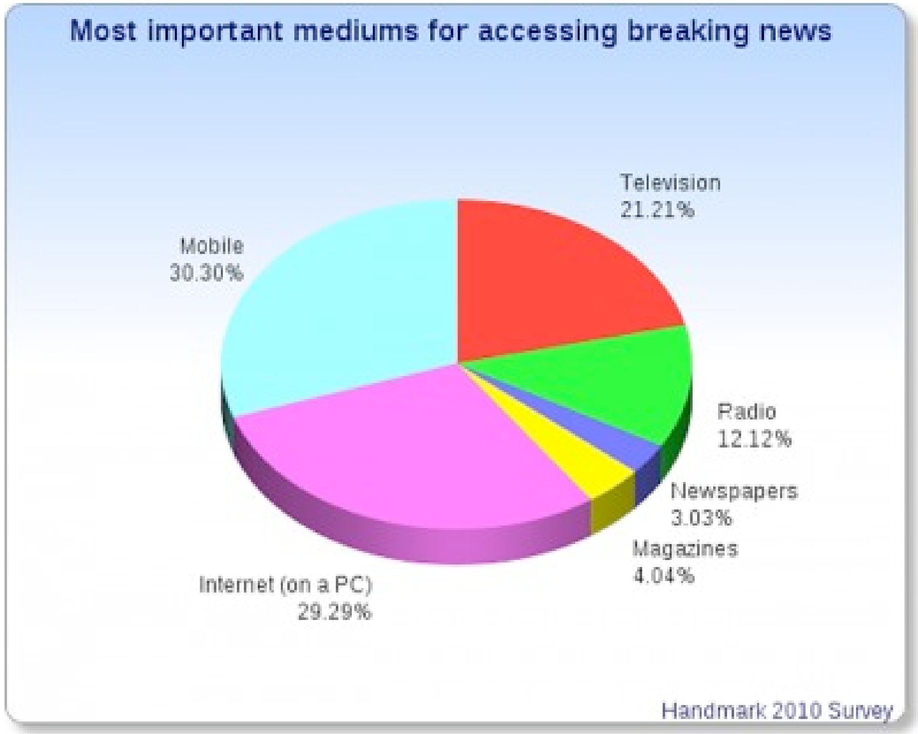
Optimal control

We introduce two controls, each representing a possible method of influenza control:



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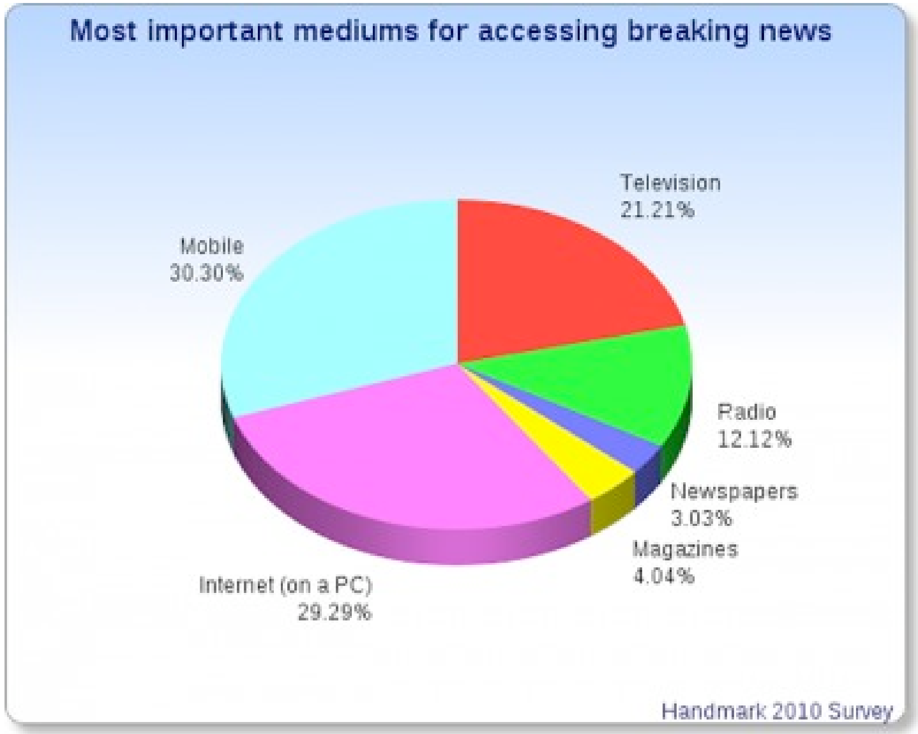

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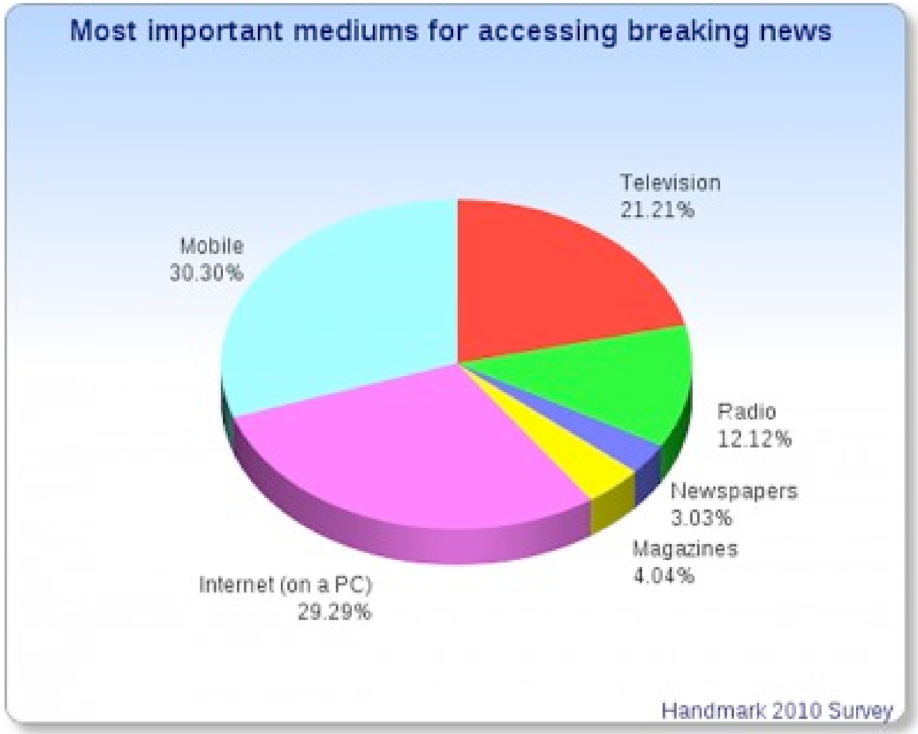

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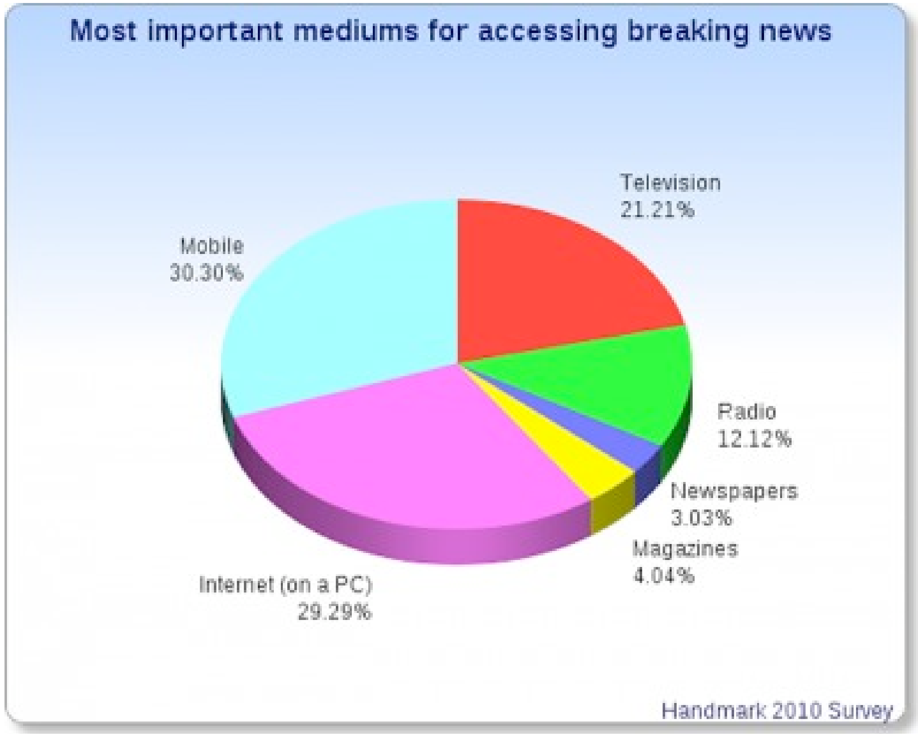

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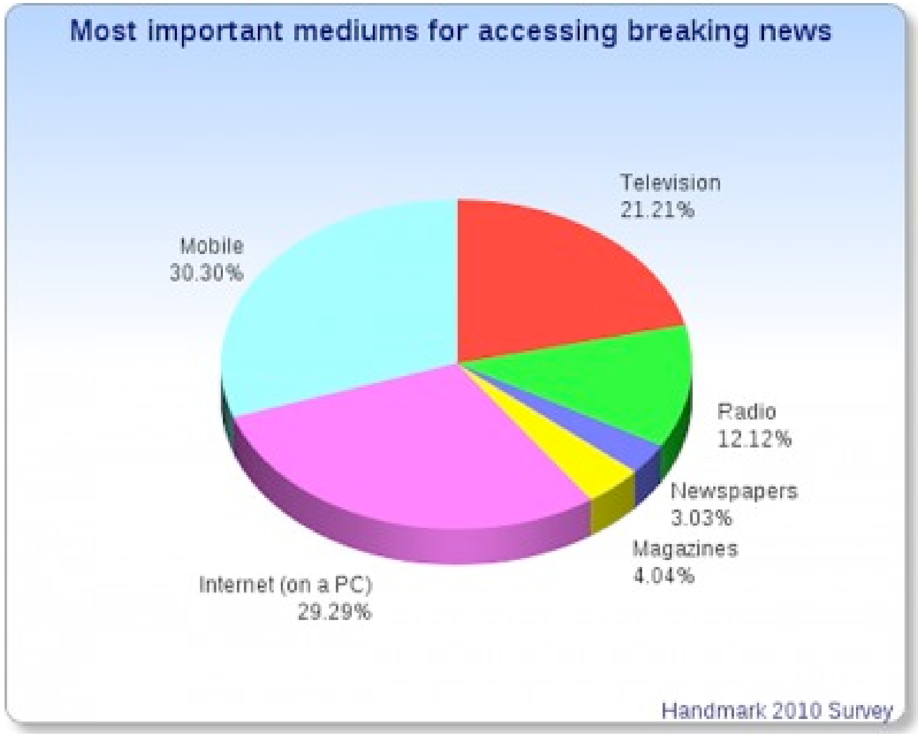

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$$J(u_v(t), u_m(t)) = \int_{t0}^{tf} [S(t) + V(t) - B_1 I(t) - B_2 (u_v^2(t) + u_m^2(t))] dt$$

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- B_1 and B_2 can represent the amount of money expended over a finite period, or the perceived risk.

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Adjoint equations

- Given optimal controls u_v and u_m, there exist adjoint variables λ_i (i=1,2,3,4) satisfying

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$$\frac{d\lambda_1}{dt} = -1 + (\lambda_1 - \lambda_2)(\beta_1 - \beta_2 \frac{I}{(1-u_m)m_I + I})I + (\lambda_1 - \lambda_3)(1-u_v)\theta + \lambda_1\mu$$

$$\begin{aligned}\frac{d\lambda_2}{dt} &= B_1 + (\lambda_1 - \lambda_2)\left[\left(\beta_1 - \beta_2 \frac{I}{(1-u_m)m_I + I}\right)S - \beta_2 \frac{(1-u_m)m_I}{((1-u_m)m_I + I)^2} IS\right] \\ &+ (\lambda_3 - \lambda_2)\left[\left(\beta_1 - \beta_3 \frac{I}{(1-u_m)m_I + I}\right)(1-\gamma)V - \beta_3 \frac{(1-u_m)m_I}{((1-u_m)m_I + I)^2}(1-\gamma)VI\right] \\ &+ \lambda_2(\alpha + \mu + \lambda) - \lambda_4\lambda\end{aligned}$$

$$\frac{d\lambda_3}{dt} = -1 + (\lambda_3 - \lambda_2)(\beta_1 - \beta_3 \frac{I}{(1-u_m)m_I + I})(1-\gamma)I + \lambda_3\mu + (\lambda_3 - \lambda_1)\omega$$

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- The optimal controls are unique if t_f is small.

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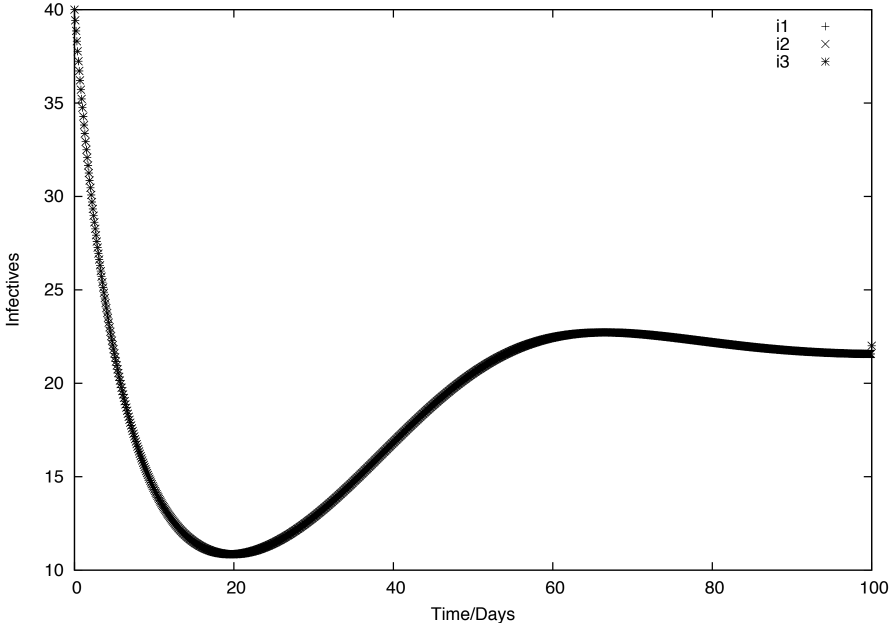
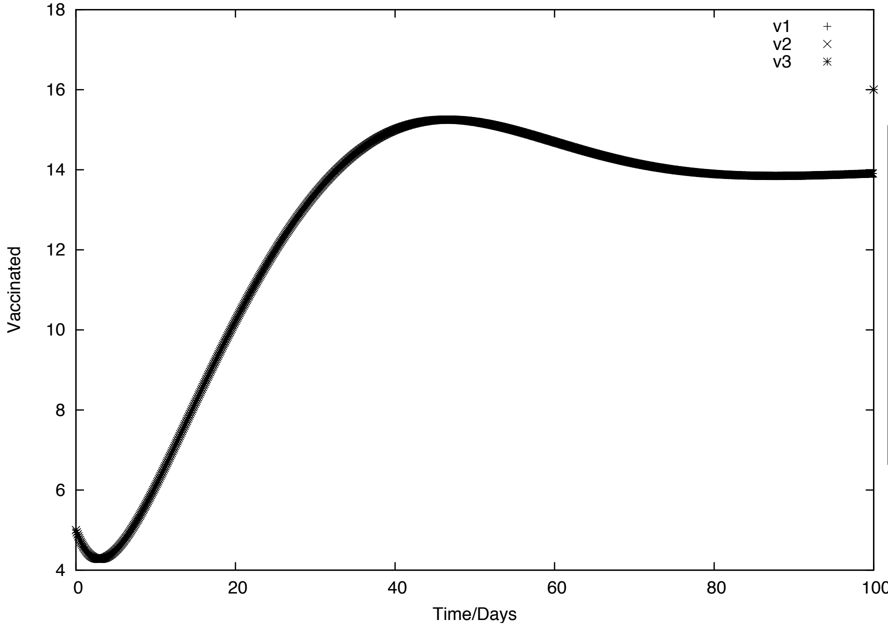
Media has beneficial effect on vaccine





Costs of infection high, control low

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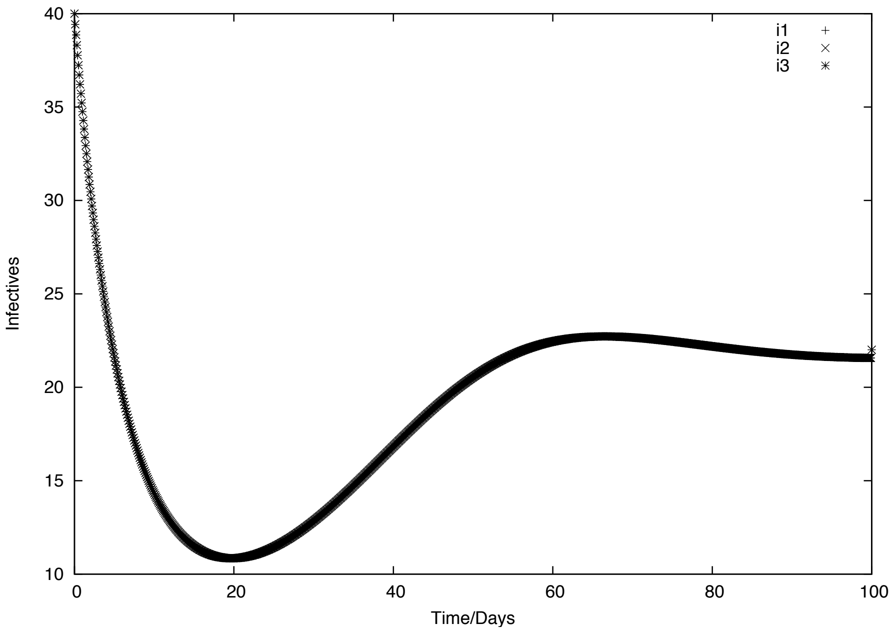

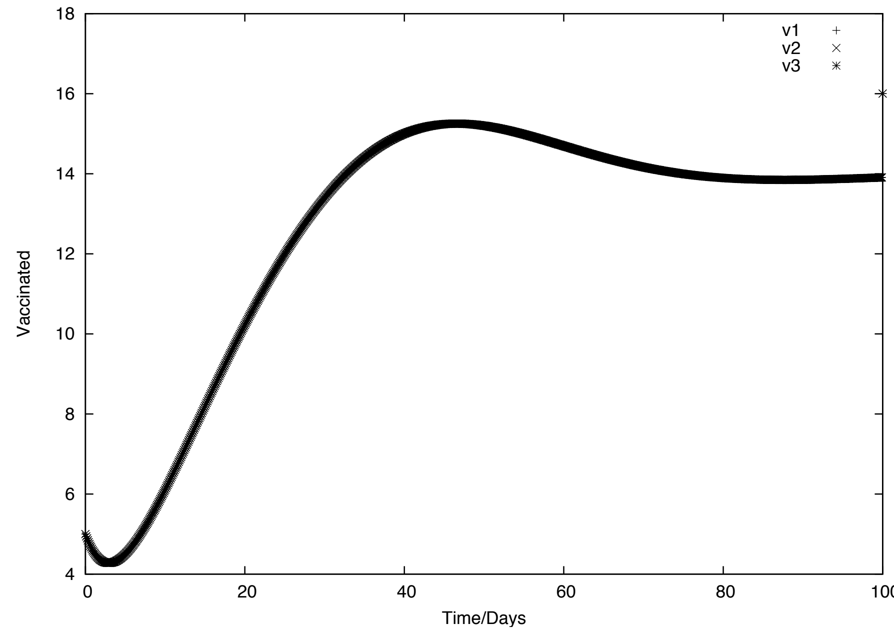

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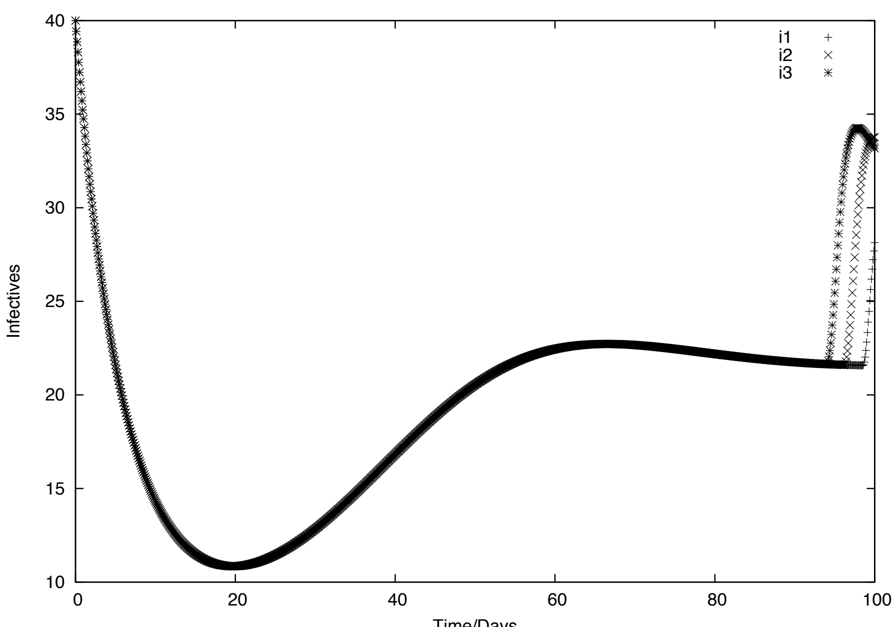

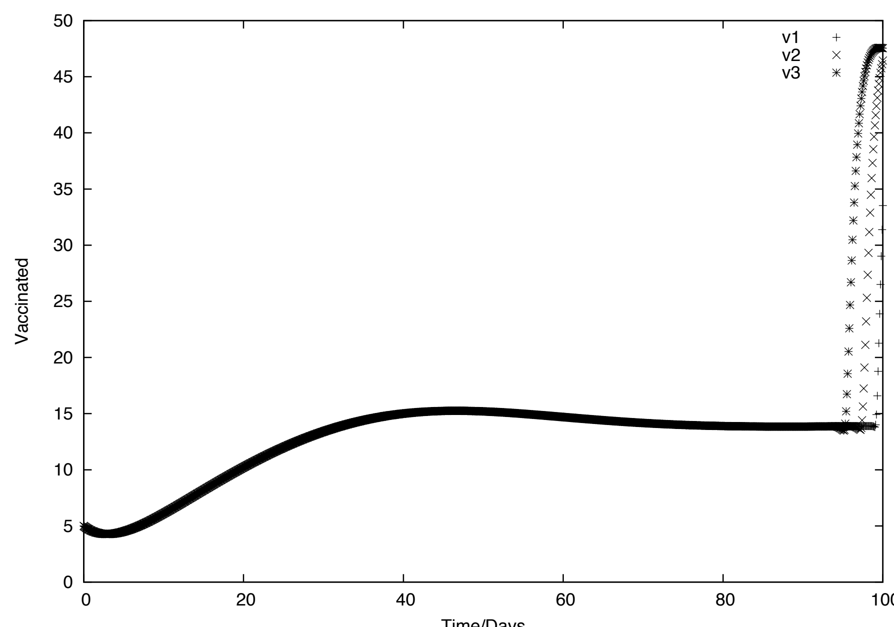

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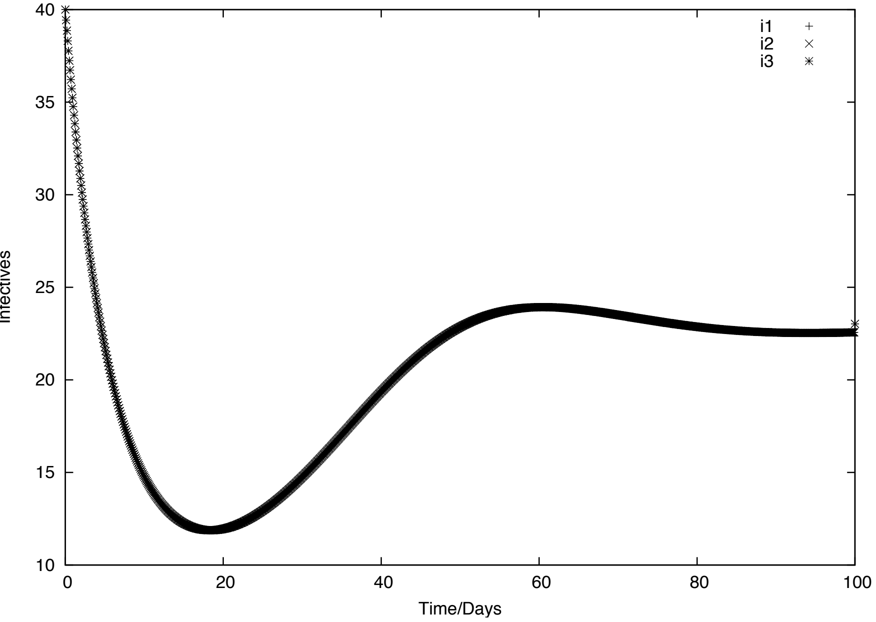

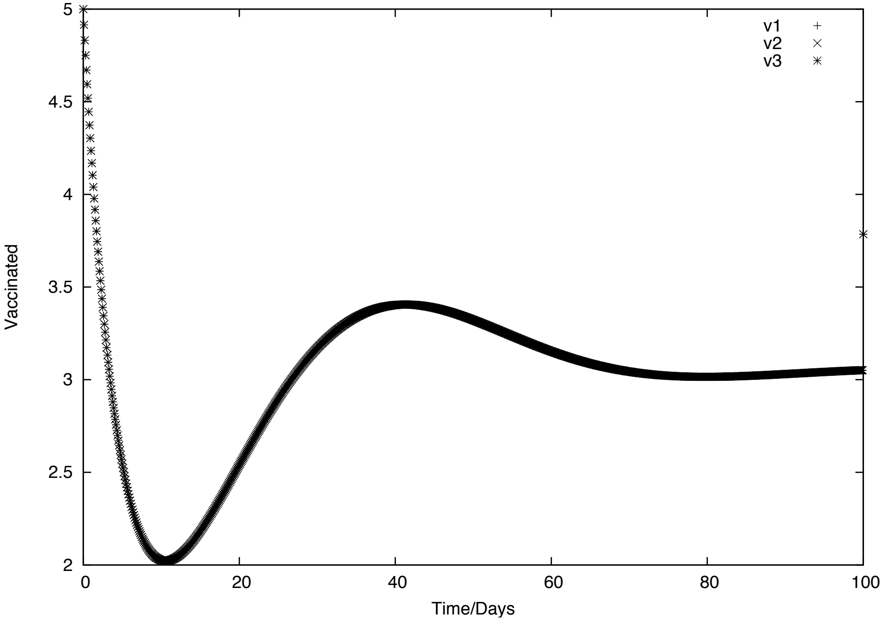

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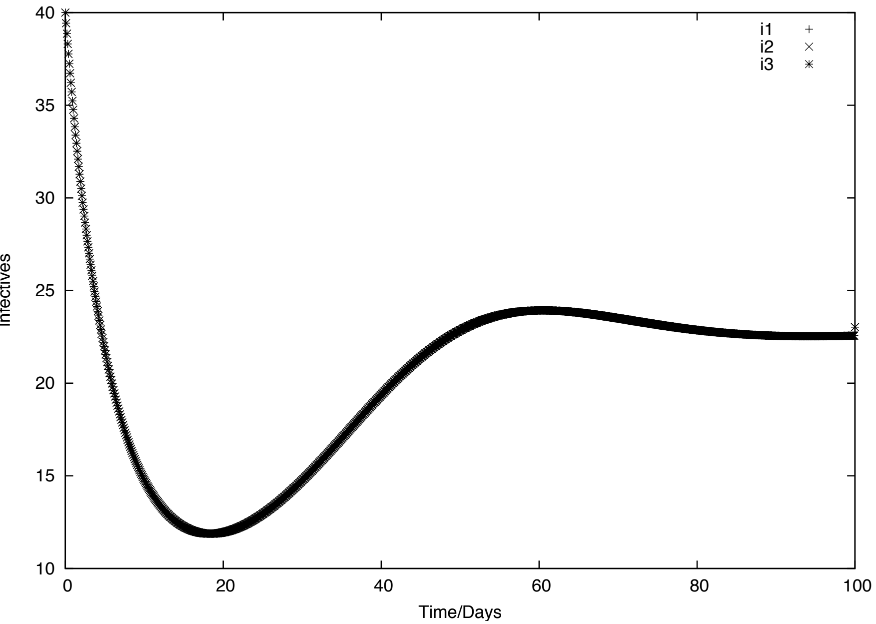

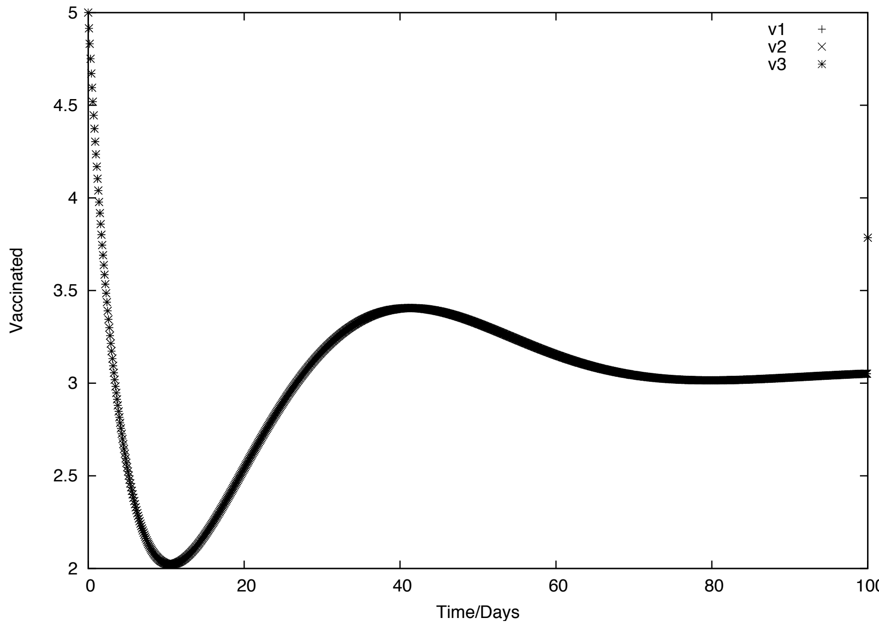

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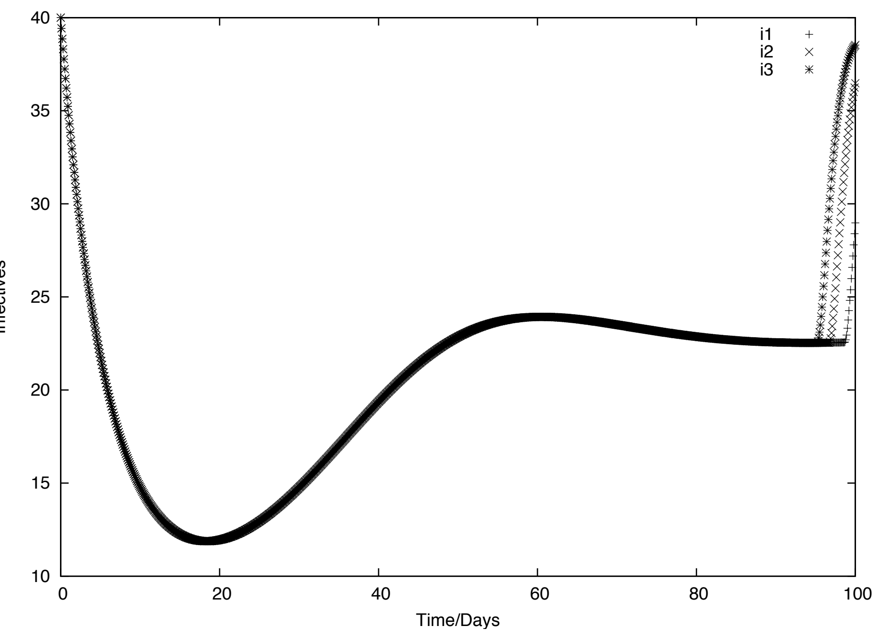

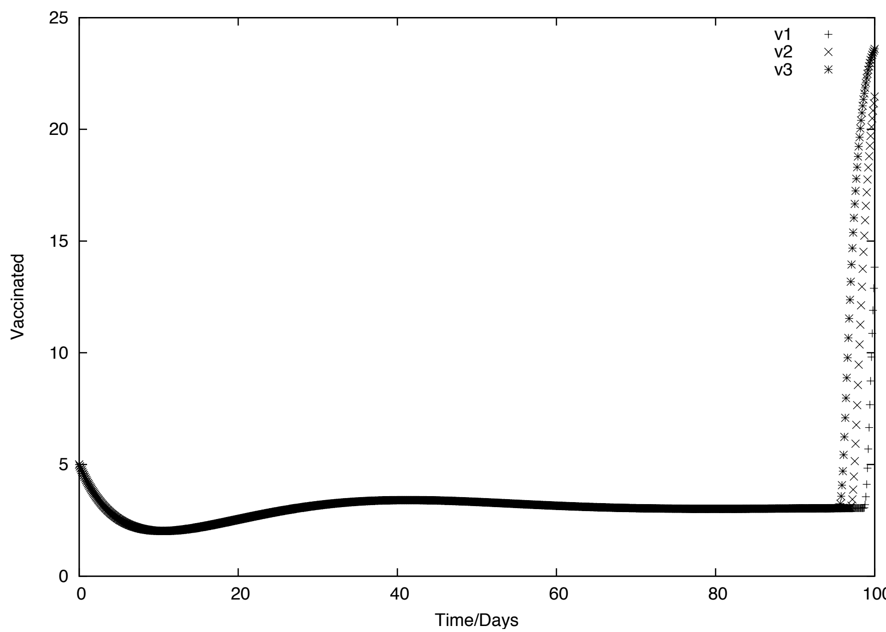

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Adverse outcome due to media?

- To illustrate a potentially adverse outcome, consider a simplified model
- Suppose, initially, the media and the general population are unaware of the disease
- Thus, nobody gets vaccinated, allowing the disease to spread initially
- New infected individuals arrive at fixed times
- We will ignore recovery in this simple model.

Media awareness threshold

- Suppose there are a critical number of infected individuals whereupon people become aware of the disease, via the media

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- However, vaccinated individuals mix significantly with infecteds
- Even though they may still potentially contract the virus.

Simplified model - lower region

- For $I<I_{crit}$, the model is

S=susceptible I=infected V=vaccinated Λ=birth rate μ=background death rate α=disease death rate ω=waning rate λ=recovery rate I_{crit}=vaccination panic threshold

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\begin{aligned}
\frac{dS}{dt} &= \Lambda + \omega V - \mu S & t \neq t_k \\
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\Delta I &= I^i & t = t_k
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- t_k are (fixed) arrival times of new infecteds
- This approximates low-level mixing
- If arrival times are not fixed, the results are broadly unchanged.

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Simplified model - upper region

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Simplified model - upper region

- For $I > I_{crit}$, the model is

$$\frac{dS}{dt} = \Lambda + \omega V - (\theta + \mu)S$$
$$\frac{dI}{dt} = \beta_5(1-\gamma)VI - (\alpha + \mu + \lambda)I$$
$$\frac{dV}{dt} = \theta S - (\mu + \omega)V - \beta_5(1-\gamma)VI$$

S=susceptible I=infected V=vaccinated Λ=birth rate μ=background death rate θ=vaccination rate α=disease death rate ω=waning rate γ=vaccine efficacy λ=recovery rate I_{crit}=vaccination panic threshold

Simplified model - upper region

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  (at low rates).

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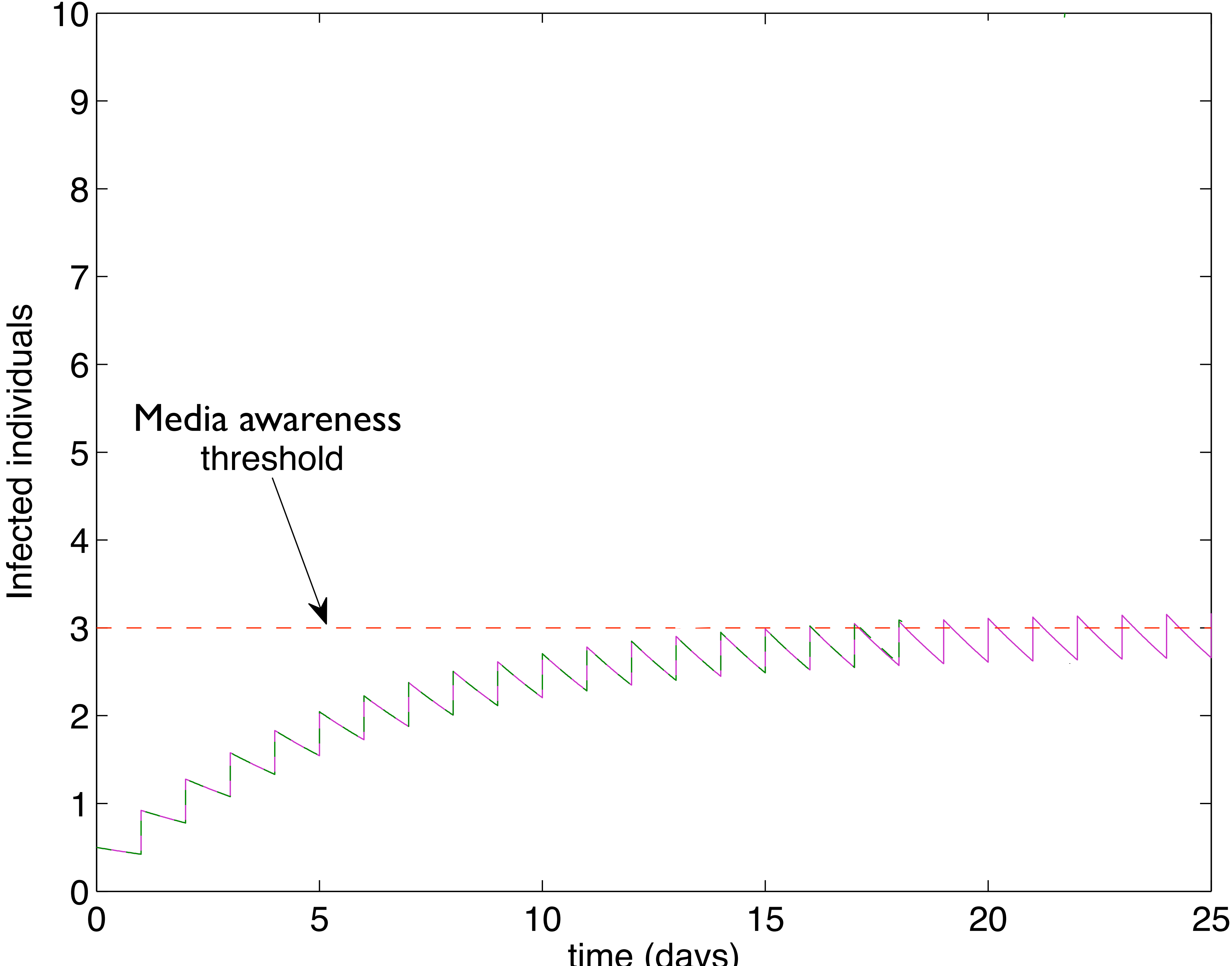
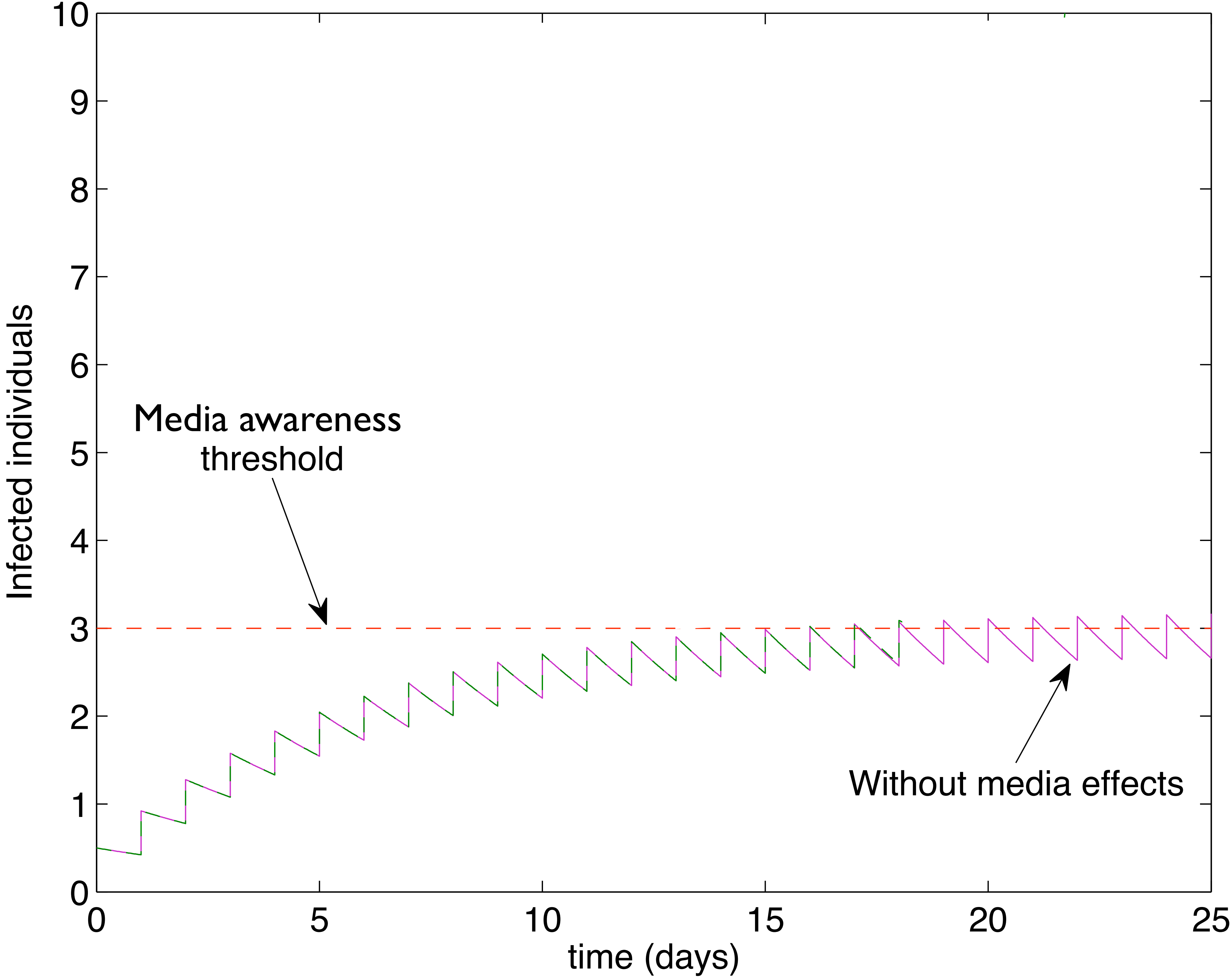
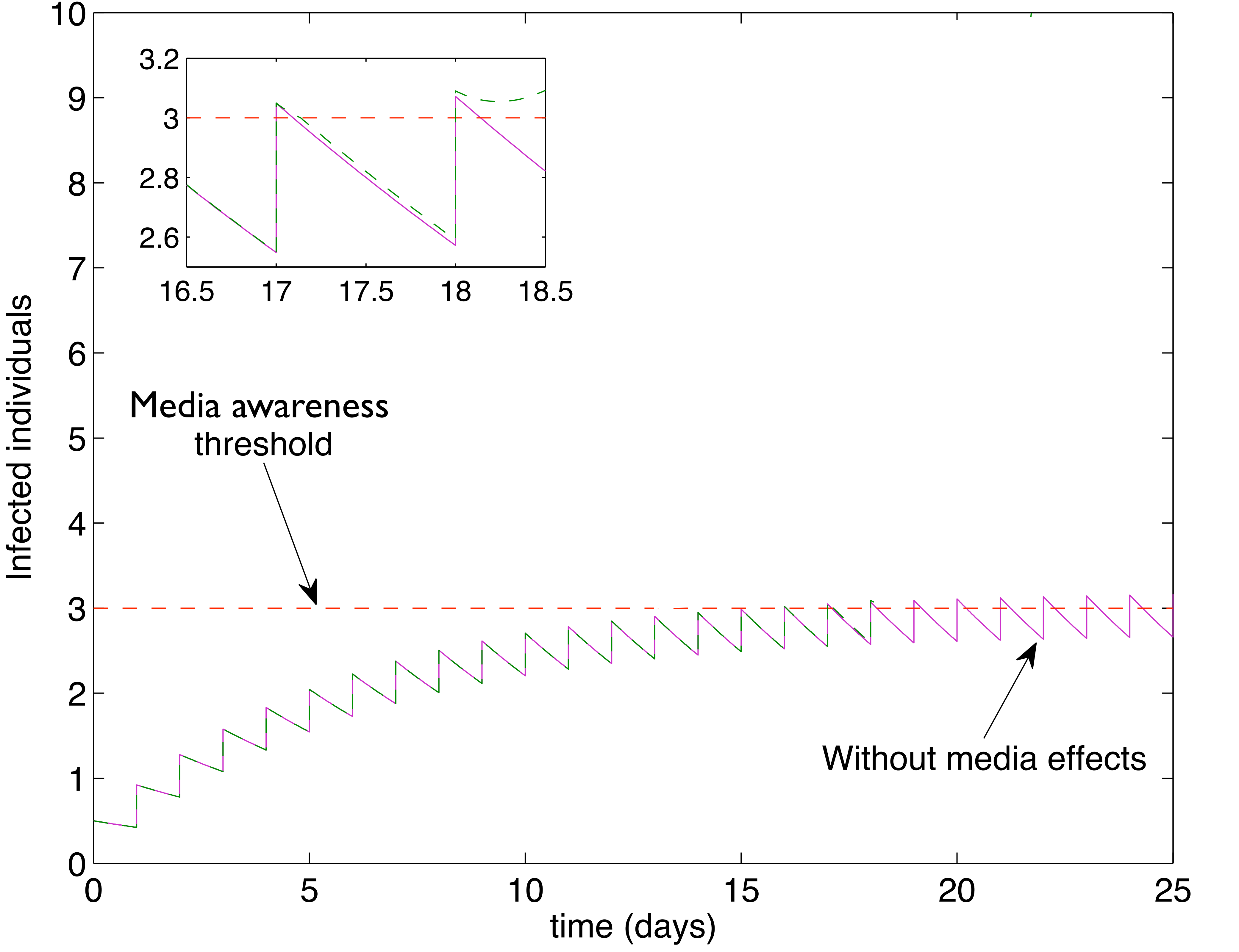


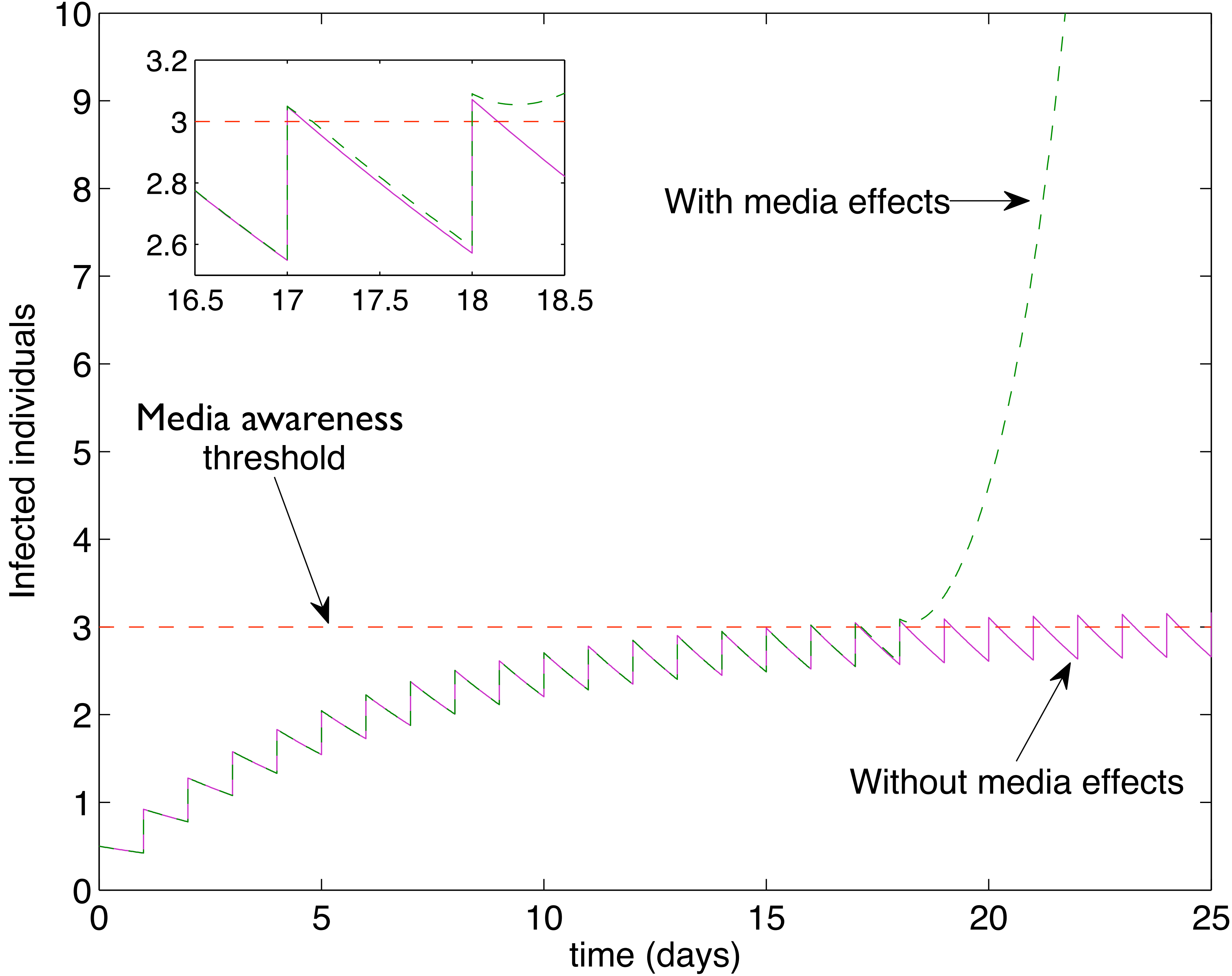
Media awareness threshold
Infected individuals
time (days)
0
1
2
3
4
5
6
7
8
9
10
0
5
10
15
20
25



Media awareness threshold
Without media effects
Infected individuals
time (days)
0
1
2
3
4
5
6
7
8
9
10
0
5
10
15
20
25



Infected individuals
time (days)
Media awareness threshold
Without media effects
0
5
10
15
20
25
0
1
2
3
4
5
6
7
8
9
10
16.5
17
17.5
18
18.5
2.6
2.8
3
3.2



10
9
8
7
6
5
4
3
2
1
0
Infected individuals
0
5
10
15
20
25
time (days)
3.2
3
2.8
2.6
16.5
17
17.5
18
18.5
With media effects
Media awareness threshold
Without media effects

Lower region

- If $I<I_{crit}$,we can prove that

μ=background death rate α=disease death rate
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Lower region

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$$I^+ \to \frac{I^i}{1-e^{-(\alpha+\mu+\lambda)\tau}} \equiv m^+$$

μ=*background death rate* α=*disease death rate*
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where $\tau = t_{k+1} - t_k$

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$$I^+ \to \frac{I^i}{1-e^{-(\alpha+\mu+\lambda)\tau}} \equiv m^+$$

  where $\tau = t_{k+1} - t_k$

- If $m^+>I_{crit}$, then the system will eventually switch from the lower region to the upper region.

μ=background death rate α=disease death rate
λ=recovery rate I_{crit}=vaccination panic threshold

Upper region

- If $I > I_{crit}$, there is an endemic equilibrium (S^*, I^*, V^*)

S=susceptible I=infected V=vaccinated m^+=non-media equilibrium I_{crit}=vaccination panic threshold

Upper region

- If $I > I_{crit}$,there is an endemic equilibrium (S^*, I^*, V^*)
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- ie once trajectories enter the upper region, they will stabilise there
- If $I^* > m^+$, then the outcome will be worse than without media effects
- Thus, even in this extremely simplified model, the media may make things significantly worse.

S=susceptible I=infected V=vaccinated m^+=non-media equilibrium I_{crit}=vaccination panic threshold

Low-level mixing of susceptibles

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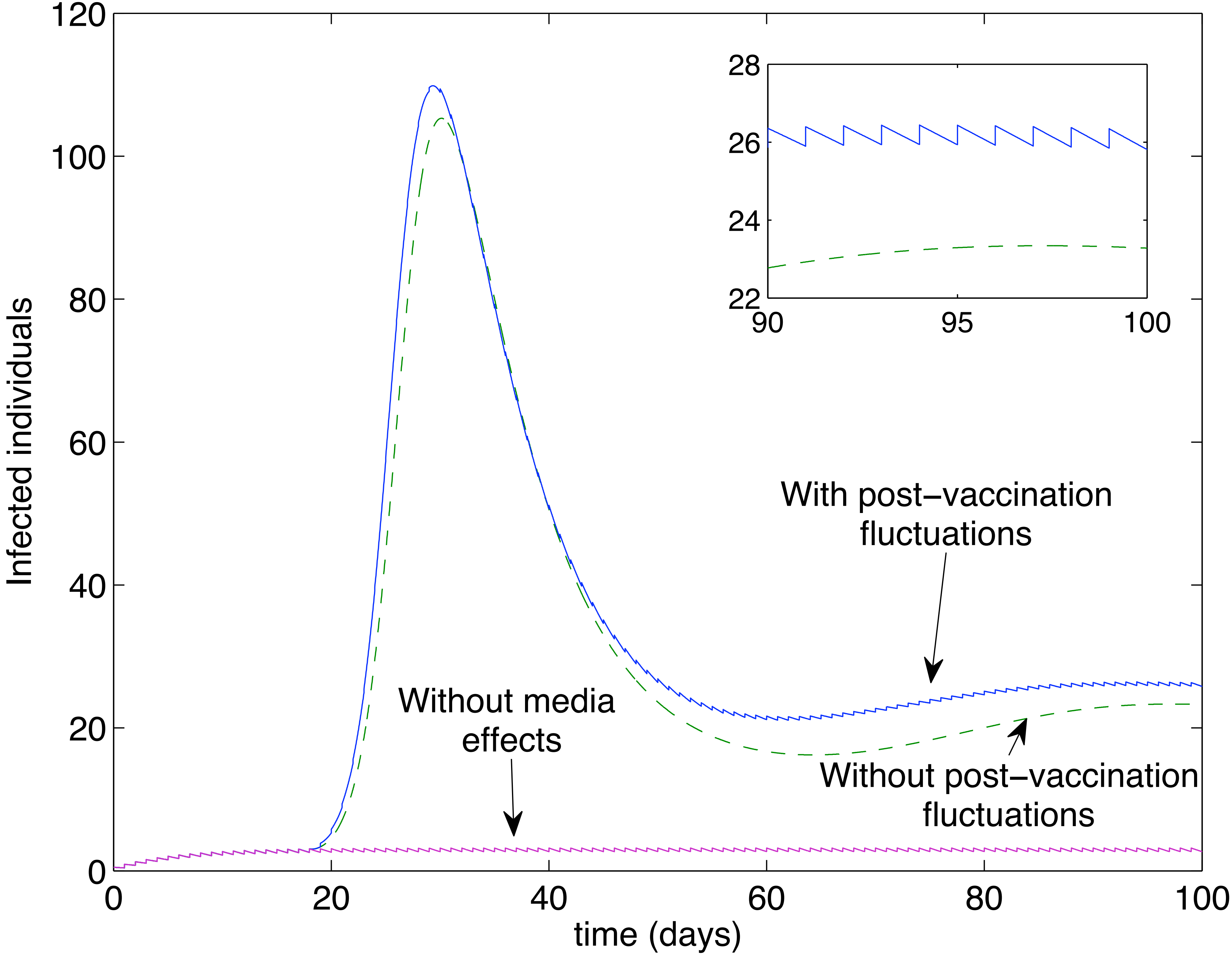
- Including these will increase the long-term number of infecteds
- It will also increase the peak of the epidemic wave.


Infected individuals
time (days)
With post–vaccination fluctuations
Without post–vaccination fluctuations
Without media effects
0
20
40
60
80
100
120
28
26
24
22
90
95
100

High-level mixing of susceptibles

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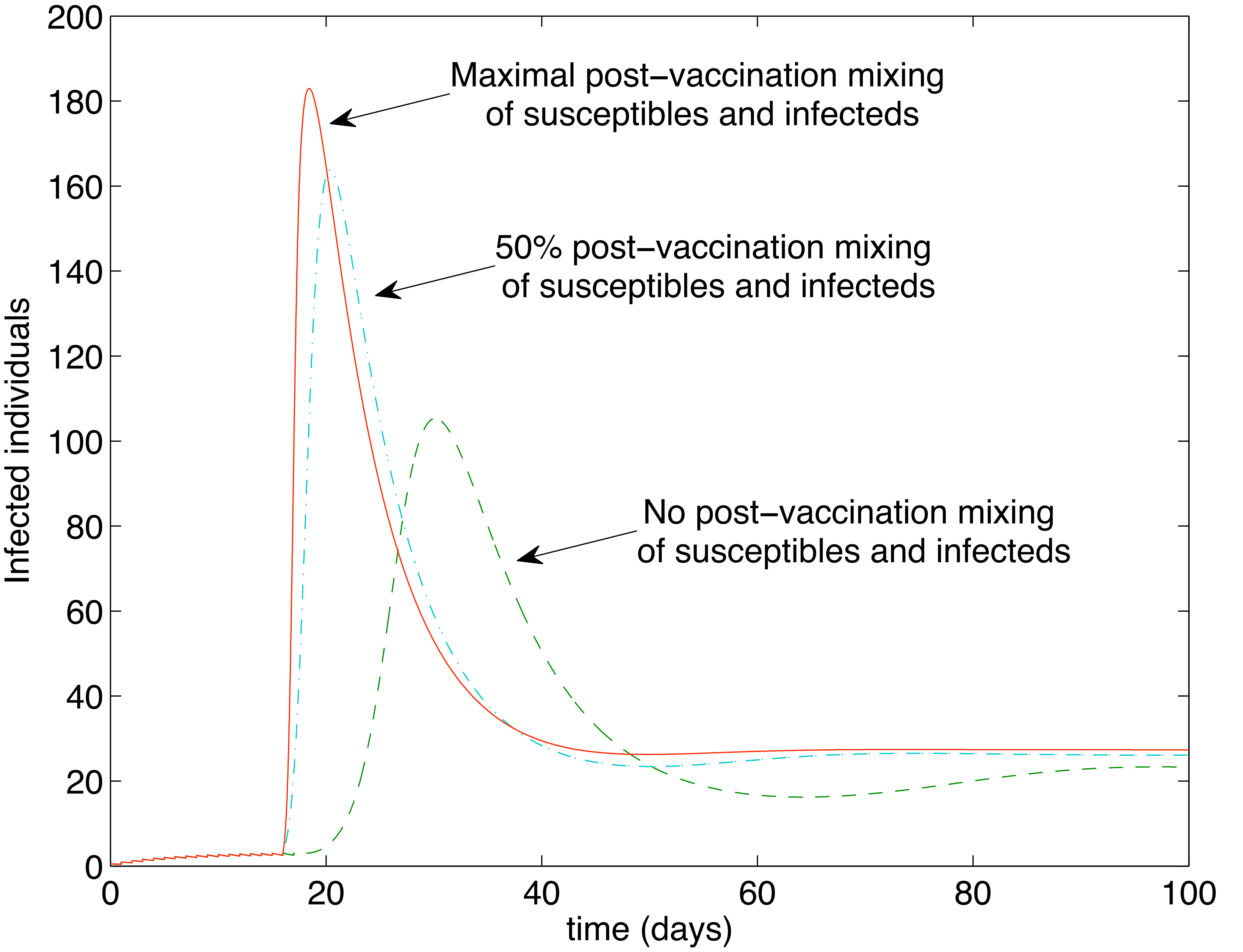
High-level mixing of susceptibles

- What if susceptibles mix with infecteds in more significant numbers?
- If these effects are included in the upper region, then the wave peak occurs earlier
- The long-term number of infecteds will also increase.



Maximal post−vaccination mixing
of susceptibles and infecteds
50% post−vaccination mixing
of susceptibles and infecteds
No post−vaccination mixing
of susceptibles and infecteds
Infected individuals
time (days)
0
20
40
60
80
100
120
140
160
180
200
0
20
40
60
80
100

Adverse outcome

- Thus, a small series of outbreaks that would equilibrate at some maximal level $m^+ > I_{crit}$ may, as a result of the media, instead equilibrate at a much larger value $I^* > m^+$

m^+=non-media equilibrium I_{crit}=vaccination panic threshold

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- The driving factor here is overconfidence in an imperfect vaccine
- ie vaccinated people mix significantly more with infecteds than susceptibles do
- This may happen if people feel invulnerable, due to media simplifications around vaccines.

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Summary

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- The result is a vaccinating panic and a net increase in the number of long-term infected
- Thus, media coverage of an emerging epidemic can have dire consequences
- It can also implicitly reinforce an imperfect solution as the only answer.

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- eg people may ignore the media, de-linking the vaccination rate from the control.

Recommendations

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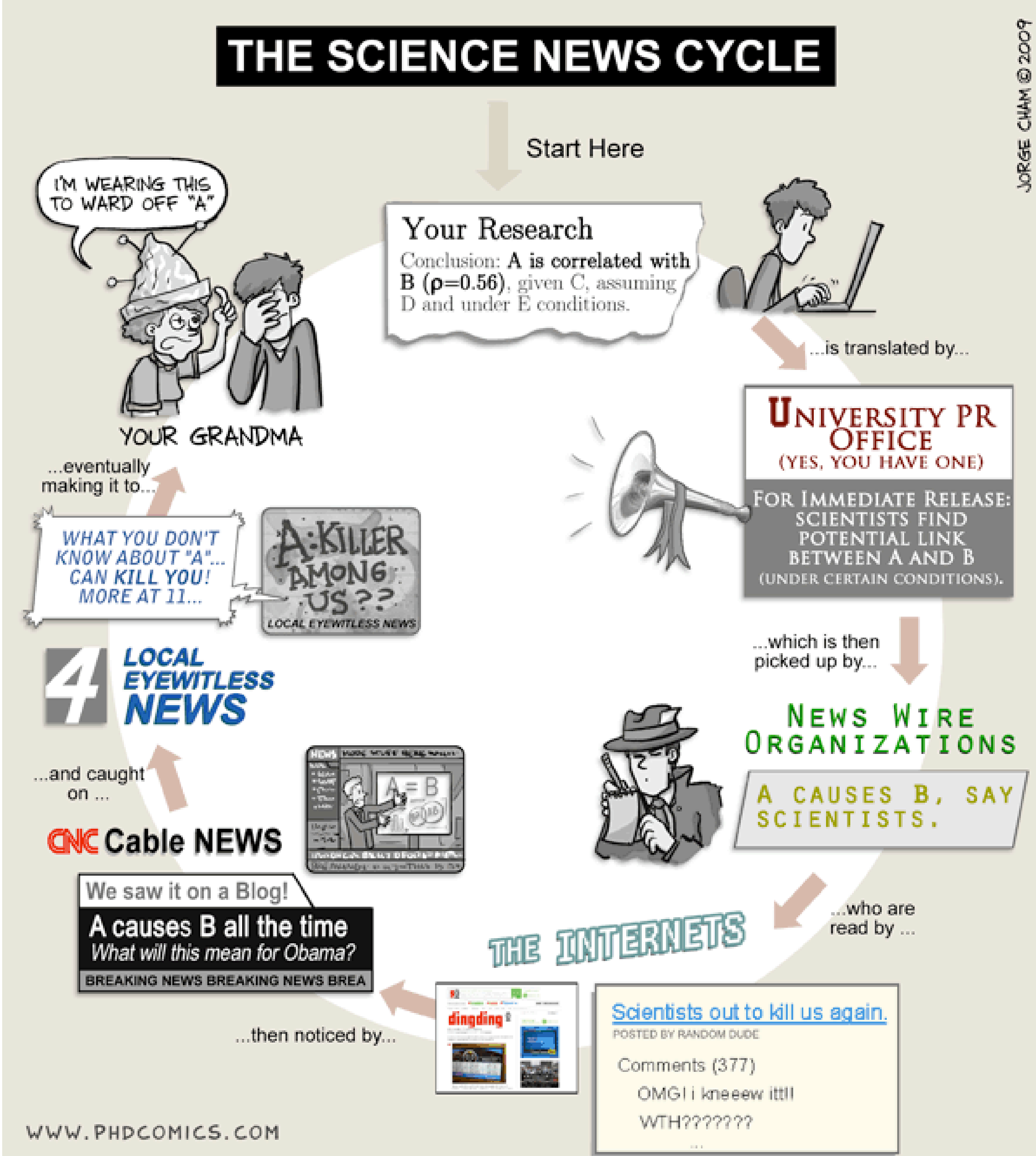
- Messages need to be straightforward
- Plain language is crucial
- Speak in quoteable phrases, not paragraphs
- If you can't explain it...

  ...you didn't do it.



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...who are read by ...
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...then noticed by...
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CNC Cable NEWS
...and caught on ...
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LOCAL EYEWITLESS NEWS
...eventually making it to...
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I'M WEARING THIS TO WARD OFF "A"
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- While the media may encourage more people to get vaccinated, they may also trigger a vaccinating panic
- Or promote overconfidence in the ability of a vaccine to fully protect against the disease
- When the next pandemic arrives, the outcome is likely to be significantly worse as a result of the media.

Key References

- J.M. Tchuenche, N. Dube, C.P. Bhunu, R.J. Smith? and C.T. Bauch (2011). The impact of media coverage on the transmission dynamics of human influenza. BMC Public Health 11(Suppl 1):S5.

http://www.mathstat.uottawa.ca/~rsmith