

Evaluating General vs. Singular Causal Prevention

 Simon Stephan^{*1}, Sarah Placi^{*2}, and Michael R. Waldmann^{*1}, University of Göttingen^{*1}, University of Trento^{*2}

Background. Most psychological studies focused on how people reason about generative causation, in which a cause *produces* an effect. We studied the *prevention* of effects both on the general and singular level. A general prevention query might ask, for example, how strongly a vaccine is expected to reduce the risk of contracting COVID-19. By contrast, a singular prevention query might ask whether the absence of COVID-19 in a *specific* vaccinated person actually resulted from this person's vaccination. We developed a computational model (**Tab. 2**) answering how knowledge about the general strength of a preventive cause can be used to assess whether a preventive link is actually instantiated in a singular case. We also discuss and show how psychological models of causal strength learning relate to mathematical models of vaccination efficacy used in medical research (**Tab. 1**). The predictions of our new model were tested in an online experiment ($N = 104$).

Experimental findings. Subjects were assigned either to a *general preventive strength query* (Cond. 1) or a *singular prevention query* (Cond. 2) condition. All subjects read a vaccination scenario in which scientists tested the efficacy of vaccines against different strains of bacteria. Subjects were shown four different learning data sets, presented in random order (see **Experiment**). For half of the subjects, the vaccine was a sufficient preventive cause. For the other half, the vaccine was a necessary preventer (see model predictions in **Tab. 1**). Subjects in Cond. 1 were asked to estimate the general preventive strengths of the tested vaccines. Subjects in Cond. 2 were asked to consider a randomly selected healthy individual from the vaccination group. They rated the probability that this individual remained healthy because of the vaccination.

We found that subjects tended to differentiate between general preventive strength queries and

queries asking for the probability of actual prevention in cases in which the preventer is present and the effect is absent. Their answers were overall quite well explained by the different models, although we also found a lot of variation (see **Results**). Part of this variation may result from some people treating general preventive strength and the probability of actual prevention equivalently (see **Cluster Analysis**).

Discussion. A crucial assumption of our singular prevention model is that actual prevention can occur only if both the preventer and generative cause are present and the generative cause would have been sufficiently strong to generate the effect if the preventer had been absent. We tested cases in which the generative cause always occurred. To obtain more evidence for the psychological reality of this assumption, we will in future studies manipulate the generative cause's base rate. We also plan to test more data sets and other scenarios.

Tab. 1: Estimating Preventive Causal Strength - Vaccination Efficacy and Preventive Power

Example Contingency Data Set:

E+		E-	
C+	N(e+,e+)	N(e-,e+)	120
C-	N(e-,e+)	N(e-,e-)	60
P(e+ c+) = 0/120 = 0	P(e+ c-) = 60/60 = 0.5	Delta-P = 0 - 0.5 = -0.50	

In this case, C (the cause; e.g., a vaccine) is a sufficient preventer of E (the effect; e.g., a disease)

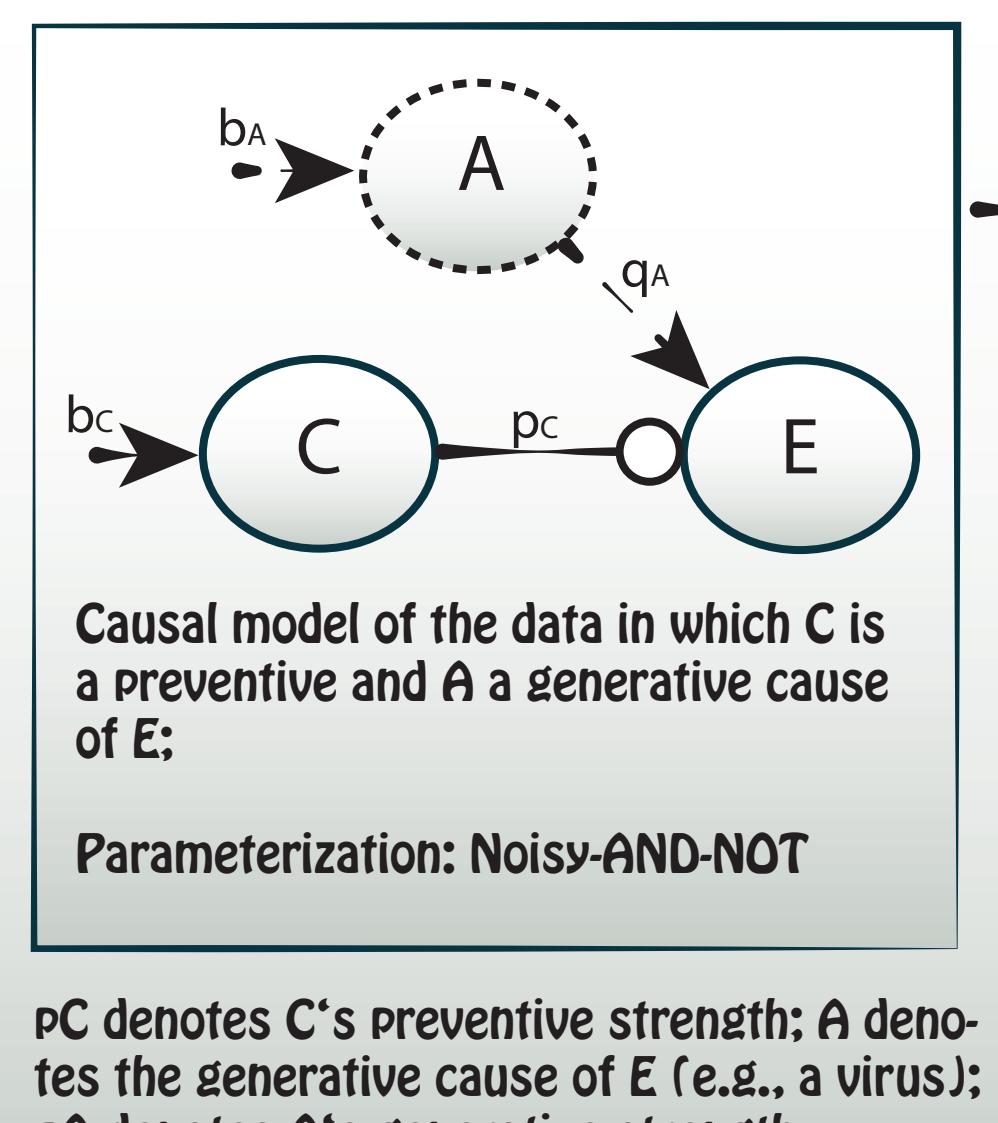
Vaccination Efficacy (VE):

$$VE = \frac{ARU - ARV}{ARU} \cdot 100$$

ARU = Attack Rate among unvaccinated individuals = $P(e+|c-J)$
 ARV = Attack Rate among vaccinated individuals = $P(e+|c+)$
 $ARU - ARV = P(e+|c-J) - P(e+|c+)$
 $= -1 \times \Delta P$
 $VE = (0.5 - 0 / 0.5) \times 100 = 100$

Computes the risk reduction in the presence of the preventer for the (hypothetical) population expected to show the effect in the preventer's absence.

General Causal Structure:



Preventive Strength (pc):

$$pc = \frac{\Delta P}{P(e+|c-)} \cdot (-1)$$

$\Delta P = P(e+|c+J) - P(e+|c-J)$
 $\Delta P = 0 - 0.5 = -0.5$
 $P(e+|c-J) = 0.5$
 $pc = (-0.5 / 0.5) \times -1 = 1.0$

Relation between VE and pc:
 $pc = VE \times 100$

Represents the probability with which C prevents the occurrence of the effect in cases in which A would be strong enough to generate the effect.

Vaccination Efficacy as defined by Yule and Greenwood (1915) incorporates the assumptions of a Noisy-AND-NOT parameterized causal model in which C represents a preventive cause, A represents a generative cause, and E represents the effect.

VE/100 thus corresponds to the strength parameter of the preventive cause C, which can also be computed by using Cheng's (1997) formula for preventive causal power.

Tab. 2: Modeling Actual/ Singular Prevention

Target question: given a singular instance in which the preventive cause is present and the effect is absent, how likely is it that the preventive cause actually prevented the effect from occurring in this singular case?

Equation formulated based on causal model parameters:

$$P(c^+ \rightarrow e^+ | c^+, e^-) = \frac{p_c b_a q_a}{(1 - b_a q_a - p_c b_a q_a)}$$

Same equation using observable probabilities:

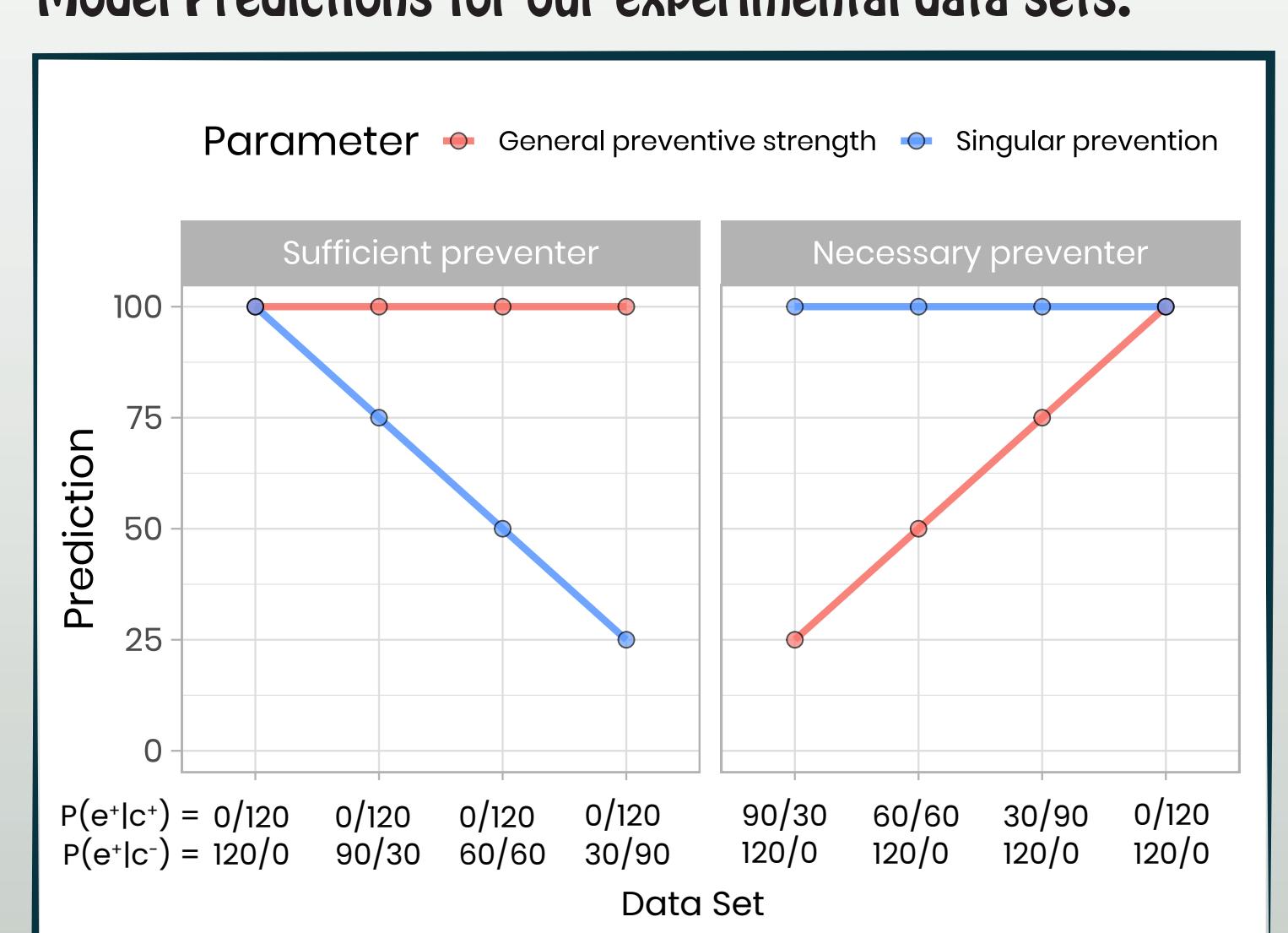
$$P(c^+ \rightarrow e^+ | c^+, e^-) = \frac{P(e^-|c^+) - P(e^-|c^-)}{P(e^-|c^+)}$$

Same equation using vaccination efficacy notation:

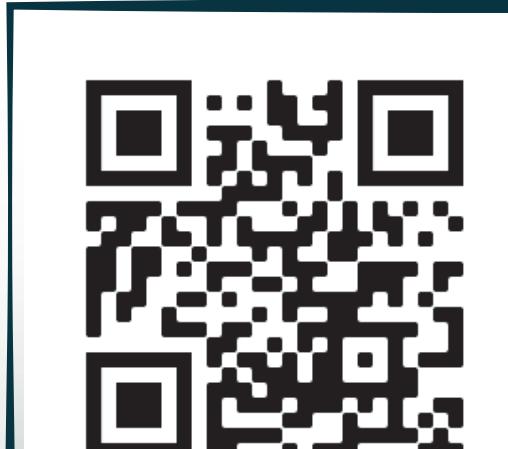
$$P(v^+ \rightarrow a^+ | v^+, a^-) = \frac{VE \cdot ARU}{1 - ARV}$$

Assumption: Actual prevention can occur only if the generative cause is present and would have been strong enough to cause the effect IF the preventer had been absent.

Model Predictions for our experimental data sets:



The Paper



<https://psyarxiv.com/c29sm/>

References

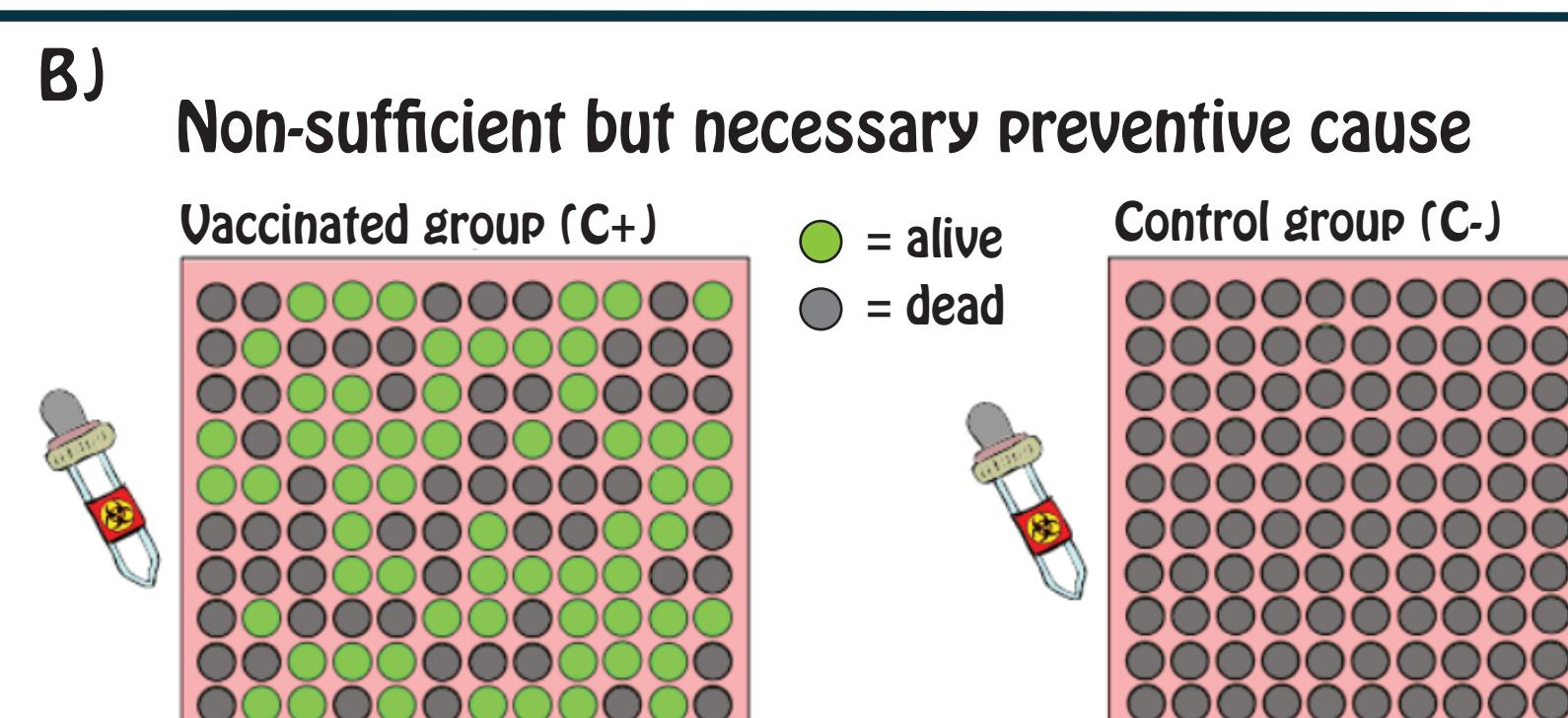
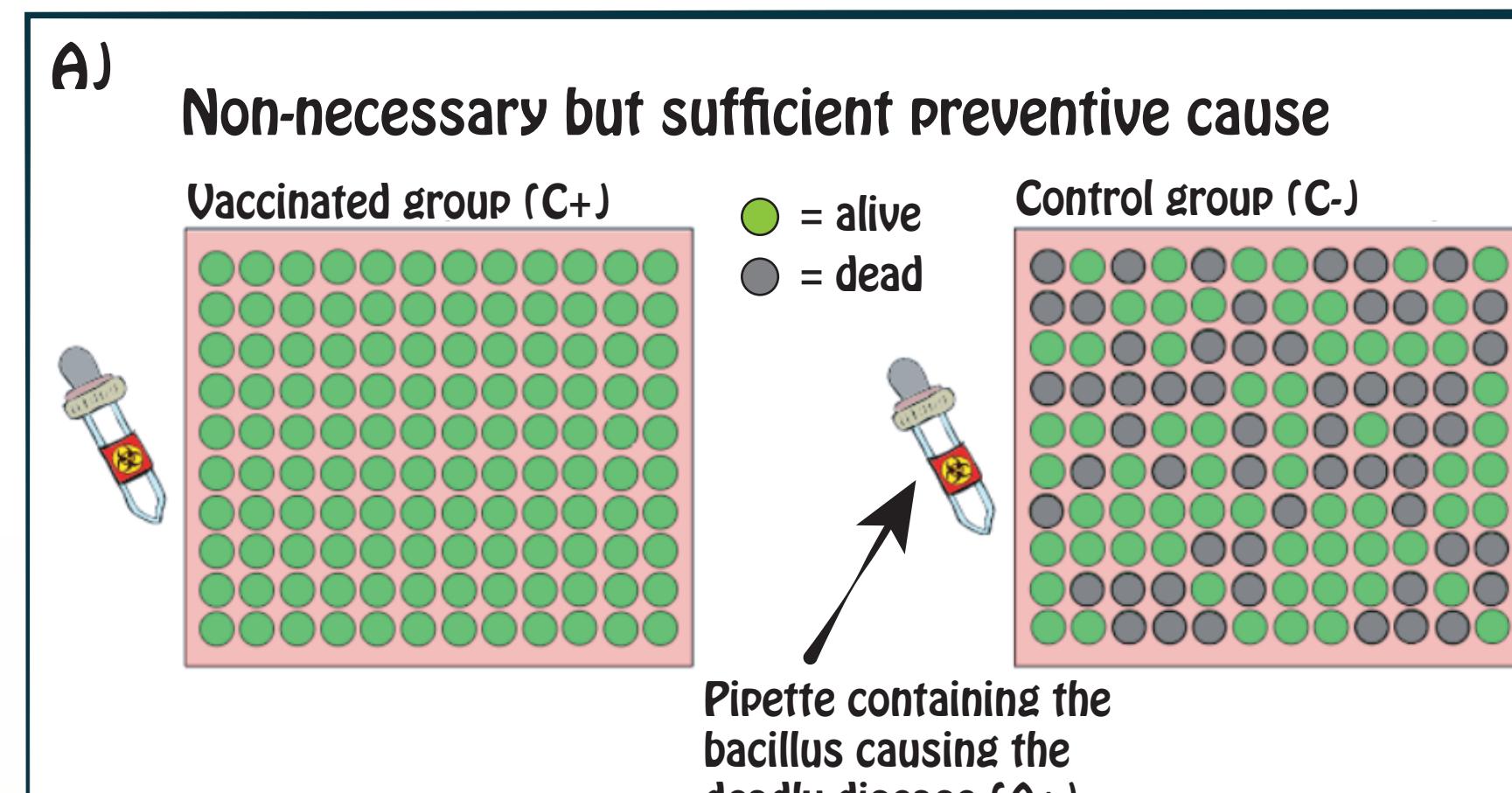
- (c) Cheng, P. W. (1997). From covariation to causation: A causal power theory. *Psychological Review*, 104(2), 367.
- (c) Yule, G. U., & Greenwood, M. (1915). The statistics of anti-typhoid and anticholera inoculations, and the interpretation of such statistics in general. *Royal Society of Medicine, Section of Epidemiology and State Medicine*, 8, 113–194.

Contact: sstepha1@gwdg.de

Experiment

demo: <https://tinyurl.com/yd2qfz3n>

Example contingency data sets as they were shown to subjects during the learning phase:



Test questions asked in the different between-subject conditions:

Condition 1: General Preventive Strength

How effectively does the vaccine prevent mice from dying from the disease that can be caused by the investigated strain of bacteria? To rate the vaccine's effectiveness, imagine a new group of 100 unvaccinated mice who all died from the disease caused by the studied strain of bacteria. Based on what you have learned, if these 100 mice had been vaccinated, how many do you think would have survived?

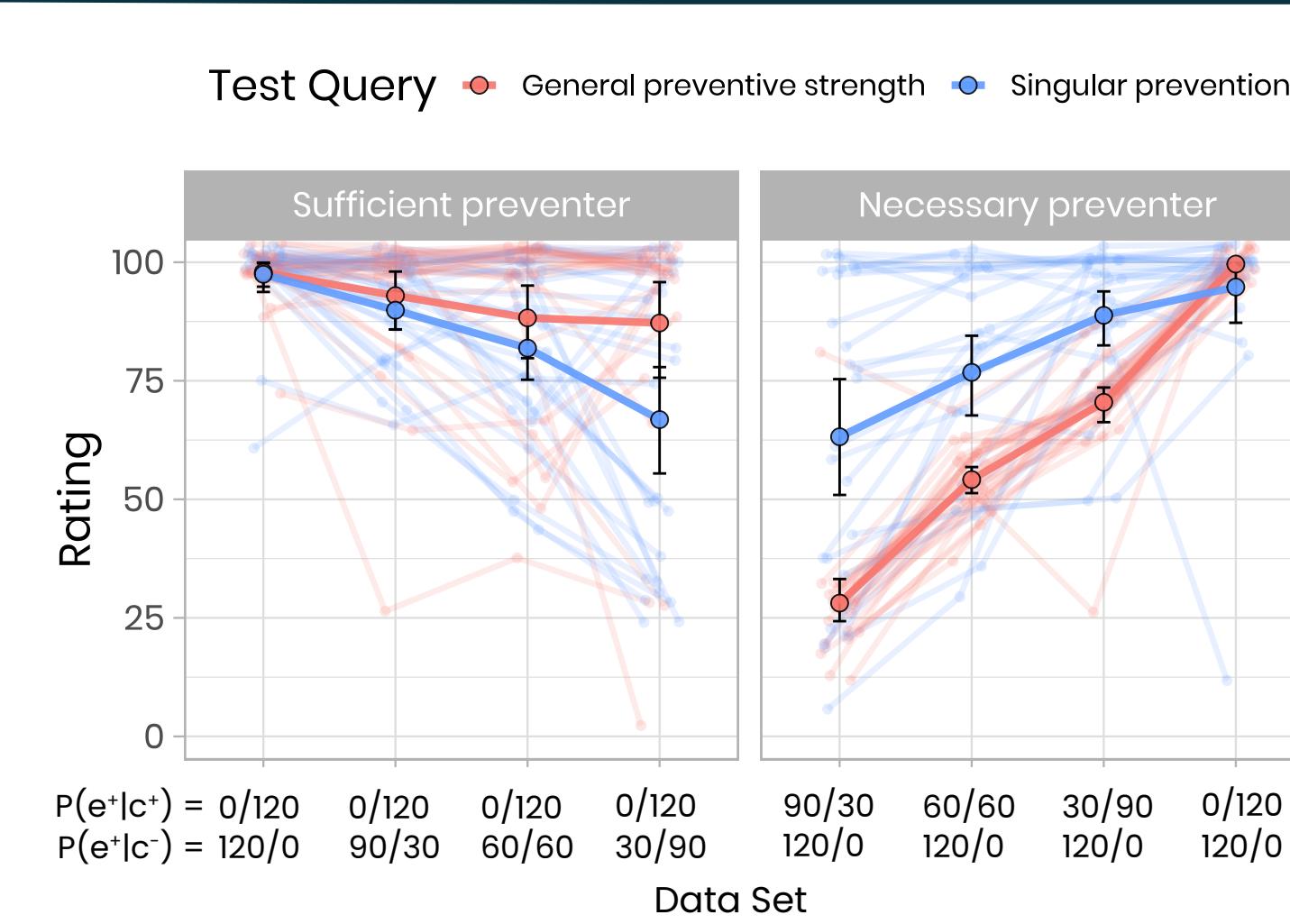
None of them → All of them

Condition 2: Singular/ Actual Prevention

Imagine one of the living mice is randomly selected from the vaccination group. Based on what you have learned, how confident are you that it actually was the vaccination that prevented this mouse from dying from the disease that can be caused by the studied strain of bacteria?

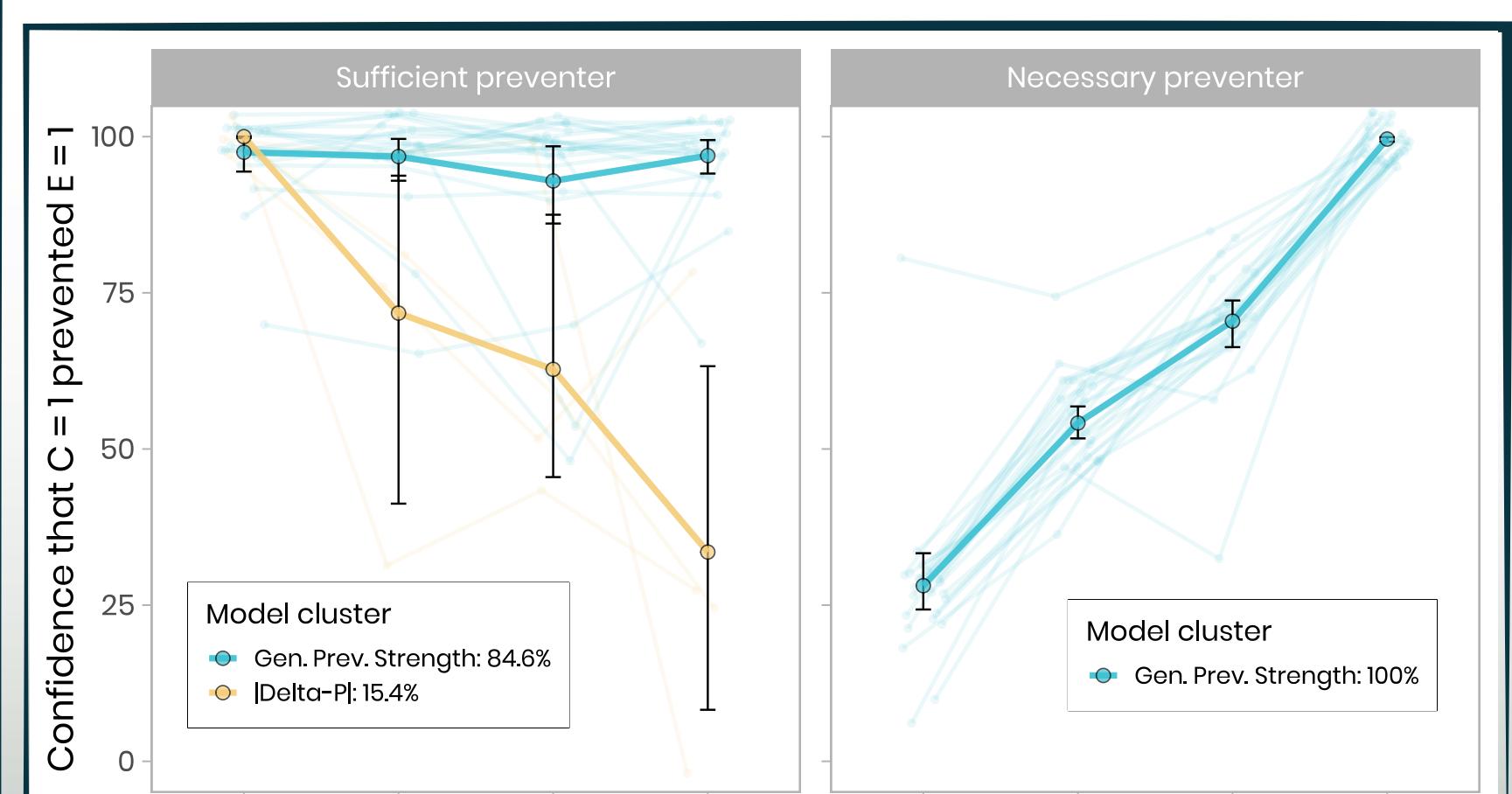
Certain that it was not the vaccination that prevented the mouse from dying → Certain that it was the vaccination that prevented the mouse from dying

Results (N = 104):



Cluster Analyses:

Condition: Test query = general preventive strength



Condition: Test query = actual/ singular prevention

