

Computational Modeling of Regional Dynamics of Pandemic Behavior using Psychologically Valid Agents

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Abstract

Regional Psychologically Valid Agents (R-PVAs) are computational models representing cognition and behavior of regional populations. R-PVAs are developed using ACT-R—a computational implementation of the Common Model of Cognition. We developed R-PVAs to model mask-wearing behavior in the U.S. over the pre-vaccination phase of COVID-19 using regionally organized demographic, psychographic, epidemiological, information diet, and behavioral data. An R-PVA using a set of five regional predictors selected by stepwise regression, a psychological self-efficacy process, and context-awareness of the effective transmission number, R_t , yields good fits to the observed proportion of the population wearing masks in 50 U.S. states [$R^2 = 0.92$]. An R-PVA based on regional Big 5 personality traits yields strong fits [$R^2 = 0.83$]. R-PVAs can be probed with combinations of population traits and time-varying context to predict behavior. R-PVAs are a novel technique to understand dynamical, nonlinear relations amongst context, traits, states, and behavior based on cognitive modeling.

The COVID-19 pandemic prompted global-scale changes in human behavior¹. It also produced a historically large set of natural experiments on behavior change due to variations in localized disease context, governmental public health policies and mandates, and regional variations in psychological and sociological makeup. In the early phases of the pandemic—prior to widespread availability of vaccines—the main response options were non-pharmaceutical interventions (NPIs) such as social distancing, mask wearing, and hand washing. This is because human behavior plays a crucial role in mediating viral transmission². Throughout history, people have typically modulated their behavior to mitigate pandemic transmission rates³. Analysis of mask wearing across countries⁴ shows that people modulate their behavior, but the impact of government mandates is weak to non-existent. A recent Royal Society report⁵ concluded that the “weight of evidence from all studies ...consistently, though not universally, reported that mask wearing, and mask mandates were an effective approach to reduce infection.” The underlying causal pathways of behavior change, and the effects of psychology and behavior on transmission, remain poorly understood.

During the early phases of COVID-19, it was argued⁶ that people’s awareness of case rates or fatality rates appeared to be driving the modulation of protective behaviors, and that it was awareness-driven behavior that produced the signature temporal phenomenon observed in virtually all regions: the damped oscillation pattern of the effective reproductive number, R_t , as presented in Figure 1. At the beginning of a pandemic, there is a rapid increase in R_t , followed by an asymmetric decline, followed by oscillations around $R_t = 1$. As noted previously,^{7,8} this oscillation is similar to that produced by a Proportional-Integral-Derivative control system in which a controlling intervention (e.g., mask wearing) occurs in proportional response to the state of the system (e.g., R_t), although there may be lags between the awareness of the system state and the response, and between the response and effecting a change. The lags may occur (for instance) because of the pathogen incubation period, news time cycles, or the observation of local social conditions.

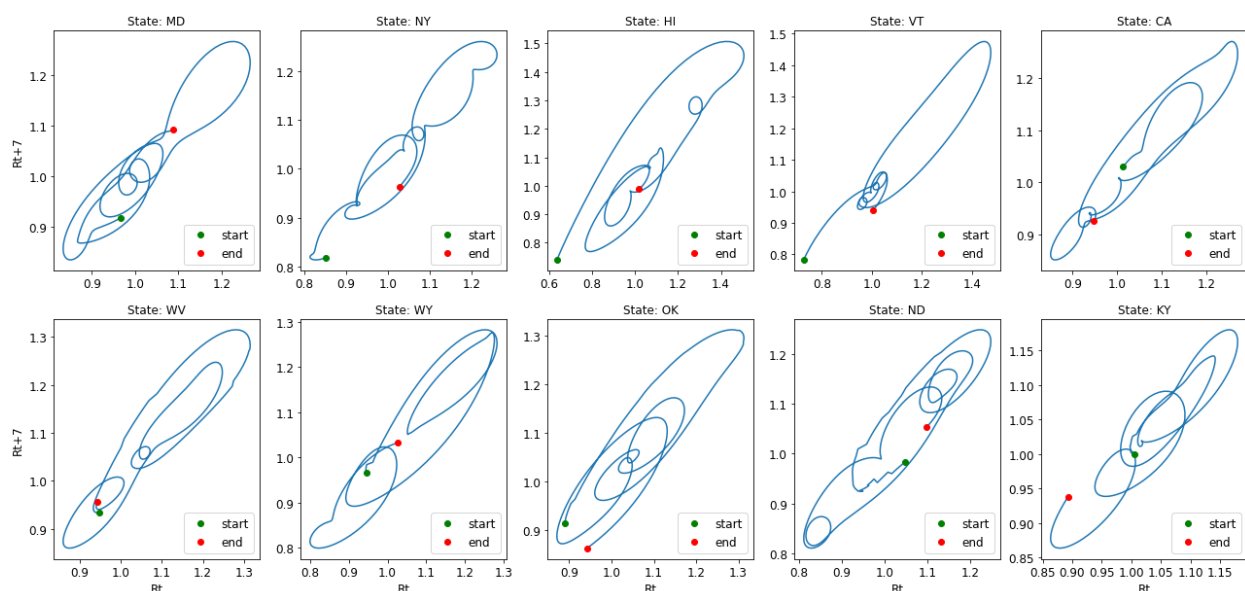


Figure 1. Dampened oscillation of R_t . The values of R_t are plotted against R_{t+7} , where t is in days.

Another factor driving the adoption and maintaining of NPIs is *self-efficacy*. Self-efficacy, in essence, refers to an individual's belief in their ability to carry out actions required to achieve specific goals. According to Bandura's Social Cognitive Theory of self-efficacy⁹, if individuals perceive their goals as excessively challenging, they are less likely to attempt them. Generally, higher levels of self-efficacy correlate with increased likelihoods of goal attainment. Assessments of self-efficacy are closely linked to people's motivation to engage in demanding activities, whether physical or cognitive. Vancouver^{10,11} observed that when self-efficacy is low in comparison to a difficult task, it tends to be perceived as more strenuous, yet high motivation can compensate for low self-efficacy, albeit within limits. This aligns with the Attributional Theory of Performance¹², a variant of Motivational Intensity Theory¹³, which suggests that beyond a certain point, as task difficulty increases, people may not be motivated to invest effort, leading to a fluctuating relationship between effort and perceived task difficulty. Self-efficacy might account for the spiraling increase with time in mask wearing, as shown in Figure 2. That is, as people successfully achieve goals, they gain self-efficacy.

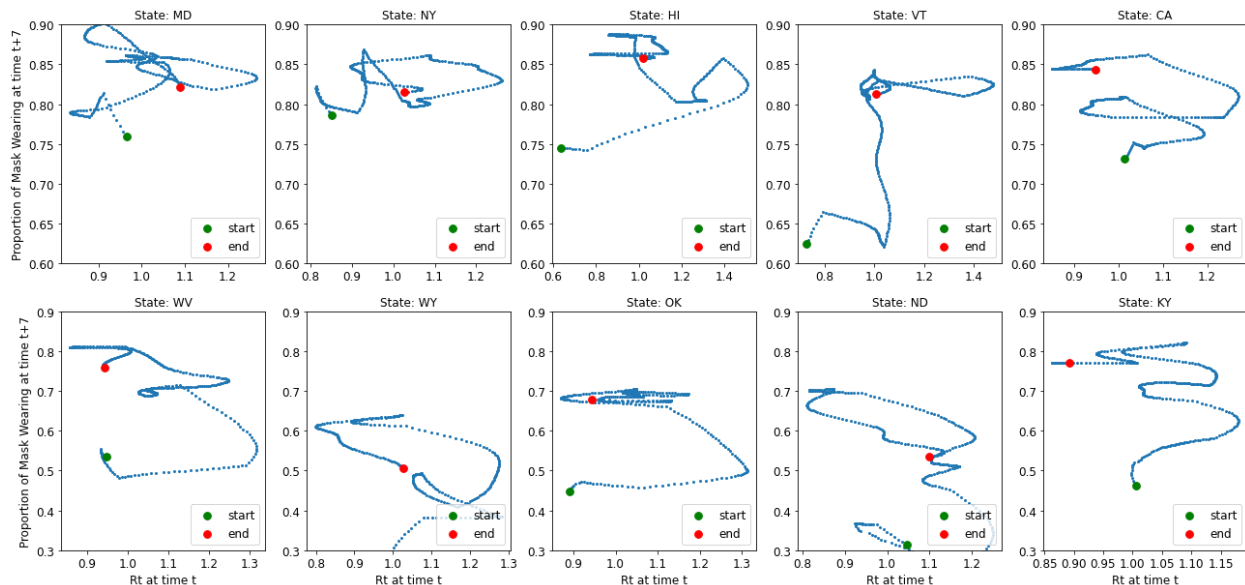


Figure 2. R_t vs. proportion of mask wearing 7 days later. A spiraling increase in the adoption of mask wearing can be observed in many cases as time progresses.

The responses of public officials in the early phases of the pandemic were guided, in part, by epidemiological models that had abundant, very large, uncertainties around the effects of NPIs¹⁴⁻¹⁷ and large regional heterogeneity^{18,19}, which has been attributed to a failure to address the crucial role of socio-psychological-behavioral mechanisms²⁰. The U.S. National Academies of Sciences, Engineering, and Medicine²¹ emphasized the importance of psychological science to the mitigation of the spread of COVID-19. Human psychology matters in controlling the dynamics of disease transmission, and people respond differently because they have different mindsets and capabilities that vary over space and time. There is a need for population-scale computational models that accurately predict the complexity and heterogeneity of human behaviors that are key to modulating pathogen transmission. Advances in computational

cognitive modeling, artificial intelligence, and machine learning provide the opportunity to build such models.^{8,22-25}

In this article, we present models based on the development of *Psychologically Valid Agents* (PVAs)²² that represent the behavior of regional populations in the U.S. over the pre-vaccination phase of COVID-19. We call these *Regional Psychologically Valid Agents* (R-PVAs). For the U.S. the availability of vast amounts of regionally organized (e.g., state, county) demographic, psychographic, epidemiological, behavioral, and information environment data makes it feasible to develop and test such models. Our work with PVAs^{22,23,26} has relied on the development of data pipelines combining demographic and psychographic data about U.S. regions and Natural Language Processing of online social media that are used to initialize Regional PVAs and to provide time series data about human behavior such as mask wearing. Similar large-scale models could be significant in other societally important areas, such as response to natural disasters, public health, climate change, civic discourse, diplomacy, economic policy, and cybersecurity.

Research on geographical psychology examines the spatial distribution of psychological features and their relation to social, psychological, and behavioral phenomena²⁷. For instance, regional differences in state-level or county-level Big Five personality scores are related to political, economic, social and health outcomes²⁸, and big data methods processing social media can identify regional personality scores related to entrepreneurship²⁹. Typically, relations between regional psychological factors and outcomes are analyzed using variations of linear regression.

In contrast to prior work on geographical psychology, the Regional PVAs presented here were developed using the ACT-R architecture. ACT-R^{30,31} is a computational implementation of a unified theory of cognition³². A wide variety of cognitive architectures have been proposed, but there is an emerging consensus regarding the central structures and processes in the form of a Common Model of Cognition (CMC)³³. ACT-R provides a computational implementation of the CMC. ACT-R is intended to be a model of individual-level cognition, and can be the basis of highly individualized learning³⁴ and behavior-change interventions³⁵. However, in other examples, ACT-R models are often used to capture cognition at an aggregate level—e.g., the average participant in a psychology experiment. Regional PVAs could be viewed as an extension of this approach: as models that capture the psychological function and behavior of a sample or population of people having some particular statistical mixture of attributes, beliefs, knowledge and experience, responding to inputs from some context.

The ACT-R theory³⁶ has evolved since the 1970s to address a wide variety of experimental results on human problem solving, decision making, memory, learning, cognitive skill acquisition, perception, and attention, as well as the fine-grained time course of neural processes. The theory has been applied to a variety of domains including education, human-computer interaction, and language learning³⁷⁻³⁹. ACT-R is implemented as a simulation environment with several software variants that can simplify its application to a specific domain or problem. Practically, ACT-R is a computational cognitive architecture that supports the development of models. A scientific understanding of behavior change in response to pandemics requires such unified models and toolkits. The literature on behavior change is extensive, lacks coherence, and needs mechanistic theory. Preliminary integrative models of behavior change have been

developed in ACT-R^{35,40}, which provide some promise of their utility to modeling behavior change during a pandemic.

ACT-R can integrate self-efficacy and motivation intensity theories^{8,41}. Such assumes that self-efficacy and intended effort are fundamentally the result of memory processes. Past experiences of efficacy at behaviors similar to a target goal are retrieved and blended to produce assessments of self-efficacy and intended effort for the new goal. Given a pending decision to pursue a behavioral goal, an assessment is made of the difficulty of achieving that goal. A blended retrieval is performed to assess self-efficacy with respect to the behavioral goal, based on memory of experiences on behaviors similar to the goal behavior. A judgment is made about the intentional level of effort required to achieve the behavior, given the judged difficulty of the behavior and assessment of efficacy towards that goal. It is assumed that the individual will put in effort if it is less than a threshold. If the behavior is performed, then a new instance is learned. That instance will be stored with a self-efficacy that includes the old self-efficacy value boosted by the additional intentional effort expended. New successes on behaviors where the perceived difficulty was high relative to self-efficacy will tend to improve self-efficacy with repeated experience.

We selected a set of *static* regional variables from several sources representing data at the county and state levels of the U.S. The sources included data aggregated by the Johns Hopkins Coronavirus Resource Center^{42,43}, regional Big 5 personality statistics²⁷, and a fused data set used in a study of predictors of social distancing behavior.⁴⁴ Guided by previous machine learning research on the same or similar data⁴⁵, we selected a subset of variables to include in our analysis (see Methods and Supplementary Materials).

In addition to the static regional variables, we selected and created a set of *time series* regional variables. For each county and/or state, we combined survey data from the CovidCast and the Covid States projects. The time series data is daily for the pre-vaccination rollout period of 4/24/2020 to 3/31/2021, which covers the time period of the first three waves of Covid-19 as defined by Pew Foundation². R_t data at the state and county level was downloaded from covidestim.org, a project of the Yale School of Public Health. Mask wearing data at the state level was downloaded from CovidStates⁴⁶, which compiled the data from survey waves deployed every three weeks. We created an imputation algorithm to combine that data with CovidCast mask-wearing data. (See Supplementary Materials for more details on the data pipeline and variables.)

Results

We present Regional PVAs of mask wearing behavior for the 50 states of the U.S. and show that these models capture the signature phenomena of transmission awareness-driven mask wearing. A change in a system is often not recognized instantaneously. It takes time for the awareness to percolate throughout the population before people react to the new situation. We utilized Granger causality analysis⁴⁶ to determine if there was a delay between a change in R_t and a change in the mask wearing behavior. The shortest lag with a significant effect was 7 days. We

² <https://www.pewresearch.org/politics/2022/03/03/the-changing-political-geography-of-covid-19-over-the-last-two-years/>.

thus offset the R_t values in the data by 7 days to reflect this dependency in all subsequent analyses.

Regression Analysis

We performed some exploratory analysis using regression models, to examine the relationship between the variables in our data set and identify candidate variables that had a significant effect on mask-wearing. We considered two variations of the R_t predictor: (1) $R\Delta_t = R_t - 1$, and (2) $R\Delta^2_t = (R_t - 1)^2 * \text{sgn}(R_t - 1)$. The intuition for the transformations is that the phenomena in Figure 1 suggest that transmission-reducing behavior increases as $R_t > 1$ and decreases as $R_t < 1$. The feature $R\Delta_t$ would capture a linear relationship with the deviations from the stable level $R_t = 1$, that is, the strength of response is linearly related to the deviation. $R\Delta^2_t$ would capture a quadratic relationship. The untransformed but standardized R_t was not included in the analysis since it is identical to $R\Delta_t$ except for a shift in the mean value.

Table 1 shows the coefficients and p-values of the predictors in the two cases. Both $R\Delta_t$ and $R\Delta^2_t$ are significant predictors in their respective runs, with the effect of $R\Delta^2_t$ being greater than $R\Delta_t$, suggesting that larger deviations from the baseline have a larger influence on mask wearing. In addition to several significant demographic and education variables, notably 'Fox News Lean' and 'PctTrump State 2016' were both significant but with opposite effects. In addition, most of the Big 5 personality variables were also significant and with relatively large effect sizes, indicating personality traits could have considerable influence on mask wearing behavior.

Table 1. Mask wearing regressed on the static predictor variables, together with $R\Delta_t$ and $R\Delta^2_t$ respectively. All regressions were random coefficients models analyzed using the LMER package in R. We included states as a random coefficient predictor.

	$R\Delta_t$		$R\Delta^2_t$	
	coefficient	p	coefficient	p
Intercept	-0.03	0.533	-0.04	0.4
$R\Delta_t$ or $R\Delta^2_t$	-0.24	<0.001	-0.32	<0.001
PC1_weather	-0.22	0.081	-0.24	0.046
PC2_weather	-0.07	0.418	-0.07	0.416
NHWA	-0.2	0.139	-0.22	0.101
NHBA	-0.38	0.001	-0.4	0.001
NHIA	-0.17	0.01	-0.17	0.008
TOM	0.17	0.359	0.16	0.354
Gender ratio	-0.16	0.163	-0.15	0.171
Percentage age 0-17 yr	0.1	0.25	0.11	0.17
Percentage age 65+ yr	-0.07	0.384	-0.1	0.214
Percentage adults with less than a high school diploma	0.26	0.048	0.23	0.07
Percentage adults with a bachelor's degree or higher	0.29	0.047	0.3	0.035

Median household income 2018	-0.18	0.151	-0.21	0.079
Unemployment rate 2018	0.05	0.456	0.05	0.459
Fox News Lean	0.27	0.003	0.31	0.001
GOP Advantage 2016	0.16	0.213	0.12	0.315
PctTrump State 2016	-0.28	0.027	-0.3	0.015
Trump approval 2020	-0.25	0.065	-0.21	0.113
Population density per square mile	-0.12	0.039	-0.14	0.019
Extraversion	0.34	0.041	0.37	0.023
Openness	0.19	0.175	0.23	0.097
Agreeableness	-0.56	<0.001	-0.59	<0.001
Conscientiousness	0.36	0.001	0.36	<0.001
Emotional Stability	-0.23	0.021	-0.23	0.018

The set of potential predictors were down-selected based on a forward stepwise regression procedure. At each step, the variable that increased the fitness of the regression model the most was added to the selection. An optimal set of variables that balanced the complexity of the model and the resulting R^2 score was selected. The set consists of 5 variables, namely, 'PctTrump State 2016', 'PC1_weather', 'Fox News Lean', 'Percentage adults with a bachelor's degree or higher' and 'Percentage age 65+ yr', encompassing a range of demographic, political and environmental factors.

There was not a lot of overlap between the variables obtained by this procedure and the ones that were significant in the multiple regression model discussed earlier. In particular, none of the Big 5 variables were selected. We will examine this divergence in more detail using the R-PVA model in a later section.

Regional Psychologically Valid Agents (R-PVAs)

ACT-R is composed of *modules*, processing different kinds of content, which are coordinated through a centralized *procedural module*. The procedural module matches the contents of other module buffers and coordinates their activity using *production rules*. R-PVAs rely on a subset of ACT-R mechanisms collectively called Instance-Based Learning⁴⁷. For the R-PVAs presented in this paper, we rely on the *declarative module*, *retrieval buffer*, and *blending buffer*. In combination, they simulate how people retrieve knowledge and past experiences from long-term declarative memory. We use the PyACTUp⁴⁸ simulation package. Knowledge and experience in the declarative module are represented formally in terms of *chunks*^{49,50}. Chunks have *activation* levels that determine the probability and time course of chunk retrieval from memory. Chunk activations are real-valued quantities produced by *subsymbolic mechanisms* in ACT-R. These subsymbolic mechanisms reflect neural-like processes that determine the time course and probability of cognitive activity and behavioral performance. Level of activation dictates retrieval probability and weighs how blended retrievals produce aggregate values over past experiences.

We developed R-PVAs to learn and predict mask wearing, using various sets of predictor variables and the R_t time lag suggested by the Granger causality analysis. In all analyses, the selected predictor variables were standardized z-scores and the data were aggregated at the state level. The time series covered the pre-vaccine rollout period of 4/24/2020 to 3/31/2021.

For each R-PVA, we first trained a base model using only the static regional variables and a 10-day initial segment of the mask wearing time series. For each day and each state, the model learned a chunk instantiated with the mask wearing value and the values for all the predictors except R_t . This was to establish an initial static baseline without considering the variations in R_t . This also provided the initial prediction of mask wearing on day 0.

Note that even though each chunk was derived from the data from a single state, and some of the results presented were aggregated at the state level, the state identifier was not used as a prediction variable. This allowed us to examine the more generalizable factors affecting mask wearing behavior rather than relying on idiosyncratic characteristics that might be attributable to each state.

The norms established in the initialization served to bootstrap a new R-PVA with varying R_t values. For each day in the time series, a prediction was made for each of the 50 states and compared to the actual mask wearing value. 10 new chunks, in proportion to the observed mask wearing percentage, were learned for each state, and we advanced to the next day. The addition of new chunks every day constitutes a form of online machine learning and refinement of the model.

In addition to the standard model, we also developed a model augmented with self-efficacy explicitly. Self-efficacy is parameterized in terms of the intentional level of effort and the amount of boost received upon success of a trial. A grid search was performed over the parameter space using a subset of the data to determine optimal values for the parameters. The values obtained from the grid search (boost factor = 0.02, effort = 1.0, difficulty = 2.0, threshold = 1.5) were used in the R-PVAs in the subsequent experiments.

Aggregated Results

We compared the performance of several R-PVAs: (1) R-PVA-1: no static predictors (predicting only with R_t); (2) R-PVA-2: one static predictor, 'PctTrump State 2016', which was the variable with the largest effect on mask wearing based on the stepwise regression procedure; (3) R-PVA-3: the five selected predictors; and (4) R-PVA-4: adding self-efficacy to the previous model. n -fold rolling origin cross-validation was used to compare and evaluate the predictions generated by the R-PVAs under these different settings and combination of variables.

Table 2 shows the comparison between the four R-PVAs. The data were the proportion of the population wearing masks in the 50 U.S. states over the first three waves of COVID-19. Both the average RMSE and R^2 scores of the models improved as more variables were included, indicating that the selected features were helpful in characterizing the mask wearing behavior. The effect was particularly large transitioning from R-PVA-1 to R-PVA-2 by including one

static variable. Successive inclusion of more predictors continued to improve the performance, although with smaller improvements in fit. In addition, modelling self-efficacy in R-PVA-4 improved the model performance over R-PVA-3, validating the utility of self-efficacy. Figure 3 shows the combined observed vs. predicted mask wearing proportions obtained from R-PVA-4, which is the best fitting model. Overall, the model achieves a good fit of $R^2 = 0.93$.

Table 2. Comparison of several R-PVA models

	Number of Predictors (in addition to R_t)	Self-Efficacy	Average RMSE	Average R^2
R-PVA-1	0	no	0.0942	0.2916
R-PVA-2	1 ('PctTrump State 2016')	no	0.0535	0.7714
R-PVA-3	5	no	0.0403	0.8699
R-PVA-4	5	yes	0.0312	0.9221

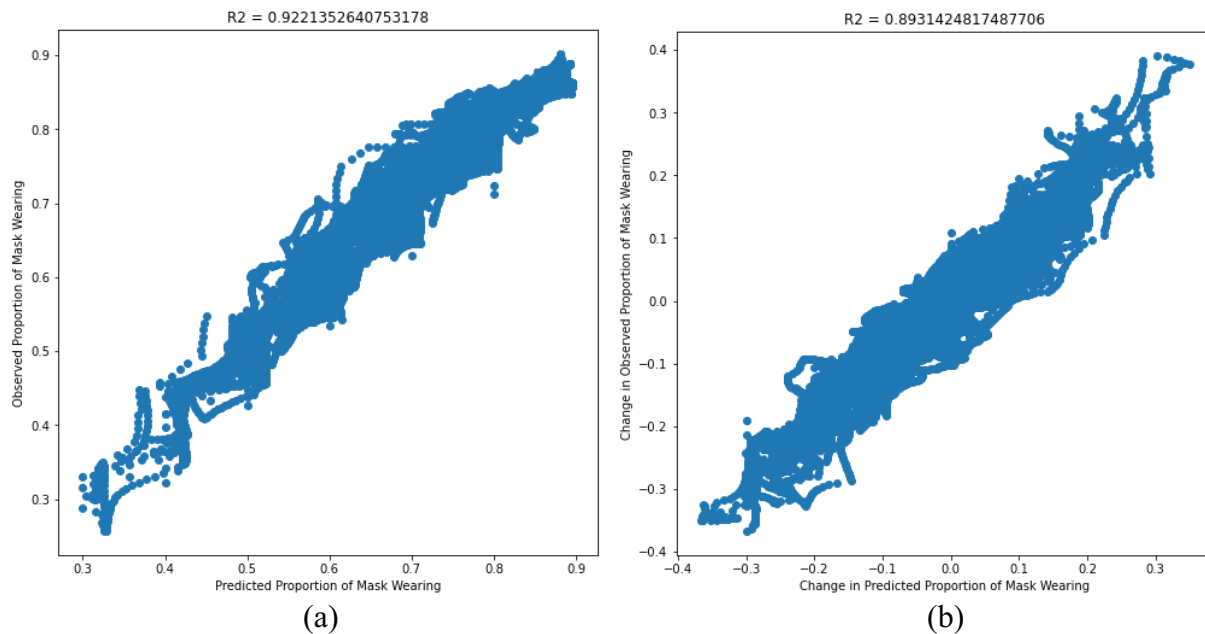


Figure 3. (a) Predicted vs. observed proportion of population wearing mask each day from 05/01/2020 to 03/31/2021 (the first three waves of COVID-19), using R-PVA-4, a model with self-efficacy and the 5 selected predictor variables (in addition to R_t). (b) Change in observed proportion of mask wearing versus change in predicted proportion.

Results in High/Low Pro-Trump States

To examine the results in more detail, we broke down the model outputs by state. Our analysis agreed with previous work that suggested partisanship was strongly associated with adherence to physical distancing measures.⁴⁴ The predictor with the largest effect on mask wearing based on the stepwise regression procedure was 'PctTrump State 2016'. We conjectured that separating

the results into the dichotomy of states with high and low values for 'PctTrump State 2016' might provide further insight.

The five states with the highest 'PctTrump State 2016' values were West Virginia, Wyoming, Oklahoma, North Dakota and Kentucky. The five states with the lowest 'PctTrump State 2016' values were Maryland, New York, Hawaii, Vermont and California. Figure 4 plots observed and R-PVA-4-predicted mask wearing proportion over time for these 10 states³. For convenience, we denote the highly pro-Trump states as *highTrump* states and the low pro-Trump states as *lowTrump* states.

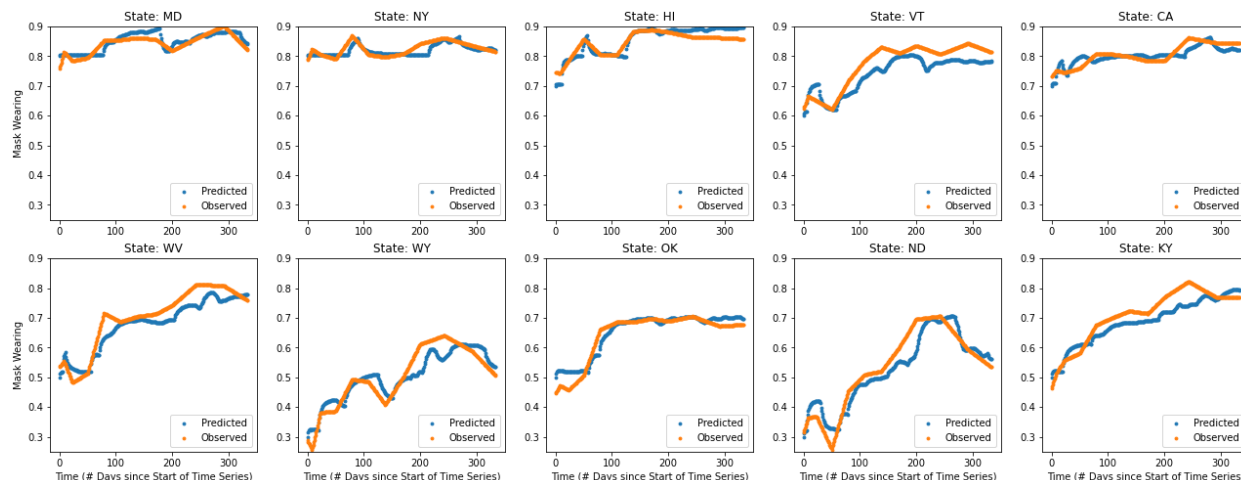


Figure 4. Observed proportion of mask wearing and proportion predicted by R-PVA-4 for 10 U.S. states over the first three waves of COVID-19. The top row shows the lowTrump states (5 states with the lowest proportion voting for Trump in 2016) and the bottom row shows the highTrump states (5 states with the highest proportion voting for Trump in 2016).

The highTrump states had a lower mask wearing proportion than the lowTrump states. In addition, in the highTrump states, the mask wearing proportion fluctuated but in general increased over time, whereas in the lowTrump states, the mask wearing proportion stayed relatively stable. The latter might be partially due to the limiting effect of a higher initial mask wearing proportion, since there was not as much room to increase from an already high baseline.

For the R-PVAs, in general the model predictions improved as more of the selected predictor variables were included (R-PVA 1-2-3) and with the addition of the self-efficacy process (R-PVA-4). The first model (predicting using only R_t) tended to undershoot in the lowTrump states and overshoot in the highTrump states. In the two exceptions in which R-PVA-1 did not overshoot (West Virginia and Kentucky, both highTrump states), R-PVA-2 performed noticeably worse than the other models, including even R-PVA-1 with no static predictor variables. This suggested that perhaps the R-PVAs had learned that 'PctTrump State 2016' had a dampening effect on mask wearing, and thus including this variable in R-PVA-2 sometimes lowered the

³ Note that the scale varies between plots. This makes some of the plots look more hectic (e.g. NY in the later plots).

predicted mask wearing values more than needed. (See Supplementary Materials for the predictions of the R-PVA 1, 2 and 3.)

Probing the R-PVA Models

Once an R-PVA model is built, we can probe it with novel combinations of features to make predictions about other features, not necessarily mask wearing. Figure 5 shows an example of mask wearing predicted from a range of values of 'PctTrump State 2016', under different mismatch penalties for the blending of partially-matched memory chunks. These penalties are controlled by a mismatch penalty parameter, MP (see the Methods section). As the mismatch penalty, MP, increases, the activation levels become more concentrated in the better-matched memory chunks, giving rise to a closer fit. In general, the predictions of the probings show a decrease in mask wearing as Trump support increases, which matches the trend observed in the actual data. Even though the data did not extend to the very low and high values for 'PctTrump State 2016', the model was able to predict values of mask wearing that seem intuitively reasonable for the whole range of hypothetical 'PctTrump State 2016' values.

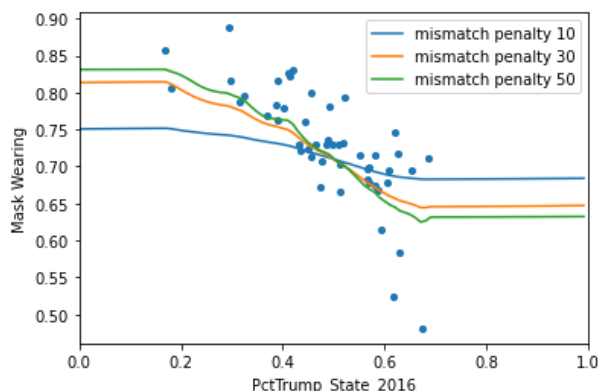


Figure 5. Probing the model with hypothetical values of predictors and different penalties for partial matching.

The Big 5 Personality Model

Earlier we observed that the Big 5 Personality features were significant in the multiple regression analysis but not selected with the stepwise regression procedure. To examine this in more detail, we constructed a R-PVA model with self-efficacy and using the Big 5 variables (and R_t). We are interested in this model because it is purely based on measurements of what are considered basic stable psychological traits. We hypothesized that some of these traits could have different effects in states with different mask wearing norms. For instance, an agreeable person would prefer a homogeneous environment. They might be more inclined to wear a mask if mask wearing is prevalent in their surroundings, but this same person might be more inclined *not* to wear a mask if mask wearing is scarce in their surroundings.

Figure 6 shows the observed and predicted values using this Big 5 R-PVA model for the lowTrump and highTrump states. The average RMSE = 0.0463 and $R^2 = 0.8286$. This model

performed somewhat worse than the comparable model using the selected variables (R-PVA-4); however it still accounts for a large proportion of the variance.

The Big 5 features performed better in the highTrump states than in the lowTrump states (see Supplementary Material Figure S7). It appears that the relationship between the Big 5 traits and mask wearing does differ to some extent. For instance, Agreeableness is negatively correlated with mask wearing in the highTrump states but not much in the lowTrump states. Perhaps these differences in responses to the Big 5 traits might make them less useful for modelling mask wearing by themselves in the R-PVA. However, richer versions of R-PVAs (e.g., R-PVA-4) can be trained and probed with various combinations of demographic, psychographic, and physical variables characterizing regions.

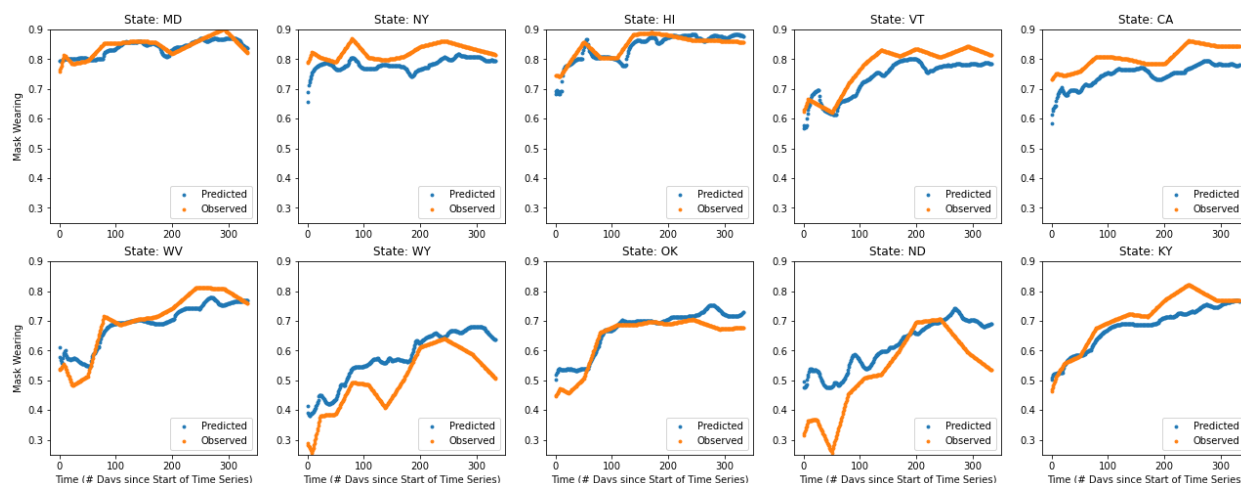


Figure 6. Observed proportion of mask wearing and proportion predicted by an R-PVA with self-efficacy and using Big 5 Personality trait data for 10 U.S. states over the first three waves of COVID-19. The top row shows lowTrump states and the bottom row shows highTrump states.

Discussion

Human psychology plays a crucial role in disease transmission dynamics. Individuals' diverse mindsets and capabilities change over space and time, leading to varying responses. We employ Regional PVAs to address the need for population-scale computational cognitive models that accurately predict the complexity and heterogeneity of human behaviors that are key to modulating pathogen transmission. Our R-PVA approach is developed specifically to address the data related to behavior changes during pandemics in response to varying disease contexts and government policies.

Our approach builds on decades of work on the ACT-R cognitive architecture and our recent development of Psychologically Valid Agents for modeling COVID-19 behavior change. A previously unappreciated feature of the learning mechanisms of the computational cognitive architecture used in the R-PVAs is that they provide a way of capturing non-linear statistical relations between input features (demographic, psychographic, media diet, political leanings) and the behaviors of interest. We show how our PVA models can be used to identify the effects on mask wearing based on demographic, geographic, and psychographic variables.

Leveraging extensive COVID-19 data repositories and online social media, we have created Regional PVAs to simulate the behavior of regional U.S. populations during the pre-vaccination phase of COVID-19. The PVA pipeline includes demographic, psychographic, epidemiological, behavioral, and information environment data about U.S. regions. These data are used to initialize agents and provide time-series inputs representing the pandemic context (e.g., local transmission rates). The PVAs iteratively assess the current context and make decisions (e.g., to wear a mask or not) over discrete time steps (e.g., every day). They are thus capable of predicting various regional time series data, e.g., the U.S. county- or state-level daily mobility patterns or daily mask wearing. These Regional PVAs offer a unique opportunity to explore demographic or psychographic factors related to behavior, using a variety of methods. Regional PVAs can be used as a novel data mining technique to understand possibly nonlinear relations between context and behavior.

Methods

Granger Analysis

The R_t time series was shifted successively from 0 (no delay) to 60 days earlier. Using the shifted R_t data and the mask-wearing data from the previous days to predict the proportion of mask wearing of the current day, the shortest lag with a significant difference at the 0.05 level, compared to using only the mask-wearing data for prediction, was taken to be the effective lag length.

At the state level, the lags obtained did not exhibit a clear trend. It was hypothesized that geographical granularity and urbanicity of the area could be additional factors. We reanalyzed the data at the county level, with the addition of three population and urbanicity indicators: (1) population density from the 2010 US Census⁵¹, categorized into low (≤ 500 persons/sq. mile), medium (> 500 and ≤ 1000 /sq. mile) and high (> 1000 /sq. mile); (2) 2013 NCHS Urban-Rural Classification Scheme⁵² and (3) 2013 Rural-Urban Continuum Codes⁵³. Overall, for the counties, 7 days was the most common lag for R_t to make a significant difference in the prediction of mask-wearing. Augmenting the county level data with the three population/urbanicity indicators gave similar results, suggesting that the time it takes for a change of R_t to elicit a behavioral response in mask wearing is ubiquitous.

Feature Selection using Stepwise Regression

We used one day of data at the mid-point of the time series (2020/10/11) for the evaluation. Starting with an empty set of variables, at each step a regression model was constructed with the current set of selected variables plus one of the unselected variables to predict mask-wearing. The unselected variable that resulted in the best average R^2 in a 10-fold cross validation was added to the selected set. The successive scores were inspected and a cutoff of 5 variables was deemed the optimal balance between the number of variables and the resulting score. The 5 variables are 'PctTrump State 2016', 'PC1_weather', 'Fox News Lean', 'Percentage adults with a bachelor's degree or higher' and 'Percentage age 65+ yr'. (See Supplementary Materials for the scores for each set of variables.)

The ACT-R Model and Regional Psychologically Valid Agents

ACT-R has subsymbolic mechanisms that determine the dynamics of the R-PVAs. Equations 1-3 define how the levels of activation of chunks in memory determine the probabilities of chunk retrieval.

Blended retrieval determines the value V , based on the probability, P_i , of retrieval of value V_i , and the similarity of V to V_i :

$$V = \operatorname{argmin} \sum_i P_i (1 - \operatorname{Sim}(V, V_i))^2 \quad (1)$$

The probability of retrieval is

$$P_i = \frac{e^{A_i/s}}{\sum_j e^{A_j/s}} \quad (2)$$

Where the activation, A , is

$$A_i = B_i + \sum_f MP_f * \operatorname{Sim}(f, V) + \epsilon_i \quad (3)$$

and s and ϵ are noise factors, B is a base-level activation. MP_f is a mismatch penalty representing the dissimilarity between the representation of two values. Equation 4 defines how activation levels are increased by repeated experiences, or decay with time.

$$B_i = \ln\left(\sum_{j=1}^n t_j^{-d}\right) + \beta_i \quad (4)$$

where t_j is the time since the t^{th} storage or retrieval trial of chunk j , n is the number of trials, $0 < d < 1$ is a decay parameter, and β is a constant.

Chunks generally can be represented as an unordered feature-value list of the form

$$\{<\text{feature}_1: \text{value}_1>, <\text{feature}_2: \text{value}_2>, \dots, <\text{feature}_n: \text{value}_n>\}$$

For the R-PVAs modelling mask wearing behavior, the chunks are of the form

$$\{<\text{predictor}_1: \text{value}_1>, \dots, <\text{predictor}_n: \text{value}_n>, <\text{mask_wearing}: m>\},$$

where $m \in [0.0, 1.0]$ is the proportion of the state population wearing a mask.

To make a prediction of the prototypical value of a feature given a (partial) set of predictor values, chunks that are similar to this chunk are retrieved and blended, weighted by a similarity function. Our R-PVA models use the similarity function

$$\operatorname{Sim}(x, y) = 1/(1 + \exp(y - x))^2, \text{ with } y > x. \quad (5)$$

For R-PVAs that model self-efficacy, two additional features are included:

$\{<\text{predictor}_1: \text{value}_1>, \dots, <\text{predictor}_n: \text{value}_n>, <\text{difficulty}: \delta>, <\text{effort}: e>, <\text{mask_value}: m>\},$

where δ is the difficulty of the task of mask wearing, and e is the amount of perceived effort to accomplish the task. Self-efficacy is modelled as the difference between the difficulty and effort. For each success in accomplishing a goal (e.g., wearing a mask for a day in our scenario), self-efficacy is boosted by

$$(1-m) * \text{boost_factor} * (\exp(\delta-e) / (\exp(\delta-e) + \exp(e))) \quad (6)$$

where m is the mask wearing proportion, boost_factor is a small quantity that promotes the self-efficacy upon success. The threshold above which the intended effort would be too hard to attempt was set at the mean of the initial difficulty and effort.

Norm Initialization of R-PVAs

For the norm-initialization phase, we used the initial 10 days of our time series data. For each state, the blended mask-wearing norm x was obtained using the predictor values from the first 10 days in the time series. 10 new chunks in proportion to this value x were learned, such that, keeping the other variable values as given, a proportion of x of the chunks had a mask wearing value of 1.0 (wearing a mask), and the rest of the 10 chunks had a mask wearing value of 0.0 (not wearing a mask). In addition, two extreme chunks were also added, one corresponding to wearing a mask (1.0) when R_t is very high (2.0) and the other corresponding to not wearing a mask (0.0) when R_t is non-existent (0.0).

Rolling Origin Cross-Validation

Because of the sequential nature of the data, regular cross validation, with random assignment to folds, was not appropriate, as this would enable the prediction of a data point using future data points that should not have occurred yet. We instead analyze the models using n -fold rolling origin cross-validation⁵⁴, n being the length of the time series minus 1. For the i -th fold, the data from the initial time sequence $\langle t_0, t_1, \dots, t_{i-1} \rangle$ was used for training, and the data at time point t_i was used for testing. Each successive training data set was a longer time series and included the previous training set.

Parameter Tuning

We performed a grid search over the parameter space of effort and boost factor, with the value of difficulty fixed at 2.0. We used only the data for two states, California and Wyoming, in the date range 2020/04/24-2020/06/30, corresponding to the first wave of COVID-19. n -fold rolling origin cross-validation was used for scoring the models. The best RMSE was 0.0369, for boost factor = 0.02 and effort = 1.0. These boost factor and effort values were used in the R-PVAs where self-efficacy was modelled. (See Supplementary Materials for the values obtained for each combination of parameter values.)

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Data availability

The datasets used and analyzed in this study were compiled from public sources described in the paper. The compiled data and Jupyter notebooks used for analysis are available at the OSF repository at https://osf.io/wb5vm/?view_only=dda08de194a44b0d95b58ec6f17850c9

References

- 1 Saha, L. *et al.* The impact of the COVID-19 lockdown on global air quality: A review. *Environ Sustain (Singap)* **5**, 5-23 (2022). <https://doi.org/10.1007/s42398-021-00213-6>
- 2 West, R., Michie, S., Rubin, G. J. & Amlôt, R. Applying principles of behaviour change to reduce SARS-CoV-2 transmission. *Nature Human Behaviour* **4**, 451-459 (2020). <https://doi.org/10.1038/s41562-020-0887-9>
- 3 Christakis, N. A. *Apollo's arrow*. (Little, Brown Spark, 2020).
- 4 Leech, G. *et al.* Mask wearing in community settings reduces SARS-CoV-2 transmission. *Proc Natl Acad Sci U S A* **119**, e2119266119 (2022). <https://doi.org/10.1073/pnas.2119266119>
- 5 Walport, M. J. & Professor Sir Mark Walport on behalf of the Expert Working Group for the Royal Society's programme on non-pharmaceutical, i. Executive Summary to the Royal Society report "COVID-19: examining the effectiveness of non-pharmaceutical interventions". *Philos Trans A Math Phys Eng Sci* **381**, 20230211 (2023). <https://doi.org/10.1098/rsta.2023.0211>
- 6 Weitz, J. S., Park, S. W., Eksin, C. & Dushoff, J. Awareness-driven behavior changes can shift the shape of epidemics away from peaks and toward plateaus, shoulders, and oscillations. *Proceedings of the National Academy of Sciences* **117**, 32764 (2020). <https://doi.org/10.1073/pnas.2009911117>
- 7 Ianni, A. & Rossi, N. SIR-PID: A Proportional–Integral–Derivative Controller for COVID-19 Outbreak Containment. *Physics* **3**, 459-472 (2021).
- 8 Pirolli, P., Lebiere, C. & Orr, M. A computational cognitive model of behaviors and decisions that modulate pandemic transmission: Expectancy-value, attitudes, self-efficacy, and motivational intensity. *Front Psychol* **13**, 981983 (2022). <https://doi.org/10.3389/fpsyg.2022.981983>
- 9 Bandura, A. *Self-efficacy: The exercise of control*. (W.H. Freeman, 1998).
- 10 Vancouver, J. B. Integrating self-regulation theories of work motivation into a dynamic process theory. *Human Resource Management Review* **18**, 1-18 (2008). <https://doi.org/10.1016/j.hrmr.2008.02.001>
- 11 Vancouver, J. B., More, K. M. & Yoder, R. J. Self-efficacy and resource allocation: Support for a nonmonotonic, discontinuous, model. *Journal of Applied Psychology* **93**, 35-47 (2008).
- 12 Kukla, A. Foundations of an attributional theory of performance. *Psychological Review* **79**, 454-470 (1972). <https://doi.org/10.1037/h0033494>
- 13 Silvestrini, N., Musslick, S., Berry, A. S. & Vassena, E. An integrative effort: Bridging motivational intensity theory and recent neurocomputational and neuronal models of effort and control allocation. *Psychol Rev* (2022). <https://doi.org/10.1037/rev0000372>
- 14 Ferguson, N. M. *et al.* Impact of non-pharmaceutical interventions (NPIs) to reduce COVID- 19 mortality and healthcare demand. (2020).
- 15 Ioannidis, J. P. A., Cripps, S. & Tanner, M. A. Forecasting for COVID-19 has failed. *Int J Forecast* **38**, 423-438 (2022). <https://doi.org/10.1016/j.ijforecast.2020.08.004>
- 16 Aviral, C. *et al.* Accuracy of US CDC COVID-19 Forecasting Models. *medRxiv*, 2022.2004.2020.22274097 (2022). <https://doi.org/10.1101/2022.04.20.22274097>

- 17 Cramer, E. Y. *et al.* Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States. *Proc Natl Acad Sci U S A* **119**, e2113561119 (2022). <https://doi.org/10.1073/pnas.2113561119>
- 18 Flaxman, S. *et al.* Imperial College Report 13: Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries. (Imperial College, London, 2020).
- 19 Redlin, M. Differences in NPI strategies against COVID-19. *J Regul Econ* **62**, 1-23 (2022). <https://doi.org/10.1007/s11149-022-09452-9>
- 20 Spiliopoulos, L. On the effectiveness of COVID-19 restrictions and lockdowns: Pan metron ariston. *BMC Public Health* **22**, 1842 (2022). <https://doi.org/10.1186/s12889-022-14177-7>
- 21 Brossard, D., Wood, W., Cialdini, R. & Groves, R. M. National Academies of Sciences, Engineering, and Medicine: Encouraging Adoption of Protective Behaviors to Mitigate the Spread of COVID-19: Strategies for Behavior Change., (The National Academies Press, Washington, D.C., 2020).
- 22 Pirolli, P., Bhatia, A., Mitsopoulos, K., Lebiere, C. & Orr, M. in *2020 International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation (SPB-BRIMS 2020)* (eds R. Thomson *et al.*) (Springer, 2020).
- 23 Pirolli, P. *et al.* in *Social, Cultural, and Behavioral Modeling* (eds Robert Thomson, Muhammad Nihal Hussain, Christopher Dancy, & Aryn Pyke) 46-56 (Springer International Publishing, 2021).
- 24 Mitsopoulos, K. *et al.* in *2023 AAAI Fall Symposium*. (AAAI Press).
- 25 Grossmann, I. *et al.* AI and the transformation of social science research. *Science* **380**, 1108-1109 (2023). <https://doi.org/10.1126/science.ad1778>
- 26 Mather, B., Dorr, B., Rambow, O. & Strzalkowski, T. in *The International FLAIRS Conference Proceedings* (2021).
- 27 Ebert, T. *et al.* Are Regional Differences in Psychological Characteristics and Their Correlates Robust? Applying Spatial-Analysis Techniques to Examine Regional Variation in Personality. *Perspectives on Psychological Science* **17**, 407-441 (2022). <https://doi.org/10.1177/1745691621998326>
- 28 Bedson, J. *et al.* A review and agenda for integrated disease models including social and behavioural factors. *Nat Hum Behav* **5**, 834-846 (2021). <https://doi.org/10.1038/s41562-021-01136-2>
- 29 Obschonka, M., Lee, N., Rodríguez-Pose, A., Eichstaedt, J. C. & Ebert, T. Big data methods, social media, and the psychology of entrepreneurial regions: capturing cross-county personality traits and their impact on entrepreneurship in the USA. *Small Business Economics* **55**, 567-588 (2020). <https://doi.org/10.1007/s11187-019-00204-2>
- 30 Anderson, J. R. & Lebiere, C. *The atomic components of thought*. (Lawrence Erlbaum Associates, 1998).
- 31 Anderson, J. R. *et al.* An integrated theory of mind. *Psychological Review* **11**, 1036-1060 (2004).
- 32 Newell, A. *Unified theories of cognition*. (Harvard University Press, 1990).
- 33 Laird, J. E., Lebiere, C. & Rosenbloom, P. S. A Standard Model of the Mind: Toward a Common Computational Framework across Artificial Intelligence, Cognitive Science,

- Neuroscience, and Robotics. *AI Magazine* **38**, 13-16 (2017).
<https://doi.org/10.1609/aimag.v38i4.2744>
- 34 Anderson, J. R., Boyle, C. F., Corbett, A. T. & Lewis, M. W. Cognitive modelling and intelligent tutoring. *Artificial Intelligence* **42**, 7-49 (1990).
- 35 Pirolli, P. *et al.* Scaffolding the Mastery of Healthy Behaviors with Fittle+ Systems: Evidence-Based Interventions and Theory. *Human-Computer Interaction*, 1-34 (2018).
<https://doi.org/10.1080/07370024.2018.1512414>
- 36 Anderson, J. R. *How can the human mind occur in the physical universe?* , (Oxford University Press, 2007).
- 37 Corbett, A. T. in *User Modeling 2001: 8th International Conference*. (eds M. Bauer, P.J. Gmytrasiewicz, & J. Vassileva) (Springer-Verlag).
- 38 Pirolli, P. in *Handbook of applied cognition (2nd ed.)* (ed F.T. Durso) 443-470 (John Wiley & Sons, 2007).
- 39 Pavlik, P. I. & Anderson, J. R. Practice and forgetting effects on vocabulary memory: An activation-based model of the spacing effect. *Cognitive Science* **29**, 559-586 (2005).
- 40 Pirolli, P. From good intentions to healthy habits: towards integrated computational models of goal striving and habit formation. *Conf Proc IEEE Eng Med Biol Soc* **2016**, 181-185 (2016). <https://doi.org/10.1109/EMBC.2016.7590670>
- 41 Pirolli, P. A computational cognitive model of self-efficacy and daily adherence in mHealth. *Transl Behav Med* **6**, 1-13 (2016). <https://doi.org/10.1007/s13142-016-0391-y>
- 42 Center, J. H. C. R. (ed Johns Hopkins University and Medicine) (n.d.).
- 43 Killeen, B. D. *et al.* A County-level Dataset for Informing the United States' Response to COVID-19. arXiv:2004.00756 (2020).
<https://ui.adsabs.harvard.edu/abs/2020arXiv200400756K>.
- 44 Gollwitzer, A. *et al.* Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nature Human Behaviour* **4**, 1186-1197 (2020). <https://doi.org/10.1038/s41562-020-00977-7>
- 45 Nicholson, C., Beattie, L., Beattie, M., Razzaghi, T. & Chen, S. A machine learning and clustering-based approach for county-level COVID-19 analysis. *PLoS One* **17**, e0267558 (2022). <https://doi.org/10.1371/journal.pone.0267558>
- 46 Lazer, D. *et al.* The COVID States Project #26: Trajectory of COVID-19-related behaviors. (2021).
- 47 Gonzalez, C., Lerch, J. F. & Lebiere, C. Instance-based learning in dynamic decision making. *Cognitive Science* **27**, 591-635 (2003).
- 48 Reitter, D. & Lebiere, C. in *Proceedings of the 10th International Conference on Cognitive Modeling* (eds D. D. Salvucci & G. Gunzelmann) 199-204 (Drexel, 2010).
- 49 Miller, G. A. The magical number seven plus or minus two: Some limits on our capacity for processing information. *Psychological Review* **63**, 81-97 (1956).
- 50 Simon, H. A. How big is a chunk? *Science* **183**, 482-488 (1974).
- 51 U.S. Census Bureau. *U.S. 2010 Census*, <<https://www.census.gov/>> (n.d.).
- 52 National Center for Health Statistics. *NCHS Urban-Rural Classification Scheme for Counties*, <https://www.cdc.gov/nchs/data_access/urban_rural.htm> (n.d.).
- 53 USDA Economic Research Service. *Rural-Urban Continuum Codes*, <<https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/>> (n.d.).
- 54 Hyndman, R. J. & Athanasopoulos, G. *Forecasting: Principles and Practice (3rd edition)*. (OTexts, 2021).

