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Neural signals predict information sharing across cultures

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Information sharing influences which messages spread and shape beliefs, behavior, and culture. In a preregistered neuroimaging study conducted in the United States and the Netherlands, we demonstrate replicability, predictive validity, and generalizability of a brain-based prediction model of information sharing. Replicating findings in Scholz et al., *Proc. Natl. Acad. Sci. U.S.A.* 114, 2881–2886 (2017), self-, social-, and value-related neural signals in a group of individuals tracked the population sharing of US news articles. Preregistered brain-based prediction models trained on Scholz et al. (2017) data proved generalizable to the new data, explaining more variance in population sharing than self-report ratings alone. Neural signals (versus self-reports) more reliably predicted sharing cross-culturally, suggesting that they capture more universal psychological mechanisms underlying sharing behavior. These findings highlight key neurocognitive foundations of sharing, suggest potential target mechanisms for interventions to increase message effectiveness, and advance brain-as-predictor research.

information sharing | fMRI | brain-based prediction

Information sharing, online or offline, influences what messages reach people and shapes beliefs, behavior, and culture (1–4). Diverse actors, from social media users to politicians, marketers, and public health officials, are motivated to predict and maximize the reach of their content via sharing.

The value-based model of information sharing (5–8) posits that sharing is more likely if it is perceived to be valuable to the would-be sharer and that self- and social relevance are key sources of value. In two functional MRI (fMRI) studies using online news articles, Scholz et al. (5) showed that domain-general value signals in the brain tracked information sharing in the population. Furthermore, brain activity associated with self- and social relevance correlated with the value signal, supporting the idea that content which serves self- and social-related motives (e.g., expressing viewpoints or connecting with others) has higher sharing value (6, 8, 9).

The discovery that neural signals from a group of individuals hold information about large-scale behavior (10, 11) requires further tests on the replicability of the findings, the predictive validity of brain-based models in novel contexts, and the generalizability of these effects across populations.

This preregistered study (DOI: 10.17605/OSF.IO/JCVZ7) evaluates brain-based predictions against these three criteria. Adapting task procedures from ref. 5, participants from the United States and the Netherlands read and rated a new set of US-based news articles while undergoing fMRI.

First, we tested the replicability of the findings in ref. 5 by examining whether population sharing (defined as a news article's number of shares on Facebook, see *Materials and Methods*) was associated with participants' self-report ratings (preregistered hypothesis H1), as well as their self-, social- and value-related neural signals (H2a-c) in the new data.

Second, we trained and preregistered two prediction models with neuroimaging data from ref. 5—one with a priori brain's regions of interest (ROI-based) and the other with voxels across the brain (voxel-based). A third ensemble model incorporated ROI- and voxel-based model scores and self-report ratings. We tested whether these model scores tracked population sharing of novel articles (H3-5).

Finally, to test the generalizability of brain-based predictions, we aggregated self-report ratings and neural signals per article as the expected sharing outcome and examined whether their predictiveness differed between the US and Dutch subsamples.

Results

Value-Based Sharing Model Replication. Testing preregistered hypotheses, self-report (H1), and self-, social- and value-related neural responses to news articles (H2a-c) tracked population sharing (Table 1, part A).

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Table 1. Standardized coefficients of models predicting population sharing (DV) with self-report rating and neural signal IVs

A. Trial-level linear mixed models (Pre-registered hypothesis H1-5)

DV (Population sharing) ~ IV	Scholz et al. (5) (N = 787 trials)	Current study (N = 2,973 trials)
Replicating previous findings		
IV: Self-report rating (H1)	0.186 *** [0.108, 0.265]	0.081 *** [0.045, 0.117]
IV: Self-related neural signal (H2a)	0.111 ** [0.036, 0.186]	0.074 ** [0.030, 0.118]
IV: Social-related neural signal (H2b)	0.106 ** [0.030, 0.182]	0.059 ** [0.018, 0.101]
IV: Value-related neural signal (H2c)	0.083 * [0.012, 0.154]	0.040 * [0.004, 0.076]
Testing pre-trained models		
IV: ROI-based prediction score (H3)	0.135 ** [0.061, 0.208]	0.081 *** [0.039, 0.124]
IV: Voxel-based prediction score (H4)	0.802 *** [0.756, 0.848]	0.012 [−0.027, 0.052]
IV: Ensemble score (H5)	0.584 *** [0.520, 0.648]	0.075 *** [0.039, 0.111]

B. Article-level linear models (Cross-national generalizability of brain-based predictions)

DV (Population sharing) ~ IV1 + IV2	Scholz et al. (5) (N = 80 articles)	Current study (N = 96 articles)		
	US participants	US+NL	US only	NL only
IV1: Aggregate self-report rating	0.295 ** [0.077, 0.513]	0.248 * [0.056, 0.440]	0.366 *** [0.181, 0.551]	0.125 [−0.074, 0.325]
IV2: Aggregate ROI-based prediction score	0.222 * [0.004, 0.440]	0.273 ** [0.081, 0.465]	0.222 * [0.037, 0.407]	235 * [0.036, 0.435]
R^2	0.179	0.160	0.202	0.079
AIC	217.2	261.6	256.7	270.5

AIC = Akaike information criterion. Square brackets indicate 95% CIs. *P < 0.05; **P < 0.01; ***P < 0.001.

Predictive Validity of Neural Signals. Prediction scores from the ROI-based model tracked population sharing (H3), while the voxel-based model did not (H4) and the ensemble model did (H5).

Generalizability of Brain-Based Predictions. Both aggregate self-report ratings and ROI-based prediction scores tracked population sharing in ref. 5 and this study (Fig. 1*A*). Aggregate self-report ratings of US participants were more predictive than those of Dutch participants (Steiger's test of two dependent correlations: Z = 2.003, P = 0.045), while the predictiveness of aggregate ROI-based prediction scores did not differ significantly between subsamples (Z = 0.108, P = 0.914). Finally, aggregate ROI-based prediction scores provided additional explanatory power beyond self-report ratings, whether for all participants or within national subsample (Table 1, part B).

Discussion

Can neural signals deepen our understanding of the psychological bases of large-scale behaviors, such as information sharing, and help predict message effects in the population (10, 11)? For the brain-as-predictor literature to fulfill its potential, we need to test the replicability of specific findings, the predictive validity of brain-based models in novel contexts, and its generalizability across populations.

Here, we demonstrated all three qualities in an extended, conceptual replication of ref. 5, which showed again self-, social- and value-related neural signals in study participants track population sharing of information. While the voxel-based model did not generalize to the new data, the theory-informed ROI-based model showed predictive validity in different participants and stimuli. This could indicate overfitting in the voxel-based model and/or more robust signals in the theory-informed ROIs. Consistent with prior literature (12, 13), neural signals explained variance in large-scale behaviors above and beyond self-reports alone. Finally, the predictive effect of neural signals was more generalizable across national subsamples than self-reports, suggesting that neural signals capture more universal psychological mechanisms underlying sharing behavior.

These findings highlight the importance of self-, social-, and value-related neural processes in sharing and suggest potential intervention targets to increase message effectiveness. More generally for the brain-as-predictor research, this work demonstrates the robustness of neural signals for explaining and predicting large-scale behaviors.

Materials and Methods

This study was preregistered (DOI: 10.17605/OSF.IO/JCVZ7) and approved by the Institutional Review Board at the University of Pennsylvania and the Faculty Ethics Review Board at the University of Amsterdam before data collection. Data and analysis code are available at http://doi.org/10.17605/OSF.IO/CAXFQ.

Participants. Ninety-four individuals (mean age = 21.4, SD = 2.6, range = 18 to 31) received verbal and written information about the study at a Dutch (n = 50) and a US university (n = 44), offered informed consent, and participated during Summer and Fall 2021.

Stimuli and Task. During fMRI, participants read a subset of 96 New York Times news abstracts (published 2016–2019) then rated their intention to read the full article (Fig. 1*B*).

Population Sharing Measure. The dependent variable (DV) of all analyses is population sharing, defined as the normalized log-transformed total number of shares of all private and public Facebook posts containing the article's URL (mean = 3,167, SD = 5255, range= 44 to 25,091), available via CrowdTangle, a Meta-owned tool that tracks content interactions.

Neuroimaging Data Acquisition and Processing. Blood oxygenation level dependent signal time series were preprocessed and modeled with boxcar regressors of news abstracts and regressors of no interest, yielding one beta image per abstract per participant. Details on neuroimaging data analysis are described in the preregistration and *SI Appendix*.

Hypothesis Testing. Self-, social-, and value-related neural signals were mean activity in the single-trial beta images within preregistered ROIs based on Neurosynth (14) term association maps of "self-referential," "mentalizing," and "value," excluding overlapping voxels (Fig. 1*C*). We estimated four linear mixed models, each model with the population sharing DV and one of the predictors (self-report rating and the three ROIs) as independent variable (IV) with random intercepts and slopes for participants.

Prediction Model Training and Testing. We trained and preregistered two prediction models with neuroimaging data in ref. 5 (Fig. 1*D*): the ROI-based model used nine Neurosynth ROIs, while the voxel-based model had 5,137 voxels that significantly tracked reading intention in ref. 5. Feature weights were estimated by ridge regression with eightfold cross-validation. The ensemble model had

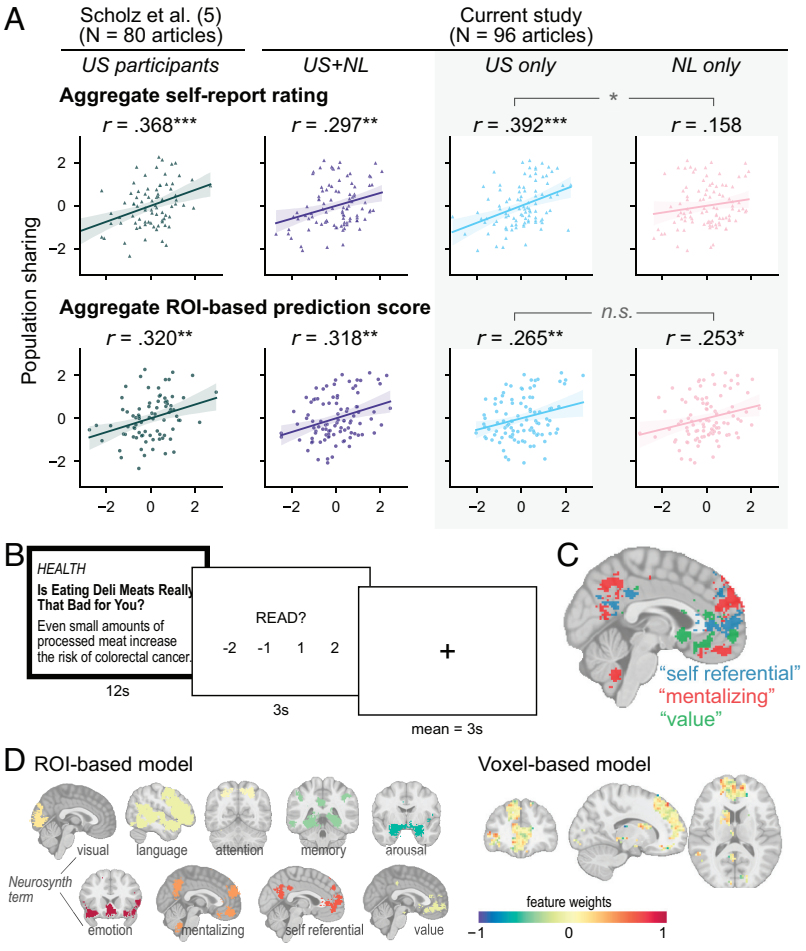

Fig. 1. (*A*) Standardized correlation plots of aggregate self-report ratings and ROI-based prediction scores (*X* axis) against population sharing (*Y* axis). *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$ (*B*) Task overview (*C*) Self- (blue), social- (red), and value-related (green) region-of-interest (ROI) masks based on respective Neurosynth terms for hypothesis testing (*D*) Preregistered weights (scaled −1 to 1) of ROI-based and voxel-based prediction models.

self-report ratings, ROI-based, and voxel-based prediction scores as features. We estimated three linear mixed regressions, each with the population sharing DV and one of the prediction scores (ROI-based, voxel-based, and ensemble) as IV with random intercepts and slopes for participants.

Article-Level Analysis. The expected population sharing for each article was calculated by aggregating self-report and neural responses per article, first from all participants and then separately within US and Dutch subsamples. We then calculated pairwise correlations with the population sharing DV for aggregate self-report ratings and ROI-based prediction scores separately and finally estimated linear regressions with both IVs together.

Citation Diversity Statement

The gender makeup of papers cited within this work (excluding self-citations) is 37% woman(first)/woman(last), 12% man/woman, 12% woman/man, and 37% man/man.

Data, Materials, and Software Availability. Data and analysis scripts data have been deposited in Open Science Framework (OSF; https://doi.org/10.17605/OSF.IO/CAXFQ). Anonymized (Preregistration) data have been deposited in OSF (https://doi.org/10.17605/OSF.IO/JCVZ7). Previously published data were used for this work (https://doi.org/10.1073/pnas.1615259114) (5). All other data are included in the manuscript and/or *SI Appendix*.

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