Title: Social cognitive processes explain bias in juror decisions

Authors:

Jaime J. Castrellon^{1,2}, Shabnam Hakimi^{2,3}, Jacob M. Parelman^{3,4}, Lun Yin², Jonathan R. Law^{1,2}, Jesse A.G. Skene^{1,2}, David A. Ball⁵, Artemis Malekpour⁵, Donald H. Beskind⁶, Neil Vidmar⁶, John M. Pearson^{1,2,7,8}, J. H. Pate Skene^{3,8,9*}, R. McKell Carter^{3,10,11*}

* - Senior authors contributed equally to this work.

Affiliations:

- 1 - Department of Psychology and Neuroscience, Duke University
- 2 - Center for Cognitive Neuroscience, Duke University
- 3 - Institute of Cognitive Science, University of Colorado Boulder
- 4 - Annenberg School for Communication, University of Pennsylvania
- 5 - Malekpour & Ball Consulting (JuryWatch, Inc.)
- 6 - School of Law, Duke University
- 7 - Departments of Biostatistics & Bioinformatics, Duke University
- 8 - Department of Neurobiology, Duke University
- 9 - Initiative in Science and Society, Duke University
- 10 - Department of Psychology and Neuroscience, University of Colorado Boulder
- 11 - Electrical, Computer, & Energy Engineering, University of Colorado Boulder

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Data availability:

Unthresholded fMRI statistical maps can be viewed/downloaded from Neurovault: <https://neurovault.org/collections/11105/>. Code and fMRI analysis pre-registration for hypothesis grouping can be viewed and downloaded from OSF: <https://osf.io/rk92x/> and Github: https://github.com/jcastrel/juror_fmri_bias

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Abstract: Jury decisions are among the most consequential social decisions in which bias plays a notable role. While courts take measures to reduce the influence of non-evidentiary factors, jurors may still incorporate biases into their decisions. One common bias, crime-type bias, is the extent to which the perceived strength of a prosecutor's case depends on the severity of the crime. Moral judgment, affect, and social cognition have been proposed as core processes underlying this and other biases. Behavioral evidence alone has been insufficient to distinguish these explanations. To identify the mechanism underlying crime-type bias, we collected fMRI patterns of brain activation from mock jurors reading criminal scenarios. Brain patterns from crime-type bias were most similar to those associated with social cognition (mentalizing and racial bias) but not affect or moral judgment. Our results support a central role for social cognition in juror decisions and suggest crime-type bias and cultural bias may arise from similar mechanisms.

Introduction:

Recent public discourse has heightened interest in the biases that make their way into complex social decisions. From public policy choices to decisions about vaccination or climate change, the way people interpret factual evidence has been shown to depend on social and cultural beliefs and attitudes (Unsworth and Fielding, 2014; Agarwal et al., 2021; Ruiz and Bell, 2021), which may also be related to additional, general, forms of bias. Juror decisions about whether a defendant is guilty or not guilty are among the most consequential decisions in society. Like other complex social decisions, juror decisions require people to evaluate the cumulative weight of the available evidence in light of personal experience, emotions, and biases. In addition to weighing evidence directly relevant to a decision, jurors tend to consider factors not logically informative for deciding the facts of the case (Devine, 2012). We refer to those factors as extra-evidentiary. Various extra-evidentiary factors can bias the outcome of juror decisions.

The most prominently studied of these biasing factors include racial or cultural prejudices and stereotypes. For example, a number of studies have focused on the effects of race and gender on convictions in the criminal justice system (Anwar et al., 2012; Devine et al., 2016; Flanagan, 2018). Experimental evidence complements this research. Mock jurors' decisions about guilt, culpability, and sentencing are biased against outgroup ethnicity and socioeconomic status regardless of the severity of the crime (Mitchell et al., 2005; Esqueda et al., 2008).

Research on racial and cultural bias has framed theories of cognitive mechanisms underlying bias in terms of emotional, moral, and social cognitive processes. Public understanding of racial prejudice has often assumed that prejudice and stereotypes are driven primarily by emotional animus or moral judgment (e.g., *dominative racism* (Kovel, 1984)). However, people can behave in racially biased ways even when they deny feelings of racial animus or superiority. Social cognitive theories like Aversive racism theory (Dovidio and Gaertner, 2004) and Social identity theory (Stets and Burke, 2000; Ingriselli, 2014) characterize bias in behavior as a means to preserve in-group value in the (claimed) absence of emotion. Are these emotional, moral, and social cognitive mechanisms inferred from race and cultural bias unique, or do they apply to other types of decision making biases?

In criminal justice decisions, biases related to certain types of crime are of particular concern. Documented cases of wrongful conviction have most often involved very serious crimes like murder or rape. It is not clear whether this reflects a higher rate of wrongful conviction for serious crimes or simply a greater likelihood that wrongful

convictions will be discovered in those cases. Supporting the former possibility, several studies indicate that the seriousness of crimes can contribute to bias in juror decisions (Vidmar, 2002, 2003; Gastwirth and Sinclair, 2004; Wiener et al., 2006; Gross et al., 2014). For example, Vidmar found that jurors are predisposed toward a belief in the guilt of anyone accused of sexual abuse (Vidmar, 1997). In a previous study using simplified crime scenarios, we found a more general relationship between the seriousness of a crime and mock juror ratings of the strength of the prosecutor's case against a particular defendant, independent of the evidence presented (Pearson et al., 2018). We refer to this as crime-type bias.

While social processes are proposed to underlie many forms of bias, several theories have been proposed to explain crime-type bias specifically, including the roles of emotional responses (Holloway and Wiener, 2018) and moral judgment (Greene and Haidt, 2002). Each of the theories proposes different cognitive processes as the mechanisms for bias. Understanding the precise underlying cognitive processes can shed light on how different kinds of biases arise. Because there are a number of combinations of cognitive processes that could lead to the same behavioral outcome, it is difficult to distinguish these theories using behavior alone. Resolving these overlapping social-affective explanations requires a new approach.

Here, we use neural data to test for the involvement of cognitive processes associated with crime-type bias by using whole brain pattern analysis (Li et al., 2017) to compare patterns of brain activation associated with a range of cognitive processes to those observed during the processing of crime scenarios independent of evidence. We then synthesize results from this pattern analysis to link social-affective models about extra-evidentiary factors from the literature. To implement this approach, we collected functional magnetic resonance imaging (fMRI) data from jury-eligible participants as they viewed a series of simplified crime scenarios that vary in the type of crime and amount of evidence supporting guilt (Pearson et al., 2018). In real-world criminal proceedings, courts often suggest that eliminating graphic descriptions or inflammatory language is sufficient to avoid prejudicial effects of very serious crimes. In our scenarios, the crime descriptions lack graphic details or other contextual information often considered to evoke prejudices or strong emotional reactions. Instead, we are able to focus on bias inherent in the accusation of different types of crime. We characterize the cognitive processes underlying this crime-type bias.

Materials and Methods

Subjects, recruitment, and sampling

Thirty-three healthy, jury-eligible adults between the ages of 18 and 52 were recruited from the Durham, NC community and underwent a single-session fMRI scan. All participants were screened for significant health or neurological problems and had normal or corrected-to-normal vision, and all gave written informed consent before the start of the experiment. Neuroimaging data from four participants were excluded from the analysis because of technical issues. Twenty-nine participants (mean age = 30.6 ± 9.58 years, 15 women and 14 men) remained for neuroimaging analyses. The experiment was approved by the local ethics committee at Duke University Medical Center.

Experimental procedures

The mock-juror task (Fig. 1A), answering a call to use engaging narratives in neuroscience (Willems et al., 2020), was adapted from earlier work (Pearson et al., 2018) for use in the fMRI scanner. Subjects viewed 33 scenarios, each of which describes an accusation of a specific crime — from shoplifting to rape, murder, and child sexual abuse. The task was split into three runs with 10-12 trials (scenarios) per run. For each scenario, participants first viewed a textual description of a crime type (a ‘scenario’; text was presented one sentence at a time across multiple screens for 5-30s). The initial description contained no evidence of who committed the crime. While type of crime was the primary difference between scenarios, the scenarios also differed in other details, including names of defendants and victims, and the circumstances of the crime. These other details were varied to keep subjects engaged throughout the task and to encourage participants to treat each scenario as a distinct crime. At the same time, the varied descriptions raised the potential for differences other than crime type to influence effects of the crime scenario on judgments of guilt. However, the large number of scenarios and the range of crime seriousness across those scenarios provided an opportunity to test for a main effect of crime seriousness on judgments of guilt (for scenario and evidence text see Table S1).

After viewing the crime scenario description, participants were shown three types of evidence implicating the named suspect (text presented one sentence at a time across multiple screens for 2-12s). Subjects viewed evidence that was: (1) physical evidence, (2) eyewitness, and (3) criminal history. The order of presentation for these

evidence types was randomized. Types of evidence linking the accused to the crime included (1) one of three options of physical evidence (no physical evidence, DNA evidence or non-DNA physical evidence such as fingerprint or ballistic evidence); (2) either of two levels of eyewitness (eyewitness or a non-eyewitness) or (3) one of three options of criminal history (no prior convictions, prior conviction for a related crime, or prior conviction for an unrelated crime). This resulted in 18 unique evidence combinations ($3 \times 2 \times 3$) for each crime scenario. Participants viewed all 33 crime scenarios paired with only one randomized combination of evidence. Although each participant saw only one randomized combination of evidence for each crime scenario, we can test each of the 33 crime scenarios with all 18 evidence combinations (594 unique combinations) using a computational modeling approach (See Supplementary Materials for modeling details). Following presentation of the scenario and evidence, participants were asked to rate the strength of the case against the accused and recommend a degree of punishment (on a scale of 0-100) for 6s each.

The crimes shown varied in seriousness according to their legal classification (misdemeanor versus felony) and victim type (victimless, loss of property, and personal harm or injury). For example, while a misdemeanor victimless crime described operating a still without a license, a misdemeanor loss of property crime described larceny and a misdemeanor crime about personal harm described vehicular manslaughter. Among felony crimes shown, a victimless crime described money laundering, a property loss crime described breaking and entering, and a crime with a personal harm described first-degree murder. See Tables S1 and S2 for detailed crime scenario texts and classification for all 33 scenarios.

Computational modeling of juror behavior

Using this task (Fig. 1A), we previously showed that evidence and extra-evidentiary information about the crime independently influence participant judgments about the strength of the case against the accused (Pearson et al., 2018). We used a hierarchical Bayesian model to estimate the effects of crime type and evidence type (independent of each other) on case strength and punishment ratings (see Supplementary Materials). Since this model has the advantage of accounting for sparsely sampled data, we can estimate effects for all scenarios even though participants did not view all possible combinations of scenarios and evidence types. We previously applied this model to a large online sample of participants (Pearson et al., 2018) and show here that the model replicates case strength and punishment effects (Fig. S1). As in the online sample, computational modeling of ratings by the current participants also distinguished the effects of different types of crime on rated case

strength (Fig. 1B). Participants' mean case strength ratings for all fixed evidence are presented in Fig. S2.

We had hypothesized that the seriousness of a crime might affect the likelihood of guilt. In our task, crime seriousness can be indexed by subject ratings of how much punishment the crime deserves (Pearson et al., 2018). We used PCA to explore the relationship between crime seriousness and contribution of the crime scenario to perceived case strength. The first component describing shared variance between the two (PC1) explains ~95% of the variance (Fig. 1C). Similarly, in the prior online sample, PC1 explained 69.5% of the variability (Fig. S3). We therefore utilize the slope of PC1 as a summary of the common process, our operational definition of crime-type bias. To check that there were no additional processes driving similarity between punishment and the scenario contribution to case strength, we added PC2 as an additional explanatory variable in our analysis.

Univariate fMRI analysis

Acquisition and preprocessing were performed as described in supplementary information. Statistical modeling of fMRI data was performed using FSL FEAT (v 6.0.0) (Smith et al., 2004; Woolrich et al., 2009). First-level analyses used FILM prewhitening for autocorrelation correction. Event variables and parametric regressors were convolved with a double-gamma hemodynamic response function. For each subject, a general linear model was fit to the data with event regressors for (1.) scenario viewing, (2.) evidence viewing, (3.) case strength rating, and (4.) punishment rating. To identify regions associated with modulation of BOLD signal with crime-type bias, we included two parametric regressors for loading scores on the principal components (crime-type bias/PC1 and PC2) from the PCA described above between case strength and punishment model weights. Evidence accumulation during evidence viewing was modeled with a parametric regressor as the within-trial successive cumulative sum of evidence weights for case strength with each additional piece of evidence. Additional parametric regressors included the scenario-level case strength model weights during the case strength rating phase and scenario-level punishment model weights during the punishment rating phase. The present paper focuses on the parametric effect of crime-type bias during the scenario viewing event. Second-level analyses averaged within-subjects' data across runs using a fixed-effects model. Higher-level analysis used a mixed-effects model (FLAME1) to combine data across subjects. Statistical maps were thresholded using a cluster-forming threshold with a height of $Z > 2.3$, and cluster-corrected significance threshold of $p < 0.05$.

Neurosynth similarity analysis

In order to evaluate support for different explanations of sources of crime-type bias, we compared the parametric crime-type bias map to patterns taken from a meta-analytic database, Neurosynth (Yarkoni et al., 2011). This meta-analytic database identifies brain activation patterns associated with defined terms and topics from the neuroimaging literature.

We first performed a data-driven spatial correlation analysis between the crime-type bias activation map and each and every topic in the database. We estimated the spatial voxelwise Pearson correlation between our parametric fMRI maps and each of all the possible 200 topic maps in the Neurosynth database (version 5, 200 topics release: <https://neurosynth.org/analyses/topics/v5-topics-200/>) (Yarkoni et al., 2011). We visualized these correlations using histograms for thresholded (Fig. 2B) and unthresholded (Fig. S6) fMRI maps. We refer to this analysis as “model-free” because the topics are neither selected nor grouped on the basis of any theories of bias. We note, however, that there are assumptions that stem from the underlying topic model (Poldrack et al., 2012).

In addition to the model-free correlation analysis, we grouped topics according to their hypothesized role in theories of bias. We refer to this analysis as “model-based”. We therefore constructed a series of a priori models which consisted of groups of cognitive processes associated with the social-affective model families. We grouped meta-analytic association (reverse inference) fMRI statistical maps from the Neurosynth database that reflect cognitive features associated with distinctive models of juror decision making. To limit user degrees of freedom while defining model structure, we preregistered the list of topics associated with each model of decision making (details at <https://osf.io/rk92x/>) prior to model-free and model-based analyses (Table S3). After defining the models, we ran spatial linear regression using the topic maps as predictors of each model’s similarity to our parametric statistical maps for evidence accumulation and crime-type bias using the form

$$Y(fMRI\ map) = \beta_0 + \beta_1(topic_1) + \beta_2(topic_2) + \dots + \beta_i(topic_i) + \epsilon \text{ for } i \text{ topics}$$

included in each model (Fig. S5). This allows for topic maps to vary in their contribution to the overall model’s similarity to the crime-type bias map. We used both thresholded and unthresholded z-statistic maps from our results and unthresholded z-statistic Neurosynth topic maps provided by the Neurosynth developer, Tal Yarkoni (since the viewable maps on the Neurosynth website are thresholded). For thresholded map analysis, we restricted inclusion to voxels that survived cluster-based thresholding for positive parametric effects of crime-type bias (Fig. 2). This prevents describing a

cognitive process as being involved in a decision if it was suppressed rather than activated.

To identify meaningful associations, we adopted a non-parametric approach. In order to conclude that one model of juror bias explains the decision-making process, the topics associated with that model should explain more variance than a randomly chosen set of topics (see SI for details).

Post-hoc analysis of crime-type bias

Next, we examined the features of crime scenarios that best account for crime-type bias. In particular, we explored why brain regions involved in social cognition explain much of the variance in crime-type bias. One possibility is that crime type could be driven by inferences about seriousness based on societal definitions according to legal classification and may engage similar cognitive processes as those associated with culture and ideation bias. Alternatively (or in addition), the effect of crime type is driven by theory of mind or perspective-taking from the point of view of a victim. We used ROI analysis to test whether crime seriousness (according to statute) or the type of victim harm (victimless, loss of property, and injury or loss of life) better correlate with activations associated with crime-type bias (see SI).

Following this, we performed a model comparison analysis to identify whether crime-type bias is best predicted by victim type or legal classification as singular predictors, independent complementary predictors, or interacting predictors. We performed a likelihood-ratio test (χ^2) and evaluated the BIC scores of each model compared to an intercept-only model.

Results

Brain regions associated with social cognition track crime-type bias

To identify the patterns of brain activation associated with crime-type bias, we modeled the neuroimaging data using a parametric regressor (see SI). We observed constellations of activations associated with crime-type bias (Fig. 2A, SI). In particular, positive activations included temporal parietal junction, posterior cingulate and precuneus, thalamus, midbrain, striatum, and inferior frontal gyrus and negative activations included the medial prefrontal cortex. These brain regions are associated with a range of cognitive processes. No significant clusters were associated with the second principal component of the PCA (PC2). The unthresholded statistical map for

crime-type bias is accessible on Neurovault (<https://neurovault.org/collections/11105/>). To clarify the cognitive processes linked to crime-type bias, we employed a data-driven approach to ask which of all 200 possible topics in the Neurosynth database (version 5, 200 topics release: <https://neurosynth.org/analyses/topics/v5-topics-200/>) (Yarkoni et al., 2011) were most strongly associated with crime-type bias.

To do so, we compared the patterns of activation from crime-type bias to association (reverse inference) maps for all topic maps included in the Neurosynth database. We limited our analysis to significant clusters of positive activation. We calculated the Pearson correlation between the thresholded parametric crime-type-bias map and each of the 200 topic maps in Neurosynth (Yarkoni et al., 2011) (see SI). Higher correlations reflect greater similarity between the pattern of activation associated with crime-type bias and the neural signatures associated with a given Neurosynth topic. Notably, the topic most strongly correlated with crime-type bias is topic 100 ($r = 0.233$) (Fig. 2B). Neurosynth terms associated with topic 100 include “race”, “racial”, “stereotypes”, “american”, “black”, “white”, “prejudice”, “biases”, and “chinese”, suggesting a possible link between the brain regions and cognitive processes associated with crime-type and racial biases. The top ten topics correlated with crime-type bias also includes several additional topics centered on social cognition, (topics 145 “mind, mental, social” topic: $r = 0.213$; 154 “social, interactions”: $r = 0.126$), or on brain regions regions often associated with social cognition (topic 123 “junction, tpj, temporoparietal”: $r = 0.213$; topic 155 “temporal, sulcus, superior”: $r = 0.177$) (Fig. 2B). The top ten Neurosynth topic maps correlated with crime-type bias did not include topics related to affective processes or moral judgment. However, one topic related to moral judgment (topic 135 “moral”, “guilt”, “judgment”, “morality”, “justice”, “wrong”, “norms”, “good”, “legal”, “shame”) had a relatively high correlation with crime-type bias ($r = 0.107$) (Fig. 2B) although it was below the top 10 out of 200 topics. The magnitude of the correlations we observed here are within the range reported in other studies testing the similarity of Neurosynth topic maps with fMRI effects related to decision making (Bowring et al., 2019) and social cognition (Boccadoro et al., 2019).

Our model-free analysis suggested that crime-type bias might be associated with cognitive processes related to social cognition, to racial and other cultural biases, and potentially to moral judgment, but we did not find evidence that crime-type bias in our task is related to affect. To test those suggestions systematically, we selected and grouped topic maps from Neurosynth into four potential models (preregistered at <https://osf.io/rk92x/>): (1) affect, (2) moral judgment, (3) social cognition, and (4) culture and ideation bias (see Methods, Table S3). We compared the variance explained by each of our models to the null distribution for randomly assigned groups of topics randomly drawn from the 191 Neurosynth topics not associated with one of the a priori models. The null distribution for each test was defined for a number of topics matched

to each model. Specifically, the affect model was compared to null models that contained 3 topics and the other models were compared to null models that contained 2 topics. Hereafter, a model is described as significant if it explains more variance than 95% of models composed of randomly drawn topics.

We find that patterns of brain activation in response to crime-type bias (Fig 2B) were strongly correlated with the social cognition model centered on theory of mind and mentalizing processes ($p = 0.0094$, resampled null, Fig. 3B) and the culture and ideation bias model centered on processing stereotypes and personal biases ($p = 0.0012$). The affect (Fig. 3A) and moral judgment (Fig. 3B) models were not significant. Within the social cognition and culture and ideation bias models, three topics showed positive associations with crime-type bias: topic map 145 (“mind, mental, social”), topic map 154 (“social, interactions”), and topic map 100 (“gestures, abstract, race”).

Finally, we examined the specific brain regions that contribute to the similar activation patterns associated with crime-type bias, social cognition, and culture/ideation bias (Fig. 4A). The social cognition topic maps (145 and 154) overlap with activation for crime-type bias in the temporal parietal junction and posterior cingulate (Fig. 4A), which have been identified as hub regions for the mentalizing or theory-of-mind component of social cognition (Spreng and Andrews-Hanna, 2015). Notably, the overlap between crime-type bias and topic 100 also localized to the temporal parietal junction (Fig. 4A). This very specific overlap suggests that crime-type and racial biases may share at least one cognitive component related to social cognition.

Sensitivity to victim harm modulates crime-type bias

To test whether crime seriousness or victimhood was related to cognitive measures of crime-type bias (scenario PC1 from the model estimates of case strength and punishment), we applied an ANOVA for each classification type. This revealed a statistically-significant effect of victimhood ($F(2,30) = 32.08$, $p < 0.0001$) (Figure 4B) but not seriousness ($F(1,31) = 1.681$, $p = 0.204$) on PC1 (Figure S8A). Specifically, crimes resulting in injury or loss of life ($M_{PC1} = 2.345$, 95% CI = [1.607, 3.083]) were associated with substantially higher PC1 loading scores than victimless ($M_{PC1} = -1.26$, 95% CI = [-1.880, -0.637]) or property crimes ($M_{PC1} = 0.185$, 95% CI = [-0.643, 1.013]). To test whether crime seriousness or victimhood was related to neural measures of crime-type bias (mean fMRI activation from the ROI defined above), we again applied a mixed-effects model with a random intercept for each participant using the “lme4” and “lmerTest” packages in R. This revealed a statistically-significant effect of victimhood ($F(2,926) = 13.04$, $p < 0.0001$) (Figure 4C) but not seriousness ($F(1,927) = 3.25$, $p = 0.072$) (Figure S8B). Specifically, crimes resulting in injury or loss of life ($M_{z-stat} = 0.25$, 95% CI = [0.162, 0.428]) were associated with substantially increased and greater fMRI

activation than victimless ($M_{z\text{-stat}} = -0.050$, 95% CI = [-0.219, 0.130]) or property crimes ($M_{z\text{-stat}} = 0.007$, 95% CI = [-0.098, 0.201]). Overall, we found that those scenarios that result in bodily harm or death (but not victimless or property loss crimes) drove both the increases in case-strength ratings (Fig. 4B, SI) and neural activation associated with crime-type bias (Fig. 4C, SI).

Although these analyses failed to identify strong associations between variability in legal classification and crime-type bias, the effect sizes do indicate some contributing role for legal classification in driving ratings. To pinpoint exactly how victim type and legal definition could each contribute to crime-type bias, we performed a model comparison testing whether the best model is explained by these variables as singular, independent, or interacting. A likelihood-ratio test (χ^2) using the “lrttest” package in R revealed that legal classification alone did not explain crime-type bias ratings better than an intercept-only model ($\chi^2(1) = 1.74$, $p = 0.187$) and that victim type as a singular predictor provided a better fit than legal definition alone ($\chi^2(1) = 35.99$, $p < 0.001$). Nevertheless, a model that included legal classification and victim type as independent predictors provided a better fit than a victim-only model ($\chi^2(1) = 5.38$, $p = 0.020$). A model that included an interaction term between legal classification and victim type did not explain additional variance than the independent predictors ($\chi^2(1) = 0.980$, $p = 0.613$). The BIC score difference (ΔBIC) from an intercept only model (which penalizes complex models) also indicated that the best parsimonious model included independent predictors for legal classification and victim type (Fig. S9). Similarly, fMRI activation associated with crime-type bias was also best explained by a linear model that included victim type as a singular predictor. Specifically, a likelihood-ratio test (χ^2) revealed that legal classification alone did not explain crime-type bias fMRI activation better than an intercept-only model ($\chi^2(1) = 3.25$, $p = 0.072$) and that victim type as a singular predictor provided a better fit than legal classification alone ($\chi^2(1) = 22.5$, $p < 0.001$). Whereas a model that included legal classification and victim type as independent predictors did not provide a better fit than a victim-only model ($\chi^2(1) = 3.27$, $p = 0.071$), a model that included an interaction term between legal classification and victim type did explain additional variance than the independent predictors ($\chi^2(2) = 10.65$, $p = 0.005$). Since this interaction model is complex, the best parsimonious model according to the ΔBIC score was the victim-type only model (Fig. S9). Results from the model comparisons are shown in Table S8 and Table S9.

Discussion

We used the pattern of brain activations during juror decisions to show that crime-type bias is associated with social cognition. Notably, the cognitive processes we find to be associated with crime-type bias are similar to those that give rise to other

biases like stereotypes about culture and race. Although bias is often thought to occur as part of an emotional response, we find that crime-type bias can occur even in the absence of strong emotional processes. It thus serves as a counter example to affect or animus as the sole driver of bias, one of the most popular explanations of bias.

Social cognitive processes track crime-type bias

Topic maps reflecting processes associated with culture and ideation bias and mentalizing are overlapping and highly similar to the parametric effect of crime-type bias (Fig. 4A), reflecting a common underlying use of social cognition. This is consistent with the theory of generic prejudice which speculates that jurors' personal knowledge, beliefs, and stereotypes can influence the perceived strength of the case against a particular defendant (Vidmar, 2003). In the context of this theory, our results indicate that crime-type bias may rely on similar neural and cognitive processes that give rise to other biases like stereotypes about culture and race.

Social cognition, and specifically the integration of culture, personal knowledge, and biases comprises a core component of broader models of narrative decision making (Shiller, 2017). In fact, Yuan et al. have noted the overlap between brain regions involved in narrative and social cognition (Yuan et al., 2018). This overlap is consistent with a proposed role for storytelling in the evolution of cooperation in human societies. Similar regions of the brain are also expanded in modern humans compared to non-human primates (Smaers and Vanier, 2019; Van Essen et al., 2019) and Neanderthals (Kochiyama et al., 2018; Neubauer et al., 2018). In this social role, narratives serve as means of transmitting cultural beliefs and knowledge beyond the first-hand experience of any individual (Smith et al., 2017; Bietti et al., 2019; Hitchcock, 2019).

In the context of juror decision making, narrative models propose that evidence integration by jurors relies on the extent to which the evidence can be assembled into a cohesive, compelling, and credible story (Pennington and Hastie, 1986; Shiller, 2017). Specifically, for jury decisions, narrative explanations are based on the extent to which the information about a case can be structured into a coherent account and how closely the competing narratives offered by prosecution and defense match the juror's background knowledge, experience, and beliefs (Arkes and Garske, 1982; Devine, 2012; Allen and Pardo, 2019; Hastie, 2019). Within this framework, social cognition could be understood as providing a basis for evaluating the plausibility of a narrative suggested by uncertain or incomplete evidence in a particular case.

We found that increased social cognitive processing was dependent on the presence of bodily harm as well as legal classification of the crime. This result is consistent with the notion that people rely on shared legal culture and norms in society

that shape their understanding about how laws should be applied to others (Buckholtz and Marois, 2012; Vilares et al., 2017). These shared ideas about the law are infused in personal identities and inform narratives about society (Somers, 1994; Loseke, 2007) and are consistent with the social communication of laws and expectations through narratives.

While we have examined one specific type of bias that applies to juror decisions in criminal justice, the cognitive model we describe here suggests a more general context for understanding the interaction of biases, stereotypes, and cultural prejudices in complex decisions. In this view, bias does not necessarily require emotion or judgment, consistent with connections between social neuroscience and bias proposed by others (Amodio and Cikara, 2020). The overlap between neural correlates of social cognition and bias (noted also by others (Harris and Fiske, 2009; Cikara and Van Bavel, 2014)) implies that biases, stereotypes, and cultural beliefs are an important part of the knowledge base by which people make predictions about the world and evaluate alternative explanations, the narratives. The incorporation of social cognition in the narrative model provides a means by which bias (how likely is this story to happen in general?) and evidence presented at trial (what is the magnitude of support for this story?) can be integrated to reach a conclusion.

Relationship between crime-type bias and third-party punishment

Social cognition is considered critical to moral judgment from both theoretic (Gray et al., 2012; Royzman and Borislow, 2022) and cognitive neuroscience perspectives (Young et al., 2007). Notably, we did not observe an association between crime-type bias and moral judgment or affect (Kragel and LaBar, 2016). This is initially surprising because crime-type bias, as we operationalized it here, is correlated with subject ratings of the punishment deserved by each type of crime (Fig. 1C and Fig. S3). Previous studies have found that third-party punishment is correlated with activation of brain regions associated with affect and norm enforcement, in some instances modulated by regions associated with social cognition (De Quervain et al., 2004; Buckholtz et al., 2008; Buckholtz and Marois, 2012; FeldmanHall et al., 2012; Treadway et al., 2014; Ginther et al., 2016; Stallen et al., 2018; Zinchenko, 2019).

The differences in brain activation between the two tasks emphasize that crime-type bias and punishment decisions represent separable processes. Punishment ratings reflect a direct assessment of crime seriousness, while crime-type bias represents an effect of crime seriousness on the probability it happened. Although the overall model for moral judgment was not associated with crime-type bias, one topic from that model (topic 135 - “moral”, “guilt”, “judgment”...) was relatively strongly correlated. Topic map 135 has a small overlap with crime-type bias activation within the

TPJ and midbrain. For affect, brain regions involved in affective responses (e.g., amygdala) have been linked to moral judgments about actions that harm others (Treadway et al., 2014; Ngo et al., 2015) but results from our task show no direct link between affect and crime-type bias. This contrast emphasizes the difference between punishment and the decision about the strength of the prosecutor's case.

The absence of affect as a component of crime-type bias is notable in the context of broader theories of bias (e.g. dominative racism). Our results are consistent with social-cognitive models of bias. It is important to point out that our experimental task, by design, presents a minimal description of the crime and the evidence, without graphic details or discussion of the harm to victims that might increase emotional or moral responses (see supplement). Our results therefore do not address the potential roles of affect and/or moral judgment on decisions about guilt in the context of a real trial. We are however, able to show significant bias in the absence of activation associated with affect. We therefore conclude that social cognition can drive bias in addition to any bias from affect and moral reactions. Even when steps are taken to mitigate emotional responses or moral outrage, bias driven by social cognitive processes may persist.

Limitations of the use of Neurosynth

We have attempted to separate the cognitive processes contributing to crime-type bias. In doing so, we have relied on a large body of literature from tens of thousands of researchers as well as a set of tools designed to assess the consistency of conclusions across those studies. While the use of meta-analytic data should increase reliability and generalizability, it also carries the limitations of the work on which it was based. We note that statistical maps from Neurosynth are based on association with a list of terms determined by a topic model generated by the authors of Neurosynth (Yarkoni et al., 2011; Poldrack et al., 2012). The use of a topic model then carries some assumptions: first, that the corpus of studies modeled in Neurosynth contains adequate representation of each of the targeted cognitive processes; second, that the researchers studied the intended concept; third, that the areas of research treated as independent within the cognitive neuroscience community are indeed independent.

If these assumptions are violated, we would find a lack of association between the topics and fMRI activity included by Neurosynth. We therefore attempted to address these concerns by ensuring that each of our cognitive processes contained an adequate number of studies and showed clear clusters of significance in their maps. Each topic in the Neurosynth topic model includes at least 79 studies. The topics included in our categorical model comparisons each had significant clusters of associated activations. Within the model-free analysis, there are clearly topics for which there were not reliably associated clusters of activity. This likely slightly exaggerates the p values calculated

from the bootstrapped null. We note that this would not affect the ordering of topics which would still lead us to include a similar set of topics in the subsequent analyses.

Conclusion

Our results thus support a model in which crime-type bias influences complex decisions through social cognitive processes. This offers a process by which biases can influence complex decisions even in the absence of evidence for strong affective experience. Thus, even after taking steps to minimize undue influence of emotional responses or moral outrage, bias-mitigation strategies in legal proceedings should also consider bias driven by social cognitive processes.

Understanding the cognitive processes underlying bias is especially important in light of the limited effectiveness of current methods for mitigating its effects in juror decisions (Ingriselli, 2014). In fact, the most effective methods for addressing racial and cultural biases generally may be tied to the use of social cognition (Paluck et al., 2021). Understanding jurors' reliance on social cognition may be important for judges and lawyers in crafting more effective means of countering bias in the justice system.

In addition to informing best practices in the legal system, we offer this study as an example of a neuroscience-based approach to elucidate a broad range of complex decision making processes in humans. Linking narrative and social cognitive processes to juror decision making may offer a template for explaining social/cultural influences in other consequential decisions (Brady et al., 2020). The approach we describe here might therefore be applied to quantifying the contributions of social cognition to biased decisions in a range of social phenomena from the spread of fake news to anti-vaccination movements.

Fig. 1. A mock-juror task tests the effects of crime scenario on bias.

During the task (**A**), participants read a crime scenario paired with variable evidence from each of three types and rated the strength of the case against the accused and the recommended punishment severity. (**B**) Case-strength contributions from scenario independent of evidence. Symbols represent mean effect size (scale 0-100); error bars represent 95% credible intervals. Scenario depicted in panel A is distinguished with a triangle. Scenario effects are shown in rank order. (**C**) Correlation plot showing the relationship between model estimates of case strength and punishment for crime scenarios independent of evidence. This correlation (Pearson $R = 0.90$, $p < 0.001$) captures crime-type bias, which is the extent to which the seriousness of a crime increases the perceived strength of the case against the accused, independent of the evidence.

Fig. 2. Variability in crime-type bias modulates neural activation patterns.

(A) Univariate fMRI patterns are shown for the effect of crime-type bias during scenario presentation. Results shown are corrected for multiple comparisons using a whole brain cluster-forming threshold $Z > 2.3$, cluster-corrected $p < 0.05$. **(B)** Histogram represents the distribution of spatial correlations between 200 Neurosynth topic maps and fMRI map for crime-type bias. Below each histogram are points that correspond to the location of the correlation coefficients in the histogram for each topic included in each of the indicated decision-making models. The top and bottom 10 correlated topics (95 percentile) from the entire set of 200 topics are indicated beside the histograms (top panels) and topics within each model that appear in the top 10 list are labeled beside their associated point for each model (bottom panels). The moral judgment topic that has the highest correlation (topic 135) falls below the top 10 (ranked 14).

A

B

Fig. 3. Patterns of brain activation associated with crime-type bias support social cognition and bias but not moral judgment and affect.

A permutation test identified which decision making models best explained neural activation related to crime-type bias. Histograms of permuted regression models containing random topics were compared to four models: (1) affect, (2) moral judgment, (3) social cognition, and (4) culture and ideation bias. The affect model (**A**) which included three topics was compared to 5,000 permuted null models with three topics. The moral judgment, social cognition, and culture and ideation bias models (**B**), which included two topics, were compared to 5,000 permuted null models with two topics. Models with BIC scores (solid black lines) that surpass the 95 percentile of permuted null models (dotted red line) are considered statistically significant. Lower BIC scores indicate better fit of the model to the data. The social cognition (green) and culture and ideation bias (yellow) models but not the affect (purple) or moral judgment models were statistically significant.

Fig. 4. Social cognitive processes related to victim harm explain crime-type bias.

(A) Overlap between crime-type bias and Neurosynth association (reverse inference) maps from topics related to social cognitive processes (topic map 145: “mind, mental, social”; topic map 154: “social, interactions”; and topic map 100: “gestures, abstract, race”). The social cognition topic maps are averaged and shown in blue, the culture and ideation bias topic map 100 is shown in red, and the thresholded significant clusters associated with crime-type bias are shown in yellow. Neurosynth maps are thresholded to correct for multiple comparisons (false-discovery rate threshold = 0.01). (B) Model estimates of crime-type bias from ratings (PC1) and (C) mean fMRI activation from patterns associated with crime-type bias depend on the presence of an identifiable victim. Crimes that resulted in harm to a person were uniquely associated with higher cognitive ($F(2,30) = 32.08, p < 0.001$) and neural ($F(2,926) = 13.04, p < 0.001$) measures of crime-type bias than crimes without a victim or crimes that resulted in a loss of property. Error bars represent 95% confidence intervals.

A

B

C

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Supplementary Information

Supplementary Methods

Computational model

To account for both case strength and punishment ratings multiple ratings for a given scenario, we model the resulting vector of ratings, R_r , $r = 1 \dots N_r$, similarly:

$$R_i \sim \left[\mathcal{N}(\theta_i, \sigma_{r(i)}^2) \right]_0^{100} \quad (1)$$

$$\theta_i = X_i \cdot \beta_{s(i)c(i) \cdot r(i)} \quad (2)$$

$$\beta_{scpr} = \mu_{p,r} + \gamma_{cpr} + \epsilon_{spr} \quad (3)$$

$$\gamma_{cp \cdot} \sim \mathcal{T}_\nu(0, \Sigma_p) \quad (4)$$

$$\epsilon_{spr} \sim \mathcal{T}_{\nu'}(0, \tau^2 pr) \quad (5)$$

$$\Sigma_p = L_p \text{diag}(\eta_p) L_p^\top \quad (6)$$

$$\Omega_p = L_p L_p^\top \sim \text{LKJ}(1) \quad (7)$$

$$\mu_{pr} \sim \mathcal{N}(50, 50) \quad (8)$$

$$\eta_{pr} \sim \text{Ca}^+(0, 50) \quad (9)$$

$$\tau_{pr} \sim \text{Ca}^+(0, 50) \quad (10)$$

$$\sigma_r \sim \text{Ca}^+(0, 5) \quad (11)$$

$$\nu, \nu' \sim \mathcal{N}^+(0, 100) \quad (12)$$

Here, we have used a "long" or "melted" representation of R in which each index i corresponds to a single observation of a single rating scale $r(i)$. This allows us to more easily handle missing data in the model fitting procedure (see below). The model is almost equivalent to concatenating N_r versions of the first model, one for each rating, aside from two key differences: First (4) and (7) involve a multivariate t-distribution on the population effects specific to each case (γ). That is, we allow for covariance among the ratings for each effect at the population level, where the magnitudes of the variances are again controlled by η and the correlations $\Omega = LL^\top$ are modeled according to the LKJ distribution (Lewandowski et al., 2009) through their Cholesky factorization (7). Second, in order to more accurately estimate variances in the presence of missing data, we have restricted this model to a single value of τ across all cases (for each outcome and regressor) (3).

Model fitting

We calculated posterior distributions and credible intervals for each variable of interest using Markov Chain Monte Carlo methods as implemented in the Stan probabilistic programming language (Carpenter et al., 2017). Full code for all analyses is available at https://github.com/jcastrel/juror_fmri_bias. Models were fit by running 4 chains of either 1000 samples (case strength only model) with a thinning fraction of 1 or 2000 samples (multiple outcome models) with a thinning fraction of 2. For both models, the first half of samples were discarded as burn-in. This resulted in 2000 total samples for each variable, for which we report means as well as 95% equal-tailed credible intervals (bounded by the 2.5% and 97.5% samples from the distribution). We assessed convergence via effective sample size and the Gelman-Rubin statistic, for which all runs had $\hat{R} < 1.1$ (Gelman, 2004).

Crime scenario text analysis

To rule out the possibility that textual features of the scenarios account for variability in ratings about punishment and case strength, we conducted analyses to evaluate the extent to which scenario model weights were related to word count and complexity/readability. Using the “quanteda” R package, we calculated the number of words, syllables, and sentences for each crime scenario. We estimated reading complexity using the Flesch-Kincaid formula ($F-K = (0.39 \times \text{words per sentence}) + (11.8 \times \text{syllables per word}) - 15.59$) (Kincaid et al., 1975). Word count was not associated with case strength (Spearman’s $\rho = 0.224$, $p = 0.210$) or punishment weights (Spearman’s $\rho = 0.309$, $p = 0.080$). Complexity was also not associated with case strength (Spearman’s $\rho = 0.108$, $p = 0.548$) or punishment weights (Spearman’s $\rho = 0.089$, $p = 0.623$). Punishment weights were associated with word count using a linear regression ($t(31) = 2.268$, $p = 0.030$) due to two outliers. Follow-up with robust regression did not identify a relationship between punishment weights and word count using either an MM ($t(31) = 1.262$, $p = 0.216$), Tukey-bisquare ($t(31) = 1.248$, $p = 0.221$), or Huber ($t(31) = 1.774$, $p = 0.086$) estimator. The lack of a clear association between these scenario text features suggests that neither crime description length nor complexity accounted for variability in case strength or punishment.

Crime scenario sentiment analysis

Descriptions of crimes are inherently negative and so we sought to understand which components of the crime descriptions were driving the scenario effects on case strength and punishment ratings. We tested whether scenario text sentiment was related to case strength and punishment weights for each crime scenario. We used the “tidytext” R package to estimate the valence of each criminal scenario using the built-in Bing (Liu, 2012), NRC (Mohammad & Turney, 2013), and AFINN (Nielsen, 2011) lexicons. Whereas the Bing and NRC lexicons categorize words as either positive or negative, the AFINN lexicon scores words between -5 (negative sentiment) and 5 (positive sentiment). The sentiment score from the AFINN lexicon was generated for each scenario from the sum of the word scores. To generate scores for the Bing and NRC lexicons, we summed the number of positive and negative words per scenario and generated a sentiment score from the difference between those sums (positive sum minus negative sum) so that higher values reflect positive emotion and negative values reflect negative emotion. Since these lexicons differ in the words in their databases, scores could only be estimated for 32 scenarios using the AFINN lexicon and 19 scenarios using the Bing lexicon. Sentiment scores could be estimated for all 33 scenarios using the NRC lexicon. Generally, sentiment score was negatively correlated with case strength weights (Bing Spearman’s $\rho = -0.56$, $p = 0.013$; NRC Spearman’s $\rho = -0.33$, $p = 0.06$; AFINN Spearman’s $\rho = -0.41$, $p = 0.018$) and punishment weights (Bing Spearman’s $\rho = -0.60$, $p = 0.007$; NRC Spearman’s $\rho = -0.27$, $p = 0.13$; AFINN Spearman’s $\rho = -0.38$, $p = 0.03$). Inspection of which

words contributed to sentiment scores revealed that sentiment was driven by words related to the nature of the crime (e.g. “accused,” “murder,” or “fraud”) and not adjectives, confirming that crime severity rather than words unrelated to the crimes accounted for variability in case strength and punishment (**Fig. S4**). This is in agreement with our findings from the spatial similarity analysis of fMRI data which found no role for affect-related processes.

fMRI data acquisition

Brain images were collected using a 3T GE MR750 with an 8-channel head coil. For each of the 3 runs of the mock juror task, we acquired a T2*-weighted spiral-in sensitivity-encoding sequence (acceleration factor = 2) with slices parallel to the axial plane connecting the anterior and posterior commissures to acquire 488 volumes of 37 ascending interleaved slices, in-plane resolution = 3.75 x 3.75 x 3.75 mm, acquisition matrix = 64 x 64 and FOV = 243 x 243 mm, flip angle = 60°, TR = 1580 ms, TE = 30 ms. Before preprocessing these functional data, we discarded the first 7 volumes of each run to allow for stabilization of the T2* signal. To facilitate coregistration and normalization of these functional data, we also acquired whole-brain high-resolution anatomical scans (T1-weighted fast spoiled gradient echo sequence, in-plane resolution 1 x 1 x 1 mm; acquisition matrix = 256 x 256, FOV = 256 x 256 mm; 206 axial slices; flip angle = 12°, TR, 8.16 ms; TE, 3.18 ms).

fMRI data preprocessing

Preprocessing was performed using FSL software (version 5.0.1). Functional data were motion-corrected with MCFLIRT and aligned to the middle volume in the time series (Jenkinson et al., 2002). Non-brain tissue from anatomical and functional data was removed using BET (Smith, 2002). Functional data were high-pass filtered with a cutoff of 100 seconds, spatially-smoothed with a 6 mm FWHM Gaussian kernel, and grand-mean intensity normalized. Functional images from each run were coregistered to subject’s anatomical images using FLIRT with 6 degrees of freedom and nonlinearly transformed to a standard MNI space 2-mm³ template (MNI152) using FNIRT with 12 degrees of freedom (Jenkinson and Smith, 2001).

Neurosynth similarity analysis

We grouped meta-analytic association (reverse inference) fMRI statistical maps from the Neurosynth database that reflect cognitive features associated with distinctive models of juror decision making. For example, a moral judgment model included Neurosynth maps from topic 112 (“context”, “empathy”, “prosocial”, etc.) and topic 135 (“moral”, “guilt”, “harm”, etc.), a social cognition model included topic 145 (“mind”, “mental”, “social”, etc.) and topic 154 (“social”, “interactions”, “interpersonal”, etc.), an affect model included topic 126 (“anxiety”, “aggression”, “anxious,” etc.), topic 139 (“faces”, “emotional”, “expressions”, etc.), and topic 180 (“amygdala”, “threat”, “fear”, etc.) and a culture and ideation bias model included topic 30 (“events”, “future”, “personal”, “past”, “thinking”, etc.) and topic 100 (“gestures”, “abstract”, “race”, “stereotypes”). To limit user degrees of freedom while defining model structure, we preregistered the list of topics associated with each model of decision making (details at <https://osf.io/rk92x/>) prior to model-free and model-based analyses.

fMRI spatial maps were vectorized into one-dimensional arrays using the ‘nibabel’ package. Linear regression was implemented using the ‘OLS’ and ‘fit’ functions from the ‘statsmodels’ Python package to extract Bayesian Information Criterion (BIC) scores. Lower BIC scores indicate greater fit or similarity of the crime-type bias map to the decision-making models.

We estimated a model-specific lower bound threshold of BIC scores by comparing each decision making model BIC score to a null model that consisted of topic maps that were not included in any a priori model (191/200 remaining topic maps). The number of topic maps included in a null model matched the number of topic maps in a given model. We resampled 5,000 combinations of the randomly selected topic maps without replacement. Our lower bound threshold was defined as the 95 percentile of null model BIC scores (indicating a model fit was higher than 4,750 null models ($p < .05$)). Model fit and regression coefficients are presented in Table S4. Because the analysis of thresholded maps is limited to the identifying cognitive processes that are actively engaged during the decision, we also ran the same regression analysis using unthresholded maps to identify processes that are commonly suppressed. The results of this analysis are presented in Fig. S7 and Table S5. In the unthresholded map analysis, only the social cognition model was statistically significant. The null model BIC threshold values are presented in Table S6 for the thresholded map analysis and Table S7 for the unthresholded map analysis.

Post-hoc analysis of crime-type bias

As described in the main text, we tested whether legally-defined seriousness and the nature of the harm described in each crime scenario account for the resulting crime-type bias in case strength ratings and neural activation patterns. We classified each scenario according to two different dimensions: (1) seriousness, based on the crime's classification as a misdemeanor or felony with reference to the North Carolina criminal code (27 felony crimes and 6 misdemeanor crimes) and (2) victimhood based on a crime's associated social harm including: victimless, loss of property, and injury or loss of life (7 victimless crimes, 9 loss of property crimes, and 17 crimes resulting in injury or loss of life) (victim type and legal classification shown in Table S2). We used ROI analysis to test the conclusions from the Neurosynth analyses. For crime-type bias, we examined the features of the crime scenarios that drive the recruitment of brain regions linked to social cognition and cultural biases.

Using FSL FEAT, we performed a least-squares analysis (Rissman et al., 2004; Mumford et al., 2012) on the preprocessed fMRI data such that each participant's data was modeled with a design matrix composed of 132 columns for each trial's event period with a single event in each column (33 scenarios x 4 event types: scenario, evidence (which includes all 3 evidence presentations), case strength rating, and punishment rating). These single-trial estimates were modeled with a double-gamma hemodynamic response function and the contrast representing the mean effect was extracted as a Z-statistic image. Next, we estimated the mean activation associated with the scenario viewing event for each trial from a mask of the significant clusters associated with crime-type bias (Fig. 2B). We then tested whether differences across victim type or legal classification explain variability in crime-type bias.

Following this, we performed a model comparison analysis to identify whether crime-type bias is best predicted by victim type or legal classification as singular predictors, independent complementary predictors, or interacting predictors. We performed a likelihood-ratio test (χ^2) and evaluated the BIC scores of each model compared to an intercept-only model.

Supplementary Figures and Tables

Fig. S1. Behavioral model estimates replicate across samples.

In the present sample (fMRI in yellow) and a separate larger online sample (mTurk in blue), model estimates for case strength similarly varied at the crime type/scenario level (**A**) and at the evidence type level (**B**). Symbols represent mean effect size (scale 0-100); error bars represent 95% credible intervals.

Fig. S2. Different combinations of evidence produce varying levels of case strength ratings. Case-strength contributions from fixed evidence combinations of evidence. The mean ratings for each scenario are shown as individual dots. Red diamonds illustrate mean strength estimated by our statistical model (N = 33 scenarios). The middle bar represents the median, and the lower and upper edges of the box are 25th and 75th percentiles of the data. Whiskers extend either to the range of the data or 1.5 times the interquartile range, whichever is smaller.

Fig. S3. Crime-type bias effect replicates across samples. (A) In the present sample (fMRI in yellow) and a separate larger online sample (mTurk in blue), estimates of the effect of scenario on case strength and punishment independent of evidence were highly correlated. Crime-type bias is represented in the first principal component (PC) of a PCA on the model estimates (fMRI in B, mTurk in C). Error bars represent 95% credible intervals

Fig. S4. Crime descriptions contribute to negative sentiment. In general, words associated with crimes contributed to negative sentiment. Each plot shows the number of times different words categorized as positive or negative, based on the Bing lexicon, occurred in our scenarios.

Fig. S5. Illustration of Neurosynth similarity analysis.

To evaluate the similarity of each model of juror decision making, we performed a spatial linear regression combining the set of Neurosynth topic maps associated with each model as explanatory variables of fMRI statistical maps for evidence accumulation and crime-type bias. We used the z-statistic maps for Neurosynth reverse inference topic maps and fMRI parametric maps from our univariate fMRI analysis.

$$Y_{Crime-Type\ Bias} = \beta_0 + \beta_1(t_{145}) + \dots + \beta_4(t_{154}) + \epsilon$$

Fig.S6. Unthresholded brain activation patterns associated with crime-type bias is associated with different cognitive processes. Histogram represents the distribution of spatial correlations between 200 Neurosynth topic maps and fMRI map for crime-type bias. Below each histogram are points that correspond to the location of the correlation coefficients in the histogram for each topic included in each of the indicated decision-making models. The top and bottom 10 correlated topics (95 percentile) from the entire set of 200 topics are indicated beside the histograms (top panels) and topics within each model that appear in the top 10 list are labeled beside their associated point for each model (bottom panels).

Fig. S7. Unthresholded patterns of brain activation associated with crime-type bias support social cognition, but not affect, moral judgment, or culture and ideation bias.

A permutation test identified which decision making models best explained neural activation related to crime-type bias. Histograms of permuted regression models containing random topics were compared to four models: (1) affect, (2) moral judgment, (3) social cognition, and (4) culture and ideation bias. The affect model (A) which included three topics was compared to 5,000 permuted null models with three topics. The moral judgment, social cognition, and culture and ideation bias models (B), which included two topics, were compared to 5,000 permuted null models with two topics. Models with BIC scores (solid black lines) that surpass the 95 percentile of permuted null models (dotted red line) are considered statistically significant. Lower BIC scores indicate better fit of the model to the data. The social cognition (green) model was statistically significant but not the culture and ideation bias (yellow), affect (purple), or moral judgment models were not statistically significant.

Fig.S8. Crime-type bias and legal classification of seriousness. (A) Model estimates of bias from ratings (PC1) ($F(1,31) = 1.681$, $p = 0.204$) and (B) mean fMRI activation ($F(1,927) = 3.25$, $p = 0.072$) from patterns associated with crime-type bias do not depend on seriousness classification (felony or misdemeanor) as defined by the North Carolina criminal code. Error bars represent 95% confidence intervals.

Fig. S9. Results of BIC model comparison predicting crime-type bias. Bayesian information criterion (BIC) scores for four different linear models predicting crime-type bias. Lower values indicate better fits of the models relative to an intercept-only model. **(A)** Crime-type bias (PC1) was best predicted by a model that included independent predictors for victim type (“victimless,” “loss of property,” or “injury or loss of life”) and legal classification (statute) (“misdemeanor” or “felony”). **(B)** fMRI activation associated with crime-type bias was best explained by a model that only included a victim type predictor. Δ BIC = difference between model BIC score and intercept-only model BIC score.

Table S1. Scenario crime descriptions and evidence options.

Scenario			
1	Crime Description	Chelsea McNeil is accused of drug possession. McNeil allegedly sold two 80-microgram hits of LSD from an Altoids tin.	
	Criminal History	Related	McNeil has a prior conviction for possession of methamphetamine.
		Unrelated	McNeil has a prior conviction for reckless driving.
		No prior	McNeil has no criminal record.
	Witness	Witness	A witness saw McNeil accept cash in exchange for the tin's contents.
		No witness	No witnesses saw McNeil with the LSD.
	Physical Evidence	DNA	Hairs matching McNeil's DNA were found in a tin containing a small vial of LSD.
		Non DNA	Fingerprints matching McNeil's were found on tin containing a small vial of LSD.
		None	No physical evidence links McNeil to the drug-laden tin.
2	Crime Description	Jackie Archer stands accused of burglary. Archer allegedly entered a cafe after closing and took \$230 from the cash register.	
	Criminal History	Related	Archer was previously convicted of breaking and entering.
		Unrelated	Archer was previously convicted of disturbing the peace.
		No prior	Archer has no criminal record.
	Witness	Witness	An eyewitness saw Archer enter the back door of the coffee shop after closing.
		No witness	No witnesses saw Archer enter the coffee shop
	Physical Evidence	DNA	Skin flakes matching Archer's DNA were found in the cash register.
		Non DNA	A fingerprint matching Archer's was found on the cash register.
		None	No physical evidence links Archer to the burglary.
3	Crime Description	Dan Montes is accused of theft. Montes allegedly took an unattended laptop from a library desk.	
	Criminal History	Related	Montes was previously convicted of burglary.
		Unrelated	Montes was previously convicted of driving while intoxicated.
		No prior	Montes has no criminal record.
	Witness	Witness	A witness saw Montes take the computer.
		No witness	There were no witnesses to the laptop theft.
	Physical Evidence	DNA	Police discovered hairs on the library desk matching Montes's DNA.
		Non DNA	Cloth fibers matching a tear in Montes's jacket were found on the library desk.

		None	No physical evidence links Dan to the theft.
4	Crime Description	Keith Galloway is on trial for bribing a public official. Galloway allegedly offered jewelry cash and other perks to a zoning official due to vote on a potential business development.	
		Related	Galloway was previously convicted of making illegal campaign contributions.
		Unrelated	Galloway was previously convicted of cocaine possession.
	Criminal History	No prior	Galloway has no criminal record.
		Witness	A golf caddy saw Galloway pass several pieces of jewelry to the official while playing on the course.
		No witness	No one saw Galloway bribe the official.
	Physical Evidence	DNA	Saliva matching Galloway's DNA was found on the seal of cash envelopes in the official's office.
		Non DNA	Fingerprints matching Galloway's were found on cash envelopes at the official's office.
		None	No physical evidence supports the bribery allegations.
5	Crime Description	Dennis Fray is accused of producing child pornography. Fray allegedly filmed 70 minutes of pornographic footage involving a child.	
		Related	Fray was previously convicted of statutory rape.
		Unrelated	Fray was previously convicted of tax fraud.
	Criminal History	No prior	Fray has no criminal record.
		Witness	An eyewitness testified that she saw Fray leading children into the hotel in which the videos were filmed.
		No witness	There are no witnesses linking Fray to the pornographic videos.
	Physical Evidence	DNA	Police discovered traces of semen matching Fray's DNA on memory sticks containing the footage.
		Non DNA	Police discovered fingerprints matching Fray's on memory sticks containing the footage.
		None	No physical evidence links Fray to the videos.
6	Crime Description	Quentin MacDonough is accused of shoplifting. MacDonough allegedly smuggled a guitar out of a music store in a case he carried in with him.	
		Related	MacDonough was previously convicted of larceny.
		Unrelated	MacDonough was previously convicted of reckless driving.
	Criminal History	No prior	MacDonough has no prior convictions.
		Witness	A witness testified that he saw MacDonough place the guitar into a case.
		No witness	There were no witnesses to the theft.
	Physical Evidence	DNA	Skin flakes matching MacDonough's DNA were found on the strings and bridge of the stolen guitar.
		Non DNA	Fingerprints matching MacDonough's were found on the stolen guitar.

		None	No physical evidence links MacDonough to the stolen guitar.
7	Crime Description	Dylan Turner stands accused of voluntary manslaughter. Turner allegedly bludgeoned his wife Marie and her lover with a table leg upon discovering them together in a motel killing them.	
	Criminal History	Related	Turner was previously convicted of domestic assault.
		Unrelated	Turner was previously convicted of income tax evasion.
		No prior	Turner has no criminal history.
	Witness	Witness	A witness saw Turner fleeing the hotel shortly after the killings.
		No witness	There are no witnesses to link Turner to the killings.
	Physical Evidence	DNA	Blood matching Dylan Turner's DNA was discovered in the hotel room.
		Non DNA	Fingerprints matching Turner's were found on the table leg used to kill Marie.
		None	No physical evidence links Turner to the killings.
8	Crime Description	Teri Anderson is accused of telemarketing fraud. Anderson allegedly used a prepaid cell phone to make calls in which she impersonated an insurance agent to collect the personal information of two dozen victims.	
	Criminal History	Related	Anderson was previously convicted of wire fraud.
		Unrelated	Anderson was previously convicted of driving while impaired.
		No prior	Anderson has no record of prior offenses.
	Witness	Witness	A store clerk testified that he sold Anderson the cell phone used to make the calls.
		No witness	There are no witnesses linking Anderson to the calls.
	Physical Evidence	DNA	Police found skin flakes matching Anderson's DNA in the casing of the phone used to place the calls.
		Non DNA	Police found fingerprints matching Anderson's on the phone used to place the calls.
		None	No physical evidence links Anderson to the phone used to place the calls.
9	Crime Description	Miranda Rasmussen is on trial for money laundering. Rasmussen an accountant allegedly helped a pair of convicted drug dealers disguise their profits by preparing financial documents on their behalf.	
	Criminal History	Related	Rasmussen was previously convicted of extortion.
		Unrelated	Rasmussen was previously convicted of providing alcohol to a minor.
		No prior	Rasmussen has no record of any prior convictions.
	Witness	Witness	A bystander saw the drug dealers entering and leaving Rasmussen's office.
		No witness	No witnesses link Rasmussen to the drug dealers.
	Physical Evidence	DNA	Hairs matching Rasmussen's DNA were found on financial documents seized from the drug dealers.
		Non DNA	Fingerprints matching Rasmussen's were found on financial documents seized from the drug dealers.

		None	No physical evidence links Rasmussen to the fraudulent transactions.
10	Crime Description	Maxine Franks is accused of first-degree murder. Franks allegedly waited in a parking deck for Gerald Dodd before fatally stabbing him in the back arm and throat with a six-inch knife.	
	Criminal History	Related	Franks was previously convicted of assault.
		Unrelated	Franks was previously convicted of writing bad checks.
		No prior	Franks has no record of prior convictions.
	Witness	Witness	A woman saw Franks enter the parking lot clutching a small bundle half an hour before Dodd's death.
		No witness	No witnesses have linked Franks to Dodd's death.
	Physical Evidence	DNA	Hairs matching Franks's DNA were found on and around Dodd's body.
		Non DNA	Fingerprints matching Franks's were found on the handle of the knife used to kill Dodd.
		None	No physical evidence links Franks to Dodd's death.
11	Crime Description	Luke Friedman is accused of second-degree murder. Friedman allegedly struck James Cole with a tire iron during a traffic altercation killing him.	
	Criminal History	Related	Friedman was previously convicted of aggravated assault.
		Unrelated	Friedman was previously convicted of possessing drug paraphernalia.
		No prior	Friedman has no record of prior convictions.
	Witness	Witness	A witness testified that she saw Friedman reaching into his trunk while arguing with Cole.
		No witness	There were no witnesses to Cole's killing.
	Physical Evidence	DNA	Blood matching Friedman's DNA was found on a sharp edge of the tire iron used to kill Cole.
		Non DNA	Fingerprints matching Friedman's were found on the tire iron used to kill Cole.
		None	No physical evidence links Friedman to Cole's death.
12	Crime Description	Steven Douglas stands accused of robbery. Douglas allegedly stole Sabine Hoffman's purse and \$250 by approaching her from behind and claiming to have a gun.	
	Criminal History	Related	Douglas was previously convicted of larceny.
		Unrelated	Douglas was previously convicted of animal cruelty.
		No prior	Douglas has no history of prior convictions.
	Witness	Witness	A bystander identified Douglas as the only man hurrying from the scene.
		No witness	There were no witnesses to the robbery.
	Physical Evidence	DNA	Hoffman's empty purse was recovered nearby containing skin flakes and hair matching Douglas's DNA.
		Non DNA	Hoffman's empty purse was recovered nearby bearing fingerprints matching Douglas's.

		None	No physical evidence links Douglas to the robbery.
13	Crime Description	Harold Butler stands accused of sexual battery. Butler allegedly groped Carrie Bryant's thigh and buttocks while she was jogging.	
	Criminal History	Related	Butler was previously convicted of rape.
		Unrelated	Butler was previously convicted of reselling prescription drugs.
		No prior	Butler has no criminal record.
	Witness	Witness	A witness saw Butler grope Bryant.
		No witness	There were no witnesses to the groping.
	Physical Evidence	DNA	Skin flakes matching Butler's DNA were recovered from the fabric of Bryant's running shorts.
		Non DNA	Police found a swatch of cloth matching a tear in Bryant's shorts in Butler's home.
		None	No physical evidence supports the allegations against Butler.
14	Crime Description		Miranda Hamlin stands accused of vehicular manslaughter. Hamlin allegedly crashed a stolen vehicle into Diana Masters's Prius killing her before fleeing the scene.
	Criminal History	Related	Hamlin was previously convicted of reckless driving.
		Unrelated	Hamlin was previously convicted of bribing a public official.
		No prior	Hamlin has no criminal record.
	Witness	Witness	A driver testified that Hamlin was the woman he saw running from the stolen vehicle.
		No witness	There were no witnesses to the crash.
	Physical Evidence	DNA	Police discovered blood matching Hamlin's on the steering wheel of the stolen vehicle.
		Non DNA	Police discovered fingerprints matching Hamlin's on the steering wheel and gearshift of the stolen vehicle.
		None	No physical evidence links Hamlin to the fatal crash.
15	Crime Description		Virginia Davis is accused of stealing dogs from backyards and demanding a ransom from the owners for their safe return.
	Criminal History	Related	Davis was previously convicted of animal cruelty.
		Unrelated	Davis was previously convicted of running an unlicensed gambling operation.
		No prior	Davis has no criminal history.
	Witness	Witness	A postal carrier identified Davis as the woman he saw herding dogs into a van in the neighborhood.
		No witness	There are no witnesses.
	Physical Evidence	DNA	Police found skin flakes matching Davis's DNA on the post of an enclosure from which one of the dogs went missing.

		Non DNA	Police have found Davis' fingerprints on the gates of several yards from which dogs went missing.
		None	There is no physical evidence associating Davis with the thefts.
16	Crime Description	Atlee Newman is accused of shooting Melanie Farris while stealing her car. Newman allegedly dragged Farris out of her Acura before shooting her twice in the head and driving off.	
	Criminal History	Related	Newman was previously convicted of mugging a couple at gunpoint.
		Unrelated	Newman was previously convicted of poaching endangered bears.
		No prior	Newman has no prior convictions.
	Witness	Witness	A cyclist identified Newman as the driver of the Acura that nearly ran him off the road near the crime.
		No witness	No witnesses observed Newman shoot Farris or steal the car.
	Physical Evidence	DNA	Hairs matching Newman's DNA were found in the fabric of the Acura's driver's seat.
		Non DNA	Newman's fingerprints were found on the Acura's steering wheel and dash.
		None	No physical evidence links Newman to the carjacking.
17	Crime Description	Thomas Mitchell is accused of injuring two gang members in a drive-by shooting.	
	Criminal History	Related	Mitchell previously served a sentence for assaulting a gang member with a knife.
		Unrelated	Mitchell previously served a sentence for identity theft.
		No prior	Mitchell has no prior convictions.
	Witness	Witness	A witness saw Mitchell's red Suzuki and Mitchell's distinctive arm tattoos during the shooting.
		No witness	There are no other witnesses.
	Physical Evidence	DNA	Blood matching Mitchell's DNA was discovered on a handkerchief discarded near the scene.
		Non DNA	Mitchell's fingerprints were discovered on the ejected bullet casings at the scene.
		None	No physical evidence links Mitchell to the shooting.
18	Crime Description	Arthur Jefferson is accused of starting a four-alarm fire that burned his own warehouse to the ground in order to collect the insurance on it.	
	Criminal History	Related	Jefferson was previously convicted of arson.
		Unrelated	Jefferson was previously convicted of domestic assault.
		No prior	Jefferson has no record of prior convictions.
	Witness	Witness	An eyewitness saw Jefferson's red pickup pulling away just after the fire started.
		No witness	There were no witnesses to who started the fire.

	Physical Evidence	DNA	Traces of Jefferson's DNA were found on a lighter near the blaze.
		Non DNA	Jefferson's fingerprints were found on a lighter near the blaze.
		None	No physical evidence links Jefferson to the blaze.
19	Crime Description	Samuel Minor is accused of picking the lock on the front door of Thomas and Linda Harringtons' home as they slept and stealing a television a computer and some artwork.	
	Criminal History	Related	Minor was previously convicted of breaking into a parked car to steal stereo equipment.
		Unrelated	Minor was previously convicted of driving while impaired.
		No prior	Minor has no record of previous criminal activity.
	Witness	Witness	A neighbor testified that he saw Minor hunched over the doorknob of the front door for a long time before entering.
		No witness	There were no witnesses to the break-in at the Harringtons' home.
	Physical Evidence	DNA	Skin flakes containing Minor's DNA have been found near the broken lock of the Harringtons' front door.
		Non DNA	Minor's fingerprints have been found along the doorjamb of the house.
		None	No physical evidence links Minor to the scene.
20	Crime Description		Mark Pearson is accused of locking 24-year-old Brianne Mills an African American student into the trunk of her car and pushing it into a river nearly drowning her. He also spray-painted the car with a large swastika and racial and sexual epithets including "slut," "dyke," and "nigger".
	Criminal History	Related	Pearson was previously convicted of battery alongside several known members of a local skinhead gang.
		Unrelated	Pearson was previously convicted of using false identification to purchase alcohol.
		No prior	Pearson has no record of prior convictions.
	Witness	Witness	A fisherman walking by the river identified Pearson as the person who discarded a ski mask near the riverbank.
		No witness	There were no witnesses to Mills's assault.
	Physical Evidence	DNA	Police discovered blood containing Pearson's DNA under Mills's fingernails.
		Non DNA	Pearson's fingerprints were found on a can of spray paint dropped by the sinking car.
		None	There is no physical evidence linking Pearson to the crime.
21	Crime Description	Ronald Parker is accused of breaking through a townhouse back door entering the bedroom of Tammy King and raping her at knife-point.	
	Criminal History	Related	Parker has a previous conviction for rape.
		Unrelated	Parker has a previous conviction for fraud.
		No prior	Parker has never been arrested for a felony.

	Witness	Witness	The victim did not see her attacker but a neighbor identified Parker as the man who ran out of the house.
		No witness	The victim did not see her attacker and there are no other witnesses.
	Physical Evidence	DNA	Blood with Parker's DNA is found on the knife blade.
		Non DNA	Fingerprints matching Parker's are found at the scene.
		None	No physical evidence links Parker to the crime scene.
22	Crime Description		Robert Campbell is accused of mugging Jack and Rosa Smith in a grocery store parking lot.
	Criminal History	Related	Campbell has served prison time in the past for armed robbery.
		Unrelated	Campbell has served prison time in the past for possession of heroin.
		No prior	Campbell has no record of prior offenses.
	Witness	Witness	A greeter at the store identified Campbell as the Smiths' assailant.
		No witness	There were no other witnesses to the crime.
	Physical Evidence	DNA	A pistol was found discarded nearby with Campbell's DNA on the grip.
		Non DNA	Jack's empty wallet was found discarded nearby bearing Campbell's fingerprints.
		None	No physical evidence links Campbell to the Smiths' assault.
23	Crime Description		Jerry Lee a known gang member is accused of the murder of a grocery store owner and his wife after they refused to pay him 'protection' money.
	Criminal History	Related	Lee has a prior conviction for extortion.
		Unrelated	Lee has a prior conviction for possession of crack cocaine.
		No prior	Lee has no criminal record.
	Witness	Witness	A neighboring shopkeeper identified Lee as the man fleeing after the shooting.
		No witness	No witnesses saw Lee at the scene.
	Physical Evidence	DNA	Blood matching Lee's DNA was found on a broken bottle near the grocer's body.
		Non DNA	Lee's fingerprints were found on the pistol used in the shooting.
		None	No physical evidence links Lee to the murders.
24	Crime Description		Christopher Pepper and Alva Bennett are accused of manufacturing counterfeit cashier's cheques using a printing press located in a condemned office building.
	Criminal History	Related	Pepper has a past conviction for fraud and Bennett for selling knockoff handbags on eBay.
		Unrelated	Pepper has a past conviction for battery and Bennett for driving with a suspended license.
		No prior	Neither Pepper nor Bennett has any prior record of convictions.

	Witness	Witness	A barista at a nearby cafe observed Pepper and Bennett going in and out of the condemned building.
		No witness	No witnesses observed Peppers or Bennett entering the condemned building during the past few months.
	Physical Evidence	DNA	Hair and skin flakes with Pepper's and Bennett's DNA were found on and around the counterfeit press.
		Non DNA	Pepper's and Bennett's fingerprints were found on and around the counterfeit press.
		None	No physical evidence links Pepper or Bennett to the counterfeiting.
25	Crime Description	Janet Norment is accused of smuggling a suitcase of marijuana into the United States.	
	Criminal History	Related	Norment was recently released from prison following a sentence for manufacturing methamphetamine.
		Unrelated	Norment was recently released from prison following an armed robbery sentence.
		No prior	Norment has no prior convictions.
	Witness	Witness	A check-in attendant at the airport identified Norment as the woman who checked the suitcase in.
		No witness	No witnesses saw Norment check the bags in.
	Physical Evidence	DNA	Eyelashes with Norment's DNA were discovered in the suitcase.
		Non DNA	Cloth fibers matching several articles of clothing in Norment's home were discovered in the suitcase.
		None	No physical evidence was discovered linking Norment to the luggage.
26	Crime Description	Trevor Allen and Kenneth Green are accused of leaving 13 undocumented immigrants to die in a truck. Allen and Green were allegedly smuggling the immigrants across the U.S. border but after the truck stopped working they allegedly fled while leaving the immigrants locked in the back. By the time the immigrants were found they had all died of exposure.	
	Criminal History	Related	Green and Allen both have prior convictions for illegally transporting noncitizens into the United States.
		Unrelated	Green has a prior conviction for marijuana possession and Allen for domestic violence.
		No prior	Neither Green nor Allen has a record of prior convictions.
	Witness	Witness	A gas station attendant identified Green and Allen as the men who borrowed his phone to call for a ride near where the truck was discovered.
		No witness	No witnesses saw either of the men load or depart from the vehicle.
	Physical Evidence	DNA	Green's and Allen's DNA was found on the lips of several empty soda bottles in the truck.
		Non DNA	Green and Allen's fingerprints were found on the truck's front seat.
		None	No physical evidence links Allen or Green to the truck.

27	Crime Description	Clarence Warren is accused of operating an unlicensed distillery. Police discovered a makeshift pot still several hundred pounds of white sugar some coiled copper piping and forty gallons of moonshine on an abandoned farm.	
	Criminal History	Related	Warren has a previous conviction for manufacturing methamphetamine.
		Unrelated	Warren has a previous conviction for armed robbery.
		No prior	Warren has no record of prior convictions.
	Witness	Witness	An electrical maintenance worker testified that he saw Warren around the still.
		No witness	No witnesses saw Warren in or around the farmhouse.
	Physical Evidence	DNA	Warren's DNA was found on the lips of mason jars at the scene.
		Non DNA	A strip of fabric matching a tear in Warren's jacket was found on a nail protruding from the farmhouse.
		None	No physical evidence links Warren to the distillery.
28	Crime Description	Jeff Martinez is accused of bombing a shopping center. An unregistered black pickup truck was loaded with explosives driven through the main entrance and detonated after the driver fled.	
	Criminal History	Related	Martinez was previously convicted of aggravated arson.
		Unrelated	Martinez was previously convicted of indecent exposure.
		No prior	Martinez has no criminal history.
	Witness	Witness	A bystander identified Martinez as the truck's driver.
		No witness	No witnesses were able to identify the truck's driver.
	Physical Evidence	DNA	Blood matching Martinez's DNA was found on a piece of shrapnel near the mall entrance.
		Non DNA	Martinez's fingerprints were found on an undamaged section of the truck.
		None	No physical evidence links Martinez to the bombing.
29	Crime Description	Bret Botham is accused of critically injuring two people while illegally racing. The car collided with a stopped van after he skidded out of control on a patch of gravel.	
	Criminal History	Related	Botham had his license suspended last year for driving recklessly.
		Unrelated	Botham had been convicted of shoplifting last year.
		No prior	Botham has no prior convictions.
	Witness	Witness	The driver of the van testified that Botham was the driver.
		No witness	The driver of the van dazed by the impact was unable to identify the fleeing motorist.
	Physical Evidence	DNA	The car's driver fled into the woods leaving blood with Botham's DNA on the car's airbag and dash.
		Non DNA	The car's driver fled into the woods but Botham's fingerprints were found on the car's dash console and gearshift.
		None	The car's driver fled into the woods leaving no recoverable physical evidence.

30	Crime Description	Virginia MacPherson is accused of sending anthrax-laced envelopes to a United States senator and the father of her boyfriend. After intercepting the envelopes the FBI arrested MacPherson.	
	Criminal History	Related	As a high school student MacPherson sent threatening letters to the parents of a previous boyfriend.
		Unrelated	MacPherson had previously been convicted for shoplifting.
		No prior	MacPherson has no criminal record.
	Witness	Witness	A researcher testified that he saw MacPherson walking around a lab from which anthrax samples went missing.
		No witness	Investigators were unable to find anyone who could link MacPherson to the anthrax.
	Physical Evidence	DNA	FBI agents discovered saliva matching MacPherson's DNA on the stamps of several envelopes.
		Non DNA	FBI agents discovered MacPherson's fingerprints on several of the tainted envelopes.
		None	No physical evidence was found to link MacPherson to the envelopes.
31	Crime Description	Nathan Lewis is accused of sexually abusing a fourteen-year-old boy after police find a camera with pornographic images of the boy in the junior high locker room.	
	Criminal History	Related	Lewis was previously convicted of sexually harassing an intern.
		Unrelated	Lewis was previously convicted of fraud.
		No prior	Lewis has no prior convictions.
	Witness	Witness	The boy is too traumatized to testify but a school custodian saw Saunders carrying photo equipment into the locker room.
		No witness	The boy is too traumatized to testify and there are no witnesses.
	Physical Evidence	DNA	Semen with Lewis's DNA was found on the camera.
		Non DNA	Lewis's fingerprints were found on the camera.
		None	No physical evidence links Lewis to the photos.
32	Crime Description	Brian Jones is accused of shooting Judge Timothy Baker in the back outside a courthouse. As Jones fled he banged his hand into a door jamb and dropped his gun.	
	Criminal History	Related	Jones was previously convicted of battery.
		Unrelated	Jones was previously convicted of fraud.
		No prior	Jones has no criminal record.
	Witness	Witness	A bystander saw Jones running away after she heard a gunshot.
		No witness	No witnesses were present in the courthouse alley to identify Baker's attacker.
	Physical Evidence	DNA	Blood with Jones's DNA is found on an ejected bullet casing.
		Non DNA	Jones's fingerprints were found on the pistol's grip and trigger.
		None	No usable physical evidence identifying Jones could be found.

33	Crime Description	Samantha Harris is accused of vehicular manslaughter during a hit-and-run. She had been texting while driving and collided with Cameron Bailey who later died.	
	Criminal History	Related	Harris had previously been convicted of leaving a child she was babysitting locked in a hot car.
		Unrelated	Harris had previously been convicted of shoplifting.
		No prior	Harris has no criminal record.
	Witness	Witness	A witness saw Harris texting at a red light two blocks from where the accident happened.
		No witness	No witness saw Harris either texting or driving.
	Physical Evidence	DNA	A paper soda cup with Harris's saliva was found near Bailey's body.
		Non DNA	Paint matching the color of Harris's car was found scraped onto Bailey's belt buckle.
		None	There was no physical evidence found linking Harris to Bailey.

Table S2. Crime classification

Scenario	Crime Description	Crime Type	Statute Definition	Victim Type	Class
1	Chelsea McNeil is accused of drug possession. McNeil allegedly sold two 80-microgram hits of LSD from an Altoids tin	Possession of Sch III	Felony	Victimless	Class I
2	Jackie Archer stands accused of burglary. Archer allegedly entered a cafe after closing and took \$230 from the cash register	Felony Breaking and Entering	Felony	Loss of property	Class H
3	Dan Montes is accused of theft. Montes allegedly took an unattended laptop from a library desk	Larceny of more than \$1,000	Felony	Loss of property	Class H
4	Keith Galloway is on trial for bribing a public official. Galloway allegedly offered jewelry, cash, and other perks to a zoning official due to vote on a potential business development	Offering a Bribe	Felony	Victimless	Class F
5	Dennis Fray is accused of producing child pornography. Fray allegedly filmed 70 minutes of pornographic footage involving a child	First Degree Sexual Exploitation of a Minor	Felony	Injury or loss of life	Class C
6	Quentin MacDonough is accused of shoplifting. MacDonough allegedly smuggled a guitar out of a music store in a case he carried in with him	Larceny of less than \$1,000	Misdemeanor	Loss of property	Class 1
7	Dylan Turner stands accused of voluntary manslaughter. Turner allegedly bludgeoned his wife Marie and her lover with a table leg upon discovering them together in a motel, killing them	Voluntary Manslaughter	Felony	Injury or loss of life	Class D
8	Teri Anderson is accused of telemarketing fraud. Anderson allegedly used a prepaid cell phone to make calls in which she impersonated an insurance agent to collect the personal information of two dozen victims	Obtaining Property by False Pretenses	Felony	Loss of property	Class H
9	Miranda Rasmussen is on trial for money laundering. Rasmussen, an accountant, allegedly helped a pair of convicted drug dealers disguise their profits by preparing financial documents on their behalf	Federal Money Laundering (state continuing criminal enterprise)	Felony	Victimless	Class G
10	Maxine Franks is accused of first-degree murder. Franks allegedly waited in a parking deck for Gerald Dodd before fatally stabbing him in the back, arm, and throat with a six-inch knife	First Degree Murder	Felony	Injury or loss of life	Class A
11	Luke Friedman is accused of second-degree murder. Friedman allegedly struck James Cole with a tire iron during a traffic altercation, killing him	Second Degree Murder / Ethnic intimidation	Felony	Injury or loss of life	Class B2 + Class 1 misdemeanor
12	Steven Douglas stands accused of robbery. Douglas allegedly stole Sabine Hoffman's purse and \$250 by approaching her from behind and claiming to have a gun	Misdemeanor Larceny	Misdemeanor	Loss of property	Class 1

13	Harold Butler stands accused of sexual battery. Butler allegedly groped Carrie Bryant's thigh and buttocks while she was jogging	Sexual Battery	Misdemeanor	Injury or loss of life	Class A1
14	Miranda Hamlin stands accused of vehicular manslaughter. Hamlin allegedly crashed a stolen vehicle into Diana Masters's Prius, killing her, before fleeing the scene	Misdemeanor Death by Vehicle	Misdemeanor	Injury or loss of life	Class A1
15	Virginia Davis is accused of stealing dogs from backyards and demanding a ransom from the owners for their safe return	Larceny of a Dog / Extortion	Felony	Loss of property	Class F + Class I
16	Atlee Newman is accused of shooting Melanie Farris while stealing her car. Newman allegedly dragged Farris out of her Acura before shooting her twice in the head and driving off	First Degree Murder	Felony	Injury or loss of life	Class A
17	Thomas Mitchell is accused of injuring two gang members in a drive-by shooting	Second Degree Murder	Felony	Injury or loss of life	Class B2
18	Arthur Jefferson is accused of starting a four-alarm fire that burned his own warehouse to the ground in order to collect the insurance on it	Burning an Uninhabited Building / Insurance Fraud	Felony	Victimless	Class F + Class H
19	Samuel Minor is accused of picking the lock on the front door of Thomas and Linda Harringtons' home as they slept, and stealing a television, a computer, and some artwork	1st Degree Burglary	Felony	Loss of property	Class D
20	Mark Pearson is accused of locking 24-year-old Brianne Mills, an African American student, into the trunk of her car and pushing it into a river, nearly drowning her. He also spray-painted the car with a large swastika and racial and sexual epithets including 'slut', 'dyke', and 'nigger'	Attempted First Degree Murder / Ethnic Intimidation	Felony	Injury or loss of life	Class B2 + Class 1 misdemeanor
21	Ronald Parker is accused of breaking through a townhouse back door, entering the bedroom of Tammy King and raping her at knife-point	Forceable Rape / First Degree Burlary	Felony	Injury or loss of life	Class B1 + Class D
22	Robert Campbell is accused of mugging Jack and Rosa Smith in a grocery store parking lot	Felony Larceny	Felony	Loss of property	Class H
23	Jerry Lee, a known gang member, is accused of the murder of a grocery store owner and his wife after they refused to pay him 'protection' money	First Degree Murder	Felony	Injury or loss of life	Class A
24	Christopher Pepper and Alva Bennett are accused of manufacturing counterfeit cashier's cheques using a printing press located in a condemned office building	Counterfeiting	Felony	Victimless	Class I (state)
25	Janet Norment is accused of smuggling a suitcase of marijuana into the United States	Trafficking of less than 50 lbs.	Felony	victimless	Class H
26	Trevor Allen and Kenneth Green are accused of leaving 13 undocumented immigrants to die in a truck. Allen and Green were allegedly smuggling the immigrants across the U.S. border, but after the truck stopped working, they allegedly fled while leaving the immigrants locked in the back. By the time the immigrants were found, they had all died of exposure	Second Degree Murder	Felony	Injury or loss of life	Class B2

27	Clarence Warren is accused of operating an unlicensed distillery. Police discovered a makeshift pot still, several hundred pounds of white sugar, some coiled copper piping, and forty gallons of moonshine on an abandoned farm	Federal Operating a Still Without a License	Misdemeanor	Victimless	Class 1 (state)
28	Jeff Martinez is accused of bombing a shopping center. An unregistered black pickup truck was loaded with explosives, driven through the main entrance, and detonated after the driver fled	Malicious Damage by Bomb	Felony	Loss of property	Class D
29	Bret Botham is accused of critically injuring two people while illegally racing. The car collided with a stopped van after he skidded out of control on a patch of gravel	Prearranged Racing	Misdemeanor	Injury or loss of life	Class 1
30	Virginia MacPherson is accused of sending anthrax-laced envelopes to a United States senator and the father of her boyfriend. After intercepting the envelopes, the FBI arrested MacPherson	Federal Mailing of Injurious Products	Felony	Injury or loss of life	Class B1
31	Nathan Lewis is accused of sexually abusing a fourteen-year-old boy after police find a camera with pornographic images of the boy in the junior high locker room	Taking Indecent Liberties with a Minor	Felony	Injury or loss of life	Class B1
32	Brian Jones is accused of shooting Judge Timothy Baker in the back outside a courthouse. As Jones fled, he banged his hand into a door jamb and dropped his gun	Assault with a Deadly Weapon with Intent to Kill Inflicting Serious injury	Felony	Injury or loss of life	Class C
33	Samantha Harris is accused of vehicular manslaughter during a hit-and-run. She had been texting while driving and collided with Cameron Bailey, who later died	Involuntary Manslaughter	Felony	Injury or loss of life	Class F

Table S3. Neurosynth topic maps included in cognitive models and submodels.

Model	Topic	Top Terms
Affect	126	anxiety, aggression, anxious, trait, amygdala, cr, disorder, gad, anticipation, emotional, anticipatory, high, aggressive, ha, social, worry, fear, temperament, individuals, panic, scores, anger, threat, symptoms, phobia, reactivity, dental, relationship, limbic, iu, provocation, reactive, generalized, characterized, subclinical, bi, regulation, insula, somatic, paradigm
	139	faces, emotional, facial, expressions, emotion, amygdala, neutral, fearful, happy, face, sad, emotions, angry, expression, social, fear, response, perception, affective, recognition, anger, affect, disgust, viewing, happiness, gender, sadness, magnetic, fusiform, presented, resonance, interaction, emotionally, salient, expressing, masked, threat, limbic, viewed, sensitivity
	180	amygdala, threat, fear, anxiety, response, avoidance, reactivity, threatening, habituation, responding, shock, aversive, heightened, emotional, cues, approach, affective, amygdalar, threats, bnst, research, bla, individuals, emotion, basolateral, hippocampus, danger, periaqueductal, limbic, nucleus, amygdalae, implicated, defensive, stress, insula, trait, exaggerated, safe, anxious, startle
Social Cognition	145	mind, mental, social, tom, states, theory, mentalizing, belief, state, attribution, person, reasoning, empathy, people, cognitive, beliefs, affective, junction, medial, prefrontal, precuneus, perspective, inference, intentional, inferences, intentions, wandering, lsf, cognition, inferring, agency, temporoparietal, stories, mpfc, infer, physical, recruited, hsf, temporo, emotions
	154	social, interactions, interaction, cognition, partner, human, interpersonal, exclusion, person, oxytocin, people, game, socially, cooperation, partners, individuals, ot, rejection, trust, participant, insula, played, mentalizing, context, relationships, nonsocial, animacy, cues, cooperative, interactive, friends, paradigm, predicted, friend, prosocial, correlates, political, animate, personal, ball
Moral Judgment	112	context, empathy, contextual, contexts, ambiguity, ambiguous, empathic, dominant, prosocial, concern, modulated, resolution, situations, automatic, unambiguous, presence, subordinate, meanings, contextually, altruistic, frequent, social, representations, interpretation, flexible, embedded, situational, affects, empathize, scanned, donation, architecture, disambiguating, embedding, settings, occurs, dominance, oriented, occurred, involve
	135	basal, ganglia, moral, guilt, harm, judgments, judgment, thalamus, forebrain, care, transgressions, scenarios, violations, gratitude, actions, lying, harmful, morally, justice, personal, wrong, dilemmas, acts, judged, cost, sentiments, cholinergic, benefit, bad, morality, norms, issues, conventional, good, utilitarian, anti, accidental, unified, legal, shame
Culture & Ideation Bias	030	events, future, personal, past, cultural, thinking, construction, episodic, experiences, imagining, culture, imagined, counterfactual, autobiographical, engaged, simulation, american, experience, imagination, hippocampus, simulations, construal, world, real, remembering, engage, contextual, east, thought, elaboration, cultures, projection, imagine, interdependent, statements, thoughts, core, ep, western, episodes
	100	gestures, abstract, race, concrete, intention, gesture, communicative, prospective, intentions, speech, racial, communication, context, actor, iconic, stereotypes, mp, indirect, pointing, american, black, action, videos, stereotype, unrelated, white, aa, intended, ig, performing, verbal, meaningless, isolated, prejudice, gr, situation, biases, chinese, ongoing, img

Table S4. Spatial similarity (linear regression fit) for juror decision-making models and thresholded brain activation patterns associated with evidence accumulation and crime-type bias. For evidence accumulation and crime-type bias fMRI maps, the table includes overall model spatial similarity (R^2), BIC score, p-value, and topic map standardized coefficient measures (beta and standard error (se)). P-values reflect the number of R^2 values from the null distribution (n=5,000 permutations) that are greater than the model's R^2 .

Model	Similarity	Topic #	Coefficients	
			beta	se
Affect	$R^2 = 0.004$, BIC=3512.750, p=0.793	intercept	2.777	0.005
		126	0.003	0.006
		139	-0.01	0.006
		180	-0.019	0.006
Social Cognition	$R^2 = 0.045$, BIC=3308.006, p=0.0122	intercept	2.777	0.005
		145	0.079	0.006
		154	-0.006	0.006
Moral Judgment	$R^2 = 0.012$, BIC=3469.884, p=0.332	intercept	2.777	0.005
		112	-0.009	0.005
		135	0.038	0.005
Culture & Ideation Bias	$R^2 = 0.054$, BIC=3263.757, p=0.002	intercept	2.777	0.005
		30	-0.004	0.005
		100	0.082	0.005

Table S5. Spatial similarity (linear regression fit) for juror decision-making models and unthresholded brain activation patterns associated with evidence accumulation and crime-type bias. For evidence accumulation and crime-type bias fMRI maps, the table includes overall model spatial similarity (R^2), BIC score, and topic map standardized coefficient measures (beta and standard error (se)). P-values reflect the number of R^2 values from the null distribution (n=5,000 permutations) that are greater than the model's R^2 .

Model	Similarity	Topic #	Coefficients	
			beta	se
Affect	$R^2 = 0.020$, BIC=686870.824, $p=0.206$	intercept	0.166	0.002
		126	-0.097	0.002
		139	0.121	0.003
		180	0.053	0.003
Social Cognition	$R^2 = 0.04$, BIC=682150.871, $p=0.015$	intercept	0.166	0.002
		145	0.237	0.003
		154	-0.045	0.003
Moral Judgment	$R^2 = 0.004$, BIC=690570.658, $p=0.676$	intercept	0.166	0.002
		112	0.061	0.002
		135	0.03	0.002
Culture & Ideation Bias	$R^2 = 0.019$, BIC=687110.558 $p=0.119$	intercept	0.166	0.002
		30	0.044	0.002
		100	0.14	0.002

Table S6. Null model spatial similarity threshold for juror decision-making models models and thresholded brain activation patterns associated with evidence accumulation and crime-type bias. For the crime-type bias fMRI map, the table includes overall model spatial similarity (BIC score) threshold dependent on the number of topics included in a model. The threshold BIC score is the 95 percentile of the null distribution of 5,000 random models.

Model	Number of Topics	Similarity Threshold (BIC)
Social Cognition	2	3382.6288
Moral Judgment		
Culture & Ideation Bias		
Affect	3	3345.7715

Table S7. Null model spatial similarity threshold for juror decision-making models models and unthresholded brain activation patterns associated with evidence accumulation and crime-type bias. For the crime-type bias fMRI map, the table includes overall model spatial similarity (BIC score) threshold dependent on the number of topics included in a model. The threshold BIC score is the 95 percentile of the null distribution of 5,000 random models.

Model	Number of Topics	Similarity Threshold (BIC)
Social Cognition	2	684085.511
Moral Judgment		
Culture & Ideation Bias		
Affect	3	682312.846

Table S8. Likelihood ratio test results comparing models explaining crime-type bias ratings from ratings by victim type and criminal statute definition. Δ DF = change in degrees of freedom relative to the prior (above) model.

Model Name	DF	BIC	Δ DF	χ^2	$\text{Pr}(> \chi^2)$
Intercept Only	2	120.9			
Legal Classification	3	122.6	1	1.74	0.187
Victim Type	4	90.1	1	35.99	< 0.001
Victim + Legal Classification	5	88.2	1	5.38	0.020
Victim x Legal Classification	7	94.3	2	0.98	0.613

Table S9. Likelihood ratio test results comparing models explaining crime-type bias fMRI activation by victim type and legal classification. Δ DF = change in degrees of freedom relative to the prior (above) model.

Model Name	DF	BIC	Δ DF	χ^2	$\text{Pr}(> \chi^2)$
Intercept Only	3	2421.8			
Statute	4	2425.4	1	3.25	0.072
Victim Type	5	2409.7	1	22.5	< 0.001
Victim + Legal Classification	6	2413.3	1	3.27	0.071
Victim x Legal Classification	8	2416.4	2	10.65	0.005

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