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Prejudice Model 1.0: A Predictive Model of Prejudice

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The present research develops a predictive model of prejudice. For nearly a century, psychology and other fields have sought to scientifically understand and describe the causes of prejudice. Numerous theories of prejudice now exist. Yet these theories are overwhelmingly defined verbally and thus lack the ability to precisely predict when and to what extent prejudice will emerge. The abundance of theory also raises the possibility of undetected overlap between constructs theorized to cause prejudice. Predictive models enable falsification and provide a way for the field to move forward. To this end, here we present 18 studies with ~5,000 participants in seven phases of model development. After initially identifying major theorized causes of prejudice in the literature, we used a model selection approach to winnow constructs into a parsimonious predictive model of prejudice (Phases I and II). We confirm this model in a preregistered out-of-sample test (Phase III), test variations in operationalizations and boundary conditions (Phases IV and V), and test generalizability on a U.S. representative sample, an Indian sample, and a U.K. sample (Phase VI). Finally, we consulted the predictions of experts in the field to examine how well they align with our results (Phase VII). We believe this initial predictive model is limited and bad, but by developing a model that makes highly specific predictions, drawing on the state of the art, we hope to provide a foundation from which research can build to improve science of prejudice.

Keywords: prediction, prejudice, bias, intergroup

Supplemental materials: https://doi.org/10.1037/rev0000470.supp

Psychologists have long sought to understand prejudice. Here, integrating and building on this rich literature, we develop a predictive model of prejudice. Below, we first discuss why the time is ripe for developing such a model, then describe seven phases of development, before ending with a parsimonious model.

A Rich Literature

World War II spurred social psychologists to understand prejudice. Since then, researchers have developed numerous theories explaining why people might feel and behave negatively toward one another. The study of intergroup dynamics and prejudice has now become a mainstay of social psychology, with approximately 25,000 citations in Web of Science whose abstracts or keywords include "prejudice" at the time of writing.

This long-standing and consistent focus has generated an immense scientific literature, and modern social scientists understand prejudice better than did their counterparts in the 1940s. Notably, this literature contains many theories of how prejudice develops, manifests in behavior, and is caused by various personality and situational factors. For example, research focusing on social categorization and group boundaries reveals that people regularly favor members of their ingroup over individuals in other groups, even when these groups are arbitrary and meaningless (S. L. Gaertner & Dovidio, 2000; Tajfel et al., 1971; Turner et al., 1987). This is thought to be because humans desire a positive and distinctive view of self, which is partially derived from the groups with which one identifies (Tajfel & Turner, 1979).

Other research has revealed that intergroup prejudice is a functional response to threat (Campbell, 1965; Riek et al., 2006; Schaller & Neuberg, 2012). When other groups are perceived to threaten one's resources, safety, or other needs, prejudice may enable behaviors to secure such resources. Some have theorized that prejudice arises when there is a clash of values between two groups (Chambers et al., 2013; Kinder & Sears, 1981; McConahay, 1982). Still others argue that prejudice emerges from both structural and psychological factors and that some people are particularly likely to exhibit prejudice, such as those who favor inequality between groups (Pratto et al., 1994). These are but a few major theoretical frameworks and traditions that have sought to understand prejudice. This proliferation of theories and perspectives would be expected

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for a topic of active study by multiple fields for approximately 80 years.

A Saturated Theoretical Space

Numerous scholars of varying backgrounds and perspectives have contributed to the science of prejudice, producing a vast and rich literature. Yet such a long-standing focus and proliferation of theories brings problems as well. These theories identify a multitude of predictors of prejudice, spanning personality variables (e.g., Social Dominance Orientation [SDO]), perceptions of the group (e.g., entitativity), and developmental influences (e.g., parents' beliefs). Can they all meaningfully predict prejudice? When considering these theories together, several problematic possibilities arise. If all predictors of prejudice are valid, then each one, on its own, is less important. There is a finite amount of variance in prejudice to be explained: 100%. Two theoretical predictors can each, on average, only explain 50% of the variance in prejudice. Following the same logic, 50 theoretical predictors can on average each explain only 2% of the variance in prejudice. As more true predictors are identified, the average unique variance explained by each predictor must be smaller, with some predictors unlikely to substantially improve the prediction of prejudice above and beyond what is already known.

Another possibility is that some of the proposed theoretical causes may not be true when taking into account all the other causes. In this possibility, there is likely some conceptual overlap between constructs of different names, proposed (perhaps in different decades) by different groups of researchers, but involving the same "true" latent constructs. This is known as the jangle fallacy, or assuming two constructs are different because they have been named differently (Kelley, 1927). There might appear to be different theories of prejudice that are essentially tapping the same latent construct, such that the theories are essentially redundant.

A recent mathematical proof addresses a similar conceptual issue, known as the "piranha problem" (Gelman, 2017). For a given phenomenon, if a few predictors explain a large amount of variance, it becomes increasingly unlikely that there are more predictors (discovered or not) that also explain a large amount of variance. Regarding prejudice, if a single predictor consistently explains a large amount of variance, it is unlikely that all the other theoretical predictors are important.

Thus, the saturated theoretical space of prejudice indicates it is likely that either (a) many theorized constructs have only weak relationships to prejudice, explaining small amounts of variance, (b) there is redundancy between established theorized constructs, and/or (c) many proposed theoretical constructs predict no or only a small amount of the variance in prejudice when accounting for constructs in all the other theories. All these cases require a reckoning of theories for the field to move forward, allowing the field to drop from the literature theories with less support, and identify and scrutinize the strongest predictors of prejudice.

The Value of Formal Models

Compounding this problem of numerous theories is an issue of falsification. How do we determine when the data do not support a theory? Ideally, the scientific process works in a straightforward way. A theory is proposed, and researchers collect evidence to test whether or not the pattern of data supports the theory. If the data do support the theory, researchers temporarily accept the theory as true and move forward with more stringent tests. If the data do not, researchers consider that the theory might be false. Yet, in the past decade, there have been numerous opportunities to observe how this process works in practice. A theory is proposed, some initial evidence supporting that theory is provided, and articles are published. Other researchers may then point out logical flaws in the theory or collect data inconsistent with the theory. How do we interpret these challenges to the theory? Have the other researchers misinterpreted the theory or not actually tested the theory, do some of the original claims in the theory need to be adjusted for the theory to hold, or is the theory in fact false? Often, this sequence reveals that the original theories were not sufficiently precise to be falsifiable. The field has observed versions of this process with debates over power posing (Credé & Phillips, 2017) and ego depletion (Hagger et al., 2016), among others.

Verbal theories enable such confusion and ambiguity. Translating words into specific constructs and their relationships requires some interpretation because a single word or statement can mean many different things. Verbally defined theories thus allow a wide range of observations to potentially support the theory, and some ambiguity on what evidence would falsify the theory. These limitations have led to calls to more widely incorporate formal theory in psychological science (Borsboom et al., 2021; Devezer et al., 2021; Robinaugh et al., 2021; Smaldino, 2020). When a theory is formally specified, it has been mathematically defined, specifying the magnitude of expected effects, and making clear whether observed evidence is consistent with predictions from that model (Forstmann & Wagenmakers, 2015; Fum et al., 2007). In model evaluation parlance, most modern social psychological theories are "weak" or "low risk" since they often only predict values that are different from zero rather than effects of specific magnitudes (Meehl, 1967; Popper, 1959). Theoretical models are considered stronger to the extent they make more precise predictions since precise predictions are easier to falsify (Dunn, 2000; Roberts & Pashler, 2000).

Predictive models can be thought of as a cookie recipe, a metaphor we borrow from previous work (Crockett, 2016; Jolly & Chang, 2019). The ingredients must be identified: flour, butter, sugar, chocolate chips. Not having all the ingredients or adding ingredients would change the recipe and create something else. Identifying the ingredients is, in our view, the current state of most verbal theories in the psychological social sciences (i.e., identifying the constructs associated with a phenomenon). Yet, in baking, just as in predictive models, the recipe must go beyond this point if we want to make cookies. We must know how much of each ingredient we need. To have 4 lbs of chocolate chips and 1 oz of flour is a very different recipe than the reverse. Finally, how these ingredients are combined is critical. To take the same amount of the same ingredients, but to combine them in different ways, is to make a different cookie.

Linear regression provides a simple and familiar example of how to specify ingredients, their amounts, and how to combine them. The dependent variable is the type of cookie we are making. The predictors in the model are the ingredients deemed important for making this dependent variable. The parameter weights are the amount of the ingredients or how much we think each coefficient will contribute to the dependent variable. And finally, the signs between the predictors specify how to combine the ingredients. Simple linear regression models include addition signs, indicating predictors are combined additively, and we expect a linear relationship with the dependent variable. As the predictors increase in value, the dependent variable should increase or decrease a corresponding amount. Should our model not explain a meaningful amount of variance in the dependent variable, the recipe is not good.

Articulating theories mathematically has benefitted science's understanding of numerous phenomena. A classic example is in astronomy (Lewandowsky & Farrell, 2010), in which the transition from a geocentric to a heliocentric model of the universe was facilitated by observations (e.g., retrograde motion) that poorly fit predictions of the geocentric model. Without the precise description of the geocentric model, the realization that some observations did not fit with this model would have been more difficult. Such an approach has also advanced psychological science. Game theoretic models test a range of strategies for decision making, illuminating optimal strategies for different situations (Osborne & Rubinstein, 1994). Models of cultural evolutionary processes examine the conditions that can give rise to reciprocity, punishment, and the use of markers to distinguish ethnic groups (Boyd & Richerson, 1988; McElreath et al., 2003). Others have modeled emotions as infectious diseases to examine how they spread throughout networks (Hill et al., 2010). In the area of intergroup relations and prejudice, specifically, some formal and predictive models do exist. A model of cross-group friendships as complex adaptive systems predicts increased or reduced prejudice as a function of the characteristics of the friendships over time (Page-Gould et al., 2022). Others have developed models predicting the specific relationship between ideology and prejudice (Brandt, 2017) or compared predictive models of identification, conflict, and threat (Grigoryan et al., 2022). And indeed, some have argued that psychology should increase such a focus on prediction (Yarkoni & Westfall, 2017). Yet, for the most part, the development and testing of predictive models in social psychology in general, and prejudice specifically, is quite rare.

The Present Research

We believe for the field to move forward effectively, developing a predictive model of prejudice is necessary. Doing so will address the problems laid out above, as predictive models enable precise falsification and iterative improvement. These advances are more difficult with verbal theories of prejudice. Accordingly, our aim was to develop a simple and initial model. We expected this model to be bad and wrong. Yet, like the geocentric model of the universe, this bad and wrong model can serve as a necessary starting point for subsequent research and improvement of the model, such that subsequent iterations explain more variance in prejudice than those preceding it. This concretely advances the science of prejudice and is the progression that occurs with modeling in all fields.

Our analytic pipeline consisted of seven phases. Phase I: We first identified a large number of constructs theorized to cause prejudice from the literature. We collected data from participants using validated scales tapping these constructs. To build a parsimonious model of prejudice and identify key constructs, we used elastic net regularization for model selection. Phase II: Having identified key predictors, we further honed the model by examining the performance of the resulting standardized model of prejudice across a number of new target groups. Phase III: We preregistered the further winnowed predictive models and used a Bayesian approach to confirm their performance in an out-of-sample data set. Phase IV: We tested the generality of our model beyond specific operationalizations by testing whether changing the measurement of constructs in our predictive models changed the models' performance. Phase V: We tested boundary conditions of how broadly the model applies. Phase VI: We confirmed that our model generalized to a representative U.S. sample and two other cultures (i.e., the United Kingdom, India). Phase VII: Finally, to assess to what extent our predictive model corresponds to what is known by the field, we surveyed other experts in prejudice. We describe these phases further below.

Operationalizing Prejudice

Conceptually, we define prejudice as a more negative (or less positive) evaluation of a group or individual on the basis of group membership (Bergh & Brandt, 2022; Crandall & Eshleman, 2003; Fiske, 1998; Stangor, 2016). Prejudice, commonly defined this way, is an attitude rather than a behavior. Throughout the literature, prejudice conceptualized in this way has tended to be operationalized in two distinct ways. The first is intuitive: evaluative ratings of a group, or essentially, "How much do you like [group]?" The second operationalization also involves this first component, but instead of asking about only an outgroup, attitudes toward an ingroup are also assessed, and prejudice is operationalized as the difference between the two such that prejudice might be interpreted as either a more negative or less positive evaluation relative to the ingroup. For example, the Implicit Association Test is essentially a difference score between responses to the ingroup and outgroup (Greenwald et al., 1998), as are a wide variety of explicit measures (Axt, 2018). This approach has the advantage of adjusting for individual differences in a few factors. For example, there may be individuals who take a dim view of humanity in general and rate all groups, including their own, quite negatively. There may be other more agreeable individuals who rate all groups quite positively. By operationalizing prejudice as a difference score, these idiosyncratic tendencies and differences in the use of scale response items are automatically adjusted for. The present authors disagree on which operationalization better reflects the construct of "prejudice," and because both operationalizations have been regularly examined in prejudice research, we here developed predictive models of both conceptualizations. Developing these two models with the same process enables the exploration of similarities and differences in the predictors that account for these operationalizations of prejudice.

Various research groups over the decades have developed a smorgasbord of scales that aim to measure explicit prejudice, in addition to the two described above. While many of these scales certainly tap prejudice, some are known to also tap other independent constructs, such as political attitudes (e.g., modern racism; McConahay, 1983). In addition, many of these scales were developed to measure prejudice toward particular groups, by measuring specific beliefs or social contexts that apply uniquely to one group and are not readily portable to other social groups. To maximize the likelihood that our predictive model would universally apply to any type of prejudice, we built models based on the simplest conceptualizations of prejudice that correspond to validated measures of prejudice: negative feelings toward a group, as operationalized in feeling thermometers. We revisit this decision in Phase IV.

It is important to keep in mind our above definition of prejudice when interpreting the present research. Like many constructs in psychology, the word prejudice has been used by different scholars to represent different ideas. For example, Social Dominance Theory (Sidanius & Pratto, 1999) defines prejudice as a system of oppression across systems, institutions, and individuals to maintain a group's dominance. In this tradition, only dominant groups can express prejudice. For example, Black Americans with negative evaluations of members of the Ku Klux Klan are not prejudiced from this perspective. Other definitions of prejudice also exist, some of which encompass other types of attitudes rather than purely negative, such as ambivalence. Critically, these other definitions are simply not the constructs we are modeling here. To the extent that a given construct is not defined as feeling negatively toward a group, or feeling warmer to one group relative to another, *it is unrelated to the present research*. While the definition of prejudice we have adopted is very common in the literature, different readers might prefer to call this construct something like "intergroup evaluations" or another related term. We endorse the perspective that it is the operationalization, and the mapping of the operationalization to the theoretical definition, that is important, rather than semantics. Our results are germane to the theoretical definitions above and the measurement below.

Philosophical Approach

Our aim was to begin a process toward a universal, causal, model of prejudice. A universal model of prejudice should predict attitudes toward all groups of humans; past, present, and future; and not just toward social groups traditionally targeted with prejudice nor just those often studied by social science researchers (Brandt & Crawford, 2019; Crandall et al., 2002; Koch et al., 2016). That is, not only should a universal model of prejudice predict attitudes toward Black people and gay people but it should also predict attitudes toward vegetarians and members of the Ku Klux Klan and the attitudes that people will develop toward other human social groups in any culture or context or that do not yet exist.

Though the current state of psychological research is far from being able to develop such a universal causal model (see the Limitations section), we examined attitudes toward a wide variety of groups in order to identify those constructs that are theorized to cause prejudice, regularly predict prejudice in the present work, and are not idiosyncratic predictors for a particular social group. Furthermore, in Phase V we test the boundary conditions of our predictive models, and in Phase VI test how well these models generalize to the prejudice of individuals in other cultures.

Identifying Constructs

Though our model is built for prediction and does not test causation directly, it is advantageous to researchers moving forward if the identified predictors are theoretically causal and temporally upstream of prejudice, to best support future predictions of prejudice. Further, with an abundance of psychological constructs in the literature, identifying those argued to be causal aided us in narrowing down the range of candidates to measure and potentially include in the models. Accordingly, to identify likely predictors for our model, we examined the literature for constructs that researchers have argued or theorized to cause prejudice. We have organized these into a taxonomy of construct types: personality characteristics, characteristics of the environment, socialization processes, and perceptions of groups. This taxonomy is but one scheme for discussing these constructs, and other researchers might organize these constructs in a different way.

Individual Differences

Personality and individual differences have long been investigated as a major cause of prejudice and form the largest group of predictors here. Early research found that individuals were not prejudiced only toward specific groups but rather were either prejudiced or not prejudiced toward a wide variety of groups, giving rise to the personality perspective (Allport, 1954; Altemeyer, 1988). Various personality constructs postulated over the years to predict prejudice have earned varying amounts of empirical support. For instance, SDO, or one's preference for inequality among social groups (Pratto et al., 1994), regularly corresponds to more prejudiced attitudes. Modern psychometric work has identified two subfactors to SDO: Dominance and Egalitarianism (Ho et al., 2015). Similarly, Right-Wing Authoritarianism (RWA) is a personality variable describing a tendency toward conformity, submission to authority, and aggression in defense of existing authority. Theorized in the 1950s (Adorno et al., 1950), it has received a great deal of research in the intervening decades (Altemeyer, 1988). It is thought to have three subfactors: Authoritarianism, Conservatism, and Traditionalism.

Belief in a Just World is the tendency to believe that outcomes and consequences reflect one's actions (Lerner, 1980). Research has shown that individuals scoring higher on this personality characteristic tend to support the existing status quo and group hierarchies, as those social groups "on top" are superior to those below (Jost et al., 2004). System Justification is a related construct based on the idea that people desire to support the social structures in which they live, which has been associated with an acceptance of inferiority among lower status groups (Jost & Hunyady, 2003). Protestant Work Ethic is an older but related construct, capturing the idea that if an individual works hard enough they can succeed in life—which can lead to negative attitudes toward those who are of lower status (Weber, 1905).

The Big Five is perhaps the most widely used model of personality traits, with some research arguing that it is an organizing framework for almost all psychological trait scales (Bainbridge et al., 2022; John & Srivastava, 1999), including many of those examined here. Past research has specifically found that Openness to Experience and Agreeableness correspond to lesser prejudice (Crawford & Brandt, 2019; Sibley & Duckitt, 2008). Need for Cognition—a construct related to Openness (Mussel, 2010; Sadowski & Cogburn, 1997)—describes the inclination toward effortful cognitive activities (Cohen et al., 1955). It is associated with characteristics such as problem solving, enjoying thinking, and appreciating debate. Some research has found that those with greater Need for Cognition report less prejudice (Waller, 1993), as they have theoretically invested greater effort in shaping their attitudes rather than relying on common stereotypes. Individuals who are lonelier are more sensitive to social threats and may show greater accessibility of negative information (Cacioppo & Hawkley, 2009), which may correspond to more prejudiced attitudes toward outgroups.

Greater identification with a particular ingroup has been associated with a greater preference for the ingroup relative to the outgroup (i.e., bias; Brewer, 1999; Tajfel & Turner, 1979). Modern scale tapping identification have described two major subfactors: Self-Investment, or the salience and importance of group membership, and Self-Definition, or seeing oneself as similar to any part of the ingroup (Leach et al., 2008). This construct may capture a love of the ingroup more than a dislike of the outgroup, but this would still translate to increased bias when prejudice is operationalized as the difference in liking between two groups. And finally, individuals scoring higher on religiosity or a belief in the supernatural tend to report higher levels of prejudice (Johnson et al., 2012).

Characteristics of One's Environment

A growing area of research has taken advantage of larger public repositories of psychological data to test hypotheses of how differences between geographic regions can account for prejudice, for example, by geolocating individuals who have completed various measures of prejudice. Research adopting such an approach has identified relationships between regional prejudice and group segregation, the proportion of Black people killed by police, various health outcomes, educational disparities, the specific groups targeted, local legislation, migration, and more (Cikara et al., 2022; Esposito & Calanchini, in press; Hehman et al., 2018; Leitner et al., 2016; Ofosu et al., 2019; Rae et al., 2015). This growing body of evidence has prompted some to call for a refocusing on the role of local context in shaping prejudice (Calanchini et al., 2022; Payne et al., 2017; Rentfrow et al., 2008). Consistent with theories of norms, the prejudices of one's environment might shape one's own prejudices to a substantial degree.

To allow for this possibility in a predictive model of prejudice, we included several metrics used by previous research that correspond to regional prejudice. The average implicitly and explicitly measured prejudice of one's country toward a group can be an index of descriptive norms of prejudice or how common it is to hold prejudiced attitudes in a particular region (Hehman et al., 2019). In addition, research adopting a data-driven model selection approach additionally identified two predictors associated with a wide variety of regional prejudices. The percentage of mental health providers in a region is negatively associated with prejudice, and the average premature death rate is positively associated with prejudice (Hehman et al., 2021).

Socialization Processes

Developmental environment and experiences are also theorized to influence a person's current and future prejudices. For example, nonverbal behaviors toward actors of different genders on television (and presumably other forms of media) can shape viewers' stereotypes (Lamer et al., 2022). Conversations with one's parents and role models about race-related issues can also shape attitudes (Perry et al., 2022). Finally, intergroup contact reduces prejudices between groups (Corno et al., 2022; Mousa, 2020; Van Laar et al., 2005). The relationship between contact and prejudice has been widely documented for decades (Hewstone & Swart, 2011; Lemmer & Wagner, 2015; Pettigrew, 1997; Pettigrew & Tropp, 2006; Tropp & Pettigrew, 2005) and is perhaps one of the most robust phenomena identified in the intergroup literature. Intergroup contact has been operationalized in a wide variety of ways, ranging from the quantity of friendships, proximity in living, coworkers, the positivity of contact, frequency of interactions, and indirect connections (Hässler et al., 2020; Pettigrew, 1997).

Perceptions of Other Groups

The idea that threat increases conflict between groups has a long history (Campbell, 1965), and much work has demonstrated that perceiving a group to pose various threats can increase prejudice toward that group. Recent research has found that "worldview conflict," or the idea that those representing different ideas and values pose a threat to one's worldview, parsimoniously explains prejudices toward a wide variety of groups (Brandt & Crawford, 2020). Different types of perceived threats can produce distinct prejudices (Cottrell & Neuberg, 2005). Roughly, threats can be grouped into threats to one's physical well-being and resources (realistic threats) and threats to one's values or beliefs (Symbolic Threats; Earle & Hodson, 2020; Riek et al., 2006; Stephan & Stephan, 2000). The specific nature of these threats can be diverse and come from diverse sources (Cottrell & Neuberg, 2005; Lassetter et al., 2021; Neel & Lassetter, 2019; Schaller & Neuberg, 2012), but perceived threat in whatever form has a robust tendency to increase feelings of prejudice toward the threatening group.

Perceptions that a group is unpredictable or difficult to control can contribute to judgments that they pose a threat (Magliano et al., 2004). Other research has argued that groups are more threatening when they are highly entitative, that is, are more cohesive and perceived to be a single entity (L. Gaertner & Schopler, 1998; Lickel et al., 2000). Finally, recent work on perceptions of racial groups has found that perceptions of the group's status within a society, or how foreign the group is perceived compared to the local culture, can predict distinct prejudices (L. X. Zou & Cheryan, 2017).

While the above is what our search of the literature on theorized causes of prejudice revealed, the state of the art is not such that all these theorized constructs can be effectively measured. For example, there is currently no satisfactory way of operationalizing and measuring a lifetime of media exposure nor many other constructs that would have an ongoing influence on prejudice over the course of development. Thus, the results of the present approach will essentially reflect the state of the field: If the field has not developed reliable methods of capturing such a construct, they will not be present in our analyses, and any variance that could be attributable to those specific constructs will remain unexplained. A nonexhaustive list of constructs we believe fall into this general category includes structural components of the environment (Murphy & Walton, 2013; Trawalter et al., 2020), socialization processes (Perry et al., 2022), historical context (Payne et al., 2019), and media exposure (Lamer et al., 2022).

For the constructs for which functional operationalizations exist, we sought out existing and validated measures to include in the analysis. This ultimately resulted in 32 distinct constructs (Table 1) that we included in the initial model selection pipeline.

Excluded Variables

Our exclusions of potential predictors of prejudice are as important to consider as our inclusions. Some variables considered to be strong predictors of prejudice may, in fact, overlap substantially with prejudice. Including constructs that are in fact a measure of prejudice would undermine the validity of our model. Imagine a statistical model in which we included a construct that was truly a measure of prejudice but under a different name (i.e., jangle fallacy). This variable, because it is essentially the same construct as the dependent

Table 1
Constructs and Scale Sources

Construct	Citation for scale
Prejudice	Axt (2018)
Belief in a Just World	Dalbert et al. (1987)
Big Five: Agreeableness	Rammstedt and John (2007)
Big Five: Openness	Rammstedt and John (2007)
Contact: Positive	Hässler et al. (2020)
Contact: Negative	Hässler et al. (2020)
Contact: Quantity	Hässler et al. (2020)
Contact: Number of Friends	Hässler et al. (2020)
Contact: Frequency	Hässler et al. (2020)
Controllability	generated for this research
Entitativity	Denson et al. (2006)
Generalized Threat	Cottrell and Neuberg (2005)
Identification: Self-Investment	Leach et al. (2008)
Identification: Self-Definition	Leach et al. (2008)
Loneliness	Hughes et al. (2004)
Need for Cognition	Lins de Holanda Coelho et al. (2020)
Protestant Work Ethic	Katz and Hass (1988)
Racial Position: Foreignness	L. X. Zou and Cheryan (2017)
Racial Position: Inferiority	L. X. Zou and Cheryan (2017)
Right-Wing Authoritarianism: Conservatism	Bizumic and Duckitt (2018)
Right-Wing Authoritarianism: Authoritarian	Bizumic and Duckitt (2018)
Right-Wing Authoritarianism: Traditionalism	Bizumic and Duckitt (2018)
Religiosity	Huber and Huber (2012)
Regional: Mean explicit bias (norms)	Project implicit
Regional: Mean implicit bias (norms)	Project implicit
Regional: Percentage of mental health providers	Center for Disease Control and Prevention's WONDER database
Regional: Premature death rate	Web-based injury statistics query and reporting system
Values Threat	Cottrell and Neuberg (2005)
Social Dominance Orientation: Dominance	Ho et al. (2015)
Social Dominance Orientation: Egalitarianism	Ho et al. (2015)
Symbolic Threat	Earle and Hodson (2020)
System Justification	Kay and Jost (2003)
Unpredictability	Kenny et al. (2018)

variable, would exhibit a strong relationship with the dependent variable. In turn, this strong relationship would lead all the other coefficients to be smaller and the relationships misestimated. In such a scenario, some constructs that might truly be important in predicting prejudice might seem not particularly important and be dropped entirely. Thus, including constructs in the model that are actually part of the dependent variable would produce entirely invalid results. It was important that we included only variables that could be argued to be independent and temporally upstream of prejudice. Accordingly, we adopted a conservative approach and did not include variables if we considered there to be a possibility they were part of the prejudice construct. These decisions are unavoidably subjective, and other researchers might have made different decisions. So that others can evaluate the model, we transparently provide the justifications for our decisions below.

Emotions. We did not include emotions toward groups as a distinct construct that causes prejudice. Intergroup emotions are an essential component of intergroup dynamics (Mackie et al., 2000), yet prominent theories identify emotions as synonymous with prejudice—that is, prejudice, as the affective component of intergroup psychology, is itself characterized by emotions (Cottrell & Neuberg, 2005; Cuddy et al., 2007). Accordingly, measures of affect toward particular groups were excluded from our models, including fear, disgust, anger, and anxiety.

Valenced Associations. Stereotypes are cognitive associations between groups and concepts. By definition, stereotypes are distinct from prejudice, given that prejudice involves a valenced evaluative component of essentially good or bad (Dovidio et al., 2010). Yet to the extent that a cognitive association between a social group and a concept is strongly valenced, we believe the distinction between a stereotype and prejudice breaks down. Consider an extreme example, in which a social group, vampires, is associated with the concept of "evil." While this is technically a stereotype, endorsing this stereotype likely also reflects prejudice since evil is strongly valenced and considered bad by most. Valenced stereotypical associations like this abound throughout the literature, with Black people associated with the concept of crime (Devine, 1989; Eberhardt et al., 2004), Muslims associated with terrorism (Ghavami & Peplau, 2013), and atheists perceived as amoral (Gervais et al., 2011).

With regard to perceptions of groups and intergroup dynamics, common associations examined are perceptions of warmth, competence, or morality (Brambilla et al., 2012; Cuddy et al., 2007; Fiske et al., 2002; Koch et al., 2016). Yet these are strongly valenced characteristics, and evaluating a group as low on warmth may not be sufficiently distinct from disliking that group, given that warmth is such a positive and valued characteristic. As described above, including a predictor in the model that is essentially part of the dependent variable would undermine the model. Accordingly, though sometimes evaluations such as "warmth" have been treated as causes of prejudice, we restricted more valenced associations in our initial model. However, as with emotions, we test this assumption regarding valenced associations in Phase IV.

Demographics. We included no demographic variables in the model. Demographic variables would likely improve the model's overall ability to explain variance in prejudice. Yet our goal was to develop a psychological predictive model. A demographic variable that meaningfully explains prejudice likely does so because it corresponds to the kinds of predictors our model includes, such as psychological tendencies or structural factors. For example, it may be that membership in one ethnic group predicts prejudice toward another ethnic group, but the reason it does so is because it corresponds to psychological variables like group identification, socialization processes, opportunities for contact, and so forth. To include demographic variables in the model is to essentialize that demographic variable as a *cause* of prejudice, presuming that no psychological mechanisms would explain why that variable predicts prejudice. We do not believe this ever to be the case.

Assumptions

Because this is an initial model of prejudice, we made some necessary assumptions for simplification. The first was that relationships between our predictors and prejudice are linear. We made this simplification for both theoretical and practical reasons. It may be that in fact, some predictors demonstrate a nonlinear relationship to prejudice, or they interact with another variable in predicting prejudice. But, because we are aiming to create an initial, bad, and simplified model of prejudice as a starting point, we explicitly sought to identify those variables that linearly predict a substantial portion of the variance in prejudice. To the extent that a variable meaningfully and uniquely predicts prejudice in a linear fashion, that will provide a useful foundation from which future, more complex models can build. In addition, given our approach to model selection, allowing for nonlinear relationships and testing for higher order interactions quickly becomes unwieldy and computationally demanding. Testing for main effects is not only more theoretically parsimonious but subsequent iterations of the model that allow for interactions will need to explain meaningful amounts of variance above and beyond the main effects. Thus, identifying the main effects forms a useful base for our model.

Some additional assumptions are built into the analytical approach adopted below. The present research uses elastic net regularization to identify a parsimonious model of prejudice. This approach retains variables that explain unique percentages of variance. Such an approach, and any approach using variance explained, will likely prioritize more proximate than distal predictors of prejudice. For example, it is possible an element of childhood experience, such as conversations with a parent about prejudice, plays a large role in shaping that individual's prejudice as they move into adulthood (Perry et al., 2022). Yet because such events happen in early childhood, those conversations likely operate through other variables to shape an adult's prejudice. In geography, Tobler's first law states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This law can be applied temporally as well. Because there are fewer intervening influences on one's prejudice, variables reflecting more temporally proximate forces are likely to, on average, exert a stronger effect on one's prejudice. Thus, dropped variables may still play a critical role in prejudice but are simply more distally influential in the causal chain. We return to this important issue in the General Discussion section.

Furthermore, it is important to emphasize that our goal was to meaningfully describe attitudes toward any group of humans. There will certainly be important predictors that might explain large amounts of prejudice toward a particular group. Yet if this is specific to only one or several groups of humans, we do not consider this part of the universal model of prejudice, and such variables would be removed. We also address this issue in the General Discussion section.

As mentioned above, not every construct theorized to cause prejudice has an existing measure. Importantly, however, unmeasured variables would not invalidate the model's results but rather suggest factors that contribute in addition to those our model identifies. Just how important these unmeasured constructs are in predicting prejudice *can* be estimated from our model. For example, if our models explain 99% of variance in prejudice, this would indicate unmeasured variables are likely playing a very small role. If our developed models of prejudice explain only 1% of the variance, unmeasured variables are playing a large role.

Method

Constructs

Prejudice

We operationalized prejudice in two related ways. The first was the difference in reported liking for ingroup and outgroup, henceforth called Bias. Participants responded to six items total, three for the ingroup and three for the outgroup, asking about their liking, feelings of warmth, and positivity toward each group. Using structural equation modeling, a latent factor was derived for the ingroup and outgroup items, respectively, and then the difference between these latent factors functioned as the measure of Bias. More positive values reflect more of an ingroup preference. The second operationalization used the outgroup liking items alone. This operationalization is henceforth called Outgroup Attitudes.

Predictors

Due to the large number of constructs, brief versions of most scales were included in the initial models, if published validation was available. Scale items that explicitly mentioned an ingroup or outgroup were worded differently depending on the study. Data, full scales with items, model fit indices, and correlation tables between all constructs in Studies 1–3 are available in the Supplemental Materials at https://osf.io/vz6gc/.

Procedure

Throughout, except where noted, participants from the United States completed a survey accessed through Mechanical Turk and Cloud Research (Litman et al., 2017). Question order was randomized by the participant, with the exception of demographics and then the prejudice items, which always came first (recommended in planned missingness designs; Graham et al., 2006). Because we were interested in prejudice toward outgroups, individuals belonging to the target group were removed from each test. This research received research ethics approval from McGill University and the University of Toronto.

Analytic Approach

Planned Missingness

Due to the large amount of items, to maximize data quality, we implemented a planned missingness approach, following best practice guidelines (Graham et al., 2006; Rhemtulla & Little, 2012). Participants randomly received approximately 70%–80% of the items throughout each study. Because we randomized which items were missed, data are missing completely at random, and missingness procedures could be adopted. Then, when fitting models, we used full information maximum likelihood estimation, which accommodates missing data and uses all of the observed data to create parameter estimates maximizing the probability of the observed data having come from the population implied by those estimates (Rhemtulla & Little, 2012).

Model Fit

In pursuit of common elements of prejudice across a wide variety of groups, throughout the article, we examine attitudes toward many groups. A central tenet of construct validation is the importance of confirming that a given instrument works in the same way in different situations (Kane, 2013). To this end, we fit confirmatory factor models for each construct in each study. Model fit was examined to ensure each construct's fit was equivalent to its initial validation studies. When model fit for a given construct was poor or notably worse than the initial published validation studies, these constructs were not used in analysis due to open questions about what, exactly, was being measured. Confirmatory factor models were fit in a structural equation modeling framework using lavaan (Rosseel, 2012). Latent factor values were then saved for use in subsequent analysis.

Model Selection

Model selection was completed using elastic net regularization (H. Zou & Hastie, 2005). Elastic net regularization seeks to balance two competing goals in model development: explanatory power and parsimony. Maximizing variance explained focuses the model on the factors most related to the phenomenon. All else equal, models with more variables will explain more variance than models with fewer variables, yet highly complex models (i.e., large numbers of predictors) become unwieldy and less likely to generalize. Therefore, parsimonious models that predict the most variance from the fewest predictors are desirable. Regularization helps find an optimal balance of explanatory power and parsimony—that is, minimizing both error and complexity—by including an extra term in the regression equation (λ) reflecting the complexity of the model. This term "shrinks" coefficients in the model to zero as model complexity increases. When $\lambda = 0$, the model is the same as traditional linear regression (i.e., no shrinkage). When $\lambda = \infty$, there are no variables in the model (i.e., all coefficients shrunk to zero). Simple models will have higher overall error and lower complexity, while models with many predictors will have reduced error but higher complexity. The optimal value of λ balances error with complexity. Elastic net is a type of regularization ideal for the present research because many of our predictors are likely to be correlated with one another (Lohmann et al., 2023; H. Zou & Hastie, 2005).

In the present research, the optimal value of λ was selected using cross-validation in the R package glmnet (Friedman et al., 2021). Specifically, we performed 10-fold cross-validation, randomly dividing the data set into 10 nonoverlapping subsets (i.e., folds) of roughly equal size. The model is fit on the first nine folds and validated on the remaining fold, repeatedly in an iterative fashion. This process reduces the possibility of developing a model so specific to our data that it would not generalize (i.e., overfitting). A standard approach is to select λ based on the value that minimizes cross-validated 10-fold error plus one standard error (Friedman et al., 2021).

Variables with nonzero coefficients at optimal levels of λ were subsequently entered into linear regression models to assess their coefficients and overall variance explained by each model.

Phase I: Elastic Net Regularization

In Phase I Studies 1–3 used elastic net regularization for model selection, with the aim of developing parsimonious models. Our plan was to collect all constructs with regard to three different groups, reflecting attitudes toward Black, gay, and extremely wealthy people. Some research suggests that there are three subclusters of bias (Bergh & Brandt, 2022), and we selected exemplar groups among these subclusters to cover this theoretical space (and continued to do so in Phase II), as our goal was to create a model that generalizes across all prejudices.

Samples

Study 1: Prejudice Toward Black People. Five participants told us not to use their data, and four were removed for failing an attention check. Individuals identifying as Black were removed. This left 369 for analysis ($M_{age} = 41.2$, $SD = 12.3$, 47% women, 89% White, 7% East Asian, 3% South Asian, <1% Pacific Islander).

Study 2: Prejudice Toward Gay People. Five participants were removed for failing an attention check. Individuals identifying as anything other than heterosexual were removed. This left 382 for analysis ($M_{age} = 42.0$, $SD = 12.2$, 47% women, 84% White, 9% Black, 4% East Asian, 2% South Asian, 1% First Nation, <1% Pacific Islander).

Study 3: Prejudice Toward Extremely Wealthy People. Two participants told us not to use their data, and six were removed for failing an attention check. Individuals identifying as extremely wealthy were removed. This left 406 for analysis ($M_{age} = 41.2$, $SD = 13.5$, 55% women, 79% White, 9% Black, 7% East Asian, 2% South Asian, 1% First Nation, 1% Pacific Islander).

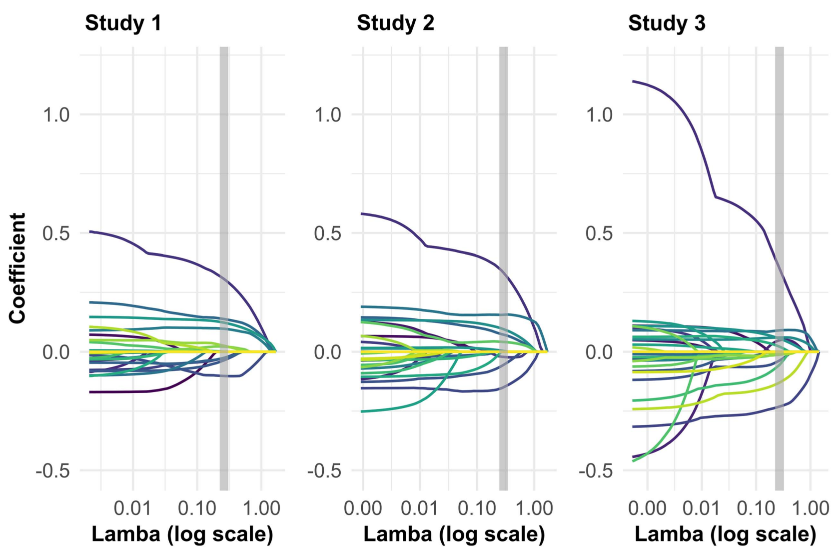
Results. All variables were entered into each model, and the optimal lambda was determined through cross-validation (Figure 1).

Constructs with a nonzero value at the optimal lamba were then included in a linear regression model in which Bias was regressed on all constructs. Results for Bias are presented in Table 2.

This process was repeated for the models of Outgroup Attitudes. Results are presented in Table 3.

The variance explained can be interpreted as the accuracy of the models. First, it is notable that all models performed quite well, explaining between 52% and 62% of the variance in Bias and

Figure 1
Values of Each Coefficient in the Model at Different Levels of Lambda as They Are Shrunk Toward Zero



Note. Thick gray vertical lines represent the selected lambda. All parameters with nonzero values at that point were retained. See the online article for the color version of this figure.

Outgroup Attitudes. Further, of the 32 constructs entered in the elastic net, on average, 10.5 were retained. Because the elastic net approach is intended to remove redundant constructs, this result supports the possibility raised in the introduction that there may be some overlap in the various psychological constructs posited in the literature to predict prejudice. Next, given our interest in common elements of prejudice, we looked for the constructs that most consistently predicted Bias and Outgroup Attitudes across all groups. Some commonalities were observed, such as measures of Contact, Threat, and the Self-Investment subfactor of Identification.

Phase II: Trimming the Model

While elastic net regularization in Studies 1–3 greatly helped to reduce the number of variables included in the models, the constructs included across models still slightly varied, as did the performance of

Table 2
Coefficients From Regression Model for Bias, Phase I

	Target group		
Construct	Black people	Gay people	Extremely wealthy people
Contact: Frequency	−0.058		
Contact: Negative	0.179	0.103	
Contact: Number of Friends	−0.055	**−0.130**	**−0.106**
Contact: Quality	−0.071	**−0.211**	**−0.026**
Contact: Quantity	−0.056		
Generalized Threat	**0.146**	**0.138**	**0.056**
Identification: Self-Definition			**−0.476**
Identification: Self-Investment	**0.404**	**0.471**	**1.148**
Racial Position: Inferiority			0.060
Religiosity			**−0.164**
RWA: Conservatism		0.045	−0.042
SDO: Dominance	−0.011		−0.034
SDO: Egalitarian	0.089		0.020
Values Threat	0.007	0.023	**0.098**
Symbolic Threat	0.107	**0.134**	0.065
System Justification			−0.196
Adjusted R^2	0.62	0.56	0.52

Note. Significant relationships are in bold. Only those constructs selected from the regularization approach were included in the models. RWA = Right-Wing Authoritarianism; SDO = Social Dominance Orientation.

Table 3
Coefficients From Regression Model for Out-Group Attitudes, Phase I

Construct	Target group		
	Black people	Gay people	Extremely wealthy people
Belief in Just World	**−0.100**		
Big Five: Agreeableness	−0.171	**−0.189**	
Contact: Frequency	−0.025	−0.062	**−0.094**
Contact: Negative	−0.067		
Contact: Number of Friends	−0.110	**−0.196**	
Contact: Quality	**−0.405**	**−0.636**	**−0.368**
Contact: Quantity	−0.177	0.026	
Entitativity	**−0.176**	**−0.136**	
Generalized Threat	**0.098**		0.051
Identification: Self-Definition	**−0.096**		
Protestant Work Ethic			0.051
Religiosity			**−0.193**
RWA: Authoritarian			−0.090
SDO: Egalitarian	**0.102**		
Values Threat	0.062	0.031	**0.079**
Symbolic Threat	**0.140**	**0.183**	**0.127**
System Justification			**−0.188**
Unpredictability		0.019	
Adjusted R^2	0.59	0.56	0.59

Note. Significant relationships are in bold. Only those constructs selected from the regularization approach were included in the models. RWA = Right-Wing Authoritarianism; SDO = Social Dominance Orientation.

different constructs for the different types of prejudice. With the continued aim of identifying the predictors of prejudice common to any target group, in Phase II we conducted three additional studies (Studies 4–6). Our strategy was to regress each operationalization of prejudice on a single model across groups. The constructs included in this model were based on the results from Phase I: If a construct had large coefficients and was significant or marginally significant in any single model in Phase I, it was included in Phase II for both the Bias and Outgroup Attitudes models.

In Phase II we changed the target groups to maximize generalizability but still selected groups that correspond to the three potential subclusters of prejudice identified previously (Bergh & Brandt, 2022).

Samples

Study 4: Prejudice Toward Immigrants. Four participants told us not to use their data, and one was removed for failing an attention check. Individuals identifying as an immigrants were removed. This left 324 for analysis ($M_{\text{age}} = 38.8$, $SD = 12.6$, 49% women, 81% White, 9% Black, 7% East Asian, 2% South Asian, 1% First Nation, 1% Pacific Islander).

Study 5: Prejudice Toward Transgender People. Three participants told us not to use their data, and four were removed for failing an attention check. Individuals identifying as transgender were removed. This left 287 for analysis ($M_{\text{age}} = 41.2$, $SD = 12.4$, 50% women, 77% White, 9% Black, 9% East Asian, 3% South Asian, 2% First Nation).

Study 6: Prejudice Toward Upper-Class People. One participant told us not to use their data, and two were removed for failing an attention check. Individuals identifying as upper class were removed. This left 279 for analysis ($M_{\text{age}} = 39.8$, $SD = 12.0$, 49% women, 78% White, 9% Black, 6% East Asian, 3% First Nation, 3% South Asian, <1% Pacific Islander).

Results. Bias and Outgroup Attitudes were regressed on an identical model across all three target groups. As in Phase I, models from Phase II explained a high percentage of variance in prejudice, ranging from 53% to 67% (Table 4).

Despite changing the target groups, the same constructs regularly predicted prejudice as in Phase I (Table 5).

Table 4
Coefficients From Regression Model for Bias, Phase II

Construct	Target group		
	Immigrants	Transgender people	Upper-class people
Belief in Just World	0.010	0.013	−0.161
Big Five: Agreeableness	**−0.207**	−0.016	**0.236**
Contact: Frequency	−0.013	0.103	−0.036
Contact: Number of Friends	−0.098	**−0.291**	**−0.135**
Contact: Quality	**−0.248**	−0.057	**−0.325**
Contact: Quantity	−0.088	0.026	0.061
Entitativity	−0.123	−0.027	0.023
Generalized Threat	**0.111**	**0.094**	**0.068**
Identification: Self-Definition	0.070	0.050	−0.183
Identification: Self-Investment	**0.466**	0.375	**0.879**
Religiosity	0.005	−0.111	0.015
RWA: Authoritarian	0.310	0.103	−0.048
SDO: Egalitarian	0.036	0.043	−0.039
Values Threat	0.084	**0.049**	−0.013
Symbolic Threat	**0.227**	**0.355**	0.137
System Justification	0.000	−0.039	−0.102
Unpredictability	−0.016	0.028	−0.018
Adjusted R^2	0.60	0.67	0.53

Note. Significant relationships are in bold. RWA = Right-Wing Authoritarianism; SDO = Social Dominance Orientation.

Table 5
Coefficients From Regression Model for Out-Group Attitudes, Phase II

Construct	Target group		
	Immigrants	Transgender people	Upper-class people
Belief in Just World	0.106	0.032	**−0.168**
Big Five: Agreeableness	**−0.357**	**−0.231**	0.022
Contact: Frequency	−0.017	0.008	−0.016
Contact: Number of Friends	**−0.136**	**−0.250**	−0.080
Contact: Quality	**−0.386**	**−0.198**	**−0.462**
Contact: Quantity	−0.093	0.068	−0.004
Entitativity	−0.098	**−0.295**	−0.055
Generalized Threat	−0.010	−0.083	0.008
Identification: Self-Definition	0.005	0.076	−0.026
Identification: Self-Investment	−0.064	−0.141	0.041
Religiosity	−0.065	−0.004	0.052
RWA: Authoritarian	0.203	0.005	**−0.414**
SDO: Egalitarian	**0.129**	0.085	−0.050
Values Threat	−0.011	0.009	0.032
Symbolic Threat	**0.343**	**0.386**	**0.165**
System Justification	−0.118	−0.037	−0.082
Unpredictability	**0.085**	0.044	−0.020
Adjusted R^2	0.59	0.61	0.62

Note. Significant relationships are in bold. RWA = Right-Wing Authoritarianism; SDO = Social Dominance Orientation.

To identify which constructs should be included in a more parsimonious predictive model of prejudice, we considered the results from Phase II: Studies 4–6 in concert. Our plan had been to focus on the variables that had both large coefficients and significant relationships in the same direction in at least two of the three models. But in fact, every variable meeting these criteria in one model also met them in at least two. The exception to this was Values Threat, which was significant with regard to transgender Bias, but only marginally significant with regard to immigrant Bias. To maximize inclusivity pending further testing, we included all the variables that had any significant relationships in Phase II: Studies 4–6.

Next, an important feature of a predictive model is not only identifying the important variables but also identifying their precise relationship with the dependent variable. Parameter values varied somewhat across all the models in Phases I and II. To estimate the overall parameter values for each construct, we weighted each study by number of participants and averaged those weighted values to arrive at our initial model of Bias.

$$\begin{aligned}\text{Bias} = \beta_0 &+ -.189(\text{Contact}_{\text{quality}}) - .111(\text{Contact}_{\text{number}}) \\ &+ .095(\text{Threat}_{\text{generalized}}) \\ &+ .159(\text{Threat}_{\text{symbolic}}) + .042(\text{Threat}_{\text{values}}) \\ &+ .641(\text{Identification}_{\text{Self-Investment}}) + \varepsilon. \qquad (1)\end{aligned}$$

This model features two measures of Contact: the overall number of outgroup friends and contact quality. Each demonstrates a negative relationship with Bias. In addition, the strongest predictor was self-investment with the ingroup, one of two factors of ingroup identification (Leach et al., 2008). Two other measures both tapped elements of Threat: a more generalized version of Threat and a threat specific to one's culture and values. The perceived threat was associated with greater Bias. And finally, the weakest predictor was perceived Values Threat: The less one thought the outgroup shared one's values, the more Bias.

For Outgroup Attitudes, we used an identical approach of weighting the sample estimates to arrive at an initial model.

$$\begin{aligned}\text{Out-groupAttitudes} = \beta_0 &- .435(\text{Contact}_{\text{quality}}) \\ &- .106(\text{Contact}_{\text{number}}) \\ &+ .215(\text{Threat}_{\text{symbolic}}) \\ &- .130(\text{Big 5}_{\text{Agreeableness}}) + \varepsilon. \qquad (2)\end{aligned}$$

Some of the ingredients present in the model of Bias—Contact and Symbolic Threat—were also present in the model of Outgroup Attitudes. Two large differences emerged. The first was the absence of Identification: Self-Definition. This is possibly due to bias being a difference score, allowing for both ingroup liking and outgroup disliking to uniquely contribute to this operationalization of prejudice (Brewer, 1999). Identification: Self-Definition may be more related to ingroup liking than outgroup dislike, rendering it less useful for predicting outgroup dislike alone. We explore this further below.

The other large deviation between the models is for the Big Five: Agreeableness. When predicting Outgroup Attitudes, Agreeableness negatively predicts all three prejudices. In contrast, when predicting Bias, Agreeableness negatively predicts prejudice toward immigrants but *positively* predicts prejudice toward upper-class people. The Bias finding suggests that people who are highly Agreeable may generally like other people more, consistent with findings of Agreeableness as a correlate of prejudice (Crawford & Brandt, 2019). At the same time, the Outgroup Attitudes finding is consistent with norm-based models of prejudice expression (e.g., Crandall et al., 2002), which predict that people motivated to comply with prejudice expression norms (i.e., agreeable people) will express less prejudice toward groups for whom it is unacceptable to express prejudice but express *more* prejudice toward those groups toward whom it is acceptable to express prejudice. We return to this issue in greater detail in the General Discussion section but continue including Agreeableness moving forward.

Phase III: Preregistered Out-of-Sample Confirmation

The initial predictive model above was developed based on the results of Phases I and II using exploratory techniques. In Phase III we moved to a confirmatory framework, confirming the performance of the model and the precise estimation of the parameters in two new samples. Doing so would suggest our models were not overfit to the training data and can generalize to new samples.

To evaluate the models' performance, we were interested in examining not only the variance explained and the significance of individual parameters but also whether individual parameter estimates were reasonably close to the weighted average estimates of the predictions. Accordingly, we adopted a Bayesian approach as the most suitable statistical framework. Specifically, we used as priors the parameter estimates from the predictive models. Our goal was to examine Bayes factors on a parameter-by-parameter basis to see the strength of the evidence to reject the priors. The Bayes factor is a likelihood ratio of the marginal likelihood of two competing hypotheses (Ly et al., 2016). Here, the hypothesis being tested was whether the estimates of the parameters in our new data were meaningfully different than the parameter values of the predictive models. Essentially, the larger the value of a Bayes factor, the more evidence that the alternative model is supported by the data than the null model (i.e., the predictions of the model), with a value of 1 essentially meaning there is no evidence against the null.

Further, we preregistered the parameter estimates of our models prior to data collection and also preregistered that we expected models to explain ~50%–60% of the variance in prejudice, as we had observed in Phases I and II (https://osf.io/2jzbw). Analyses were conducted in brms (Bürkner, 2017) with weak (1) priors. For these studies, we revisited target groups for which we had already collected models, picking two groups commonly studied by social psychologists.

Samples

Study 7: Prejudice Toward Black People. Four participants told us not to use their data, and two were removed for failing an attention check. Individuals identifying as Black were removed. This left 223 for analysis (M_{age} = 41.4, SD = 13.4, 52% women, 90% White, 7% East Asian, 3% South Asian, <1% Pacific Islander, <1% First Nation).

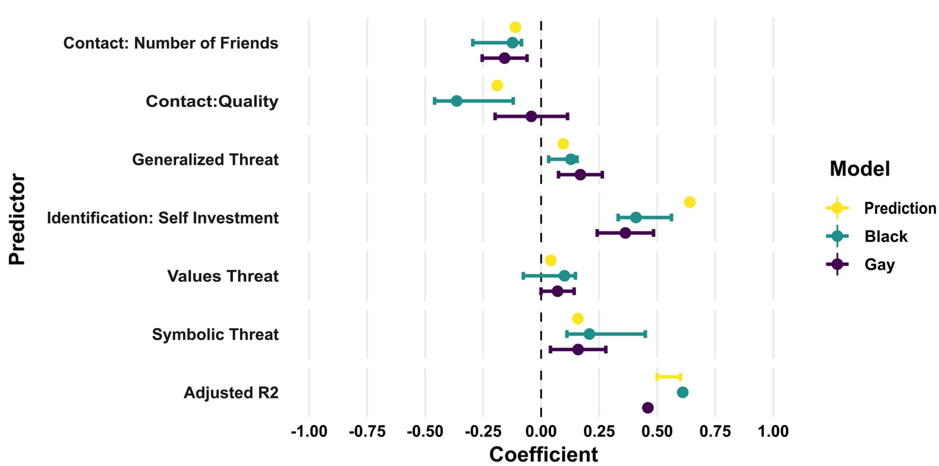
Study 8: Prejudice Toward Gay People. Three participants told us not to use their data, and one was removed for failing an attention check. Individuals identifying as anything but heterosexual were removed. This left 213 for analysis (M_{age} = 41.6, SD = 13.2, 51% women, 81% White, 12% Black, 5% East Asian, 2% South Asian, <1% Pacific Islander, <1% First Nation).

Results. The Bayes factors (Savage–Dickey density ratio) quantify just how much the observed coefficients in both Studies 7 and 8 deviated from our preregistered predictive models (see Supplemental Materials, for Bayes factor tables). But for comparison, these deviations are visualized in Figure 2. To assess model performance, we can look at the overall variance explained, the matching of the parameter estimates of each model with the predictive model estimates, and the overall error of each variable. For example, the largest deviation in the Bias model involved Identification: Self-Investment. Estimates for Bias toward Black and gay people were both less, and the predictive model estimate of .64 was outside the 95% confidence interval (CI) of each. This result suggested that the estimate of Identification: Self-Investment in the Bias model was too strong. All other predictions from the model were included in the 95% CIs of the observed data.

For the Outgroup Attitudes models (Figure 3), the greatest deviation from the predictive model was stronger estimates for Contact: Quality for Study 7 examining prejudice toward Black people and Symbolic Threat for Study 8 examining prejudice toward gay people. In each of these cases, the observed values were actually

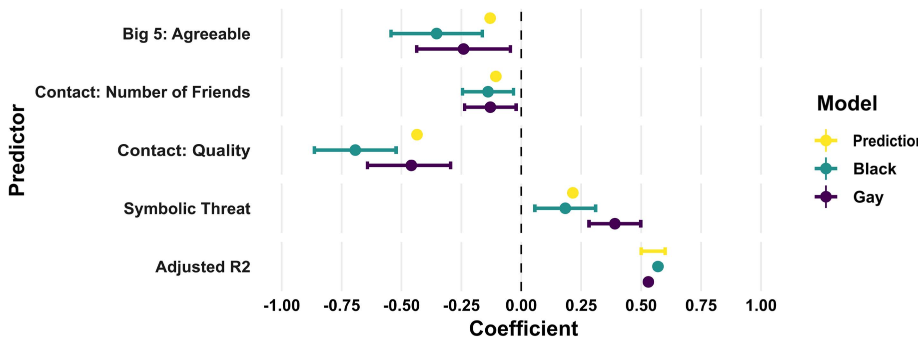
Figure 2

Comparison of Bias Models to Out-of-Sample Results



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

Figure 3
Comparison of Out-Group Attitudes Model to Out-of-Sample Results



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

stronger than the preregistered predictions. Overall, for both Studies 7 and 8, we considered the predictive models to perform well in the out-of-sample data. Evidence indicated that the predictions of the models were not overfitted to the training data and would generalize to new samples, though simultaneously suggested that continued adjustment of the values with more data would improve performance.

Phase IV: Changing Dependent Variables

In the present research, we operationalized Bias as a difference score between ratings of the ingroup and outgroup and Outgroup Attitudes as ratings of an outgroup. We chose these operationalizations due to their simple structure and their common use in the literature, yet there are numerous other scales developed with the aim of measuring prejudice and outgroup attitudes. Our predictive model of prejudice focuses on constructs, rather than specific scales, and so in Study 9, we tested how the model would perform on other developed scales intending to measure prejudice. Based on their good measurement properties (Hester et al., 2023), we decided to use Modern Racism (McConahay, 1983) and Prejudice Index (Bobo & Kluegel, 1993). Accordingly, we additionally collected these scales and examined model performance relative to our Bias and Outgroup Attitude models.

Modern Racism has seven items and asks respondents to indicate agreement with a set of beliefs that “Whites may or may not have about Blacks” (McConahay, 1983). Prejudice Index has 10 items and conceptualizes prejudice as the difference between endorsing five associations (e.g., violence-prone, patriotic) for Black and White individuals (Bobo & Kluegel, 1993). Though developed by different teams and for different reasons, modern psychometric work suggests that these two scales fall into a “generalized anti-Black bias” cluster in a nomological network of a wide variety of race-related scales (Hester et al., 2023). This analysis was additionally important because we had purposely excluded measures of valenced stereotypic associations from our initial pool of constructs. While the Prejudice Index is considered a measure of prejudice, it is essentially a scale with items asking about various valenced stereotypical associations: “Do Black people tend to be unintelligent or tend to be intelligent?” (Bobo & Kluegel, 1993). Accordingly, by analyzing the performance of the predictive models on the Prejudice Index, we could assess how well the models predicted valenced associations.

Study 9: Prejudice Toward Black People: Sample 1

Five participants told us not to use their data, and six were removed for failing an attention check. Individuals identifying as Black were removed. This left 308 for analysis (M_{age} = 42.5, *SD* = 14.2, 57% women, 91% White, 6% East Asian, 2% South Asian, 1% First Nation, 1% Pacific Islander).

Results

The correlation matrix in Table 6 reveals that all dependent measures of prejudice were moderately to strongly correlated, as expected. Unexpectedly, Outgroup Attitudes were only weakly correlated with Modern Racism, as well as the Prejudice Index. This suggests that Modern Racism is not an appropriate substitute measure to assess Outgroup Attitudes. In contrast, both the Prejudice Index and Modern Racism correlated at least moderately strongly with Bias. We thus focused on comparing the model’s performance in predicting Prejudice Index, Modern Racism, and Bias.

In general, the variables in the model predicted the Prejudice Index and Modern Racism similarly, explaining 41%–48% of the variance (Figure 4). The most important difference from our model was in the Contact items, which did not significantly predict either measure. In addition, symbolic rather than Generalized Threat seemed to play a larger role and Self-Investment a smaller role, in predicting these measures. Together, we interpret these results as indicating that our model of prejudice can predict bias assessed via measures other than that on which it was trained. Furthermore, because the models performed well in predicting values on a construct measured from valenced associations (i.e., Prejudice Index), we conclude that in this specific context, the factors that

Table 6
Correlation Matrix Between All Measures of Prejudice

Measure	Bias	Outgroup Attitudes	Prejudice Index	Modern Racism
Outgroup Attitudes	0.51	—		
Prejudice Index	0.66	.38	—	
Modern Racism	0.45	.30	.50	—

predict more valenced stereotypical associations are not distinct from those that predict prejudice and that measures of valenced associations may overlap with measures of prejudice, which helps to justify our original decisions to exclude measures of strongly valenced associations as predictors in the initial models.

At this point, we reconsidered the inclusion of Values Threat in the model based on its theoretical and conceptual overlap with Symbolic Threat, inconsistently significant relationships with prejudice, and its often near-zero parameter value. We retested earlier models of prejudice without this variable, and models explained approximately the same amount of variance throughout. For parsimony, we decided on removing it from the model and did not collect Values Threat in subsequent studies.

Emotions

We originally excluded emotions for the same theoretical reasons as strongly valenced associations. Accordingly, we further wanted to explore the performance of the models on metrics of emotions toward various groups. Therefore, in Study 10, we additionally collected measures of emotions and examined model performance relative to our Bias measure. Intergroup emotions researchers typically consider the discrete emotions of anger and disgust to be most important in predicting intergroup attitudes (Mackie et al., 2000, 2016). Modeling off this research, in a new sample, we measured each construct with two items on a 7-point Likert-type scale (Pauketat et al., 2020).

Study 10: Prejudice Toward Black People: Sample 2

Four participants told us not to use their data, and two were removed for failing an attention check. Individuals identifying as Black were removed. This left 272 for analysis ($M_{\text{age}} = 39.2$, $SD = 12.5$, 48% women, 86% White, 8% East Asian, 2% First Nation, 2% South Asian, 1% Pacific Islander).

Results

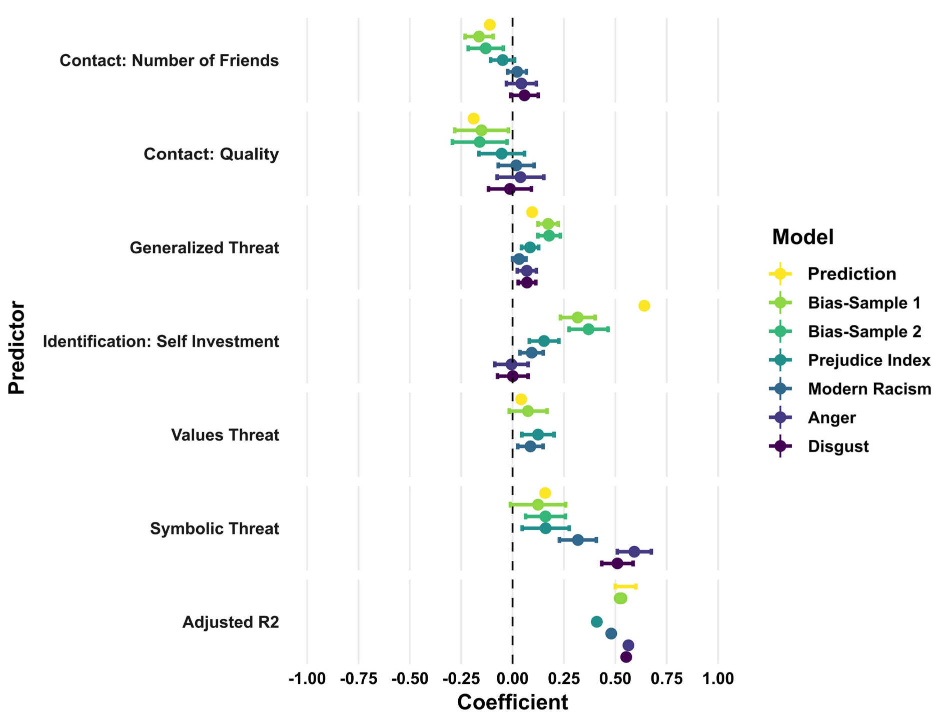
The performance of the models is additionally included in Figure 4. The models explained a high amount of variance in anger and disgust: 56% and 55%, respectively. Yet despite this, only Threat, and Symbolic Threat, in particular, emerged as significant predictors. We conclude that our model of Bias (or Outgroup Attitudes) does not predict emotional responses to outgroups. These emotions may be specific to Threat, in particular, and not influenced by Contact or Identification, for at least one target group (Black people). We return to this issue in the General Discussion section.

Phase V: Boundary Conditions

At this point, 10 studies had been completed with strong evidence for the models, and the models consistently explained a high percentage of variance. We shifted our focus to boundary conditions. Under what conditions would the models not be useful? How far would they generalize? Accordingly, in Phase V we conducted four additional studies (Phase V: Studies 11–14). Our

Figure 4

Model Performance on Different Operationalizations of Prejudice Toward Black People in Phase IV



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

strategy in this phase was to probe the boundaries of the viability of the model, by examining groups that are more conceptually "distant" from those traditionally examined in prejudice research.

Our perspective is that a successful predictive model of prejudice will be able to explain prejudice toward every human social group (Crandall et al., 2002). Study 11 examines whether the proposed models would work for attitudes toward police, a clearly defined group that may elicit negative feelings in some people, but not one traditionally studied as targets of prejudice. Also, while "police" may be an outgroup for most, there is no clear corresponding ingroup (i.e., "not police" or "citizen" is not a common or accessible group identification). Study 12 examines the viability of the models for another social group for which there is no clear outgroup, but one defined by an activity, and likely to elicit less extreme attitudes: Rollerbladers.

Our aim was to develop a model of prejudice, which has been traditionally defined and studied as attitudes toward human groups. Should we find that our models were additionally explaining attitudes toward nonhuman mammals and inanimate objects, we would need to redefine our model as capturing something about attitudes more generally, rather than prejudice specifically. Thus, Study 13 focuses on whether the model would apply to attitudes toward nonhuman mammals: squirrels. And finally, Study 14 examines whether the model would apply to attitudes toward inanimate objects: broccoli.

Together, these four groups enabled an initial test of discriminant validity to help us interpret the construct we are measuring. To do so, we asked the exact questions we have for all prior studies. This therefore included items like "How many of your friends are broccoli?" which is nonsensical and silly. Yet this item functioning differently with the target group of broccoli would provide evidence that these predictive models may not extend to these groups.

Study 11: Prejudice Toward Police

Five participants told us not to use their data, and four were removed for failing an attention check. We asked whether people identified as a police officer (no, yes), and individuals identifying as police were removed. This left 199 for analysis (M_{age} = 39.2, *SD* = 12.3, 52% women, 74% White, 11% Black, 8% East Asian, 2% South Asian, 2% First Nation, 1% Pacific Islander,).

Study 12: Prejudice Toward Rollerbladers

Four participants told us not to use their data, and one was removed for failing an attention check. We asked whether people identified as a rollerblader (no, yes), and individuals identifying as rollerbladers were removed. This left 178 for analysis (M_{age} = 39.8, *SD* = 13.3, 49% women, 83% White, 8% Black, 5% East Asian, 2% South Asian, 1% First Nation, 1% Pacific Islander).

Study 13: Prejudice Toward Squirrels

Two participants told us not to use their data, and one was removed for failing an attention check. This left 221 for analysis (M_{age} = 41.1, *SD* = 13.7, 51% women, 81% White, 8% East Asian, 6% Black, 5% South Asian, <1% Pacific Islander).

Study 14: Prejudice Toward Broccoli

Four participants told us not to use their data. This left 154 for analysis (M_{age} = 40.5, *SD* = 13.9, 54% women, 82% White, 9% Black, 6% East Asian, 1% First Nation, 1% South Asian).

Results

Based on the overall variance explained, the matching of the parameter estimates, and the error of each variable, we interpret the model as replicating for police (Figure 5). A similarly high percentage of variance was explained, and all constructs had roughly the same relationship with Bias, with good measurement. The exception was Contact: Number of Friends, which had a weak and nonsignificant relationship with attitudes toward police. For rollerbladers, however, we interpret results as beginning to see the model break down. Most notably, a much smaller percentage of variance was explained, the worst the model had performed to this point. Furthermore, while the direction of the relationships was the same as in the predictive model, neither Contact: Number of Friends nor Symbolic Threat were significantly related to attitudes toward rollerbladers. For squirrels and broccoli, the models broke down further. For squirrels, Contact: Number of Friends and Symbolic Threat had a reversed direction compared to the predictive model, and in both, neither were significantly related. Importantly, the error of these parameters also greatly increased for the squirrel and broccoli models, evidenced by the much larger 95% confidence intervals, which suggests that the predictors have little precision in predicting prejudice and that the items are functioning differently.

On the other hand, it is notable the consistency and strength with which Contact: Quality, Generalized Threat, and Identification: Self-Investment predicted attitudes in all models, even in the relatively silly situation of reporting feelings toward squirrels and broccoli.

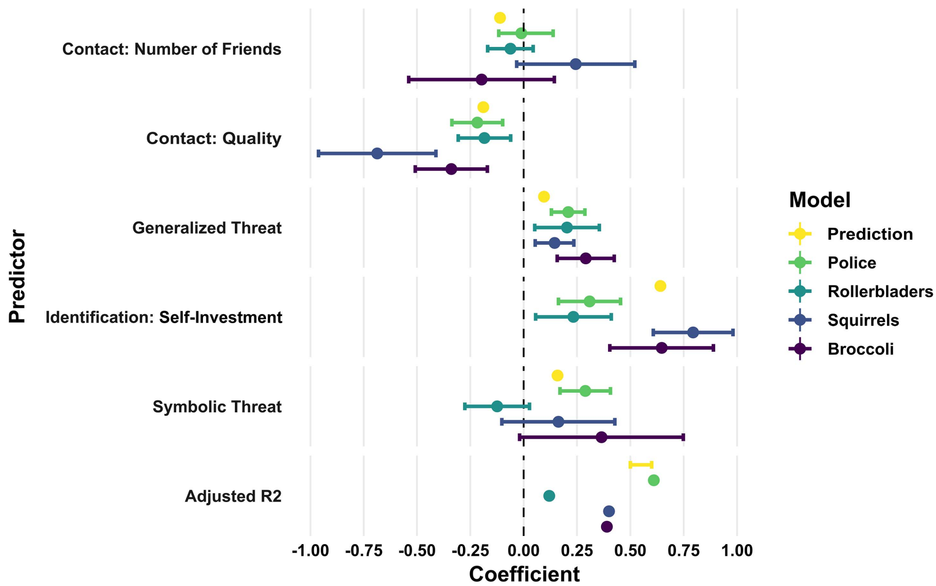
The model of Outgroup Attitudes explained a very high percentage of variance in attitudes toward police yet quickly broke down with the other groups (Figure 6). Just as we observed with Bias, the large standard errors of the variables are evidence that these variables were no longer functioning the same for the social groups in earlier phases as they were for rollerbladers, squirrels, and broccoli. Accordingly, the overall variance explained by the models was low.

These results provide some discriminant validity evidence for each model. Both models seem to work well for police. We note police are a highly entitative group, yet what the ingroup might be in this situation (i.e., not police) is hazier and less defined. Nonetheless, the models performed well here. When the outgroup was less entitative, defined by an activity, and elicited less extreme attitudes, however (i.e., rollerbladers), both models performed much worse.

We conclude that these studies provide evidence of the discriminant validity of our models: They perform well when capturing attitudes toward entitative groups of humans, clearly defined by social category and identity. Based on the results of the police, it does not seem necessary that a clearly defined ingroup is present, as the models still performed well. On the other hand, these models do not perform well when the outgroup is less entitative and defined by an activity. The predictive models clearly performed poorly with regard to nonhuman mammals and objects, providing evidence that these are not models of attitudes more generally. Yet, rollerbladers and police differ from the social groups earlier in this article in a wide variety of ways, and exactly which of these group

Figure 5

Coefficients and Variance Explained From Models for Bias, Phase V



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

characteristics restrict the predictability of the models here remains unknown. Future research might map these specific boundary conditions more systematically.

Phase VI: Generalization

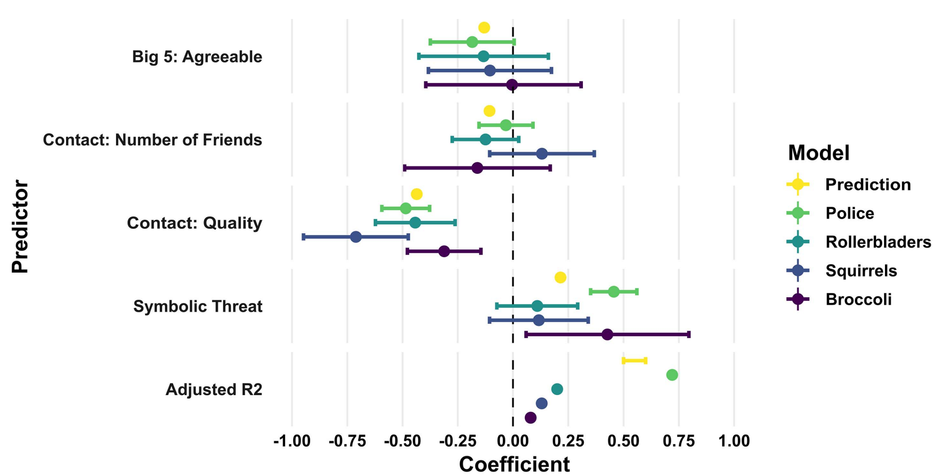
The studies to this point used online convenience samples from North America. Given that our aim is a generalizable and universal predictive model of prejudice, Phase VI tested the generalizability of the models in Studies 15–17. Study 15 examined a sample representative of the United States. Studies 16 and 17 tested the performance of the models in the United Kingdom and an Indian sample, respectively, with unique target groups. The method of data collection varied across studies and differed from those presented above.

Study 15: Prejudice Toward Gay People

A panel was collected through Cloud Research. The panel was specified to be representative of the United States by age, race, and political identification. Forty-six participants told us not to use their

Figure 6

Coefficients and Variance Explained From Models for Out-Group Attitudes, Phase V



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

data, and 76 were removed for failing an attention check. Individuals identifying as anything but heterosexual were removed (so these data are not representative by sexuality). This left 343 for analysis (M_{age} = 50.5, *SD* = 18.1, 48% women, 80% White, 9% Black, 4% First Nation, 3% East Asian, 2% South Asian, <1% Pacific Islander, 38% Democrat, 28% Republican, 38% Independent).

Study 16: Prejudice Toward Roma People

To target a sample from the United Kingdom, this study was conducted using Prolific. Five participants told us not to use their data, and four were removed for failing an attention check. Individuals identifying as White Gypsy or Roma were removed. This left 264 for analysis (M_{age} = 32.2, *SD* = 12.4, 58% women, 81% White, 9% South Asian, 8% East Asian, 3% Black).

Study 17: Prejudice Toward Muslim/Hindu People

To target a sample from India, this study was not run using Cloud Research but directly through Mechanical Turk, requiring that users were physically located in India. Because findings suggest that Mturk samples collected in India may have lesser data quality than those from the United States (Litman et al., 2015), we took additional measures to identify and exclude low-quality responses. Participants were removed for reasons that included those regularly used above: telling us not to use their data and failing an attention check. But in addition, we included a picture of a woman covering her eyes and asked participants to describe in a full sentence what had happened right before this photo was taken. Individuals were removed for not following the response instructions, displaying poor English language skills (suggesting they may not have understood the survey items), or providing canned responses unrelated to the photo (suggesting they may be a bot). Our rationale was that these responses called into question the validity of the answers provided on the rest of the survey. Ultimately, these exclusions removed a large number of participants (n = 212) and left 187 for analysis (M_{age} = 34.9, *SD* = 8.2, 29% women, 73% Hindu, 13% Christian, 6% Muslim, 1% other). Individuals identifying as any religion except Muslim answered questions about Muslims, but individuals identifying as Muslim answered questions about Hindus. This sample consists of English-speaking residents of India and is not representative. Nonetheless, we do interpret this sample as different culturally than any of those above, providing an important test of generalizability beyond Western samples.

Generally, results indicate that both predictive models perform well in representative samples from the United States and in two other countries. Notably, the model of Bias (Figure 7) explained the same percentage of variance in each culture, and the variables functioned in generally the same way. Always a measure of Contact, Identification, and Threat was significant (though which measure of Contact and Threat was stronger varied).

The Outgroup Attitudes model similarly performed well (Figure 8). The greatest deviation in these samples was Agreeableness, which was not significant in any model. We return to this issue in the General Discussion section.

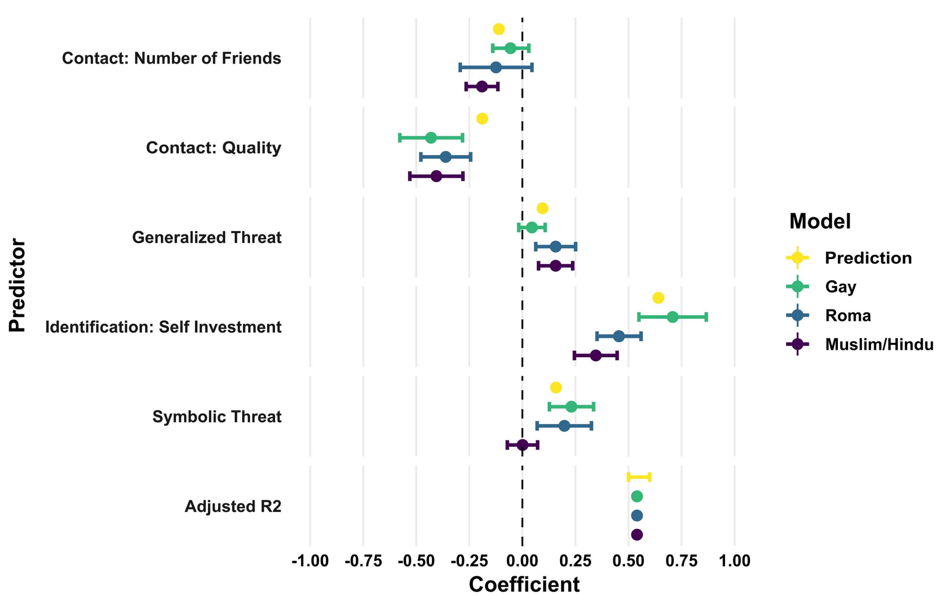
Overall, in the present research, our models performed well on convenience samples and representative samples of North America and two other distinct cultures (the United Kingdom and India). Of course, these cultures are far from representative of the global population, and falsification of these models in other cultures awaits further necessary testing.

Phase VII: Expert Survey

To what extent would the conclusions of our predictive model be anticipated by other experts in the science of prejudice? In our final

Figure 7

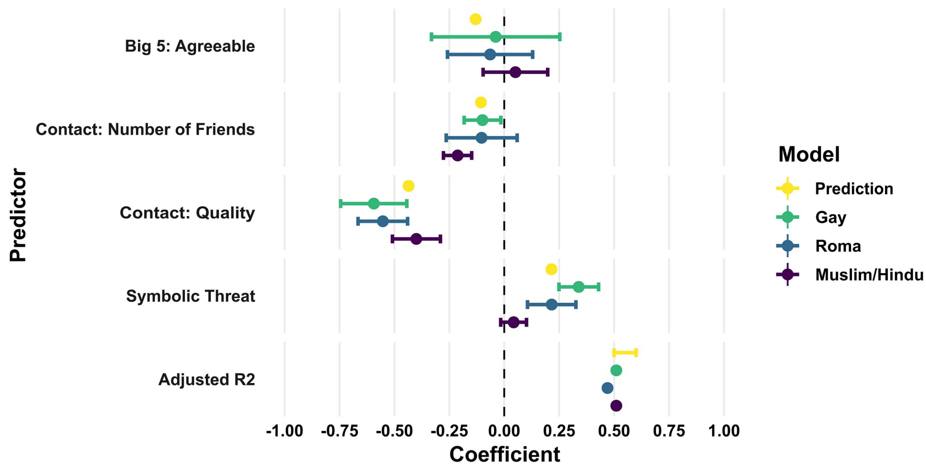
Coefficients and Variance Explained From Models for Bias, Phase VI



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

Figure 8

Coefficients and Variance Explained From Models for Out-Group Attitudes, Phase VI



Note. Error bars represent bootstrapped 95% confidence intervals around the estimate. See the online article for the color version of this figure.

phase, we assessed this directly. If our model is straightforwardly anticipated by experts, this provides one step toward more specific quantification of that consensus. And to the extent that our model is inconsistent with expert judgments—specifically, where the model suggests different variables are important or unimportant to predicting prejudice—this helps the field move forward, considering how best to integrate this model with prejudice experts' favored theories and beliefs. In this study, we asked experts to both nominate variables that would best predict prejudice and to rate the variables that we had included in our research on how strongly they would predict prejudice.

Method

Recruitment. We recruited participants with training or expertise in the science of prejudice, stereotyping, bias, stigma, intergroup relations, or related areas for a study of "psychological scientists' perceptions of what variables predict prejudice." Recruitment materials were posted on the primary and Group Processes & Intergroup Relations listservs of the Society for Personality and Social Psychology and on Twitter. Participants were required to have completed at least 1 year of graduate training in psychology, have an academic email address, and be at least 18 years old. Participants were compensated with a gift card equaling $20 USD to either https://amazon.com or a bookstore in their region.

Participants. Seven hundred eight eligible participants completed the study. To maintain anonymity, given that some combinations of identities may have identified participants (e.g., a Black woman professor with training in Psychology who graduated in 2008), we collected several items relating to career stage but only one composite item relating to whether participants identified as a member of a racial/ethnic minority group and/or sexual or gender minority group. Three hundred sixty-six participants (52%) were graduate students, 221 (31%) were faculty, 84 (12%) were postdocs, 11 (2%) were in a nonacademic position, and 26 (4%) were "other." Six hundred thirty participants (89%) said they had some graduate-level training in the science of prejudice, stereotypes, intergroup relations, or related areas. On average, participants indicated that they knew the literature on prejudice "somewhat" ($M = 3.23$, $SD = 1.01$) on a scale ranging from 1 = *I don't know the literature on prejudice at all* to 5 = *I know the literature on prejudice very well*. Three hundred thirty-one participants (47%) indicated they were a member of a racial or ethnic minority group and/or lesbian, gay, bisexual, transgender, queer, two-spirit, or another sexual or gender minority. Sample size changes slightly per analysis due to incomplete reporting.

Procedure. Participants first nominated up to 10 variables they would include in a model to best predict prejudice. Prejudice was defined as "an individual person's negative feelings toward a group or social category," and participants were instructed to consider prejudice toward any group or social category, across cultural contexts and historical periods. Participants were told to try to maximize the variance explained in prejudice; to only include variables that are conceptually distinct from prejudice; to assume resources and data collection are no barrier; to include any individual difference, target group, regional, or other variables; and to consider only linear predictors. After nominating their variables, participants rated how much they think each of those variables accounts for prejudice, with response options of 1 = *does not*, 2 = *weakly*, 3 = *moderately*, or 4 = *strongly* predicts prejudice.

Next, using the same 4-point scale, participants rated 31 variables from Phase I (Values Threat was excluded because of its close conceptual overlap with Symbolic Threat). Each variable was accompanied by a brief definition (e.g., "Agreeableness: being kind, trusting, generous, sympathetic, cooperative"). Participants then completed questions about their career stage and training and whether they identify as a member of a racial/ethnic and/or sexual/gender minority group.

Coding Variable Nominations. We coded all variables nominated by participants in the first part of the survey. After generating an initial coding scheme, we independently coded a small set of responses, compared our codes, and refined the coding scheme. After several rounds of this procedure, we independently coded the full set of nominated variables. We showed 86% agreement and resolved the remaining codes via discussion.

Our final scheme included codes for all variables from Phase I (with some variables collapsed across subfactors, e.g., there was one code for "Identification" rather than separate codes for Self-Definition and Self-Investment), a variety of other constructs that we had decided not to measure in the model for principled reasons (e.g., demographics, emotions), as well as new variables that had not been considered in our original model (e.g., personally being a target of prejudice, moral foundations). An "ambiguous" code was created for responses that we could not interpret or understand.

Results

Open-Ended Variable Nominations. Participants nominated a wide array of variables (see Table 7). Participants both nominated variables and then rated those variables' anticipated strength in predicting prejudice. However, we focus on the proportion of participants who nominated a variable, reasoning that if people mention a variable, they are likely to consider it important. There was a wide variety of responses across participants but some concordance with our models (see Figure 9). The four variables our models retained were each nominated by at least 15% of participants and were in the top eight most nominated variables. Notably, over 35% of participants nominated Contact. Furthermore, many of the other variables not retained in the models (Belief in a Just World, Need for Cognition, etc.), were mentioned by fewer than 10% of participants. However, of the variables we examined in our original models, participants most often nominated SDO (43%) and RWA (39%)—two variables that did not receive support for remaining in our final models. Substantial proportions of participants also nominated Openness (21%) and Religiosity (21%), two other variables not retained. Note that many participants also nominated a number of variables that we had a priori excluded due to their overlap with the construct of prejudice (e.g., emotions), their influence on prejudice through psychological

Table 7

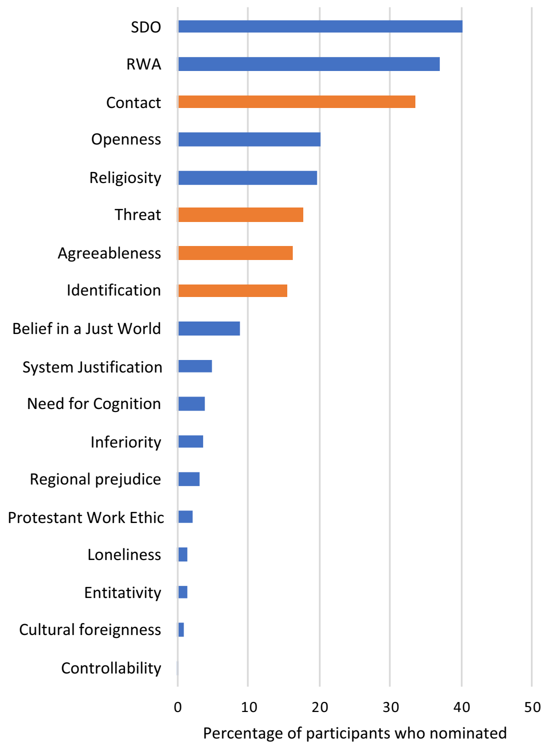
Nominated Variables From the Full Sample and Expert Faculty Subsample

Variable	Full sample (n = 668)		Expert faculty (n = 101)	
	Number of participants	Percent of sample	Number of participants	Percent of sample
Agreeableness	**115**	**17.2**	**19**	**18.8**
Ambiguous	236	35.3	25	24.8
Awareness	3	0.4	1	1.0
Belief in a Just World	63	9.4	8	7.9
Collective narcissism	13	1.9		0.0
Contact	**238**	**35.6**	**35**	**34.7**
Controllability	1	0.1		0.0
Demographics	443	66.3	61	60.4
Disgust sensitivity	15	2.2	1	1.0
Dogmatism	5	0.7	1	1.0
Emotion	46	6.9	10	9.9
Entitativity	9	1.3	2	2.0
Essentialism	19	2.8	6	5.9
Foreignness	7	1.0	2	2.0
Identification	**109**	**16.3**	**17**	**16.8**
Individualism–collectivism	8	1.2		0.0
Inferiority	25	3.7	2	2.0
Loneliness	10	1.5	2	2.0
Media	37	5.5	2	2.0
Moral foundations	7	1.0		0.0
Motivation	25	3.7	9	8.9
Need for Closure	60	9.0	17	16.8
Need for Cognition	27	4.0	2	2.0
New	220	32.9	30	29.7
Norms	67	10.0	13	12.9
Openness	143	21.4	21	20.8
Other	164	24.6	30	29.7
Personally being a target of prejudice	6	0.9		0.0
Political	244	36.5	39	38.6
Protestant Work Ethic	15	2.2	6	5.9
Regional prejudice	22	3.3	6	5.9
Religiosity	140	21.0	28	27.7
RWA	262	39.2	59	58.4
SDO	284	42.5	67	66.3
Socialization	39	5.8	6	5.9
Stereotype	60	9.0	12	11.9
Structural	109	16.3	15	14.9
System Justification	35	5.2	6	5.9
Threat	**126**	**18.9**	**34**	**33.7**

Note. Variables retained in our final models are in bold. RWA = Right-Wing Authoritarianism; SDO = Social Dominance Orientation.

Figure 9

Percentage of Participants in the Full Sample Who Nominated Each Variable From Phase I



Note. Variables retained in the final predictive models are in orange. SDO = Social Dominance Orientation; RWA = Right-Wing Authoritarianism. See the online article for the color version of this figure.

variables (e.g., demographics, political affiliation), or their difficulty in valid measurement via self-report (e.g., socialization).

The participant sample consists substantially of people relatively new to the field (i.e., graduate students) and includes many who professed only some or no familiarity with the prejudice literature. For a more stringent examination of expert nominations, we also calculated the responses of faculty members who stated they knew the literature on prejudice "moderately" or "very" well, given that these are likely to be the participants with the greatest familiarity with the prejudice literature, and who are most in a position to evaluate and shape this literature via their research, reviewing, teaching, and mentoring. These 101 expert faculty showed very similar responses to those of the full sample (see right-hand columns of Table 7). Contact, Agreeableness, and Identification were nominated at very similar rates to the full sample. The threat, on the other hand, was mentioned by nearly twice as many faculty experts (34%) as the rate in the whole sample (19%). SDO and RWA were nominated by an even greater proportion of expert faculty than the full sample—66% and 58%, respectively. Thus, despite some variations, the overall picture of the nominated variables is consistent across both the full sample and a subsample of expert faculty and shows both agreement and notable disagreement with our predictive model.

Variable Ratings. Next, we examined participant ratings of how strongly each variable we included in Phase I would predict prejudice (see Figure 10). Again, we see some concordance with our models. Both forms of Threat were rated as moderately to strongly predicting prejudice (between 3 and 4 on the 4-point scale). The two measures of Contact retained in our various models were rated as moderately predicting prejudice (between 2.5 and 3). Identification: Self-Investment and Agreeableness, each of which were retained in one model only, were rated as moderately and weakly to moderately predicting prejudice, respectively. However, consistent with the nominated variables and inconsistent with our models, facets of both SDO and RWA were rated as moderately or moderately to strongly predicting prejudice. Some other patterns are notable as well. For instance, negativity was rated as the facet of Contact that most strongly predicts prejudice, yet our models suggested that overall quality and number of friends are in fact the stronger predictors. In addition, participants expected that both regional explicit prejudice and inferiority would moderately strongly predict prejudice, yet neither was retained in our models. The results for the expert faculty subsample were again highly consistent with those for the full sample (see Figure 10, Panel B).

Discussion

Overall, this expert sample identified Contact and Threat as relatively important predictors of prejudice, consistent with our predictive models. Identification and Agreeableness were also nominated and rated as predicting prejudice as well, although to a somewhat lesser extent (perhaps consistent with our finding that these two variables each appear in only one of our two predictive models). However, participants also frequently nominated several additional variables—especially SDO and RWA—as predictors of prejudice and rated them as strong predictors. This stands in contrast to our models, as our variable selection process indicated that these variables were not among the strongest predictors of prejudice. It is possible that in fact, despite these variables' importance for understanding some prejudices (as reflected in expert responses), these variables are not universal predictors of prejudice when we consider a wide array of target groups. Another possibility, as we discuss below, is that SDO and/or RWA operate on prejudice via the variables retained in our model, such as Contact and Threat.

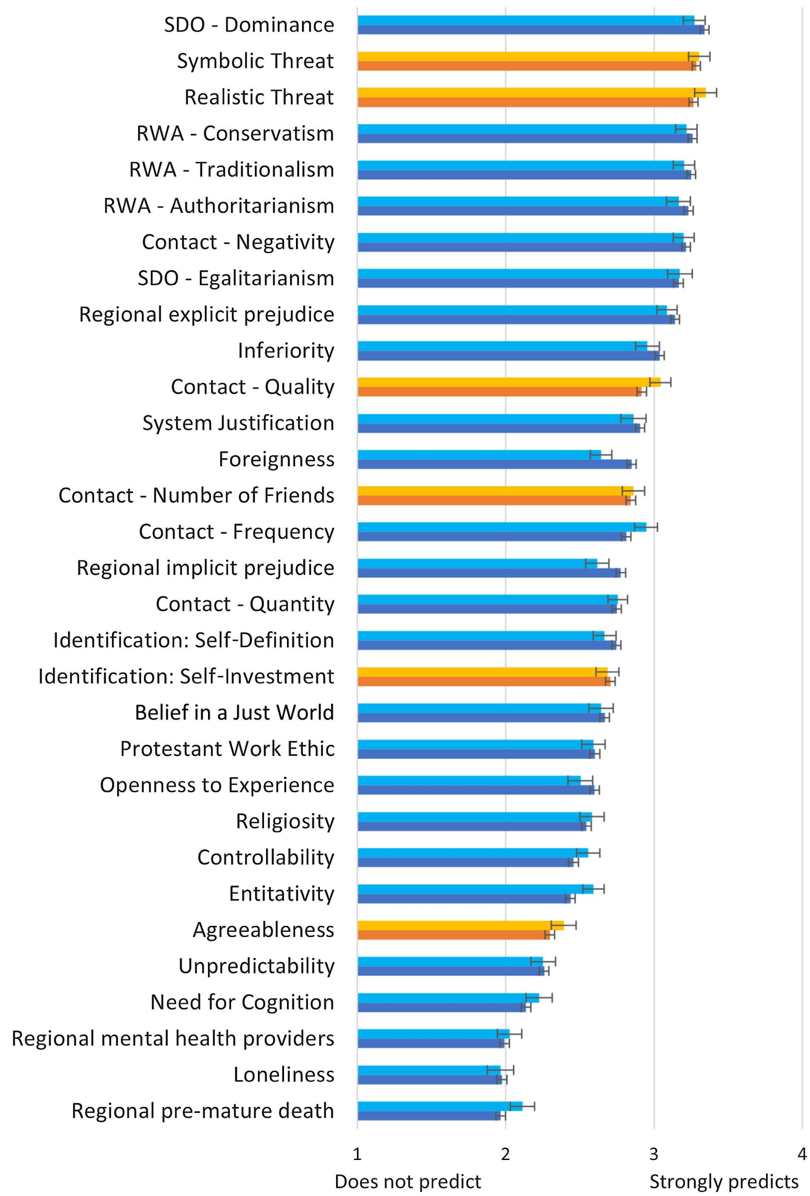
In addition, this study also provided an opportunity for us to examine whether there were variables that we could have considered or included initially, but did not, such as disgust sensitivity, essentialism, need for closure, collective narcissism, dogmatism, moral foundations, and individualism–collectivism. Each of these is, we believe, unlikely to account as substantially for universal prejudice as the variables in our predictive model. First, none of these were nominated by a substantial proportion of experts (no more than 10%). Second, the literature on some of these variables (e.g., individualism–collectivism) reveals them to be inconsistent or indirect predictors of prejudice. Third, we anticipate that some of these variables predict prejudice toward some groups, but not others (e.g., disgust sensitivity predicts prejudice toward some groups, but not others; Brandt & Crawford, 2020). That said, whether one or more of these variables deserves a place in a predictive model of prejudice is an empirical question that future research can address.

General Discussion

Over the past 80 years, numerous theories of prejudice advanced our understanding of prejudice. These theories have largely been

Figure 10

Rated Strength of Predictors of Prejudice Among the Full Sample (n = 668, Top Lighter Colors) and Expert Faculty (n = 115, Bottom Darker Colors)



Note. Variables retained in the final predictive models are in orange. SDO = Social Dominance Orientation; RWA = Right-Wing Authoritarianism. See the online article for the color version of this figure.

verbal and not often quantitatively precise in their predictions. Because these theories did not specify how much of an increase in prejudice was expected when a predictor increased, predictions from these models were vague and could apply to a very wide range of effects, essentially only testing whether an effect was different than zero. A theory is considered strong to the extent that it makes precise predictions (Lewandowsky & Farrell, 2010; Meehl, 1990), and by the criteria for theory evaluation, these theories are considered weak. It is difficult to falsify a theory when any magnitude of an effect other than zero could be taken as evidence for the theory. Over the past decades, there have been numerous calls to improve theory quality in psychology (Grahek et al., 2021; Meehl, 1978; Oberauer & Lewandowsky, 2019). Yet due to the reliance on verbal theories with vaguely specified predictions, it has been difficult to move forward (Meehl, 1978). In addition, these theories have together identified a wide array of variables predicting prejudice, and thus, it was unknown whether all these predictors are equally important for predicting prejudice. The present research is an attempt to improve the specificity of prejudice theory. We describe a model of the necessary ingredients, their amounts, and how to combine them. By the criteria of theory evaluation, the models presented here are stronger than previous models, easily falsifiable, and hopefully will improve the strength of prejudice theory.

Our process of identifying a predictive model of prejudice identified three, possibly four essential constructs (discussed further below). Though 32 measures were initially included in the elastic net regularization models, the constructs that were ultimately retained in both models—Contact and Threat—have received a great deal of research scrutiny. We take an optimistic view of this pattern, as many scientists have independently arrived at the strongest predictors of prejudice, providing converging evidence for our models. The Bias model also included Identification: Self-Investment, and the Outgroup Attitudes model also included Agreeableness, which we discuss further below.

Thus, conceptually, our models of Bias and Outgroup Attitudes are:

$$\text{Bias} = \text{Threat} - \text{Contact} + \text{Identification}_{\text{Self-Investment}}. \quad (3)$$

$$\text{Outgroup Attitudes} = \text{Threat} - \text{Contact} - \text{Agreeableness}. \quad (4)$$

But to further develop the models, we weighted all relevant studies in the present work by their sample size to calculate specific parameter estimates. We note that for each model, the parameter estimates are extremely similar to those calculated at the end of Phase II, but now additionally encompass data from seven more studies and ~2,000 more participants to increase their precision.

$$\begin{aligned}\text{Bias} = \beta_0 &+ .120(\text{Threat}_{\text{generalized}}) + .173(\text{Threat}_{\text{symbolic}}) \\ &- .209(\text{Contact}_{\text{quality}}) - .119(\text{Contact}_{\text{number}}) \\ &+ .523(\text{Identification}_{\text{Self-Investment}}) + \varepsilon. \quad (5)\end{aligned}$$

$$\begin{aligned}\text{Out-group attitudes} = \beta_0 &+ .243(\text{Threat}_{\text{symbolic}}) \\ &- .462(\text{Contact}_{\text{quality}}) \\ &- .119(\text{Contact}_{\text{number}}) \\ &- .128(\text{Big }5_{\text{Agreeableness}}) + \varepsilon. \quad (6)\end{aligned}$$

Note that these parameters are standardized to maximize generalizability.[1] Below, we discuss each of these constructs and their role in prejudice.

Final Model Constructs

Threat

The Threat has long been a theoretical and empirical focus in intergroup relations. Classic studies of intergroup conflict identified perceived threats as an important component of prejudice development (Sherif et al., 1961). In the intervening decades, numerous variants of the threat construct have been proposed, with specific predictions about how and when different threats will lead to prejudice. For example, a Realistic Threat reflects concerns for one's physical well-being and resources, while a Symbolic Threat taps concerns for one's values (Stephan & Stephan, 2000). And what threats another might pose to a person, exactly, depends on context, role in society, and one's goals (Cottrell & Neuberg, 2005; Lassetter et al., 2021; Neuberg et al., 2011).

In the present research, we initially included several operationalizations of threat: a more generalized version of Threat we called Generalized Threat, Symbolic Threat, and a measure of Values Threat. Despite all these scales measuring threat-related constructs, the regularization selection technique suggested retaining all three of them, which indicates that their relationships with Bias and Outgroup Attitudes are to some extent distinct. Like the different measures of contact, the two final measures of Threat retained in the predictive model varied somewhat in their performance across the various studies. While clear that Threat is an important predictor of prejudice, it is less clear from our models why Symbolic Threat might be particularly predictive with regard to one outgroup, Generalized Threat with another outgroup, and both important for another outgroup. Thus, we recommend that some measure of Threat is included in every model of prejudice but expect that this construct will have a stronger predictive ability to the extent that it is a type of threat relevant to the individual experiencing prejudice, the outgroup, and the context.

This pattern across our studies fits nicely with some approaches to threat, which posit that different groups present different threats (Cottrell & Neuberg, 2005). Such approaches would argue that the idea of "threat" is in fact a multifaceted collection of beliefs about the different ways that people can hurt our goals and needs (Neel & Lassetter, 2019; Pirlott & Cook, 2018; Schaller & Neuberg, 2012). Distinctions among different forms of threat may be important for precisely predicting prejudice toward any particular group, as people who feel vulnerable to specific threats (e.g., who are generally worried about their physical safety) or who are in situations that make those concerns salient (e.g., walking down a dark street alone at night) would be especially likely to be prejudiced toward groups seen to pose only relevant threats (e.g., groups stereotyped as dangerous), but not groups seen to pose other threats (e.g., groups stereotyped as wanting to educate children with values different from one's own; Schaller & Neuberg, 2012). Future research can better determine exactly how and why specific operationalizations of threat might perform better or worse in future iterations of a predictive model of prejudice.

Intergroup Contact

Another very consistent predictor of prejudice was Contact. Like Threat, Contact has been studied extensively since the beginning of social psychology (Allport, 1954). It is the construct with perhaps the strongest evidence for a negative relationship with prejudice ever identified by the social sciences (Hewstone & Swart, 2011; Pettigrew, 1997; Pettigrew & Tropp, 2006; Tropp & Pettigrew, 2005), with some evidence of causality (Corno et al., 2022; Mousa, 2020; Van Laar et al., 2005). In a meta-analysis, Pettigrew and Tropp (2006) estimated the effect of Contact on prejudice to be $r = -.21$, an estimate we note is quite similar to our estimates of Contact in the predictive models. Contact has traditionally been a difficult construct to measure, as most researchers believe that Contact consists of both quantity and quality of relationships with members of other groups. Researchers have measured it in various ways, including frequency of contact, quantity of friendships, proximity in

[1] The β_0 intercepts are not particularly meaningful here and will likely change across different target social groups. Because intercepts are the expected values of the dependent variable when all independent variables are zero, should researchers center these predictors, the intercept would represent the level of prejudice expected when individuals hold the (sample) average level of all the predictors.

living, coworkers, quality of contact, frequency of interactions, and indirect connections (Hässler et al., 2020; Pettigrew, 1997; Pettigrew & Tropp, 2006).

The present research tested the quantity of contact, quality, absence of negative interactions, number of outgroup friends, and frequency of meeting outgroup friends in the original regularization model. Yet only two measures consistently predicted prejudice across all models: one's number of outgroup friends and the rated quality of outgroup contact. However, exactly which variable was predictive in which model changed regularly across the studies. Thus, while we conclude that it is clear that Contact should be involved in any model of prejudice in some way, the exact way that Contact might be operationalized might depend on other unknown factors.

Separately, a concern with "rated quality of outgroup contact" is it suffers some overlap with prejudice. That is, rating one's contact quality with outgroup members may actually be another measure of prejudice. As outlined in the introduction, to include a predictor that indexes prejudice would be to misestimate the other relationships in the model. We have opted to maintain this measure of contact for a few reasons. First, methodologically, the coefficient for this construct is not always the largest in the model. For example, it is only −.209 in the Bias model, relative to .523 for Identification. Should this measure actually be tapping prejudice directly, we might expect this coefficient to be larger. Second, this is a popular and very commonly used item in the contact literature, seemingly believed by the majority of the field to be distinct from prejudice. Accordingly, we have maintained it in the model but believe that future research should more closely examine this measure of contact to ensure it is distinct from prejudice.

Identification: Self-Investment

When prejudice was operationalized as Bias, we found Identification: Self-Investment to be the strongest overall predictor. It is worth noting that this relationship is particularly large, several times larger than any other effect in the models. Self-Investment is only one part of the overall identification model (Leach et al., 2008) and itself has three subcomponents. These are Satisfaction, or positive feelings about the group and one's membership in it; Solidarity, a psychological bond and commitment to fellow group members; and Centrality, the salience and importance of identification to the self-concept. We did not find the other major subfactor, Self-Definition, to have any consistent relationship with either operationalization of prejudice. In and of itself, we believe that distinguishing Identification: Self-Investment as the largest contributor to Bias to be a valuable contribution of the present research and an advantage of a predictive model of prejudice. Results from the expert survey reveal that this was not expected, on average, across experts in the field.

Despite the large relationship with Bias, Self-Investment was not retained in the Outgroup Attitudes model. We believe conceptually separating Bias into the components of "ingroup love" and "outgroup hate" helps to explain this pattern (Brewer, 1999). Individuals highly identifying with the ingroup do not necessarily dislike the outgroup more but do like the ingroup more. Because Bias was operationalized as a difference score, this results in a higher level of Bias.

Agreeableness

We believe Agreeableness, included in the final predictive model of Outgroup Attitudes, to be a somewhat special case. Agreeableness was retained in the final models because it met our defined criteria for inclusion. And replicating some recent research (Crawford & Brandt, 2019) results indicate unambiguously that including Agreeableness in models of Outgroup Attitudes results in more variance explained. Yet, it is not clear whether it is an actual upstream causal predictor of prejudice in the same way the other variables are theorized to be. We see two possibilities, both of which have at least some evidence in the literature.

First, individuals who score higher in Agreeableness may just like other people more and therefore have more positive attitudes toward individuals from other groups. We note, however, that Agreeableness was not retained in the predictive model of Bias. If individuals scoring higher in Agreeableness rate everyone more positively, then because Bias is operationalized as a difference score, these higher ratings would cancel themselves out, leaving Agreeableness unassociated with Bias.

However, another possibility is that Agreeableness is capturing responding in ways that are more socially desirable. Norm-based models of prejudice expression (Crandall et al., 2002) theorize that individuals vary in their motivation to comply with prejudice expression norms. These individuals would express less prejudice toward groups for whom it is considered unacceptable to express prejudice but to express *more* prejudice toward those groups toward whom it is acceptable to express prejudice. A close look at Tables 4 and 5 shows that whereas Agreeableness predicts lower Bias and Outgroup Attitudes toward immigrants, Agreeableness has no relationship to Outgroup Attitudes toward upper-class people, and *stronger* Bias toward upper-class people.

Consistent with this perspective, Agreeableness also performed poorly in Phase V with boundary condition models examining attitudes toward police, rollerbladers, squirrels, and broccoli. How acceptable it is to express prejudice toward these groups is likely more ambiguous than toward groups traditionally studied by social science researchers, such as Black, gay, or transgender people. Ultimately, while evidence indicates that Agreeableness is a useful predictor to measure and include in models of prejudice, whether it is better conceived of as a "genuine" cause of prejudice or better described as the suppression or justification of prejudice (Crandall et al., 2002) can be more stringently examined by future work.

Consideration of Causality

Readers may note that the design and statistical approach in the present work alone do not allow for causal conclusions by themselves, and it is important to explicitly acknowledge that our models are predictive and not causal. But at the same time, we advocate that these predictive models *can* be used to inform causal theoretical models and explanations of prejudice (Hofman et al., 2017). Our goal was not to simply maximize prediction, and we purposely excluded variables that would have increased our predictive power but decreased generalizability or interpretability (e.g., latitude, demographics). Further, and critically, we constrained our pool of constructs based on theory, to those that the field argues cause prejudice. We believe there is good evidence that both Contact and Threat cause prejudice. In addition, we believe it is inconsistent with the theory that prejudice temporally precedes personality variables (e.g., Agreeableness). While we argue that prediction is important to the science of prejudice (Yarkoni & Westfall, 2017), of course understanding the causes of prejudice is an equally important goal that can be informed by and in turn inform predictive models. Indeed, some have argued that the sharp distinctions between explanation and prediction are illusory and unnecessary, each able to inform the other (Hofman et al., 2017, 2021). Consistent with this view, we believe the current predictive models can help prioritize the potential causal effects of prejudice investigated and quantify their roles with different causal designs. Further, it is certainly possible that prejudice may in some way itself cause the independent variables identified here (i.e., bidirectional relationships), but this is not inconsistent with our results and does not invalidate our conclusions. Future research with different designs can determine to what extent this may be the case.

Variables Not Included

Many constructs identified by our literature search ultimately were not retained in our models. Yet previous research has posited and regularly provided evidence that these constructs are associated with prejudice. How to reconcile this discrepancy? One explanation may be social scientists' tendency to focus on prejudices toward historically marginalized groups. These are the groups toward which individuals further on the right of the ideological spectrum show more prejudice, and liberals show less prejudice (Brandt & Crawford, 2020). Accordingly, many traditional predictors of prejudice are related to conservatism, such as a more rigid style of thinking. However, when examining the predictors of liberals' prejudice, correlates of liberalism instead emerge as predictive. We believe this is why there are many published articles finding links with constructs not identified in the present work and why many of the experts, familiar with the literature, identified these constructs in Phase VII. Yet because these constructs do not consistently predict prejudice toward targets across the ideological spectrum, they are not part of a "universal" model of prejudice.

A second possibility is the "distance" between prejudice and these independent variables. Any variance explained procedure for model selection will prioritize more proximate variables over other variables that exert influence further back in the causal chain. Some factors that have been identified as important to understanding prejudice may operate via other variables that are causally more proximate to prejudice (i.e., indirect effects). For example, SDO has been shown in past literature to reliably predict prejudice (Pratto et al., 1994). If SDO produces prejudice via increased perceptions of threat and lower outgroup contact, for example, this could explain why it was not predictive of prejudice in our model yet continues to emerge in the literature as an important factor.

Given that other constructs not selected by our models may very likely be involved in the causal pathway of prejudice, a useful next step may be to identify predictive models of the constructs involved in the predictive models of prejudice. A successful cookie recipe hinges on a suitable sugar recipe, just as a strong sugar recipe hinges on sugar cane (or sugar beet) production. As researchers move backward in the causal chain, a full understanding of the Threat, Contact, Identification, and Agreeableness constructs will allow for mapping a developmental trajectory of prejudice.

A similar conceptual issue is present with the types of variables that most successfully predicted prejudice. For example, no measures of the context in which individuals lived were ultimately retained in the models (e.g., the average explicit bias of the region). We believe this is consistent with the theory and the proximate arguments laid out above. Characteristics measured directly from an individual are likely to have a stronger association with that same individual's prejudice than characteristics measured at the more distal level of one's region. Hence, while we considered it important to allow for the possibility that regional characteristics might predict individual prejudice beyond individual characteristics, characteristics of regions should be better predictors of regional outcomes than individual outcomes. And though they may indeed exert an effect on the attitudes of those in the region, these effects are likely smaller and indirect. Specifying the mechanisms by which regional, structural, or other macro factors may influence individual prejudice would be a valuable undertaking and potentially allow for linkage between those more distal factors and the more proximate predictors favored in our model. Further, it may allow for more connections with other fields of social science, such as economics or sociology.

Finally, constructs may have been dropped from the predictive models purely for measurement or methodological reasons. For example, a construct might be strongly related *in truth* to prejudice but dropped in Phases I and II because of a high amount of error included in its measurement. Only research improving the measurement of such constructs could address this concern in the future. Similarly, for model selection, we used elastic net regularization in Phase I and examined coefficients and *p* values in Phase II. Researchers using different criteria may arrive at a slightly different set of constructs. Future work can test to what extent our results are robust to such methodological decisions (and use our publicly available data to do so).

Emotions

Given that prejudice is affective, and sometimes even operationalized as specific emotions, we a priori excluded all emotions as predictors in our model of prejudice. Instead, we explored anger and disgust as potential alternative operationalizations of prejudice when testing the generalizability of the model. Notably, our model did not as robustly predict anger and disgust as it did the other measures of prejudice. Given some perspectives on emotions and prejudice, such as the threat-specific one described above (Cottrell & Neuberg, 2005), this is perhaps not surprising. This view argues that prejudice toward different groups will be colored by different, specific emotions that correspond to the threats each group is perceived to pose. People feel any number of emotions toward outgroups, including fear of groups perceived to be dangerous, pity of groups seen as unable to contribute their fair share, anxiety about groups that may behave erratically, and so forth. Thus, although anger and disgust feature prominently in many forms of prejudice, they are unlikely to serve as a universal stand-in for general negative feelings toward a group. Because different predictors may lead to each of these different emotions, future work may profitably model the predictors that contribute to different prejudicial emotions and examine the extent to which these predictors are consistent across emotions versus emotion-specific.

Improving the Model

The models explain roughly 45%–65% of the variance. For a model in the social sciences, this is quite successful. Yet other fields with longer modeling traditions would consider this a poor model: There remains 35%–55% of variance unexplained. Other researchers may agree this model is limited, believe other ingredients should be included, or suggest other ways of combining the ingredients. We certainly hope this will be the case, as doing so will advance the science of prejudice. We have named our model Prejudice Model 1.0, following sequence-based software versioning norms, in hopes of facilitating cohesion and communication across the field. In this tradition, version numbers are assigned in increasing order to correspond to the magnitude of new developments as researchers improve the models in minor ways. For example, Model 1.01 might explain <10% more variance than Model 1.0, whereas Model 2.0 might explain >10% more variance. Below, we lay out some steps for improving the model. We encourage a model comparison approach, in which other researchers might develop a new model, compare it to previous versions of the model, and demonstrate that it explains a larger percentage of variance in prejudice to warrant a new version.

Adding Constructs

For researchers who wish to add constructs to improve the model's variance explained, we recommend a two-step process. First, researchers must confirm that their proposed new construct is fully distinct from Threat, Contact, Identification, and Agreeableness, using an approach such as a confirmatory factor analysis in a structural equation modeling framework. To include a construct that has some redundancy with the other constructs would be to muddy the interpretation of the model, as the unique variance explained by those constructs in prejudice would be shared.

Second, researchers should collect data on measures capturing all these constructs, both those in our predictive model and their new proposed constructs. Should all these constructs show a satisfactory fit in a measurement model, this would be some evidence that the researchers are, in fact, capturing the constructs they intended. They would next include these variables in some sort of regression model. If the new proposed construct explains additional variance above and beyond the constructs in our models here, this would provide evidence for an improved model. Importantly, this model would have to improve fit for prejudice toward multiple types of groups in order to be considered part of a "universal" model of prejudice, rather than one that is specific to a limited group.

For example, though regularly correlated with some types of prejudice, we did not include a measure of political ideology in our initial pool of variables, both because it could be considered demographic and because it corresponds highly with SDO and RWA (Altemeyer, 1988). We also excluded demographic variables that may predict prejudice, presuming that any important demographic variables will operate on prejudice via psychological variables. Yet other researchers might reasonably disagree with these decisions and could test whether another measure of political ideology or a measure of other demographic variables contributes to the variance explained above and beyond the rest of the model.

Replacing Constructs

An important assumption of the present work is that we are measuring what we think we are measuring. For example, future research may reveal that our measure of what we (and the field) are calling "Contact" is actually assessing a different variable and prompting a refined definition of the construct measured in our model. Or, future research may suggest that a more focused measure of that new construct would replace Contact entirely and thereby improve the model.

Similarly, some of the constructs included might be broad umbrella variables, and honing the constructs may improve prediction. For example, Agreeableness is a personality construct from the Big Five that some have argued contains six facets: trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness (Costa & McCrae, 1995). While the superordinate construct of Agreeableness might predict prejudice, one testable possibility is that one or more of these specific facets is responsible for this link with prejudice, and identifying that facet can improve the overall variance explained.

Changing the Relationships Among Constructs

As a starting point, we adopted perhaps the simplest way of combining the constructs in the present work: adding them together. However, these assumed additive and linear relationships may oversimplify the true relationship of these predictors to prejudice. For example, it is possible that relationships we have restricted to being linear are in fact curvilinear and that when the relationships between prejudice and these constructs are modeled in a curvilinear way, greater variance in prejudice is explained. For example, a recent formal model of cross-group friendship convincingly argues that the relationship between $\text{Contact}_{\text{number}}$ and prejudice is logarithmic (Page-Gould et al., 2022). Other nonlinear relationships are also possible.

Alternatively, for similar reasons, we did not allow for interactions between constructs. Allowing for interactions between the constructs we identify here and/or others might explain additional variance in prejudice and more accurately model the process that produces prejudice, but this would not invalidate the present work. Our models consistently explain between 45% and 65% of the variance, and we note that this will not decrease even if nonlinear or interactive effects are discovered. In fact, the percentage of variance explained places boundaries on just how much of prejudice might be explained by interactions. Given that these linear main effects are explaining up to 65% of the variance in prejudice, interactions are likely to explain less than that. With an assumption that a perfect model of prejudice is unlikely and that measurement error is 10%, this would indicate that interactions could maximally comprise 25%–35% of the variance in prejudice. Relaxing and testing some of these assumptions can improve the models overall and so improve understanding of prejudice, and we encourage future research to test these possibilities.

Creating Models for Specific Groups

The present research aimed to identify a universal model of prejudice, and the first step is to identify a model whose components would apply equally well across all groups. However, there may be researchers who are very specifically interested in explaining the most variance in prejudice toward a specific group. Should that be the case, it is very likely that adding other variables that are specific to that group would improve the overall model. For example, in Phase II: Study 5, Entitativity played a larger role in explaining variance in prejudice toward transgender people. While we did not observe this effect toward other groups and therefore do not consider it as a part of the universal model, it is possible that Entitativity is an important factor in attitudes toward transgender people. Similarly, SDO is a construct that has been strongly implicated in attitudes toward lower status groups. Researchers interested in specific groups could further explore the role of other group-specific constructs to best explain variation in attitudes. The present work can serve as a useful "base recipe" that researchers can tailor further for specific aims.

Attitude–Behavior Links

We have developed two predictive models of prejudice in the present research. We note that many social scientists are interested in prejudice for its theorized relationship to behaviors like hate crimes or other discriminatory behaviors. Yet the present research does not examine links with behavior (e.g., discrimination). Therefore, it offers no evidence of predictive validity, and in general, some research indicates that measures of prejudice only poorly explain behavior (Greenwald et al., 2009; Kurdi et al., 2019; Oswald et al., 2013, 2015). We do note, however, that the current work reflects the state of the field. To the extent that the social psychological literature has identified constructs that predict prejudice and that prejudice predicts behavioral outcomes, we believe our model will do so as well.

One critique of the present work is to be skeptical of a concept of "universal" prejudice attitude, instead arguing that numerous "types" of prejudice exist. Evidence supporting this idea would be that not all negative attitudes translate into discriminatory or biased behavior in the same way (e.g., Cuddy et al., 2007; Schaller & Neuberg, 2012). Yet our models regularly explain 45%–65% of the variance in prejudice across a wide variety of groups. We note that our constructs have purposely been operationalized in relatively generic ways—including "prejudice" and "threat"—which each may capture what are in fact an array of constructs when measured this way (e.g., feeling anxiety, fear, anger, or disgust may all contribute to ratings of prejudice, and seeing a group as a threat to one's health, safety, values, or freedoms may all contribute to ratings of threat). Construct validation is a continually ongoing process (Cronbach & Meehl, 1955; Loevinger, 1957), and it will be important for future research to continue to validate both the predictive models here on behaviors of consequence.

Limitations

In addition to the limitations of our relatively primitive predictive models laid out above, the current approach is also limited to making predictions of prejudice as an output of several input features. The model does not speak to the cognitive processes underlying how the mind encodes Contact or Threat and how these processes vary depending upon the Identification or Agreeableness of the mind. In other words, while these models are predictive, they are not mechanistic and do not speak to process. An important future direction would be to incorporate such intervening steps (e.g., Gershman & Cikara, 2020; Pietraszewski, 2022).

In several places, we have referred to trying to build toward a universal model of prejudice. We believe we are far from this point. This hinges on whether there was sufficient variation in the prejudice and situations of our respondents. For example, all the participants in these tests live in relatively peaceful societies, in which intergroup harmony is often considered desirable. Would the model hold for individuals engaging in ongoing, violent conflict with other groups? Will it hold for prejudices in other very different cultural contexts? The full space of prejudice and conflict has not been sampled, and therefore, it is possible that important predictors are missing (Jolly & Chang, 2019). This critique would apply to most psychological research on prejudice, but nonetheless, future work might examine how this model performs in high-conflict settings (among others). Currently, a conservative interpretation would be to consider it a predictive model of explicitly expressed contemporary prejudice in relatively peaceful societies.

Finally, some of our statistical assumptions also serve as potential limitations to the generalizability of the model to future samples. Future researchers might wish to use different measures of our predictors (e.g., to assess Symbolic Threat). Hence, we chose to standardize variables such that the coefficient weights applied to our theoretical constructs would be more likely to be independent of these measurement choices. However, should a future sample obtain very different distributions of values, it is unlikely the coefficient for that variable would be the same as in the predictive models laid out above. As a concrete example, perceptions of Symbolic Threat were normally distributed in the samples included here. Should a future sample be collected in which perceptions of Symbolic Threat were dramatically left skewed, it is less likely that the linear relationship between Symbolic Threat and Bias would be .173. Therefore, an important assumption of this model is that the distribution of constructs in future samples resembles those of the samples in the present work. The extent to which this assumption is reasonable can be tested further.

Conclusion

The scientific understanding of prejudice has made important theoretical and empirical advances since the early 20th century. Like many fields of science, it has progressed from initial description to increasingly sophisticated theories. The vast majority of these theories are verbal and are considered "weak" theoretical models in that their predictions are imprecise. We believe it is now time to transition to the next phase of prejudice research, with "stronger" theoretical models making more precise and falsifiable predictions and systematic incremental improvement of subsequent models. The present research is a step in that direction. By distilling the science of prejudice into an empirically derived predictive model, we hope to provide a solid initial foundation on which future research can build.

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