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Analytic Racecraft: Race-Based Averages Create Illusory Group Differences in Perceptions of Racism

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Research practices used by social scientists to understand and dismantle the psychological foundations that uphold racist hierarchies can backfire when they rely on racecraft. Racecraft ideology assumes the reality of race(s), an assumption that shapes study designs and inferences to the detriment of theoretical and practical goals. I showcase how racecraft manifests in studies seeking to quantify how perceptions of sociopolitical stimuli differ across racialized perceivers (e.g., black, white, latinx). The typical analysis for quantifying perceptions focuses on comparing group averages, which assumes the existence of discrete “races” whose perceptions can be sufficiently summarized by averages. Across three studies, I used variance component analyses on racism ratings of anti-immigrant tweets from differently racialized perceivers (N = 1,211) to show there was much larger disagreement than agreement within race categories, even when there were average differences in perceptions across race categories. This analysis shows how analytic practices can bolster different assumptions about the nature of race, some of which reify the illusion that race categories *are* stable cohesive groups. Researchers can improve their analytic inferences and avoid producing race-reifying caricatures of peoples’ perceptions by adding variance mapping to their toolkits and attending to racialization as a dynamic process—needed improvements within the psychological study of race and racism, group-based beliefs, and antiracist research endeavors.

Public Significance Statement

“Racial” group differences in beliefs and perceptions are often examined by comparing race category averages. I argue that this exclusive analytic focus on averages is produced by and reproduces the illusion that race categories are real psychologically discrete groups. This study shows how quantifying and mapping heterogeneity is a better *default* analysis for understanding how racialized people idiosyncratically or consensually perceive discriminatory events.

Keywords: racist discourse, immigrants, disagreement, racecraft, variance component analysis

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Quantitative social scientists have been interested in measuring how people construe racist events to better understand the psychological foundations that uphold racist hierarchies (Jefferson et al., 2020; T. E. Nelson et al., 2007; Norton & Sommers, 2011; Reinka & Leach, 2017). One important line of research has examined what or who is considered racist in the first place (Hudson & Esses, 2005; Liao et al., 2016; J. C. Nelson et al., 2013; Rasmussen et al., 2022; Rucker et al., 2019). The term “racist” itself is a moralized label that marks people or events as unacceptable (Doane, 2006), which is one reason many people avoid discussions of race and racism (Apfelbaum et al., 2008). How the term “racist” is deployed (or not) as a label offers a window into how people (a) are defining racism so that it can be perceived or occluded from view (Bonilla-Silva, 2006; Rucker & Richeson, 2021), (b) come to *know* and name experiences

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The theoretical arguments in this article are a continuation of ideas first developed in (Cikara et al., 2022; Martinez, 2023), and the analytic technique was validated in (Martinez et al., 2020). The specific studies in this article have been presented at various conferences and invited talks. Supplemental materials, data, and analysis scripts can be found at the OSF archive at https://osf.io/v2cey/?view_only=69a1bebeaf684236ad3a6ddc08d263ef. A preprint was posted to PsyArxiv at https://psyarxiv.com/kfpjg.

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of racism (Dotson, 2014), and (c) socially position themselves in relation to events considered racist (Bucholtz & Hall, 2005). Estimates of people's perceptions of racist events, therefore, operate as "racial knowledge," (Goldberg, 2000) which shapes what race and racism are understood to be for the public and social scientists. This makes identifying best quantification practices of racism perceptions an important theoretical and practical need.

Social science often compares perceptions of racism among people who are themselves racialized, that is, they are classified by social scientists, themselves, or others into distinct race categories. Racialized people's perceptions are typically quantified by comparing statistical averages between race categories. For example, average numeric ratings that significantly differ between people who occupy different racial categories are used as evidence of race differences in perceptions. These aggregate analyses rely on two underlying assumptions: (a) Race categories reflect stable and bounded social groups with collective psychologies (which presupposes *relatively* more within-category agreement than disagreement) and (b) a measure of what is shared between people (e.g., an average) sufficiently summarizes perceptions within a race category. However, in tension with both assumptions, scholarship has warned against the use of averages to study agreement as they can hide significant sources of heterogeneity (Kahneman et al., 2021; Marti et al., 2023; Martinez & Todorov, 2021; Martinez et al., 2020) and against racecraft (K. E. Fields & Fields, 2012).

The concept of racecraft helps clarify how "racism is not discrimination based on race. Rather, race is an ideology created to justify racism. Racism came first and race followed" (Torres, 2023, p. 125). Racism refers to "the practice of applying a social, civic, or legal double standard based on ancestry" (and other features used for racialization), and racecraft refers to "mental terrain and pervasive belief … racecraft originates not in nature but human action and imagination; it can exist no other way. The action and imagining are collective yet individual, day-to-day yet historical, and consequential even though nested in mundane routine … racecraft is not a euphemistic substitute for racism. It is a kind of fingerprint evidence that racism has been on the scene" (K. E. Fields & Fields, 2012, pp. 17–18). Specifically, racecraft is the ideological maneuvers that conjure and spread the illusion that races are real and explain social phenomena, akin to witchcraft's rationality that witches are real, and their magic cause social phenomena. Its causal logic shifts blame for inequality and discrimination from the racist practices that produced them to ostensible racial differences in genetics, traits, behaviors, etc—race is produced as the explanatory scapegoat for racism. Racecraft facilitates this by transforming "racism, something an aggressor *does*, into race, something the target *is*, in a sleight of hand that is easy to miss"[1] (K. E. Fields & Fields, 2012, p. 17). Worryingly, the resulting essentialization of race even occurs among scientists and scholars, and it has proven exceedingly difficult to dislodge race essentialist beliefs or communication, even among those who have been exposed to, or champion, social constructionist theories of race (Morning, 2007, 2011, 2014; Obasogie et al., 2015). One possibility for this stickiness is common research practices that propagate racecraft, which currently permeate many aspects of the scientific research process: theoretical foundations (Cikara et al., 2022; Hochman, 2017, 2021a; Loveman, 1999; Torrez et al., 2023), experimental design (Martinez, 2023), measurement and analysis (Benjamin, 2014; Helms et al., 2005; Rodríguez-Muñiz, 2021; Zuberi, 2000), and interpretation (Teo, 2011, 2022). Here, I characterize the existence of what I term "analytic racecraft," how racecraft manifests in the use of quantitative analytics or methods (such as average comparisons) that assume and/or produce the illusion that races *are* real social, biological, or demographic groupings.

To interrogate the validity of the two assumptions underlying comparative race analyses of racism perceptions, I study a rating task where average race differences in perceptions of racism could be expected (anti-immigrant discourse). I do so by comparing an analysis of averages against a novel method in perception studies, the variance component analysis (VCA; Hönekopp, 2006; Martinez et al., 2020). The VCA shifts focus from quantifying averages to quantifying *variation* within and across categories. This comparison enables us to ask: Do average race differences ensure larger within-category agreement than disagreement, and what can the answer tell us about how we should understand the nature and relation of race categories to racism perceptions? Throughout this article, I think through the assumptions about race each method produces or relies on, the inferential conclusions about group differences made possible by each method, and identify sources of (dis)agreement in perceptions of racism. I show how pairing variance component analyses with theorizations about race's illusory and dynamic nature can minimize the reification of race within quantitative analyses (i.e., analytic racecraft) and provide a better understanding of how perceptions of racism become socially patterned.

> *Assumption 1:* Lay perceptions of racism are clustered by "racial groups"

According to a Pew public poll, 61% of sampled U.S. Americans believe that Americans do not agree on what kind of language is considered racist (Pew Research Center, 2019). One heavily theorized source of disagreement is racial group membership (Carter & Murphy, 2015). Group-based theorizing highlights how one's group position in society should influence group members' perceptions (Blumer, 1958). For example, people who occupy the same race category are often discussed as sharing perspectives on racism (Blauner, 1999; Bobo, 1999), while the perspectives of people who occupy different race categories are theorized to diverge due to different knowledge of, experiences with, and relationships to racism (Adams et al., 2006; Carter & Murphy, 2015). These theories discuss how individuals classified as a particular race category within a hierarchical system share some common experiences, such that average differences in attitudes and judgments could be expected. Correspondingly, research shows that people who occupy

[1] Examples of racecraft's ideological maneuvers: "Consider the statement 'black Southerners were segregated because of their skin color'—a perfectly natural sentence to the ears of most Americans, who tend to overlook its weird causality. But in that sentence, segregation disappears as the doing of segregationists, and then, in a puff of smoke—paff—reappears as a trait of only one part of the segregated whole. In similar fashion, enslavers disappear only to reappear, disguised, in stories that append physical traits defined as slave-like to those enslaved" (K. E. Fields & Fields, 2012, p. 17). Similar transformations taint social scientific explanations of the conditions of illegalized immigrants where the consequences of racism and imperialism get portrayed as immigrant traits that circularly explain the consequences themselves: "Because undocumented immigrants are disproportionately poorly educated and low-skilled, as many as one third of them are concentrated in low-skill and low-wage service occupations" (Wang, 2012, p. 6).

different racial categories on average consider different phenomena as racist (Sommers & Norton, 2006) and perceive discrimination at different rates (Norton & Sommers, 2011), especially if they identify strongly with their ascribed race classification (Kaiser & Wilkins, 2010; Operario & Fiske, 2001; Sellers & Shelton, 2003).

However, the transition from shared experiences or categories to shared perceptions may not be so straightforward (McGuffey, 2018). It is possible that the theoretical focus on "group"' differences can facilitate statistical analyses that prevent an exploration of whether it is in fact the case that people within race categories share perceptions of concepts like racism to a meaningfully greater degree compared to other social cleavages (Brubaker, 2009; Cikara, 2021; Cikara et al., 2022). It is important from a normative and an empirical standpoint to acknowledge that race categories (a) can be unstably imposed on or adopted by people (Loveman, 1999; Richeson & Sommers, 2016; Sen & Wasow, 2016); (b) analytically confound dimensions such as identity, classification, or ancestry (B. J. Fields, 2001; Roth, 2016; Sen & Wasow, 2016); (c) are internally heterogeneous (Crenshaw, 1991; Sellers & Shelton, 2003; Wimmer, 2015; Zuckerman, 1990); and (d) are produced and maintained *by* racism as its core ideology for manufacturing oppressive double standards (K. E. Fields & Fields, 2012; Golash-Boza, 2016).

Inferring beliefs from a socially, economically, and politically determined classification is a practice that has been criticized for neglecting to check whether and how group- or consensus-forming processes are occurring among individuals who share a classification (Calnitsky & Billeaux Martinez, 2023; Lee, 2008). This has been called the *fallacy of groupism*, which is

> A tendency to treat categories of people as if they were internally homogenous and externally bounded […] and to take ethnic and racial groups as basic constituents of social life, chief protagonists of social conflict, and fundamental units of social analysis (Brubaker, 2009, p. 28)

This fallacy can occur because of psychology's overwhelming inferential focus on comparing category averages (Hanel et al., 2019), which proceeds at the expense of parsing within-category heterogeneity. I next turn to interrogate the logic of average analyses often used in group-based theorizing.

Assumption 2: Averages provide *sufficient* summary of perceptions within race categories

Psychology's theoretical focus on group differences in perceptions means explanatory weight is given to average category estimates and comparisons. This analytic approach invites reflections on the relation between measurement and ontology: Specifically, what do race category averages really represent? There is a tendency in psychology toward realist understandings of the construct being measured, whether as something existing independent of observation yet discovered by it or as created through observation (Brick et al., 2022; Guyon et al., 2018; Maul, 2013). There is also a tendency to treat averages as *the* important signal and variation as less meaningful error (Kahneman et al., 2021; Martinez et al., 2020; van Bork et al., 2022). Combine these measurement tendencies with psychological theorizing that treats race(s) as real through race and demographic realism (Martinez, 2023; Rodríguez-Muñiz, 2021), and the resulting practice is one that interprets race category averages as measuring *real* psychological tendencies of *real* "racial groups" and variation as an obstacle to capturing their true attributes (see Helms et al., 2005). In other words, the default choice to analyze "racial groups" using averages is linked to the idea that they are real entities or populations with shared cognitions or interests (Bonilla-Silva, 1997; Gould, 2008; Igo, 2007; Omi & Winant, 2015; Sysling, 2021; Winston, 2020a; Zuberi, 2000).

Interrogating the assumed ontological status of "racial groups" is often sidestepped in perception studies, yet it is important for interpreting race averages and guiding where researchers see perceptual agreement or tendencies originating from and how stable they are. One crucial theoretical divide in the study of the nature of race (i.e., race metaphysics), is realism versus antirealism (Glasgow et al., 2019; Hochman, 2017, 2019, 2021a, 2021b; Spencer, 2018a, 2018b). The former understands race(s) as existing either biologically (e.g., as genetic clusters) or socially (e.g., as identity or cultural groups with shared interests), while the latter understands race(s) as illusions produced by racism and its material and symbolic antecedents (Calnitsky & Billeaux Martinez, 2023; Cazenave, 2016; K. E. Fields & Fields, 2012; Weheliye, 2014; Wynter, 2003, 2005, 2022). I focus here on comparing how race realism versus antirealism understands race averages. The problems with race naturalism, which interprets race averages through biological differences, have been covered before (Gould, 2008; Hochman, 2014; Teo, 2011; Zuckerman, 1990).

Race realist social constructionism is becoming popular in the social sciences. For instance, the widely used racial formation theory posits that racial identities or races are "created, lived out, transformed, and destroyed" by dynamic sociohistorical processes (Omi & Winant, 2015 p. 109; Richeson & Sommers, 2016). Here, race is understood as a *real* social kind that powerfully determines our psychology, in the process creating socially real races with shared interests:

> But race is also not an illusion. While it may not be 'real' in a biological sense, race is indeed real as a social category with definite social consequences […] Notions of race do not only inform our conscious understanding of the social world; they also permeate our unconscious minds—shaping our perceptions and attitudes, and influencing our actions (Omi & Winant, 2015, p. 119)

Race realism combined with social identity and categorization theories (e.g., Adams et al., 2006; Carter & Murphy, 2015) set foundations for expecting racially grouped psychologies by casting race-in-itself *as* "difference" (the equation being racial identity = race is real). This theoretical move has been critiqued for falsely disconnecting race from racism, thus performing racecraft's trick: It obfuscates how the violence of racism requires and conjures beliefs in races, and it gives a flattened and "diverse" disguise to race's hierarchical ordering by conflating racialized identities (self or collective understandings developed in response to racism) as evidence for the realness of race (an imaginary yet hostile ascription; Brown & Lunt, 2002; Brubaker & Cooper, 2000; da Silva, 2007;. B. J. Fields, 2001, 2024; Hochman, 2021b; Loveman, 1999; Martinez, 2023; Rodríguez-Muñiz, 2021; Saucier & Woods, 2016; Smith, 2006). Put simply, and against commonsense race-talk, "race is not identity" (B. J. Fields, 2024). Race-realist discussions of race *as* "racial identities," "racial groups," or "cultural differences" imagine bounded social entities that enable race averages to act as *essential* and sufficient summaries of shared perceptions or interests within ostensibly always-socially-there races.

Race antirealism is less common in the social sciences but comes in many versions.[2] I advocate for antirealist (interactive) reconstructionism: "The term 'antirealist' indicates that race is an illusion. The term 'reconstructionism' adds that the groups people think of as 'races' are better understood to be racialized groups" (Hochman, 2021a, p. 32). Here,

> Racialized groups emerge out of the ongoing interaction between a number of factors: administrative, biological, cultural, economic, geographic, gendered, historical, lingual, phenomenological, political, psychological, religious, social, and so on. Interactive constructionism rejects the metaphysical privileging of any of these interactants as the key to what racialized groups "really are." The importance of any given interactant will depend on the context, and can change over time. None of these interactants are "racial." Yet together, in interaction, they can produce racialization (Hochman, 2017, p. 79)

Antirealist reconstructionism is therefore "careful not to infer the existence of race from the existence of racialization and racism, which do not require races, but only the *belief* in races" (Hochman, 2021a, p. 34).

If social constructionism illuminates how reification turns "names into things" (Adams & Markus, 2001, 2003; e.g., the concept of race into socially existing races, Ásta, 2018; Glasgow et al., 2019), antirealist reconstructionism course-corrects by creating a distinction between what remains the *name* or *fiction* (race or races) versus what actually becomes the *thing* created in the reification process (racialized groups). This race antirealist distinction helps ensure that race (the illusion) cannot be used as an explanatory scapegoat for racism (the concrete practices constructing inequality and racialized groups; K. E. Fields & Fields, 2012; Magubane, 2022a; Torres, 2023), it avoids issues with how social race realism can be made compatible with biological race realism and racist attitudes (Hochman, 2017, 2022; Morning, 2014; Shulman & Glasgow, 2010), and it challenges race-realist emphases on analyzing ostensibly shared psychologies of racialized groups by highlighting that "there is no reason to assume racialized groups will be culturally uniform […] racialization is a process through which large populations are falsely biologized, it would be rational to assume that such groups house great cultural diversity" (Hochman, 2019, p. 1258).

Antirealist reconstructionism does not to deny that people *can* form attachments or groupness around shared experiences and categories which *can* align their perspectives on the world. It denies that these phenomena—when or if they happen—make race-in-itself *real* (Hochman, 2021b). By rejecting the premise that racialization is race-*making* (Hochman, 2017), it calls into question the taken-for-granted nature and stability of "races" and the meaning of race averages. The switch from races or *racial* groups (static, trait-like, entities, decontextualized) to *racialized* groups (dynamic, active, event-like, require contextualization) highlights how groupings are produced by sorting events that momentarily or enduringly cohere different people together under the misperception that they are a race, as dictated by context-specific manifestations of racism (Cikara et al., 2022; Hochman, 2017, 2021; Price-Robertson & Duff, 2016). When race categories and their captive populations are understood as moving targets (Hall, 2021) and that members may or may not develop shared cognitions, within-category agreement becomes an empirical question rather than a priori (Loveman, 1999). Heterogeneity becomes more informative as a primary analysis for summarizing perceptions within racialized groups (Magubane, 2022b).

Generally, the consequence of any analytic method depends on the epistemologies and traditions it gets plugged into (Jackson, 2013). In this way, averages-in-themselves are not necessarily problematic, rather their de-contextualized use is (e.g., an inattention to surrounding variation and the constructed nature of the target being measured). For instance, while analyses of distributions are thought to buffer against essentialist inferences by framing average "group" properties as probabilities and not certainties (Lockhart, 2023), research practices often reduce distributions down to point estimate (i.e., average) comparisons and interpret them as such (Zhang et al., 2023) or interpret race distributions in a way that obscures the race realism or racist causality that underlies them (Holland, 2008; James, 2008; Winston, 2020a; Zuberi, 2000). Put simply, scientific practices powerfully shape *how* race(s) can be reified (K. E. Fields & Fields, 2012; Helms et al., 2005; Hochman, 2021a; Sen & Wasow, 2016; Winston, 2020b; Winther, 2018). The analytic racecraft critique, therefore, differs from general statistical critiques of inattention to heterogeneity in comparative analyses by problematizing the analytic categories we use to structure our analyses in the first place (Benjamin, 2014; Torres, 2023), rather than leaving them intact. Similar critiques have been levied against research on gender (Hyde, 2005, 2014; Morgenroth & Ryan, 2018) and culture (Adams & Markus, 2001, 2003) "differences." These issues highlight a need for analytic techniques and practices that place interpretive focus on variation while better buffering against essentialist interpretations of perceptions within a category or group.

Quantifying Shared and Idiosyncratic Judgments: The Variance Component Analysis

The study of collective understandings has been a longstanding concern of psychologists (Moscovici, 1981). The VCA revisits these concerns with new tools for understanding by shifting the analytic focus to variation. The analysis follows the social relations model for assessing accuracy in interpersonal perception (Kenny, 1994) and also generalizability theory, where error variance is decomposed into multiple variance components (i.e., sources of nonindependence in the data; Shavelson et al., 1989). Running a VCA requires ratings from multiple people who rate multiple stimuli multiple times (Hönekopp, 2006). Collecting repeated measures is uncommon in psychology, but even rarer in the study of racism perception. Yet, repeated measures are methodologically crucial for investigations of shared or idiosyncratic judgments to estimate the reliability of judgments and disentangle meaningful sources of agreement and disagreement from random error (Martinez et al., 2020).

The VCA quantifies the variance of judgments that can be attributed to three components of interest: the variance between participants' averages, between stimuli's averages, and between averages from each participant-stimulus pair (i.e., their interaction) as derived from random-effects regression modeling (Judd et al., 2012).

[2] This may be because the most commonly known version is race eliminativism which advocates for removing all race-talk from our practices (Cubelli & Della Sala, 2018), unpopular for disarming scholars and activists who rely on the race concept to fight against racism. Addressing this problem, the language of "racialized groups" enables us to still talk and make policies about the real groups produced by the violence of racism without reifying them as actual races (Hochman, 2019, 2021b; Mavundla, 2019).

Figure 1A provides a schematic of the specific ratings that make up each variance component. Figure 1B shows the pattern of variance component sizes to expect, given mostly shared or idiosyncratic judgments.

Consider an example where perceivers, Jose and Jake, provide numeric racism ratings of two anti-immigrant tweets: (A) “immigrants don't belong here …” and (B) “I hate immigrants! they should be rounded up!.” One source of judgment disagreement comes from perceivers' average differences (perceiver σ^2). Maybe Jose is more practiced or has more at stake in perceiving discrimination (Sachdeva et al., 2022), and so rates the set of tweets as more racist than Jake. However, another less-investigated source of judgment disagreement comes from perceivers' idiosyncratic and reliable stimulus rankings that are not shared with other perceivers (Perceiver × Stimulus interaction σ^2). Jose may consistently find tweet B as more racist than A, while the opposite is true for Jake. The interaction component represents idiosyncratic disagreement between perceivers at the level of the stimuli (and can only be estimated with repeated measures; otherwise it is confounded with residuals and labeled as noise), while the perceiver component represents an ambiguous “disagreement.” While individual perceivers might disagree via differences in means, these differences could reflect *groups* of perceivers with diverging means. They can also share stimulus rankings if there are no Perceiver × Stimulus interactions—Jose and Jake's means differ but both similarly rate tweet B as relatively more racist than A. Finally, the stimulus variance component (stimulus σ^2) reflects shared judgments because agreement about distinctions between stimuli allows stimulus means to vary (e.g., a main effect of a stimulus characteristic). Tweet B can only have a higher mean rating than A if most perceivers agree on that difference.

The VCA can accomplish the following: (a) Quantify the extent of agreement across a sample and within social categories, (b) identify the key social cleavages or stimulus characteristics that facilitate (dis) agreement, and (c) compare the relative importance of competing forces for shaping judgment. In these ways, VCA represents an advance to studying group differences in perceptions of racism.

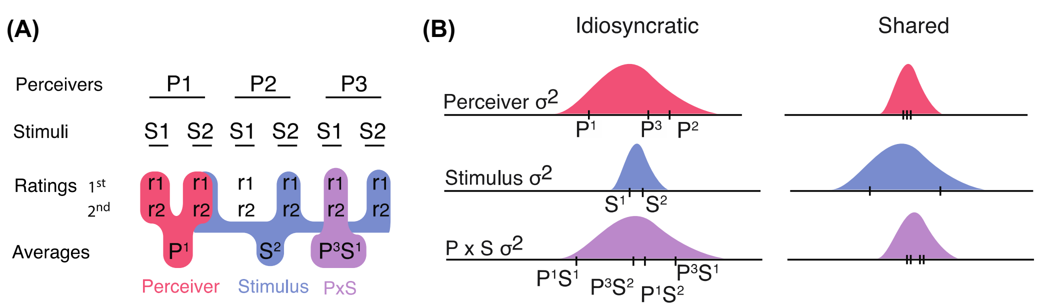
Overview of Studies

I aim to improve quantification practices for analyzing and interpreting how racialized people construe racist events. Across three studies, judgments were collected from differently racialized perceivers about the racist nature of public statements (i.e., tweets) made on the social media site Twitter in response to two Trump administration announcements: of the travel ban from seven Middle Eastern countries, and of the building of a wall along the Mexico–U.S. border in early 2017 (Amatulli, 2017). I focused on these statements and this context for two reasons. First, social media provides an arena where race and racism as concepts and perceived realities are debated, (re)constructed, and reified (Chaudhry, 2015, 2016). The second is that immigrants are often racialized through projects that profess to defend native-born citizens where immigrants are categorized as a group and interpersonally and institutionally treated as inferior and a threat to U.S. Americans (Inda, 2006; Ngai, 2004; Provine & Doty, 2011; Warner, 2005).

On Twitter, people reacted in various ways to these racializing events as suggested by tweets of support and resistance to the anti-immigrant spirit of these two announcements (González-Ramírez, 2017; Martinez et al., 2017). Social scientists, policymakers, and public polls often discuss people's political perceptions as racially grouped phenomena with predictable positions, for example, “latinx voters views on immigration,” latinxs working as border agents is seen as a surprising contradiction (Cortez, 2021). Prior research has also posited that racial groups diverge in motivational tendencies to defend or antagonize immigrants (i.e., perceive racism; Abrajano & Hajnal, 2015; Adams et al., 2006; Bonilla-Silva, 2006; Feagin, 2006; Serrano-Careaga & Huo, 2019; Sheares, 2022). The tweets therefore

Figure 1

Variance Component Analysis



Note. This figure provides an intuition about what the variance components represent; actual variance calculations involve maximum likelihood estimators rather than simple averaging. (A) A simplified schematic on deriving the main variance components from multiple perceivers repeatedly rating multiple stimuli. The average of each perceiver (e.g., P1, P2, P3) represents the average of all ratings given by each perceiver (red); the variance of the differences between these averages and the grand mean (the average of all ratings) constitutes the perceiver σ^2 component. The average of each stimulus (e.g., S1, S2, S3) represents the average of all the ratings given to each stimulus (blue); the variance of the differences between these averages and the grand mean constitutes the stimulus σ^2 component. Finally, the average of each stimulus–perceiver pairing (e.g., P1S1, P3S3) represents the average of the repeated ratings given to each stimulus by each perceiver (purple). The variance of the differences between these averages and the participant and stimulus means (e.g., P_3S_1 from P_3 and S_1) and the grand mean constitutes the Perceiver × Stimulus interaction σ^2 component. (B) The left panel provides visual examples of the relative variances one might expect for each component given largely idiosyncratic judgments, the right panel represents expectations for shared judgments. See the online article for the color version of this figure.

originate from a context in which racism perceptions could be expected to be cleaved along racialized lines. Although I acknowledge perceptual ambivalence about immigration exists within each category (Cardenas et al., 2023; Hutchings & Wong, 2014; Sheares, 2022), my goal is to show *how* group-based predictions oversimplify the relationship between categories and perceptions.

To gather a sample that could capture racialized cleavages in perceptions of racism, each study collected equal proportions of participants self-classified as latinx, black, and white.[3] This allowed me to (a) replicate the standard measurement and analysis approach in perception studies (sorting people through simple categorical race measures and then comparing race averages) to showcase potential issues with it and (b) compare theoretical and empirical insights about collective perceptions and race gained from analyses that focus on averages versus variation. The three studies included four samples. Studies 1 ($N = 306$) and 2 ($N = 301$) are direct replications and Study 3 manipulates the tweets to be more ($N = 303$) or less ($N = 301$) popular (liked by other users) to examine the impact of social norm cues on racism perceptions. This norm manipulation did not change any of the results (see Supplemental Appendix A); therefore, I only present analyses from the first two studies. In the results, I present the following three analyses. First, I test the prediction that judgments of racism are on average different across black, white, and latinx perceivers. The variance analyses then reveal whether any average differences occurred through consensual "racial group" processes (small within-category variation) or not (large within-category variation). If not, then we need to reconsider how to interpret average race differences and what other clusters may better explain racism perceptions if race was not the starting point of the analysis. Therefore, I present a last data-driven exploratory analysis attempting to identify sources of (dis)agreement in perceptions of racism, specifically which perceiver and stimulus variables, theorized to shape racism perceptions, capture the most variance in each variance component of the VCA.

Method

Transparency and Openness

I report how the sample size, all data exclusions, all manipulations, and all measures in the study were determined. All data, scripts, and study materials can be found at https://osf.io/v2cey/?view_only=69a1bebeaf684236ad3a6ddc08d263ef. The project was approved by the Princeton Institutional Review Board, No. 7301. All data collection for all studies occurred in June of 2018. All collected variables are analyzed and reported in this study. A preregistration exists for this project at https://osf.io/wz83n/?view_only=8a5abda3d2344c6e9fbb0b01d3248e0e; however, deviations regarding the focus of the article, sample sizes, exclusion criteria, and untested ideas are listed in Supplemental Appendix B.

Samples

A sample-size analysis via a simulation study showed that estimates of many of the components computed in the VCA begin to stabilize when the number of participants were 60, the number of stimuli 30, and the number of repeated measures greater than 2; diminishing improvements on precision was found with greater numbers (Martinez et al., 2020). The studies have approximately 100 participants in each racial category (total N is around 300 per study), 50 stimuli, and three repeated measures to help optimize estimate precision.

Study 1

Three hundred sixty-eight participants living in the United States were recruited from a Qualtrics panel with the goal of obtaining 100 participants in each of three racial categories: latinx, black, white. Exclusion criteria required participants show test–retest reliability on judgments of racism across the three repeated blocks: Specifically, they needed to demonstrate an intraclass correlation of judgments greater than zero. This criterion excluded individuals whose responses were completely inconsistent across repetitions and individuals who pressed the same response for all the stimuli, as there was no variance to calculate reliability.

After exclusions ($N = 62$), the final sample included 306 participants: 103 black, 103 latinx, and 100 white. There was one nonbinary person, three who did not want to disclose their gender, 84 women, and 218 men. The average age was 43, $SD = 16$, and ranged between 18 and 82. The intraclass correlations ranged from .01 to .94 (average = .45, median = .50, $SD = 0.28$). For a full composition breakdown of all measured participant factors by racial category, see Supplemental Table S1.

Study 2

From the 370 participants from Qualtrics panels, 69 were excluded for not meeting reliability criteria. The final sample ($N = 301$) included 99 black, 101 latinx, and 101 white participants. There were two people who did not want to disclose their gender, 88 women, and 211 men. The ages ranged between 18 and 81 (average = 43, $SD = 16$). The intraclass correlations ranged from .01 to .94 (average = .46, median = .49, $SD = 0.28$). For a full description of the sample, see Supplemental Table S1.

Stimuli

I collected tweets from Twitter from February 6 to February 13, 2017. Tweets were found by scraping the hashtags #AmericaFirst and #MuslimBan, which developed in reaction to these events. The set was deliberately large to avoid the confounds of other studies that present participants with a few stimuli, but also pared down to a reasonable number that could be rated multiple times within one session. To narrow down to 50 tweets, two judges (one of whom is the author) chose tweets from this collection that antagonistically targeted Muslims, illegalized immigrants, or immigrants in general. They also eliminated tweets that were not comprehensible, that only featured hashtags or images without a personal comment, and that had exceedingly offensive content (e.g., *n*-word or images of murder). Judges also excluded similar or repetitive statements, and specifically sought out comments addressing a range of social, economic, and political perspectives.

[3] I deliberately do not capitalize race labels as my small linguistic intervention against racecraft. The two exceptions in this manuscript are (a) when I describe stimuli or race measures so that readers know exactly what was shown to participants and (b) in figures because of the aesthetic rule of capitalizing every word—which does not signal any groupist significance to the capitalized race category.

This process was aimed at creating a stimulus set that incorporated relevant theoretical dimensions, rather than a representative set of tweets on immigration. For example, including only tweets that antagonistically discuss a group precluded the ability to understand how people distinguish antagonistic versus innocuous tweets in terms of racism. However, that kind of agreement is not of interest here. Instead, the focus is on statements that deride groups as interpersonal discrimination is the most common understanding of racism (Rucker et al., 2019). Likewise, removing the most egregious of tweets also precluded the ability to capture judgments of "obviously" racist tweets. One could argue this omission omits another form of agreement. There are ethical considerations to be made about the value of exposing participants to *extreme* disturbing content, but just as important many of the chosen tweets were egregious enough (Supplemental Table S2). It is an open question whether the kind of tweets left out of the set would elicit shared judgments (e.g., racist murders by police or military are often defended and non-black people still comfortably and publicly say the *n*-word despite pushback on both). While acknowledging this possible limitation, I direct readers to Supplemental Figure S1 for additional discussion regarding the tweets' content and rating ranges to better situate the results.

The final group of tweets about the Muslim ban and the wall varied along two dimensions: the aggressiveness of the content and the groups that are targeted, as subjectively judged in the pairing-down process. The set included a variety of tweets ranging from blatantly aggressive statements to more coded language that linked certain groups to economic or political worries. The more aggressive tweets contained statements that dehumanized others or called for violence (e.g., "Round up the #ILLEGALS and toss them back over the border"). The political tweets contained desires for safety from threats, financial responsibility, or helping Americans first (e.g., "It is not cruelty to Build The Wall. When we put America first, and citizens of any country are always protected first from any threat."). The stimuli contained two measures of group targeting. The first is the hashtag from where the tweet originated: *#AmericaFirst* or *#MuslimBan*. The second codes what specific group the tweet discussed: illegalized immigrants, Muslims, both, or all immigrants.

Any information about social engagement was not displayed in these studies. The tweeter's picture, username, and the number of likes, favorites, and retweets were obscured with black bars and the hashtag was removed to anonymize the tweet for the study.

Procedure

Participants first completed a demographic survey where they were asked about age, racial or ethnic identification, gender identity, and Twitter usage. Participants who did not identify as one of the three main racial categories of interest could not advance to complete the study.

Participants were instructed that they would read a series of tweets related to the two U.S. policies about the wall and the ban in three repeated blocks that randomly displayed all the stimuli. In between blocks, there were instructions that all the same tweets would be shown again for the same task. Their task was to rate "How racist is this tweet?" on a scale of 1 (*not at all*) to 9 (*extremely*). Participants were asked to use their gut judgment when rating the tweets.

The task was a fully crossed design (Westfall et al., 2014): Every participant rated all fifty tweets which were repeatedly presented in three blocks, randomized within block. Finally, participants completed four different measures theorized to relate to racism perceptions: the Social Dominance Orientation (SDO) eight-item scale (Ho et al., 2015), the Symbolic Racism eight-item scale (Henry & Sears, 2002), the blatant dehumanization scale (Kteily et al., 2015), and political orientation. There was no time pressure for completing each rating and for completing the measures, but given the number of tweets, participants moved expeditiously through the questions (average time = 35 min). The same procedures occur across both studies as Study 2 is a direct replication of Study 1.

Measures

The order of the first three scales listed was randomized across participants. Political orientation was always collected last. Correlation matrices displaying the relationship among all the collected perceiver measures for Study 1 across the sample and within racial categories can be found in Supplemental Figure S2. Average scores of these measures within racial categories can be found in Supplemental Table S1. The same correlation matrices for Study 2 can be seen in Supplemental Figure S3, which show congruent patterns to Study 1's matrices.

Demographics

Racial or ethnic background, age, gender identity, and Twitter use were measured. The race measure asked "What is your racial or ethnic background?" with the following options: "Latinx or Hispanic," "Black or African American," "Asian/Pacific Islander or Asian American," "White or European American," "Indigenous," "Other." Note that while I used categorical race measures to replicate standard practices, I do not endorse them as best practice. This common measurement approach can contribute to the analytic racecraft problems I highlight in this article by ignoring contextual, affective, and temporal resolutions of social categorization (Cikara et al., 2022), prioritizing a set of categories salient to institutions (e.g., census labels) over categories salient to participants' lived worlds (Brubaker & Cooper, 2000; Menjívar, 2023; Rodríguez-Muñiz, 2021), and thus enabling racial essentialism (Helms et al., 2005; Winston, 2020b; Zuberi, 2000; Zuckerman, 1990). The Discussion section notes promising directions for how to better measure race as a multidimensional construct (e.g., Roth, 2016; Sen & Wasow, 2016), which may subsequently improve how we should approach comparative analyses. A related limitation is that measures on religious affiliation or immigrant status were not collected to understand how raters evaluating tweets that target people who match on dimensions related to, but beyond, race. The gender measure asked "How do you identify your gender?" with the following options: "Female," "Male," "Nonbinary," "Prefer not to say," "Other" (These options conflate sex and gender categories; therefore, I relabel "female" as "women" and "male" as "men" in this article). Twitter use is treated as a continuous measure (1—*daily*, 2—*several times a week*, 3—*weekly*, 4—*less often*, 5—*never*).

Blatant Dehumanization

The blatant dehumanization scale asked participants to rate four groups (white, black, latinx/o/a or Hispanic, and Muslim) using the ascent of man diagram, a continuous rating underneath a visual scale featuring a monkey-to-man continuum of evolution (Kteily et al., 2015). The participants were instructed to use the sliders to indicate how evolved each group is. No numeric values were shown on the slider; however, the range varied from 0 (*least human*) to 100 (*most human*).

I derived five blatant dehumanization scores to understand the relative importance of general outgroup versus specific group dehumanization in judgments of racism. The first is outgroup dehumanization (BD-Outgroup) which takes each participant's ingroup rating and subtracts the average rating of the other three groups. The other scores subtracted each participant's rating of a target outgroup from their ingroup rating, so that the score is relative to their dehumanization of their own group. This means that each participant had four outgroup scores: All had BD-Outgroup and BD-Muslim and two scores from the targets that did not match their own classification (e.g., a participant self-classified as black would have a BD-latinx and BD-white score). Positive scores represent the magnitude of dehumanization while negative scores provide evidence of ingroup dehumanization. The lack of religious measures means the BD-Muslim scores should be interpreted with caution as Muslims can be classified as any race; therefore, the scores' ingroup–outgroup distinction remains ambiguous in the data.

SDO

Participants responded whether they strongly oppose or strongly favor eight items on a 7-point scale, half of which were relevant to the egalitarian component of SDO (SDOe, e.g., "It is unjust to try to make groups equal.") and the other half to the dominance component (SDOd, e.g., "Some groups of people are simply inferior to other groups"; Ho et al., 2015). After reverse coding some contrasting items, items were averaged to compute component scores. Higher scores indicated a higher level of SDOe or SDOd.

Symbolic Racism

I used the eight-item version of the Symbolic Racism scale (Henry & Sears, 2002). For example, participants would respond their level of agreement with the following statement, "It's really a matter of some people not trying hard enough; if Blacks would only try harder they could be just as well off as Whites." After reverse scoring, all the ratings were summed together following convention to create the composite score that could range from 8 to 31, where higher scores indicate more endorsement of symbolic racism.

Political Orientation

Political orientation was assessed using two questions, one about the participant's social and cultural stance and the other about their economic stance, rated from extremely liberal to extremely conservative on a 7-point scale (e.g., "In terms of [social and cultural, economic] issues, how liberal or conservative are you in an American context?"). The two were correlated at $r = .82$ across all samples and ranged between .77 and .88 within each study, and thus were averaged into one political orientation score.

Analyses

The analysis is a multistep approach to understanding judgments of racism and was used for each study. First, I report linear regression analyses to estimate average race differences in judgments of racism. Second, I use VCAs to quantify the magnitude of judgment variance that arises from perceivers, stimuli, and their interactions. I estimate a VCA with the full sample as an anchor where maximal disagreement is expected to compare against the VCAs within each race category. To better understand the relationship between the average and variance analyses, I also present descriptive plots that coarsely visualize the race-stratified distribution of ratings for quintiles of stimuli, rated least to most racist. Finally, I use characteristics of the perceivers and stimuli to quantify how much variance they explain in each component. For example, when there is high variance between perceivers, perceiver characteristics like political orientation may contribute to that disagreement. When there is high rating variance between stimuli, properties of the stimuli, like how aggressive the message is, are likely associated with that agreement.

Aggregate Judgment Analyses

Regression Analyses. I report unadjusted average race differences where race is the only predictor in the model alongside adjusted estimates that control for the rest of the measured perceiver and stimulus variables. For both analyses, I used mixed effect linear models in lme4 package Version 1.1.13 (Bates et al., 2015) with maximum likelihood estimation. The unadjusted model predicted racism ratings from race as a fixed effect and random intercepts for perceivers, stimuli, and the Perceiver × Stimulus interaction. The adjusted models predicted racism ratings from the following fixed effects: race, political orientation, age, Twitter use, gender, SDOd, SDOe, blatant dehumanization outgroup, symbolic racism, tweet hashtag, targeted group, and tweet aggressiveness. The random effects included random intercepts and slopes of tweet aggressiveness for perceivers, and random intercepts for stimuli and Perceiver × Stimulus interactions.

The random intercepts account for dependencies in the ratings due to perceivers, stimuli, and repeated measures. The random slopes (i.e., tweet aggressiveness) accounts for dependencies from perceivers' responses to within-subject manipulations. To help with convergence, models were optimized with "bobyqa," and set to run for a maximum of 500,000 iterations, and the tweet hashtag and targeted group were removed as random slopes. Confidence intervals, slope estimates, and multiple comparisons were computed using the "emmeans" package Version 2.26.3 in R with Satterthwaite approximations of the degrees of freedom. Multiple comparisons were corrected using the Benjamini and Hochberg method for controlling false discovery rate. All continuous variables were mean centered, except Twitter use which was referenced on daily use.

Rating Density Visualization. I depicted rating tendencies and variation by race category in one plot to reflect the insights from both the average and variation analyses. Each stimulus was binned into quintiles based on their average racism rating within each study. The densities of rating distributions (i.e., how often each numeric rating was given) were depicted for each race category and stimulus quintile.

Agreement Analyses

Variance Component Analysis. I calculated variance partitioning coefficients (VPC) as a measure of agreement. These measures are both derived from variance components analyses, mainly from separate components estimating variance between perceivers, stimuli, and their interaction around a grand mean (Judd et al., 2012; Martinez et al., 2020). The model equation (Equation 1), combining the two levels of the model, is (Shoukri, 2011, p. 44):

$$y_{ij} = \mu + p_i + s_j + ps_{ij} + e_{ij}. \quad (1)$$

where:

$$p_i \sim N(0, \sigma_p^2). \quad (2)$$

$$s_i \sim N(0, \sigma_s^2). \quad (3)$$

$$ps_{ij} \sim N(0, \sigma_{ps}^2). \quad (4)$$

Here, y_{ij} represents the judgment given by ith perceiver to the jth tweet, μ represents the grand mean over all judgments, p_i represents the difference of the ith perceiver's mean from the grand mean, s_j represents the difference of the jth tweet's mean from the grand mean, ps_{ij} is the divergence of ith perceiver's average rating of jth tweet from their own mean and the tweet's mean and the grand mean, and e_{ij} represents random error in ith perceiver's judgment of jth tweet. The variance components of the perceiver (σ^2_p, Equation 2), stimulus (σ^2_s, Equation 3), and Perceiver × Stimulus interaction (σ^2_{ps}, Equation 4) random effects are the focus of this analysis and are assumed to be normally distributed and have a mean of zero (Shavelson et al., 1989; Shoukri, 2011, p. 44).[4] These components were estimated on the raw data with random-effects regression models from the lme4 package Version 1.1.13 in R, with restricted maximum likelihood.

Variance Partitioning Coefficients. The reported VPCs can be interpreted as the proportion of variance explained by each variance component and are computed by taking each variance component and dividing it by the total variance, including residuals (Goldstein et al., 2002). Confidence intervals for the VPCs a computed using 1,000 bootstrapped samples of the random effect models. Differences in VPCs between studies or conditions were computed by first subtracting the bootstrapped sample traces, calculating confidence intervals of the differences, and checking if they contain zero. I used all the data to obtain overall estimates across all perceivers as the comparative reference point. I then partitioned the data into racial categories and fed them into the model to obtain category-specific estimates (i.e., black, latinx, white).

Variance Contributions. There is no established method quantifying variables' contributions to specific variance components due to their nonlinear estimation and dependency on model specification (e.g., a variance component can *increase* with an added variable; Hox, 2010, pp. 69–78). I used a two-step data-driven analysis to address this issue. The first step obtained empirical Bayes estimates of all the random effects (i.e., the adjustments of each perceiver or stimulus or interaction mean), which resulted in a distribution per random effect estimate. The estimates were calculated using 1,000 simulations from the posterior distribution of the model with the merTools R package Version 0.3.0 (Knowles & Frederick, 2016). In step two, the modes from every random effect's distribution were then submitted to ordinary least-squares regressions where each variable was independently added as a predictor, and a variance explained metric (R^2) was estimated. This R^2 metric was transformed to a percentage and represents the independent variance contribution of each predictor.

Finally, a model with all the measures (excluding the group-specific blatant dehumanization scores because of score construction overlap) was estimated for each component to examine the total variance contributed simultaneously by all variables. This process was implemented separately for each variance component. Importantly, perceiver-level variables only explained the perceiver component, stimulus-level variables only explained the stimulus component, and interactions between every perceiver and stimulus variables were used to explain the interaction component. All continuous variables were mean-centered to provide interpretable intercepts and variance components (Bryk & Raudenbush, 2002).

Results

Are There Average Race Differences in Perceptions of Anti-Immigrant Discourse?

In Study 1, the unadjusted race variable was significant, $F(2, 305.77) = 11.45$, $p < .0001$, in the expected pattern (Figure 2A). Participants self-classified as white ($M = 4.49$, 95% CI [3.92, 5.07]) rated the tweets as less racist than participants self-classified as latinx ($M = 5.81$, 95% CI [5.24, 6.38], diff. = 1.32, 95% CI [.60, 2.02]), $t(306) = 4.43$, $p < .0001$; and black ($M = 5.62$, 95% CI [5.05, 6.20], diff. = 1.13, 95% CI [.42, 1.85]), $t(306) = 3.81$, $p = .0003$. After adjustments in the full model, $F(2, 302.82) = 5.48$, $p = .005$, participants self-classified as white ($M = 5.67$, 95% CI [4.74, 6.60]) gave lower racism ratings than participants self-classified as latinx ($M = 6.36$, 95% CI [5.45, 7.27], diff. = .68, 95% CI [.05, 1.32]), $t(303) = 2.61$, $p = .014$, but not black ($M = 5.59$, 95% CI [4.71, 6.47], diff. = .08, 95% CI [−.57, .73]), $t(303) = .30$, $p = .765$ (Supplemental Table S3).

Study 2 replicated Study 1, the unadjusted race variable remained significant, $F(2, 300.8) = 5.98$, $p = .003$, in the expected pattern (Figure 2A). Participants self-classified as white ($M = 5.25$, 95% CI [4.69, 5.82]) rated the tweets as less racist than participants self-classified as black ($M = 5.90$, 95% CI [5.33, 6.47], diff. = .64, 95% CI [−.07, 1.4]), $t(301) = 1.35$, $p = .047$; or latinx ($M = 6.26$, 95% CI [5.70, 6.83], diff. = 1.0, 95% CI [.29, 1.7]), $t(301) = 3.42$, $p = .002$. However, after adjustments, the race variable was not significant, $F(2, 2.98.84) = 2.11$, $p = .123$, although the averages qualitatively held the same pattern as Study 1 (Supplemental Table S3).

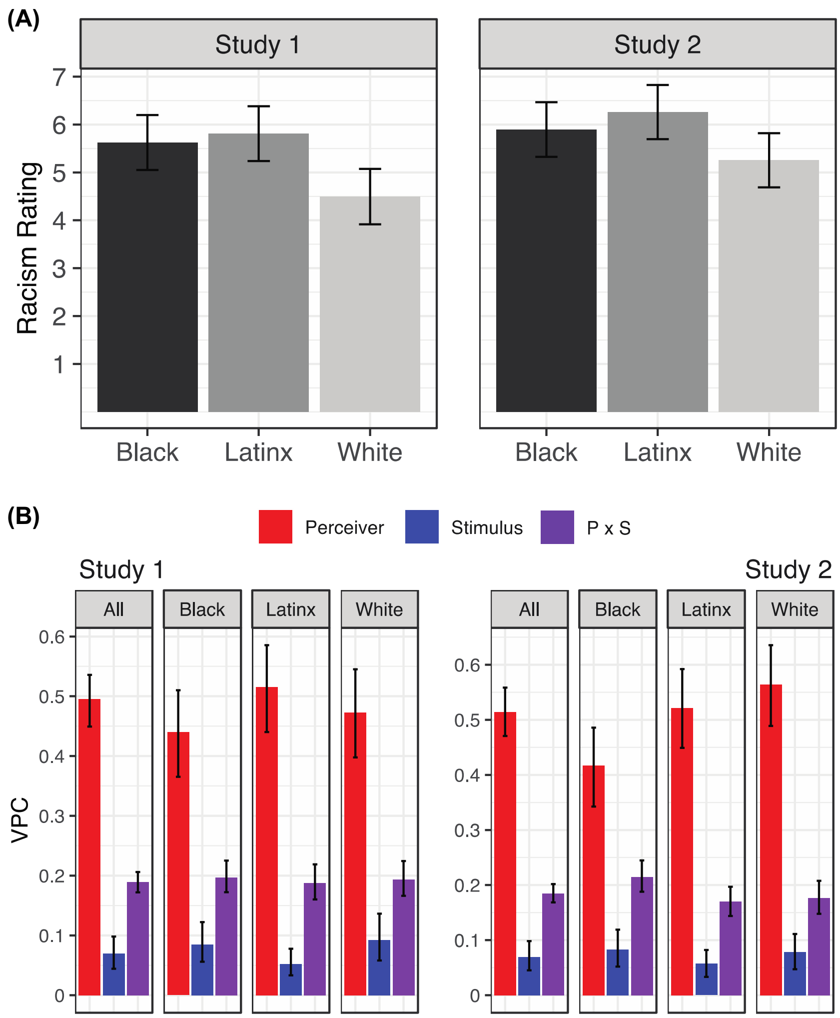
For Judgments of Racism, Is There More Agreement Than Disagreement Within Race Categories?

After establishing that race differences exist in perceptions of racism as expected (although some differences are not statistically significant after controlling for other variables), quantifying the VCA within race categories helps establish to what extent these are collectively held differences in judgment.

First, the VCA across the full sample, sets an anchor for how much disagreement can be expected when differently racialized people are analyzed together. For all participants in Study 1, the perceiver and interaction VPCs contributed over 68% of the overall variance, suggesting that judgments of racism showed major disagreements

[4] I also compute block, Block × Stimulus, and Block × Perceiver variance components. These components do not factor into the agreement estimates but can be important in interpreting the impact of repeated presentations on judgments. I find little impact in this study, but I describe their purpose in Supplemental Appendix C. For the complete set of estimated variance components for each study, see Supplemental Figure S4.

Figure 2
Average and Variance Analyses for Studies 1 and 2



Note. (A) Average unadjusted ratings per race category. Error bars represent 95% confidence intervals. (B) Variance component analysis results showing the variance partitioning coefficient for each variance component across the full sample ("All") and within each race category. Perceiver component is in red and leftmost, stimulus in blue and center, and their interaction in purple and rightmost. Error bars represent 95% bootstrapped confidence intervals. VPC = variance partitioning coefficients. See the online article for the color version of this figure.

(Figure 2B). The stimulus VPC is relatively small (7%), which can occur if the range of tweets was homogeneously racist (Supplemental Appendix C). Examining the within-stimulus variance suggests otherwise. While the range of tweet averages hovered around the middle of the scale (around 4–7), they also had large standard deviations, indicating each tweet was given ratings across the full scale (Supplemental Figure S1). Therefore, the relatively small range of tweet averages is due to rater disagreements in the ratings of each tweet, as reflected in the large perceiver and interaction components. As an interpretive anchor, these estimates show more disagreement than aesthetic judgments on the likability of different artworks where the perceiver and interaction VPCs contributed between 50% and 60%, and the stimulus VPC contributed between 16% and 18% of rating variation (Leder et al., 2016).

Within every race category, the same VCA pattern occurred, in which the perceiver and interaction components contributed most of the variance (between 64% and 70%), and the stimulus component contributed the least (between 5% and 9%; Figure 2B). This suggests that there is just as much disagreement within race categories as there is when you combine all race categories into one analysis. In other words, race categories were not the most influential cleavage in these judgments of racism.

The same occurred in Study 2, where racism ratings mostly exhibited disagreement (Figure 2B). Across the full sample, the perceiver and interaction components contributed 70% of the variance and the stimulus component only 7%. Within each race category, the perceiver and interaction components contributed between 63% and 74% of the variance and the stimulus component contributed only between 6% and 8%. These VPCs were not significantly different from Study 1 (see Supplemental Figure S7 for direct comparisons).

Overall, the Study 1 and 2 results suggest that the average race differences in racism judgments did not arise from internally consensual "racial group" processes.

How Should the Combined Results of the Average Analyses and VCAs Be Interpreted?

There is a seeming tension in the findings: On the one hand, computing averages within race categories shows significant differences between categories; on the other hand, the VCA analysis shows there is just as much disagreement about what is racist within a sample self-classified as black or white compared to the disagreement within the combined sample of participants self-classified as black, white, and latinx. To help interpret how average race category differences can arise from major within-category disagreements, I visualize all ratings using density plots for each race category per quintile batch of stimuli, rated from least (first quintile) to most (fifth quintile) racist (Figure 3). The first result to note is the heterogeneity or disagreement: Data density occurs across every rating option in every quintile, even as it skews toward lower numbers (i.e., less racist) for the least racist stimuli and toward higher numbers (i.e., more racist) for most racist stimuli. Second, there are expected density differences by race category. Across the quintiles, lower racism ratings were given within the white category, especially in the first quintile, and higher racism ratings within the black and latinx category, especially in the fifth quintile. This visualization is coarse in that it does not pinpoint who and how many gave those ratings for which specific stimuli, but it highlights how large within-category heterogeneity coexists with average race differences. In other words, expected race differences in perceptions *operated only through some people within each category toward some tweets*. In this data set, race categories do not predict or diverge perceptions of racism as strongly as is commonly discussed in the social sciences.

Which Variables Better Explain the Patterning of Racism Perceptions of Anti-Immigrant Discourse?

Instead of starting from the assumption that "racial groups" are the main cleavage in racism judgments, I employed a data-driven approach to attempt to better understand which variables most contribute to the variance components. I created a map of the sources of variation in racism ratings of anti-immigrant discourse (Figure 4).

In Study 1, the stimulus component representing agreement mainly consisted of the aggressiveness of the tweets, which explained 48% of the stimulus variance. The tweets' hashtag and the targeted group explained a small amount of the stimulus variance (3%–11%, suggesting that while some small distinction was made, perceptions of illegalized and Muslim immigrant targets were mostly entwined during the context of the tweets). Together, all the stimulus factors explained 49% of the stimulus component (3.4% of the total variance). For disagreements, the combined measures explained 37% of the perceiver component (18.5% of the total variance). The top three contributors to perceiver variance were symbolic racism, political orientation, and SDOd, explaining 27%, 17%, and 9% of the variance, respectively. The rest of the measures contributed 7% or less. Finally, none of the two-way interactions explained more than 1% of the interaction component.

In Study 2, agreement was mainly explained by tweet aggressiveness which contributed 45% of the stimulus variance. The tweets' hashtag and the targeted group explained a small amount of the stimulus variance (2%–9%). Altogether, 47% of the stimulus variance was contributed by the measured stimulus factors (3.3% of the total variance). For disagreements, the combined measures explained 33% of the perceiver variance (16.8% of the total variance). The top three contributing measures included symbolic racism (24%), political orientation (21%), and SDOe (9%). The rest contributed less than 6% of the variance each. Finally, none of the two-way interactions explained more than 1% of the interaction component. These results are consistent with Study 1.

In summary, both studies found that agreement in judgments of racism across the sample were driven relatively more by one characteristic of the tweets themselves,the aggressiveness of the language, while disagreements between perceivers occurred, to some extent, due to individual characteristics like levels of symbolic racism, political orientation, or social dominance orientation.

Discussion

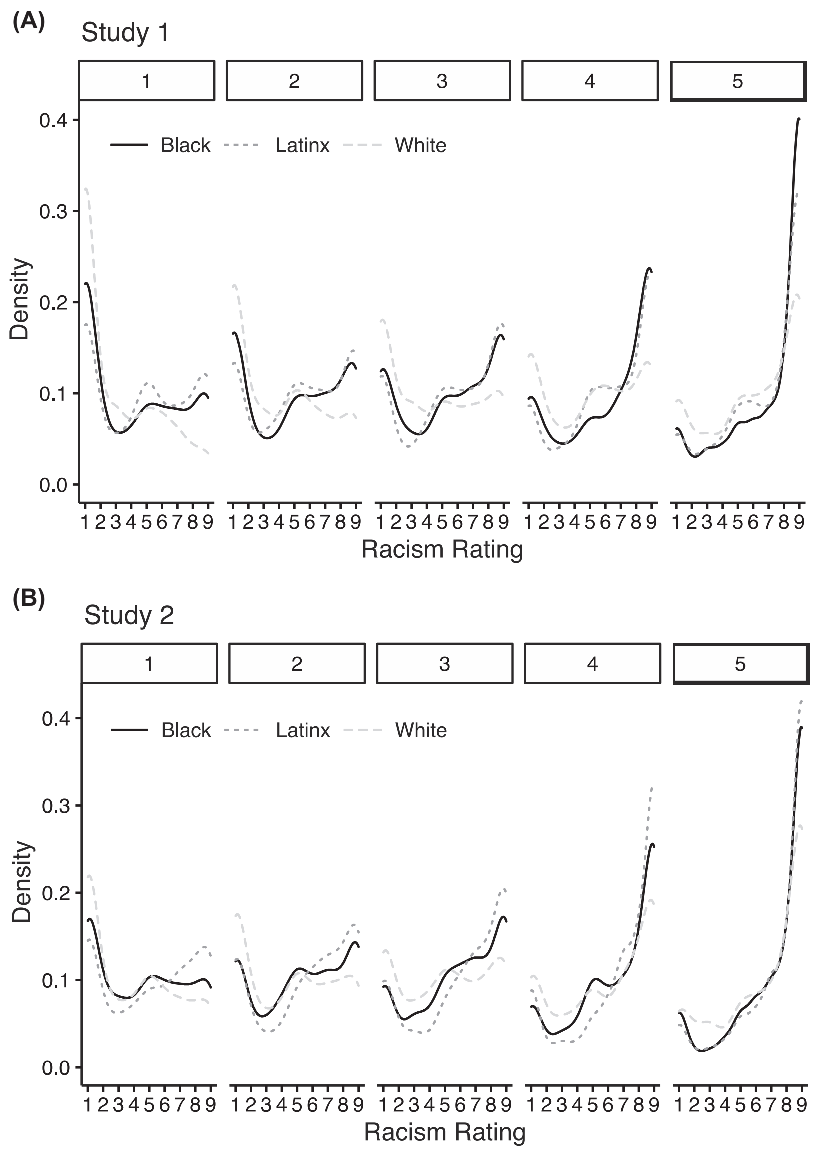
This article continues a critical conversation about the influence of racecraft ideology on research practices (K. E. Fields & Fields, 2012; Martinez, 2023), here focused on interrogating quantification practices for comparing how racialized people perceive discriminatory events. Specifically, I identified two assumptions that characterize comparative analyses: First, race should cluster racism perceptions, and second, averages are sufficient summaries of perceptions within race categories. To test these assumptions and offer a new way to analyze the role of race categories in determining perceptions, I introduced the VCA. I leveraged this analysis across three studies with balanced samples of participants self-classified as white, black, and latinx to quantify whether their judgments of racism of anti-immigrant statements were mostly idiosyncratic or shared, and among which stimulus or perceiver characteristics. I found that despite significant average race differences in judgments of racism, disagreement overshadowed agreement within every race category. Strikingly, the amount of disagreement within each race category matched the amount of disagreement when all participants are combined into one analysis.

I first discuss what was learned about each assumption: That race should cluster racism perceptions and that averages can help understand collective perception. Next, I provide alternative frameworks that could help researchers better conceptualize how racism perceptions are socially patterned.

The VCA Versus Assumptions Behind Average Analyses

In line with theories of group-motivated perceptions (e.g., Carter & Murphy, 2015), race categories differed in their average racism ratings. Perceivers self-classified as latinx rated the tweets as more racist than perceivers self-classified as other categories. However, average race differences were overshadowed by a large amount of perceiver-related variance. There was more within-category and within-person variation in racism perceptions than would be expected by theories that individuals classified as a race category have a shared perceptual psychology due to their historical

Figure 3
Density Plots of Racism Ratings



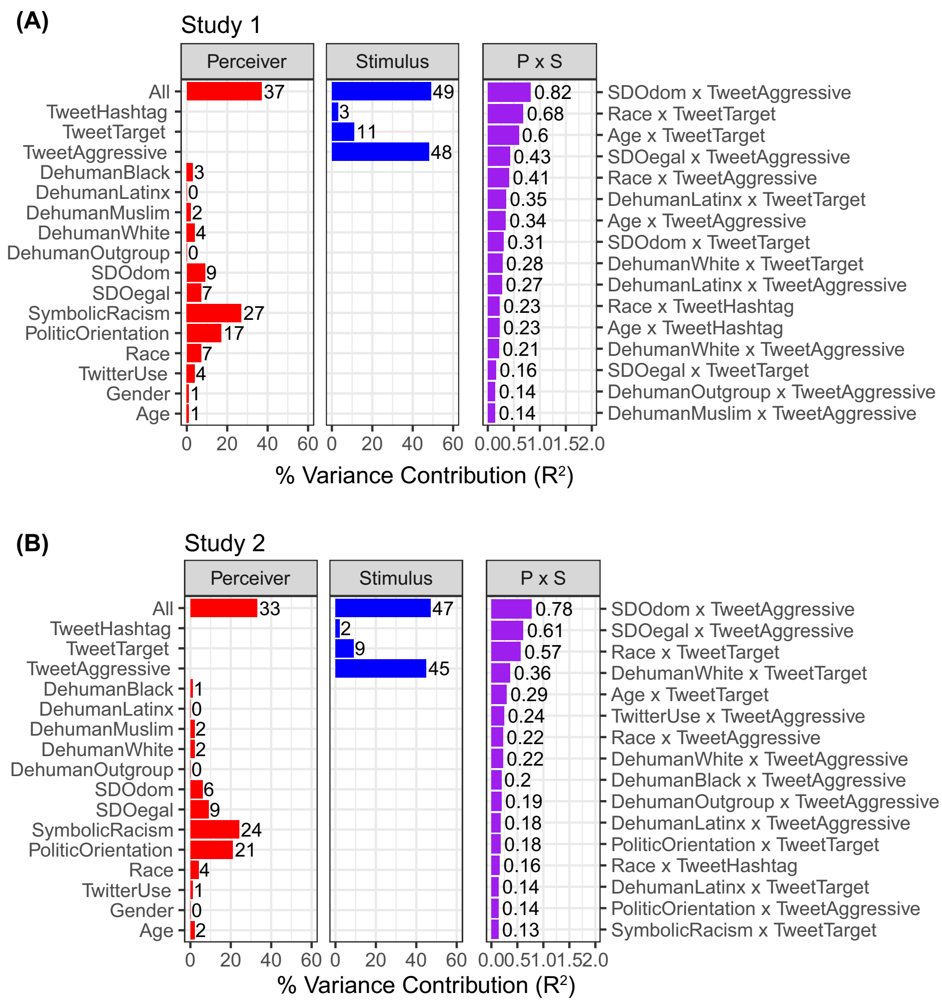
Note. (A) Study 1 and (B) Study 2. *X*-axis is the racism rating from 1 (*not racist*) to 9 (*extremely racist*), *y*-axis is the density of the data at each rating option. Densities were calculated by race category (black is solid line, latinx is small dashed line, white is large dashed line). Stimulus quintiles are batched from 1 (*lowest racism ratings*) to 5 (*highest racism ratings*).

relationship to racism (Adams et al., 2006; Blauner, 1999; Carter & Murphy, 2015). The level of disagreement was larger than disagreements in aesthetic evaluations of artwork (Leder et al., 2016). Put differently, rating distributions between race categories were more overlapping than not (Hanel et al., 2019). This pattern occurred in each sample collected, even when manipulating social norm cues (Supplemental Appendix A). The variance analyses show how average race differences do not always emerge from distinct and collective "racial group" psychologies as often implied by realist understandings of race. These results are analogous to variance partitioning analyses that counter biological race realism by showing that genetic diversity is larger within than between race categories (Winther, 2018).

The VCA therefore revealed insights that would remain hidden by analyses that solely focus on average comparisons. The findings challenge assumptions that race strongly clusters racism perceptions and that averages are sufficient summaries, given that we cannot reliably predict an individual's perception of racism in these tweets based on their race classification or on differences in means between race categories. In using race categories as predictor variables to make "group" inferences without attending to the magnitude of internal heterogeneity nor the varied and constructed nature of the "groups,"

Figure 4

Variable Contributions to Variance Components



Note. Percentage of variance contributed (R^2) (x axis) by variables (y axis) to each variance component for Study 1 (A) and 2 (B). Variables on the left reflect main perceiver and stimulus variables that contributed to the corresponding variance component, perceiver (red) or stimulus (blue). Variables on the right were interactions between perceiver and stimulus variables and contributed to the interaction component (purple). SDO = social dominance orientation. See the online article for the color version of this figure.

researchers use differences in means to *project* races with different beliefs and behaviors. In other words, an exclusive focus on race-based averages creates illusory group differences in perceptions. Narrowly focusing on category averages can lead researchers to discuss the averaged people as if psychologically interchangeable, a possibility made unlikely by idiosyncratic dynamic life histories (Cikara, 2021; Gergen, 1973; Tucker, 2012) and idiosyncratic judgment "noise" (Kahneman et al., 2021; Martinez et al., 2020).

For example, while one major source of disagreement in racism perceptions came from mean differences between perceivers, another major contributor (20% of the total variance) was disagreements between perceivers' idiosyncratic yet reliable stimulus rankings. Perception studies do not typically observe this kind of variance because repeated measures are often not collected. This large yet unexplained interaction variance arising from a specific stimulus and perceiver pairing may be better understood through idiographic analyses that center individualized experiences. We cannot assume "racist" is conceptualized and used in the same way within a perceiver across different stimuli, nor across different perceivers for the same stimuli, even when they share the same overall mean rating. A pair of liberal latinxs can differ in their personal connections and responses to the content of specific anti-immigrant tweets, even if they agree on the racist quality of the full set of tweets. Finally, after accounting for variables theorized to be strongly related to judgments of racism, a majority of the meaningful variance remained unexplained.

These insights warn researchers to be cautious about discussing categories as psychologically bounded groups (Brubaker, 2009; Lee, 2008; Loveman, 1999), flattening perceptual heterogeneity, and overclaiming variable impact when making claims about collective perceptions from aggregate analyses. They also invite researchers to continue improving methods for exploring data heterogeneity (e.g., Drouhot & Garip, 2021; Marti et al., 2023; Martinez & Todorov, 2021). Knowing variables' directional effects is one way to inform theory, but knowing how much they contribute to variance components and how much variance remains unaccounted is an underappreciated tool in theory building (Gantman et al., 2018; Yarkoni, 2019).

Alternative Frameworks for Understanding Dynamically Grouped Perceptions—Toward Assemblages

I propose disconnecting statistics from the race realism that underlies comparative analyses (Brubaker, 2009; Helms et al., 2005; Hochman, 2021b) and reconnecting them to race antirealism which highlights the dynamism of racism and racialization (Hochman, 2017, 2019, 2021b; Weheliye, 2014), combined with process theories such as assemblage theory or individuation (De Landa, 2016; Deleuze & Guattari, 1987; Simondon & Adkins, 2020). These theories reinterpret the nature of individuals or groups as assemblages that are constantly (re)made or maintained through continual interactions of heterogeneous components in a socio-material world that is always shifting—interacting matter (e.g., biology, geology, organisms, technology) and discourses (e.g., social norms, media, laws; Amaro & Khan, 2020; Brown & Lunt, 2002; Cikara et al., 2022; Nichterlein & Morss, 2016; Ponton, 2016; Price-Robertson & Duff, 2016; Puar, 2012; Sarti et al., 2022; Sullivan et al., 2022; Tucker, 2012, 2018; Weheliye, 2014). Individuals are products of relational and dynamic processes, and there are heterogeneous ways to relate to the same categories or shared experiences. No two people are completely repeated, just as racialization is felt and operates differently across people: Categories manifest, interact, and are experienced as context-specific events (Cikara et al., 2022; Ponton, 2016; Puar, 2012).

This shift allows us to reinterpret statistical averages and variance as indicators of processes, and acknowledge that racialization does not create actual races (Hochman, 2017, 2019). Instead, it reinforces racecraft which spreads belief in race(s) (Brubaker & Cooper, 2000; K. E. Fields & Fields, 2012). If we understand social psychology as dealing with fluid events (i.e., individuals, groups, contexts), then what an average really does is *project* an entity and its contours by retroactively caging ongoing processes. In this view, race category averages, and their internal variation are not measurements representative of stable "racial groups" but are rather produced through interacting forces that racialize by cohering heterogeneous people together under a category label. Forces include racializing political assemblages and symbolic orders that manufacture race categories and sort people into them (Weheliye, 2014; Wynter, 2003), as well as scientific assemblages that do the same (Fox & Alldred, 2015; Gillespie, 2023): Researchers that set the investigative focus, scientific norms that dictate acceptable practices, grants that fund certain research, technology and survey designs that ask participants from varied life contexts to sort themselves into "demographic" race categories, analytic rituals that flatten data heterogeneity and treat people in a race category as a cohesive unit, colonially inherited epistemologies that shape data interpretation and reproduce hierarchical constructions of humanity, and scientific journals that publish and spread "racial knowledge" (Goldberg, 2000) which shapes what race and racism is understood to be for the public and social scientists. This makes identifying best quantification practices of racism perceptions an important theoretical and practical need. While assemblage-thinking highlights many points of intervention for countering racecraft, I propose that the VCA intervenes at the analytic level by helping to develop an antirealist interpretation of descriptive race statistics. This interpretation foregrounds *racialization* as a dynamic sorting mechanism (i.e., how people get misperceived and treated as belonging to a real race) alongside *heterogeneity* as a default analysis to check the psychological cohesion of racialized groups on various issues.

The VCA as used here can be understood as capturing a contextual snapshot (Gergen, 1973)—a clue of the assemblages actively aligning and separating perceptions along dynamic cleavages. Larger between- than within-race category heterogeneity captures a context where racializing forces have created distinct perceptual clusters. Larger within- than between-race category heterogeneity suggests more influential forces creating perceptual (dis)agreement that may not conform to racialized cleavages. For instance, the results showed that symbolic racism, political orientation, and forms of SDO were often in the top three contributors to disagreements in anti-immigrant racism perceptions. The rated tweets evoked the context of Donald Trump's presidential speeches and policies against immigrants and Muslims, a context which increased support for hate crimes (Müller & Schwarz, 2018). Given that "racism" is a discursive battle site for definitions that are politically beneficial (Doane, 2006), his actions likely affected how "racism" was perceived in the context of immigration. Donald Trump harnessed the flow of discourse and politicized it in ways that were evoked by the tweets' content, which to some extent aligned the perceptions of differently racialized individuals into polarized clusters (i.e., anti- or proimmigration; Brown & Lunt, 2002; Kubin & Brandt, 2020; Stern & Ondish, 2018)—although a level of perceptual unpredictability remains given that racism ratings were not fully accounted for by political variables (i.e., explained less than 13.5% of the total variance). Perceptions are therefore not completely dictated by individuals' psychology or some characteristic inherent to targeted populations or significant variables (Paluck, 2012). Instead, racism perceptions can be understood as events produced by dynamic assemblages of heterogeneous forces (e.g., political elites and discourse, enforcement norms, social networks, media broadcasts and consumption, information and affective ecologies, violent and extractive atmospheres, historical continuities, unique and prior life experiences, research design and context) and how one is embedded or positioned within those assemblages.

Constraints on Generality

The race antirealist assemblage approach highlights the basis for expecting perceptual heterogeneity—the world is highly dynamic, but must race category averages *always* show large internal disagreements? An issue with these studies is that large disagreements in racism perceptions could have occurred because the public may not consider immigration a "racial" topic. A more compelling case would be to show the same patterns in evaluative contexts considered more obviously race-related. Therefore, I reanalyzed publicly accessible data using variance mapping (see OSF archive for a comprehensive summary). I found that some racialized contexts continue to show larger within-race disagreements, where fear ratings of police behavior exhibited 0%–1% of total variance explained by stimulus variance (agreement) in the full sample and within respondents classified as black or as white (Pickett et al., 2024). Some racialized contexts show both large between-race disagreements *and* agreements, where ratings of the role of race in the shooting of Michael Brown exhibited 46.8% overlap between black and white distributions (Jefferson et al., 2020). Finally, some racialized contexts show both large within- and between- race *agreement*, where ratings on the magnitude of racial discrimination across decades exhibited 31%–51% of the total variance explained by stimulus variance (agreement), which was the largest component across the full sample and within respondents classified as black or as white (Rasmussen et al., 2022). In line with assemblage thinking, the ability for racist or racializing forces to produce highly distinct racialized perceptual clusters will depend on the context. In the reanalyses, no context did so. While specific psychologies *can* arise from specific sociostructural locations, people experiencing those locations are not inevitably imbued with such psychologies. This evidence should motivate psychologists to avoid writing and theorizing practices that imply inhabiting a social location or category straightforwardly determines one's social cognition (McGuffey, 2018), such an implication would be at odds with much empirical perception data. It is instead pertinent to consider what conditions make racialized perceptual clusters more bounded and likely.

One consistent factor shown to diverge perceptions in a racialized manner is the meaning-making practices people use to interpret their social locations and experiences (e.g., identity strength or disclosure practices, Jefferson et al., 2020; McGuffey, 2018; J. C. Nelson et al., 2013; Reinka & Leach, 2017). People who attach themselves strongly to their classifications and who share similar understandings of that classification may be the most likely to agree (although this has yet to be tested using VCAs). If we understand "that race, ethnicity, and nation are not things in the world but ways of seeing the world" (Brubaker et al., 2004, p. 47), then sampling people who have experienced or participate in group-making forces that spread shared worldviews or interpretive schemas (e.g., consciousness raising, political activism) may capture more bounded perceptual clusters (Brubaker et al., 2004; Lee, 2008)—especially if the experimental context unambiguously activates that worldview.

Conclusion

Researchers often discuss average race differences in perceptions as if representative of psychological reality, a practice that can reify race(s). Acknowledging this problem is not meant to blame or accuse researchers of ill-intent nor should it discourage researchers from running comparative analyses or collecting inclusive samples. Racecraft is an ideology that spreads through conventional social and research practices. This should galvanize us to be more vigilant about how *racecraft-blindness* can derail our scientific toolkits and social justice efforts. My argument here is that quantitative race category comparisons reify race because they fail to account for the construction of those categories (they are taken for granted as cohesive groups), leading to misspecifications about how individuals' perceptions are formed in relation to those categories and how to best quantify those perceptions. Consequently, areas in need of improvement are how to analyze perceptions and how to measure race from a race antirealist perspective. For analytics, I introduced the VCA as one potential solution that centers heterogeneity. For measurement, current practices actively racialize participants by simply sorting participants into race categories without context (Benthall & Haynes, 2019; Cikara et al., 2022; Valdivia & Tazzioli, 2023). This is exactly the measurement approach I replicated in this project to help showcase the negative downstream analytic consequences of standard practices. However, researchers who want to avoid potential downsides should instead develop a practice of collecting more comprehensive participant measurements that characterize how they have been impacted by racism (e.g., experiences of discrimination, life obstacles, material conditions, or privileges), how they make sense of that impact (e.g., identity strength, disclosure practices; Helms et al., 2005; McGuffey, 2018), and how race categories are multidimensionally constructed in the micro and macro contexts of their lives (i.e., the context-specific forces that dynamically bind people, features, categories, and consequences together). For improved measurement approaches, see López et al. (2018), Monk (2022), Quintana (2022), Roth (2016), Schachter et al. (2021), and Sen and Wasow (2016). Comprehensive measurements can improve comparative analyses by identifying the stability and consequences of participants' racializations, sources of within-category heterogeneity, and the contexts where racializing forces truly create divergent psychologies. Ultimately, we need to be continuously reflexive about the tools we use. As Achille Mbembe noted, "we are increasingly surrounded by multiple and expanding wavefronts of calculation, all we are willing to ask from it is to detect patterns […] can we turn these new instruments of calculation and power into instruments of liberation?" (Mbembe, 2021, p. 130).

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