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Formally Testing the Competitive Cue Claim in Person Perception Research:

Does the Use of Social Categories Diminish the Use of Other Cues?

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Data, code, and model files can be found here: https://osf.io/sywmh

Abstract

Forming impressions of other people requires relying on multiple social cues. Prominent theories have proposed a competitive dynamic between the use of social categories and other cues (e.g., individuating cues, emotion expressions) to inform social judgments, with greater reliance on social categories inherently diminishing reliance on other cues and vice versa. Because of methodological limitations, however, this key component of person perception theorizing has remained largely untested. To overcome these limitations, we implement a novel multinomial processing tree framework to disentangle the unique contributions of multiple pieces of information (e.g., social categories, emotion expressions). If person perception is inherently cue competitive, we should find consistently negative covariation between social category use and the use of other cues. However, across 14 datasets (N = 12,239 participants) comprising a diversity of judgments (e.g., race, trustworthiness), methods (e.g., Implicit Association Test, speeded classification), and social cues (e.g., gender, emotion expression), we observed no consistent negative covariation between social category use and the use of other cues. Findings were characterized by substantial heterogeneity across methods, judgments, and social cues, suggesting that whether social cues compete, cooperate, or are integrated orthogonally is context- and perceiver-sensitive. Overall, this research challenges the position that the use of social categories and other cues in person perception is inherently competitive.

Keywords: impression formation; multinomial processing tree modeling; person perception; social categorization; stereotyping

Statement of Limitations

This research provides a comprehensive test of the competitive cue hypothesis across many studies, but its conclusions have several limitations. The findings are based largely on U.S. participants completing structured laboratory tasks; therefore, the patterns of cue integration may differ in real-world interactions and in other cultural contexts. Our meta-analysis is also constrained by its reliance on a convenience sample of archival data rather than a systematic review. On a measurement level, our modeling approach quantifies the degree to which cues are used, but it does not reveal the specific cognitive mechanisms (e.g., inhibition vs. re-interpretation) driving their contribution to person impressions. Finally, some statistical estimates of the relationships between cues were imprecise, underscoring that although the lack of consistent competition is a robust finding, the exact nature of the relationship between specific cues in specific contexts requires further investigation with large, diverse samples.

Formally Testing the Competitive Cue Claim in Person Perception: Does the Use of Social Categories Diminish the Use of Other Cues?

Impressions of other people are based on a wide variety of attributes, including observed behaviors, expressed emotions, and social categories to which they belong (e.g., race, gender, age). How person perceivers integrate the implications of these features into a coherent impression is among the most basic questions in social psychology, dating to the seminal work of Asch (1946) and Anderson (1971). Here, we formally tested one of the most canonical theoretical positions in the domain of person perception—namely, that increased use of social category cues necessarily decreases the use of other cues.

Categories as Competitive Cues

The proposition that relying on social categories diminishes reliance on other cues pervades multiple literatures. According to Social Identity Theory (SIT; Tajfel & Turner, 1986), for example, people place themselves along a continuum—as an individual on one end (i.e., personal identity) and as a group member on the other (i.e., social identity). This theory imposes a hydraulic relationship between personal versus social aspects of self-hood: As construing oneself as a group member increases, construing oneself in terms of individuating features decreases, and vice versa.[1] Moreover, SIT claims that only a single identity is active at a time, with the adoption of one identity precluding the simultaneous adoption of others. Similarly, Self-Categorization Theory (Turner et al., 1987) proposes that people categorize themselves and

[1] Following prominent models of person perception, we distinguish between cues that pertain to the social categories to which a person belongs and individuating cues that reflect information relatively unique to the person without reference to social categories. This distinction, though fuzzy, has formed the theoretical basis for person perception models proposing competition in the use of different cues.

others as members of only one group at a time, again precluding simultaneous consideration of the multiple social categories to which they belong (Hogg et al., 2004).

The role of social categories has been prominent in theorizing about person construal. The Stereotype Activation-Inhibition Model (Bodenhausen & Macrae, 1998), for example, proposes that others are categorized by a single category at a time. This model also posits that the use of alternative categories is inhibited upon selecting an initial focal social category (see also Kunda & Sinclair, 1999). Elsewhere, the Lens Model of stereotyping (Petsko & Bodenhausen, 2020; Petsko et al., 2022) proposes an extension of the selective-inhibition notion (e.g., either race or gender is focal), whereby perceiver- and contextual-based factors instigate the use of features cuing intersectional stereotypes. The model implies a competition between the use of cues reflecting an intersectional stereotype (e.g., cues to 'Black woman' stereotype) and the use of cues pertaining to a single category (e.g., cues to either 'Black' or 'woman' stereotypes).

Other perspectives suggest that perceivers simultaneously consider multiple social categories to inform their judgments; however, they still claim that competition among categories plays a central role. Various models of cross-categorization, for example, emphasize competition between multiple activated categories (Crisp & Hewstone, 2007; Deschamps & Doise 1978; Kurzban et al., 2001; see also Klauer et al., 2014). From an evolutionary perspective, race cues serve as proxies for coalitional affiliation, which compete against other, sometimes more relevant coalitional cues (e.g., team membership; but see Klauer et al., 2014, for evidence of more domain-general category competition).

Prominent dual-process models of person perception also suggest that the use of social categories diminishes the use of identity-specific features (Brewer, 1988; Fiske & Neuberg, 1990). Once again, a negative relationship is assumed: As use of one type of cue increases, use

of the other decreases. The Categorization-Individuation model (CIM) of face recognition (Hugenberg et al., 2010) proposes a similar relationship: a continuum between the encoding of category-based and identity-specific facial cues, which determine whether a face is remembered by its personal identity or as an interchangeable member of a broader group.

Importantly, however, not all models of person perception impose a negative correlation between the use of social categories and the use of other cues. Network models of person perception provide a neurally plausible framework for both inhibitory and facilitative relationships among social cues (Freeman & Ambady, 2011; Freeman et al., 2020; Kunda & Thagard, 1996; see also Crisp & Hewstone, 2007). In these models, all features may contribute to impression formation, with no inherent competition among social categories and other cues. Nonetheless, it remains the case that many predominant theoretical views and common empirical interpretations in person perception research emphasize competitive cue processing.

Testing the Competitive Cue Hypothesis

Despite the pervasiveness of the competitive cue hypothesis, there have been few attempts to carefully test the claim. In large part, this is due to methodological challenges that conventional measures face in identifying the impacts of multiple cues on impressions, as they cannot disentangle the unique contribution of each cue. To illustrate, consider the finding that social judgments are more stereotypical when making complex versus simple judgments (Bodenhausen & Lichtenstein, 1987). Although evidence clearly supports the notion that greater processing difficulty increases stereotyping, it does not clarify the information responsible for this phenomenon. Greater stereotyping could reflect (1) increased use of social categories, (2) decreased use of other cues with competing implications, or (3) both. It could also indicate that

(4) both features are used more or (5) both features are used less, but to differing degrees (e.g., a greater relative increase in the use of social categories versus person-specific cues).

As another example, consider the finding that the availability of diagnostic individuating information (e.g., descriptions of a person's past behaviors) can mitigate the influence of racial stereotypes in interpersonal judgments (Rubinstein et al., 2018; see also Navon & Bar-Anan, 2025). Although this work provides an important illustration of how the diagnosticity of individuating cues can modulate stereotypic judgment, it does not specify the information-processing mechanism producing this outcome. Does the observed reduction in stereotyping reflect a decreased reliance on the target's race, an increased reliance on their individuating behavior, or some combination of changes in the use of both cues?

Finally, consider studies using mouse-tracking to document the joint contributions of multiple features in social categorization. In one application of the method, when categorizing faces by gender, people are drawn to the incorrect response if hair style is gender-incongruent (e.g., men with long hair; women with short hair; Freeman et al., 2008). That judgments of men (women) are drawn toward "woman" ("man") classifications when they have long (short) hair suggests that multiple features are simultaneously informing those judgments, which is taken as support for network models in which all features are integrated into judgments. Although such findings support the simultaneous consideration of social categories and other cues, they do not shed light on competitive cue processing. With mouse-tracking, it is not possible to assess the unique impacts of different cues. Does the attraction to a "woman" classification for men with long hair reflect increased use of hair cues, decreased use of face cues, or a combination of both?

Limited Evidence of Cue Competition

Direct tests of competitive cue processing have been scarce. Two notable exceptions measured the activation and inhibition of categorical information after making one of two social categories salient, though their results were inconsistent regarding competitive cue processing. Macrae et al. (1995) manipulated the salience of one of two categories (gender, race) before participants completed a lexical decision task designed to measure the activation of each category. When one category was made salient, the other was inhibited (i.e., sub-baseline activation). In another case, Petsko and colleagues (2022, Experiment 1) used a memory task to assess the activation and inhibition of two applicable categories (e.g., age, gender) after making one salient. Inhibition of the non-salient category was sometimes evident.

In a final example, which used a speeded gender classification task and a modeling method described below, reliance on emotion cues facilitated reliance on gender cues, producing a *positive* correlation in cue use (Klein & Sherman, 2024). These data, though suggestive, afford a weak test of competitive cue processing. Gender cues and emotion cues are confounded in face perception (Becker et al., 2007), in that the same facial features can cue both emotion and gender (e.g., facial cues for *man* and *angry* overlap considerably). Thus, it remains unknown whether a positive relationship between category use emerges when cues are not perceptually confounded.

Overall, evidence for the competitive cue hypothesis is limited, despite longstanding theoretical assumptions of inherent cue competition. The examples relevant for testing the underlying assumption are few and inconclusive, and the breadth of cues tested is minimal.

The Present Research

Conventional measures of person perception cannot provide independent estimates of the use of different cues, hindering tests of competitive cue processing. To overcome this limitation, we used a multinomial processing tree (MPT) framework, specifically, the Multi-Cue Integration

(MCI) model (Klein & Sherman, 2024), to quantify the use of distinct person cues (e.g., emotion expression, race). The MCI model accounts for observed frequencies of discrete responses through a set of related parameters that each reflect a particular latent process: the use of one cue (C_1), the use of a second cue (C_2), and the influence of a response bias toward a particular judgment (g). Parameter estimates can vary independently, affording a test of how the use of two cues covaries.

The assumption of inherent competition in cue processing requires a broad test of its generality. Accordingly, we implemented the MCI model to measure the covariance in cue processing across a large and diverse set of social judgments, varying in social cues, methods, judgments, and participant populations. This comprehensive approach offers a key advantage by allowing us to examine two instantiations of cue competition: between-persons and within-persons. The implied focus of most theoretical models has been on *within-person* competition, whereby a perceiver dynamically trades off reliance on one cue for another. However, competition can also manifest as a *between-person* difference, whereby perceivers who rely on social categories more (less) than average rely on alternative cues less (more) than average.

The existing evidence for cue competition has solely tested between-person cue processing (i.e., mean comparisons or correlations). Here, we test competitive cue processing at both levels, offering a more comprehensive evaluation of the competitive cue hypothesis than has been attempted previously. First, we test whether perceivers who use certain cues more use other cues less (i.e., between-person cue competition). Second, we test whether perceivers use some cues more when they use other cues less (i.e., within-person cue competition).

Method

Transparency and Openness

For all datasets and their respective studies, we report participant- and trial-level data exclusion criteria and exclusion amounts, the parameter estimation strategy, and parameter analyses. For Experiment 4 (speeded trustworthiness classifications), in particular, these criteria were preregistered. Exclusions to the Judgment Bias Task (JBT) data were based on Axt and colleagues' (2018) preregistered exclusion criteria. Exclusions to Implicit Association Test (IAT) data from Navon and colleagues (2021) were based the authors' preregistered IAT-specific exclusion criterion.[2] All exclusion criterion are detailed below, for each dataset. Data, model files, parameter estimation and analysis code are available at https://osf.io/sywmh. The preregistration for Experiment 4 is available https://osf.io/6bzjw. Due to licensing restrictions, we do not make publicly available the research stimuli for the novel speeded classification task experiments. However, those stimuli will be made available upon request. Parameter estimation, parameter analysis, and data visualization were conducted in R (Version 4.4.1; R Core Team, 2024) using the *TreeBUGS* (Version 1.5.0; Heck et al., 2018), *bayesmeta* (Version 3.4; Röver, 2020), *forestploter* (Version 1.1.2; Dayimu, 2025), and *ggplot2* (Version 3.5.1; Wickham, 2016) packages.

Data

In total, we analyzed $k = 14$ datasets ($N = 12{,}239$ participants) of published and unpublished social judgment data. We conducted eight novel experiments—seven using a speeded classification task and one using the Judgment Bias Task (detailed below)—with varied cue-pairings (e.g., emotion expression and gender cues). To increase the generalizability of our findings, we gathered additional archival data based on the following criteria: the data (1) were

[2] The authors had additional exclusion criteria based on action or inaction by participants later on in the studies. As our focus is on the IAT data specifically, we focused on their IAT-specific exclusion criterion.

compatible with the task requirements of our process model framework (see below), (2) reflected information and judgments directly relevant to models predicting competitive cue processing, and (3) were easily accessible to the authors. Regarding the first criterion, the data had to include (a) many repeated measurements (all included ≥40 trials per participant) and (b) trials in which the implication of the two cues were both congruent (e.g., smiling female and scowling male faces during speeded gender classification) and incongruent (e.g., smiling male and scowling female faces during the same task). In addition, in every pair of social cues and across all datasets, one cue was more task-relevant than the other (e.g., emotion expression was more task-relevant during speeded emotion classification).[3] Each dataset reflects a unique combination of intended judgment, methodology, and social cues (see Table 1 for a summary). Below, we provide a general overview of the tasks, data, and data exclusions (see the Supplementary Materials for details on the exact number of exclusions).

Table 1

Included Datasets and Their Relevant Details

Source	Studies	Method	Cues	N
Axt et al. (2018)	1a–1d	Academic JBT	Individuating, Gender	3992
Axt et al. (2018)	2a–3	Academic JBT	Individuating, Group Identity	1296
Axt et al. (2018)	4	Dating JBT	Individuating, Race	980
Current Research	1	Academic JBT	Individuating, Gender	1875
Current Research	1a	Speeded Gender Classification	Gender, Emotion	95
Current Research	1b	Speeded Emotion Classification	Emotion, Gender	350
Current Research	2a	Speeded Race Classification	Race, Emotion	202
Current Research	2b	Speeded Emotion Classification	Emotion, Race	198
Current Research	3a	Speeded Race Classification	Race, Gender	191
Current Research	3b	Speeded Gender Classification	Gender, Race	244

[3] A difference in cue relevance helps determine which cue is conditional on insufficient use of the other. Future implementations do not need to rely on cue relevance, but they will need to justify the conditional structure of the model they rely on (i.e., which cue is assigned to C_1 vs. C_2). One method of determining parameter assignment in the MCI model is model comparison (see Klein & Sherman, 2024).

Current Research	4	Speeded Trustworthiness Classification	Emotion, Race	159
Navon et al. (2021)	2–17	IAT	Individuating, Race	2064
Todd et al. (2021)	1, 3, 4	Age Classification	Age, Race	210
Todd et al. (2021)	1; 3–6	Race Classification	Race, Age	383

Note. 'Current Research' reflects novel data collected by the authors. Cues are ordered by presumed relevance to intended judgment.

The Judgment Bias Task (JBT)

Across nine studies totaling four datasets, participants completed the JBT (Axt et al., 2018), a task designed to measure bias in selection decisions. Applicant profiles were evaluated for acceptance into an academic honor society or as potential dating partners. Each profile included individuating criteria that participants were instructed to weigh equally. For the academic selection decisions, the criteria were Science GPA, Humanities GPA, recommendation letter quality, and interview scores. For the dating decisions, the criteria were shared interests, social compatibility, and social similarity. Profiles systematically varied, with half containing individuating information that was objectively more qualified than the others.

Alongside these individuating cues, each profile contained social category cues that were task-irrelevant. The specific cues were gender (man, woman), race (White, non-White), or group membership (ingroup, outgroup [defined by the participant's university or political affiliation]).[4]

Participants sequentially evaluated 40 to 96 target profiles per task, presented one at a time, making binary accept/reject decisions without time constraints. Trials included equal proportions of congruent cue combinations (e.g., highly qualified ingroup members) and incongruent cue combinations (e.g., highly qualified outgroup members), enabling the MCI model to disentangle the use of both individuating and social category cues. Three of the four datasets were from Axt

[4] Traditionally, the JBT has been applied to test the influence of varying degrees of attractiveness among the target applicants (e.g., Axt et al., 2018; Axt & Lai, 2019). Here, we focus on gender cues instead to offer a clear comparison between social categories and individuating information.

et al. (2018): a dataset of four academic JBT studies with individuating and gender cues, another dataset of three academic JBT studies with individuating and group identity cues, and a third dataset of one dating JBT study with individuating and race cues. The fourth dataset included an additional, unpublished academic JBT study with individuating and gender cues.

Raw JBT data from Axt and colleagues (2018) were excluded based on the authors' reported exclusion criteria. Participants were excluded from the analysis if their acceptance rate was less than 20% or greater than 80%, to ensure that participants adhered to the instruction of accepting approximately half of the candidates. Additionally, participants' data were excluded if they accepted or rejected all of one type of applicant (e.g., all ingroup members), with the exception of the dating JBT (Axt et al., 2018, Study 4) because accepting all of one type of candidate might be considered a realistic preference in a dating context. Raw data from our novel JBT study did not exclude data by these criteria because the decision rule to accept approximately half of all applicants was directly manipulated, with participants in one of the two conditions receiving no decision rule instructions. Rather, participants' data were excluded only if they failed to complete all 64 trials of the task.

The Implicit Association Test (IAT)

We also included a dataset of 16 studies from Navon et al. (2021, Studies 2–17) in which participants completed an IAT (Greenwald et al., 1998) assessing evaluations of well-known people varying in race and celebrity identity. Each study assigned participants to a specific pair of celebrities: one Black and one White. Based on prior normative ratings, the Black celebrity (e.g., Eddie Murphy) was always more well-liked than the White celebrity (e.g., Ben Affleck). Participants sorted stimuli into four categories using two response keys: the two target celebrities (e.g., Murphy vs. Affleck) and the evaluative dimensions "good" and "bad." Stimuli included the

faces of the two celebrities and a standardized set of positive and negative words. Across blocks, the response key mappings of celebrity and evaluative categories varied, ensuring that race and celebrity identity cues sometimes aligned and sometimes conflicted, which enabled the MCI model to disentangle the use of both individuating and social category cues. Given our focus on person perception—in this case, the classification of targets possessing both categorical race and individuating identity information—we only modeled trials in which participants categorized target celebrities and not evaluative words.

Following Navon and colleagues (2021), we removed data based on IAT performance. Specifically, we excluded participants with more than 10% of IAT trials faster than 300 ms. Whereas Navon et al. (2021) excluded participants who did not complete the entirety of their study, our analyses focus solely on the IAT data. Therefore, we included participants who did not complete other tasks that followed the IAT.

Speeded Classification

We conducted seven studies in which participants completed a speeded face classification task designed to assess cue use under moderately difficult processing conditions. Across studies, participants "quickly and accurately" classified 160 gray-scaled target faces along a single focal dimension (race, gender, emotion, or trustworthiness) by pressing one of two response keys. Each trial presented stimuli in the following sequence: a fixation cross for 500 ms, a target face for 200 ms, and, finally, a pattern mask until a response was recorded. Each target face varied along two cue dimensions: the task-relevant cue (e.g., race in a speeded race classification task) and an irrelevant cue (e.g., emotion expression in a speeded race classification task). Cue pairings varied across studies to permit analysis of cue congruency effects.

Experiments 1a and 1b crossed emotion (smiling, scowling) and gender (woman, man) cues. Experiments 2a and 2b crossed emotion and race (Black, White) cues. Experiments 3a and 3b crossed gender and race cues. Experiment 4 collected trustworthiness judgments of faces varying in emotion and race cues, with emotion cues presumed to be more relevant (e.g., Oosterhof & Todorov, 2009). Instructions emphasized speed and accuracy in all tasks. Experiments 1a–3b used morphed face stimuli that included both ambiguous and unambiguous versions of each cue to more precisely evaluate cue-based responding (see Klein & Sherman, 2024, Supplement). Trials were evenly split between congruent cue pairings (e.g., smiling female faces during emotion classification) and incongruent pairings (e.g., scowling female faces during the same task), providing the necessary contrast for disentangling cue use with the MCI model.

Participants were excluded if they failed to complete the experiment or if they responded with the same key on >90% of trials. For gender, race, and emotion classification tasks, participants were also excluded if they had an error rate exceeding 50%.[5] At the trial level, we also excluded responses with latencies <100 ms or >2,500 ms.

(Non-speeded) Classification

Finally, we included two datasets of (non-speeded) face classification judgments from Todd et al. (2021). The first dataset comprised samples from three studies involving age classification, and the second comprised samples from five studies involving race classification. Across studies, participants completed a face classification task in which they categorized male target faces varying orthogonally in race (Black, White) and age (adult, child). Faces were drawn from established databases and included men (Ma et al., 2015) and boys (LoBue & Thrasher, 2015)

[5] Trustworthiness classifications in Experiment 4 did not have clear correct and incorrect response options.

matched on race. Each classification task allowed participants to view faces until they responded. Trial-level data were removed if their response time was <100 ms or >2,500 ms.

Analytic Strategy

Model Instantiation

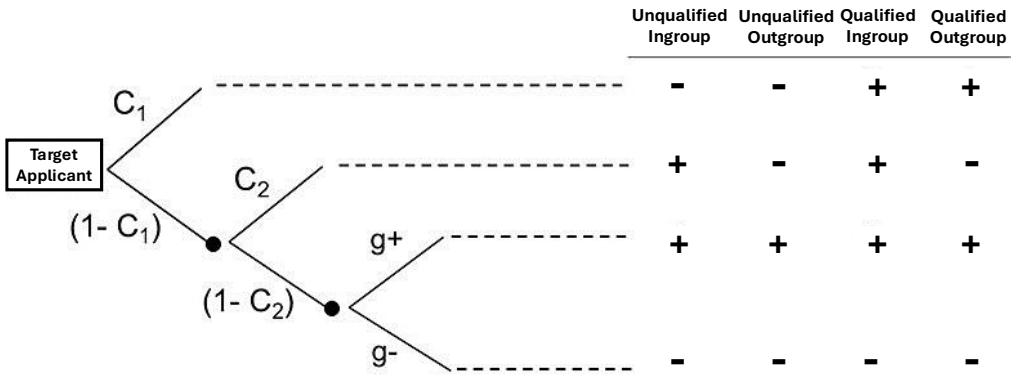
The C_1 and C_2 parameters reflect the probabilities that their respective information is integrated into a final judgment and, therefore, that the observed response is more aligned with their implications. In all studies, one of the two cues is more relevant to the intended judgment than the other, which we assign to C_1. For emotion classification judgments of targets varying in emotion cues and gender cues, for example, C_1 reflects the use of emotion cues (smiles, scowls), C_2 reflects the use of gender cues (woman, man), and g reflects a response bias toward making one judgment (e.g., *happy*) over another (e.g., *angry*).

The MCI model is flexible enough to be instantiated for numerous different person perception tasks. Here, we configured the MCI model for each dataset by deriving a pair of equations (i.e., a "tree") for each unique trial type, with each equation in the pair corresponding to one of two response options. Consider the academic JBT. The MCI model assumes decisions emerge from the joint contributions of academic qualifications (C_1: qualified, unqualified) and group identity (C_2: ingroup, outgroup). The applicant's qualifications may be used sufficiently to derive decisions [C_1]. However, if they are not used or if their use is insufficient to derive a decision, the model assumes that group membership cues may be recruited to inform the decision, [(1 – C1) × C2]. Alternatively, a response bias toward accepting [$(1 – C_1) \times (1 – C_2) \times$ g] or rejecting [$(1 – C_1) \times (1 – C_2) \times (1 – g)$] applicants may influence decisions if neither cue is used sufficiently. Each unique trial type generates two complementary equations from these relationships among the parameters: one reflecting the probability of accepting the applicant and

the other reflecting the probability of rejecting the applicant. Deriving these equations can be achieved by tracing paths along the processing tree diagram in Figure 1.

Figure 1

The MCI Model and Its Predicted Responses to the JBT (Group Identity)



Notes. Diagram of the MCI model used to measure person perception data from the JBT in which individuating (i.e., applicant qualifications) and group identity cues were varied across target applicants. The manifest outcome is represented on the right side of the figure (i.e., binary responses to accept or reject the applicant). The paths along the tree depict the processing paths assumed by the model to explain responses for each trial type.

The probability of accepting a qualified outgroup applicant, for example, is reflected by the use of their qualifications and a tendency to accept applicants when qualification and group identity cues are insufficient for deriving a decision:

$$P(\text{Accept} \mid \text{Qualified, Outgroup}) = C_1 + (1 - C_1) \times (1 - C_2) \times g$$

Conversely, the probability of rejecting the same applicant is derived from reliance on their (out)group identity cues when qualifications are unused or insufficient, or a tendency to reject applicants when qualification and group identity cues are insufficient for deriving a decision:

$$P(\text{Reject} \mid \text{Qualified, Outgroup}) = (1 - C_1) \times C_2 + (1 - C_1) \times (1 - C_2) \times (1 - g)$$

For unqualified outgroup applicants and qualified ingroup applicants, analogous equations are derived, each combining the direct effect of qualifications and the contingent use of group identity cues, along with a potential response bias, to explain the observed categorical responses. The complete set of equations for the MCI model is available at https://osf.io/sywmh.

Model Fitting

We fit the MCI model with a hierarchical Bayesian estimation method (*latent-trait* approach; Klauer, 2010) using the *TreeBUGS* package (Heck et al., 2018). This approach, which models individual-level parameters as random variables in a hierarchical distribution, often minimizes bias and noise in parameter estimation relative to approaches that either ignore individual differences entirely or fail to account for shared variance across participants (see Singmann et al., 2024). For each dataset, we ran 12 independent MCMC chains of 10,000 sampling iterations per chain (after a separate 2,000-iteration adaptation phase). The first 5,000 'burn-in' iterations per chain were discarded, and the remaining 5,000 iterations were thinned by keeping every fifth draw, yielding a total of 12,000 posterior samples (or 1,000 per chain). When datasets included multiple studies or between-participant conditions, we added study- or condition-specific factors to the model's covariance structure to capture any systematic variance.

Along with providing aggregate-level and individual-level parameter estimates, model fitting provided correlations between the parameters. Crucially, this includes the correlation between the two cue-processing parameters (e.g., $C_1 \sim C_2$). According to the competitive cue hypothesis, model fitting should reveal negative covariation between the cue-processing parameters (e.g., a compensatory increase in the estimated use of race as the estimated use of gender increases).

Results

Model Fit

To assess model fit, we conducted posterior predictive checks using 1,000 samples from each of the fitted models. Analytically, model fits were generally good, except for the trustworthiness judgments collected for one of the speeded classification studies. Visual inspection and the *w*-statistic of misfit, however, suggest that model fit was sufficiently high across all models. Model fit statistics are available in the Supplementary Materials (Table S2 and Figures S1–S14).

Parameter Correlations

To formally test the competitive cue hypothesis, we conducted a Bayesian random-effects meta-analysis using the *bayesmeta* package (Röver, 2020). The analysis integrated all 14 correlation coefficients estimating the association between the C_1 and C_2 parameters, serving as a large-scale test of between-person cue processing. A negative correlation would support the assumption of cue competition (i.e., using one cue more means using another cue less). A positive correlation would suggest that the use of two cues is facilitative. And a null effect would suggest that their use varies independently of each other. Results are reported using the median of the posterior distribution and its surrounding 95% Bayesian Credibility Intervals ($BCI_{95\%}$).

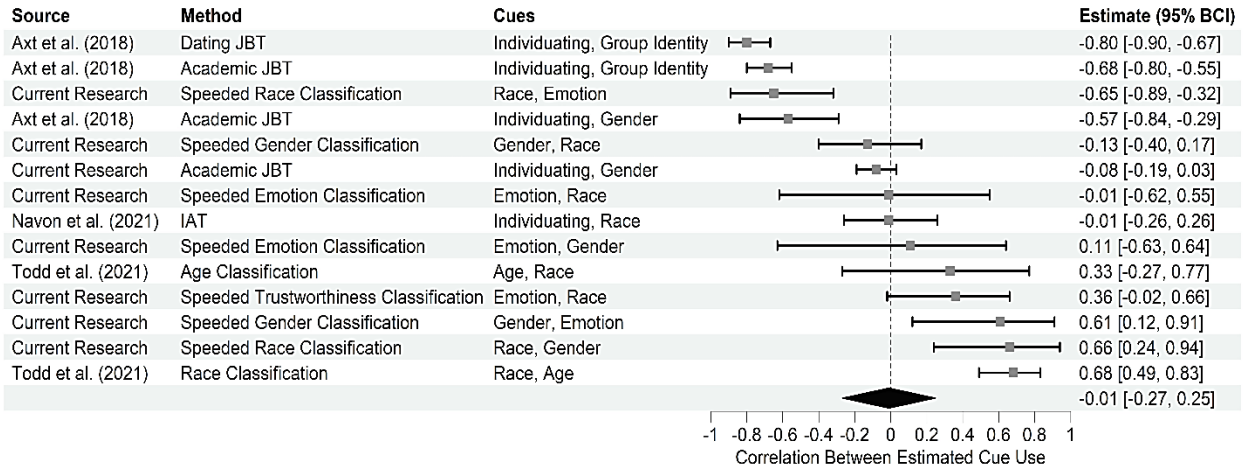
The resulting posterior meta-analytic correlation was centered credibly at zero ($r = –0.01$, $BCI_{95\%}$ [–0.27, 0.25]). With a Bayes Factor of $BF_{01} = 3.99$, this analysis suggests the data are nearly four times more likely under a null effect than a credible correlation in either direction.[6] Further examination of the posterior distribution shows a probability of a negative meta-analytic correlation being near chance, $P(r < 0) = .54$. There was considerable heterogeneity across studies ($\tau = 0.48$, $BCI_{95\%}$ [0.33, 0.69], $I^2 > 99\%$), indicating that the relationship between cues

[6] A Bayes factor in favor of the null hypothesis is denoted as BF_{10} and a Bayes factor in favor of the alternative hypothesis (i.e., negative or positive correlation) is denoted as BF_{01}. We rely on a widely used convention of considering evidence as 'weak' for Bayes factors between 1 and 3, 'moderate' between 3 and 10, and 'strong' when greater than 10 (Lee & Wagenmakers, 2014).

varied substantially between datasets. Individual correlation estimates, which appear in Figure 2, ranged from reliably negative to robustly null to reliably positive.

Figure 2

Correlation Estimates and Meta-Analysis for All 14 Datasets



Note. Gray squares reflect correlation estimates between C_1 and C_2 parameters. Error bars reflect Bayesian credibility intervals around the point estimates. The dark diamond reflects the meta-analytic correlation estimate and its 95% credibility interval. The *Cues* column reflects the cues assigned to C_1 and C_2, respectively.

Exploring Robustness in the MCI Parameter Correlations

Notably, there is substantial imprecision with some of the parameter correlations. To bolster confidence in the conclusion of our results, we re-fitted the random-effects model three additional times, after excluding parameter correlations with *SD*s >.20, .15, and .10 (see Supplementary Materials). No meaningful change in the conclusion emerged for any of the exclusion criteria. Confidence in the overall pattern of parameter correlations also comes from directly replicating the positive parameter correlation from Klein and Sherman (2024): The use of gender and emotion facial cues to inform speeded gender classifications was *positively* correlated (r = .609, $BCI_{95\%}$ [.124, .908]).

Social Category vs. Individuating Cues

The assumption of cue competition comes from two different theoretical traditions. The first, central to dual-process models, posits a fundamental trade-off between the use of social categories and more person-specific, individuating information (Brewer, 1988; Fiske & Neuberg, 1990; Hugenberg et al., 2010). The second, core to models of stereotype inhibition and cross-categorization, proposes competition between multiple categories (Bodenhausen & Macrae, 1998; Crisp & Hewstone, 2007; Kurzban et al., 2001; Petsko et al., 2022). Given these different theoretical traditions, we also test each form of competition separately.

The competition between social category and individuating (i.e., more person-specific) cues was tested using data from the IAT and the JBT, totaling $k = 5$ datasets ($N = 10{,}207$ participants). There was a credible negative association between the use of social category and individuating cues ($r = –0.40$, $BCI_{95\%}$ [–0.69, –0.08]). There was moderate evidence in favor of an effect over the null hypothesis ($BF_{10} = 6.57$). The model also confirmed substantial heterogeneity in these studies ($\tau = 0.31$, $I^2 > 99\%$). The negative estimate was driven by data from the JBT, for which there was a credible negative effect ($r = –0.50$, $BCI_{95\%}$ [–0.78, –0.18]), with strong evidence for an effect over the null ($BF_{10} = 16.08$). The correlation estimate using 16 IAT studies from Navon et al. (2021), by contrast, was not credible ($r = –.01$, $BCI_{95\%}$ [–.26, .26]).

Several factors might explain why a negative correlation in cue use emerged only in the JBT data. One that we can test directly is the presentation format of the cues. Whereas both cues in the IAT data and all other data in the current research were presented visually, most of the JBT studies use verbal individuating cues (e.g., interview scores) and visual social cues (e.g., gendered face images). However, even in the one JBT study where both cues were presented verbally, the negative correlation persisted ($r = –.45$, $BCI_{95\%}$ [–.59, –.30]), suggesting that format misalignment alone cannot account for the difference.

Another featural distinction between the two tasks is the instructions participants receive. Unlike the IAT, the typical JBT imposes a top-down decision rule whereby participants are instructed to accept 50% of applicants. Participants, therefore, must contend with the top-down goal of balancing their responses. Repeated acceptances may increase the likelihood of rejecting future applicants, meaning a reduced susceptibility to cues that inspire acceptance and an increased susceptibility to cues that inspire rejection.

To address this issue, we ran an experiment in which participants completed either a typical JBT with a decision rule or a JBT without the decision rule instructions. If a 50% acceptance decision rule is pushing participants to artificially pit the various cues against each other, we would expect a weaker (or absent) negative correlation when the decision rule is not imposed. Unexpectedly, we were unable to replicate a negative correlation in the decision rule condition. Rather, there was a positive correlation between the use of applicant qualifications and their gender (r = .28, $BCI_{95\%}$ [.05, .49]). Also, there was a substantially larger positive correlation in use of the two cues when no decision rule was imposed (r = .80, $BCI_{95\%}$ [.55, .91]). These data suggest that the negative correlation documented in the JBT may be informed by a top-down decision rule that participants follow during the task, and that further research is needed to diagnose the dynamics by which JBT responses are derived by competition versus cooperation among available social cues.

Social Category vs. Social Category Cues

We also tested for competition between category cues only. First, we meta-analyzed all datasets including either two sets of social category cues or social category and emotion category cues, which totaled k = 9 datasets (N = 2,032 participants). The meta-analytic correlation was not credibly different from zero (r = .20, $BCI_{95\%}$ [–.08, .47]). With BF_{01} = 1.11, the evidence is

inconclusive, offering no clear support for either hypothesis. The model also confirmed substantial heterogeneity in these studies ($\tau = 0.40$, $I^2 > 99\%$).

Traditionally, emotion categories are rarely considered in models of social categorization (Bodenhausen & Macrae, 1998; Macrae et al., 1995; Petsko et al., 2022; but see Freeman et al., 2020). Therefore, we also examined only datasets in which two social (i.e., non-emotional) categories varied. This analysis involved $k = 4$ datasets ($N = 1{,}028$ participants) and revealed a directionally positive association ($r = .35$, $BCI_{95\%}$ [-.004, .67]). With $BF_{10} = 3.04$, there was moderate evidence in favor of the positive effect. Overall, although the evidence for an association between category cues is weak when including emotion, it becomes stronger and directionally positive when only considering traditional social categories.

Summary of Parameter Correlations

Across 14 datasets analyzed using the MCI model, there was no consistent negative correlation between estimated cue processing: The overall meta-analytic posterior correlation between cues was near zero and non-credible, and substantial heterogeneity across datasets suggests that the relationship in the use of two social cues is context-sensitive rather than governed by a general competitive process.

Several datasets showed credible positive correlations, particularly in the speeded classification tasks, whereas others sometimes showed negative correlations, primarily in the JBT. These findings suggest that person perceivers may not pit individuating and social category cues against each other by default; instead, cue competition could emerge from features of the context or method (e.g., cue relevance, decision rule). Additionally, no evidence of competition was found between category cues, with most correlations being non-credible or credibly positive.

Within-Person Parameter Comparisons

The analyses above tested the competitive cue hypothesis as operationalized between-persons, whereby perceivers who use social category cues more than average also use other cues less than average. However, competitive cue processing can also be operationalized as a within-person process, whereby the process of diminishing one's use of social category cues augments one's use of other cues (i.e., an active offsetting of some cues for others). To examine this alternative, we turn to datasets among those analyzed above that contain within-participant variables. There were seven experiments with within-participant variables, all of which came from our studies using speeded classification tasks. For Experiments 1a–3b, target faces were morphed within each category (e.g., smiling and scowling faces) to produce more ambiguous versions of each feature (e.g., ambiguously smiling face, ambiguously scowling face). For Experiment 4, face images were presented both upright and inverted to induce disfluency in the processing of the social cues (e.g., Cloutier et al., 2005). We detail these manipulations further in the Supplementary Materials. Because each participant categorized faces from each level of ambiguity (or face orientation), we can test whether, as perceivers reduced their use of one cue, they correspondingly increased their use of the other cue.

Analytic Approach

To test for covarying cue use in within-participant conditions, we implemented the following analytic procedure. The MCI model was re-fit to estimate the parameters separately for each within-participant condition. Next, mean differences were computed between posterior samples of each condition, for both C_1 and C_2 parameters. If the resulting posterior distribution (of mean differences) had a $BCI_{95\%}$ excluding zero, the difference between conditions is deemed credible.

Experiment 1a (Emotion Classification)

Parameter comparisons revealed that introducing ambiguity in emotion cues credibly reduced both the use of emotion cues ($\Delta C_1 = -.652$, $BCI_{95\%}$ [−.674, −.629]; see Figure 3) and the use of gender cues ($\Delta C_2 = -.089$, $BCI_{95\%}$ [−.144, −.028]) during emotion classification. In contrast, introducing ambiguity in gender cues credibly reduced the use of gender cues ($\Delta C_2 = -.083$, $BCI_{95\%}$ [−.141, −.014]), but it increased the use of emotion cues ($\Delta C_1 = .043$, $BCI_{95\%}$ [.028, .058]). Thus, whereas the use of emotion and gender cues covaried negatively within-participants when introducing ambiguity in gender cues, the use of the two cues covaried positively within-participants when introducing ambiguity in emotion cues.

Experiment 1b (Gender Classification)

Introducing ambiguity in gender cues credibly reduced the use of gender cues ($\Delta C_1 = -.689$, $BCI_{95\%}$ [−.730, −.647]), but it did not credibly affect the use of emotion cues ($\Delta C_2 = -.031$, $BCI_{95\%}$ [−.207, .154]) during gender classification. Also, whereas introducing ambiguity in emotion cues credibly reduced the use of emotion cues ($\Delta C_2 = -.207$, $BCI_{95\%}$ [−.387, −.018]), it did not credibly affect the use of gender cues ($\Delta C_1 = .018$, $BCI_{95\%}$ [−.011, .046]). Thus, the use of gender and emotion cues did not covary within-participants during gender classification. Introducing ambiguity in gender cues only affected the use of gender cues, and introducing ambiguity in emotion cues only affected the use of emotion cues.

Experiment 2a (Emotion Classification)

Introducing ambiguity in emotion cues credibly reduced the use of emotion cues ($\Delta C_1 = -.736$, $BCI_{95\%}$ [−.762, −.710]), but it did not credibly affect the use of race cues ($\Delta C_2 > -.001$, $BCI_{95\%}$ [−.004, .001]) during emotion classification. Although introducing ambiguity in race cues did not credibly reduce the use of race cues ($\Delta C_2 = -.006$, $BCI_{95\%}$ [−.023, .011]), it had a small effect on the use of emotion cues ($\Delta C_1 = .007$, $BCI_{95\%}$ [<.001, .015]). Thus, the use of race

and emotion cues did not covary within-participants during emotion classification. Introducing ambiguity in either emotion cues or race cues only affected the use of emotion cues.

Experiment 2b (Race Classification)

Introducing ambiguity in race cues credibly reduced the use of race cues ($\Delta C_1 = -.736$, $BCI_{95\%}$ [−.761, −.710]), but it did not credibly affect the use of emotion cues ($\Delta C_2 = -.007$, $BCI_{95\%}$ [−.037, .001]) during race classification. Introducing ambiguity in emotion cues credibly increased the use of emotion cues ($\Delta C_2 = .108$, $BCI_{95\%}$ [.015, .205]), but it did not credibly affect the use of race cues ($\Delta C_1 = -.014$, $BCI_{95\%}$ [−.029, <.001]). Thus, the use of race and emotion cues did not covary within-participants during race classification. Introducing ambiguity in race cues only affected the use of race cues, and introducing ambiguity in emotion cues only affected the use of emotion cues.

Experiment 3a (Gender Classification)

Introducing ambiguity in gender cues credibly reduced the use of gender cues ($\Delta C_1 = -.645$, $BCI_{95\%}$ [−.673, −.614]) and race cues ($\Delta C_2 = -.084$, $BCI_{95\%}$ [−.170, −.011]) during gender classification. Although introducing ambiguity in race cues did not credibly reduce the use of race cues ($\Delta C_2 = -.054$, $BCI_{95\%}$ [−.153, .040]), it did credibly increase the use of gender cues ($\Delta C_1 = .042$, $BCI_{95\%}$ [.023, .063]). Overall, the use of gender and race cues positively covaried when introducing ambiguity in gender cues during gender classification. When introducing race ambiguity, however, cue use did not covary, and only the use of gender cues increased.

Experiment 3b (Race Classification)

Introducing ambiguity in race cues credibly reduced the use of race cues ($\Delta C_1 = -.689$, $BCI_{95\%}$ [−.716, −.661]) and gender cues ($\Delta C_2 = -.167$, $BCI_{95\%}$ [−.303, <−.001]) during race classification. Although introducing ambiguity in gender cues credibly reduced the use of gender

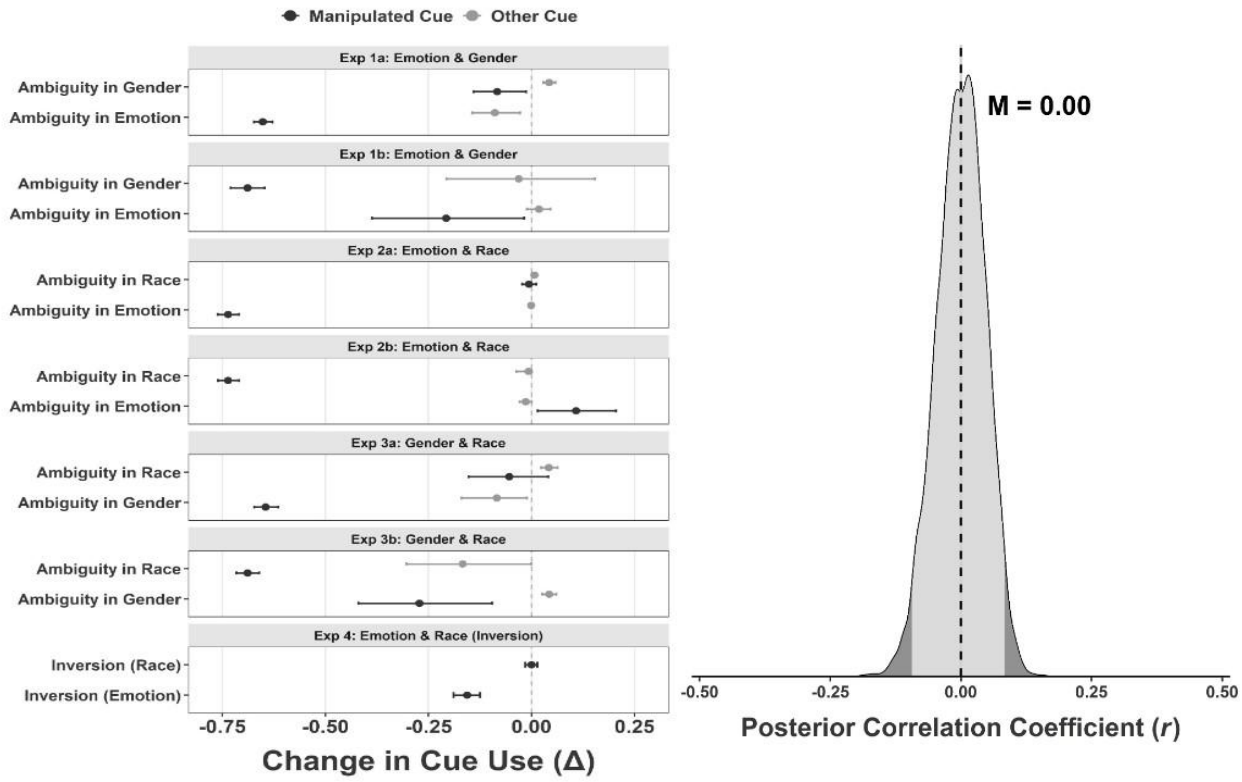
cues ($\Delta C_2 = -.272$, $BCI_{95\%}$ [−.420, −.096]), it increased the use of race cues ($\Delta C_1 = .043$, $BCI_{95\%}$ [.026, .060]). Thus, whereas the use of race and gender cues covaried negatively within-participants when introducing ambiguity in gender cues, the use of race and gender cues covaried positively within-participants when introducing ambiguity in race cues.

Experiment 4 (Trustworthiness Classification)

Parameter comparisons revealed a credible perceptual disfluency effect on the use of emotion cues ($\Delta C_1 = -.157$, $BCI_{95\%}$ [−.189, −.126]) when making trustworthiness judgments: The use of emotion cues was reduced when faces were inverted. No credible effect emerged on the use of race cues, however ($\Delta C_2 < .001$, $BCI_{95\%}$ [−.014, .015]). Thus, the use of emotion and race cues did not covary within-participants. Inverting target faces substantively lessened participants' use of emotion cues, but it did not credibly affect their use of race cues.

Figure 3

Within-Person Analyses: Individual Effects (A) and Summary Analysis (B)



Notes. Within-person analyses. Figure 3A displays the estimated change (Δ) in cue use for each experimental condition across seven experiments. Points represent the posterior mean change, and the corresponding error bars show the 95% Bayesian Credible Interval ($BCI_{95\%}$) per effect. For Experiments 1a–3b, dark gray points indicate the cue that was directly manipulated (e.g., made ambiguous), and light gray points indicate the other, non-manipulated cue. For Experiment 4, the dark gray points show the effect of the face inversion manipulation on the emotion and race cues, respectively. Figure 3B displays the full posterior distribution from the summary Monte Carlo correlation analysis across all manipulations. The solid black line indicates the posterior mean, and the dashed black line indicates the null hypothesis of no correlation. The light gray area represents the central $BCI_{95\%}$, and the dark gray shaded tails represent the 5% of the distribution that falls outside this interval.

Testing the Generality of Cue Compensation

To formally evaluate the overarching pattern emerging from the seven experiments described above, we computed a Bayesian Monte Carlo correlation assessing whether, across all manipulations, within-person changes in the use of one cue (ΔC_1) were reliably accompanied by compensatory changes in the use of the other cue (ΔC_2). We drew posterior samples from each of

the seven fitted models (one model per experiment). For each draw *j*, we extracted the estimated within-participant changes in cue processing (ΔC_1 and ΔC_2) for each manipulation, yielding two vectors: one containing ΔC_1 estimates and one containing the corresponding ΔC_2 estimates. We then computed the Pearson's *r* correlation between these two vectors, repeating for all 12,000 posterior draws.

The resulting posterior distribution of the correlation did not credibly differ from zero (M = 0.00, $BCI_{95\%}$ [−0.10, 0.08]), suggesting no systematic covariation between cues within-persons. Thus, consistent with the results observed for each experiment, this analysis fails to support a general compensatory relationship in the use of social category and other cues.

Summary of Within-Person Parameter Comparisons

Across six experiments, ambiguity in each task-relevant cue (e.g., race cues during race classification) consistently lessened reliance on that cue, as expected. Ambiguity in each task-irrelevant cue (e.g., emotion cues during race classification) was less reliable in manipulating its use. Crucially, evidence for compensatory increases in the use of unmanipulated cues was observed in only two of 12 tests. When cue covariation did occur, it was more often positive than negative. In a seventh experiment, in which faces were inverted during trustworthiness judgments, only emotion cues were used less, with no compensatory change in the use of race cues. Overall, these findings do not support the hypothesis that when perceivers increase (decrease) their use of social categories, they decrease (increase) their use of other cues.

Discussion

Social psychology has long contended with how perceivers combine multiple pieces of information to create rich impressions of other people. The assumption that using social categories reduces reliance on other social cues is foundational to many prominent theories,

particularly in the domain of person perception. However, this competitive cue hypothesis has remained largely untested due to measurement limitations. Although conventional methods effectively capture social judgments (e.g., stereotypic impressions), they struggle to distinguish between the unique contributions of multiple inputs to those judgments (e.g., race cues, gender cues). We do so here by applying the MCI model, which separately estimates the influence of different cues on social judgments, allowing us to assess their covariation directly.

Summary of Findings

We tested the competitive cue hypothesis across 14 datasets (N = 12,239 participants), covering multiple methods, cues, and judgments. We found no consistent evidence of negative covariation in the use of social category cues and other cues. The meta-analytic correlation between cue processing parameters was not credibly different from zero. In many cases, cue usage was unrelated or even positively correlated. These patterns held across two forms of theorized competition: between social category and individuating cues and between distinct category cues. There also was considerable heterogeneity in parameter correlations, suggesting that covariation in the use of two cues is highly context-sensitive. For example, the use of race and emotion facial cues negatively covaried for race classification judgments, and they were uncorrelated for emotion and trustworthiness classification judgments (though the association between emotion and race cues was descriptively positive for trustworthiness classification judgments). Our findings held across various criteria for dataset exclusion.

Only in the JBT did we find negative covariation between individuating and social category cues. However, we (1) failed to replicate that effect in a new study and (2) found that the negative covariation may be facilitated by a top-down decision rule rather than purely from spontaneous cue competition. Removing the constraints of a task-induced decision rule to accept

only half of all applicants elicited more positive covariation between the use of applicant information and gendered appearance.

It is possible that competitive cue processing is better conceptualized within- rather than between-persons, whereby as perceivers adjust their use of social category cues, they compensate with their use of other cues. We tested for within-person cue competition in seven experiments that manipulated cue ambiguity or perceptual disfluency (i.e., inverted faces). These manipulations did not reliably produce compensatory shifts in cue use. In most cases, ambiguity in one cue diminished use of that cue but not the other cue. Introducing disfluency in cue processing diminished the use of emotion cues but not race cues during trustworthiness classification. Overall, competitive cue processing does not seem to be obligatory. Rather, the relationship between the use of two cues appears to be context-sensitive and variable across judgments.

The primary contribution of this research is a large-scale refutation of a foundational assumption that has guided person perception theory for decades. This research provides evidence against the long-held assumption of obligatory competition between social categories and other cues. In doing so, it sets the stage for a more nuanced program of research. The critical follow-up question may no longer be *if* cue competition is the default, but rather *when*, *why*, and *how* different cue dynamics—be they competitive, facilitative, or orthogonal—emerge.

Implications and Future Directions

The use of particular social cues has long been treated as a contextually-sensitive process (e.g., Bruner, 1957; Turner et al., 1987). But, at times, the relationship between the use of multiple cues has, nonetheless, been treated as a fixed competition (e.g., contexts that augment race categorization inhibit gender categorization; Macrae et al., 1995). Our main finding of no

consistent negative covariation between the use of social category and other cues rejects a fixed competitive relationship and, instead, aligns with network models of person perception (Freeman & Ambady, 2011; Freeman et al., 2020; Kunda & Thagard, 1996), which suggest that the relationships among the use of various social cues are, themselves, sensitive to contexts (e.g., which social cues are available) and perceiver goals.

This position is supported by two additional findings. First, patterns of covariation between the use of two cues (e.g., emotion and race cues) varied substantially across methods, cue combinations, and judgments (e.g., race vs. trustworthiness classifications). Second, introducing versus omitting a decision rule substantially shifted the covariation in use of gender category and individuating applicant cues in the JBT.

The person perception literature has also long assumed that social category use occurs prior to the use of other cues, thereby allowing it to inhibit the use of incoming individuating cues (Brewer, 1988; Fiske & Neuberg, 1990; Hugenberg et al., 2010). However, our findings fail to support such a relationship and suggest other dynamics instead. One alternative is that social categorization sometimes simply informs the meaning of other cues. For example, rather than social categories directly conflicting with emotion cues (Kozlik & Fischer, 2020), they may inform their meaning (e.g., outgroup smiles = nefarious; Paulus & Wentura, 2014; Wentura et al., 2023). Once again, this logic aligns with the expectations of models like the dynamic interactive theory of person construal (Freeman & Ambady, 2011; Freeman et al., 2020), whereby early cue processing informs the attention to and the meaning imparted to additionally perceived information. When measured with the MCI model, this might result in a null or positive, rather than negative, correlation between the use of two cues.

Beyond occurring first, social categorization is often assumed to operate more efficiently than other social cues. Paired with the competitive cue hypothesis, this view suggests that social category use will increase and individuating feature use will decrease when cognitive resources are limited (e.g., Brewer, 1988). Future research can directly manipulate the cognitive resources available to perceivers (e.g., via distraction, time pressure) to test whether these factors produce more competitive dynamics between social category and other cues. Such work would clarify whether cue competition emerges selectively under conditions theorized to foster (over-)reliance on rapid, heuristic-based social categorization. For example, consider the negative covariation between the use of cues in the JBT. This pattern may be driven, in part, by a 'competitive' context: The imposed decision rule about how many applicants to accept/reject combined with the need to quickly review many individuating applicant qualifications may constitute a complex environment that facilitates competitive processing (Bodenhausen & Lichtenstein, 1987).

Future research could examine individual differences that may modulate the relationship between the use of various cues. Recent findings suggest that a perceiver's prior experience predicts those relationships. For example, greater contact with Black people may increase the overlap in Black and trustworthy facial cues (Hutchings et al., 2024), thereby increasing positive covariation in the use of the two cues. Similarly, increasing exposure to non-race cues reduces racially biased decision-making (e.g., Klein & Todd, 2024; Todd et al., 2021), perhaps inducing negative covariation in the use of social category and other cues. The MCI model can clarify when and how a perceiver's prior experience shapes how they use social information.

Better understanding the assumption of competitive cue processing also has implications for reducing stereotyping and prejudice. The competitive cue perspective implies that interventions designed to increase the use of certain cues will decrease the use of social category cues, thereby

reducing intergroup bias. However, if competitive cue processing is not obligatory, then interventions that heighten the impact of some cues (e.g., behavior) may not minimize the impact of others (e.g., race). Future research may benefit from measuring the relationships among the cues used to inform biased judgments before seeking to de-bias those judgments.

Limitations

Notably, some parameter correlations were estimated imprecisely (see Table 2). The hierarchical Bayesian framework allows for uncertainty around parameter estimates to propagate into the estimate of the parameter correlation, resulting in larger uncertainty estimates than in alternative fitting procedures or relative to analyses of behavioral data using conventional measures. Nonetheless, this imprecision may be a more appropriate accounting of how certain one can be, given current state-of-the-art methods to account for uncertainty in the covariation between the use of two cues. Also, the C_2 parameter estimates were often small (see Supplemental Materials), complicating precise estimation of covariance between two parameters.

Table 2

Limitations and Suggestions for Future Research

Limitations	Suggested Future Research
Data were sampled only from U.S. participants, limiting the generalizability of our findings	Replicate findings across diverse cultural and national samples
The data only consist of binary social judgments. Cues may relate differently when judgments are made through more continuous or unconstrained response options	Use continuous rating scales or open-ended impression tasks
MCI model parameters cannot diagnose how the cues are processed, only how much they are processed	Combine MCI modeling with process-tracing or neuroimaging methods Increase sample sizes and optimize model specification for greater precision

Limitations	Suggested Future Research
Substantive levels of uncertainty estimated around some parameter correlations, limiting conclusions about the specific relationship in cue processing	
Only tested a small sample of cue pairings for within-person competitive cue processing	Design within-subject experiments varying in more pairings of cues (e.g., race, trustworthiness)
Only tested with a small sample of methods common in person perception	Expand to additional paradigms, such as spontaneous trait inference or real-time interaction tasks
Included archival data were selected in a biased manner (e.g., accessibility to authors)	Full-scale meta-analysis of person perception data fitting for MCI analyses

Although uncertainty around some of the parameter correlations is high, confidence in our conclusions from these analyses is still warranted. Excluding datasets with parameter correlation *SD*s >.20, .15, or even .10 did not alter any conclusions. Furthermore, $k = 7$ datasets with within-subject manipulations confirm the same conclusion—that no consistent negative covariation emerges between the use of two cues. Future research concerned with the strength of the relationship between a pair of social cues could consider our results for appropriate sample size planning and method selection (e.g., JBT vs. IAT).

The generalizability of our findings is also constrained by our selection of archival data. These datasets were not intended to be an exhaustive sample of all MCI-compatible person perception studies; rather, they were chosen as a convenient supplement to our eight novel experiments. It is important to contextualize this limitation within our primary goal: to test the foundational assumption of cue competition, not to conduct a definitive meta-analysis of cue processing relationships. For this theory-testing purpose, we maintain that the substantial diversity across our datasets—spanning various methods, judgments, and social cues—provided

a suitable and rigorous testing ground. A systematic meta-analysis would be necessary to comprehensively quantify the landscape of cue integration across all person perception research.

Finally, the MCI model measures *how much* particular information is used in social judgments but not *how* it is used. Social cognition research has identified many mental processes that operate when thinking about other people, including activation of associations, self-regulatory processes, holistic versus featural processing, among others (e.g., Maurer et al., 2002; Sherman et al., 2008). Any or all these processes may underlie the social judgments we analyzed, but the MCI model cannot clarify which ones. Future research could determine which of these processes underlie competitive versus facilitative cue processing. For example, is self-regulatory processing less prominent when cue use covaries positively versus negatively?

Conclusion

This research provides compelling evidence against the long-standing assumption that the use of social category and other cues is inherently competitive. These findings suggest that multi-cue integration is flexible and context-dependent, not governed by fixed trade-offs. Theories of person perception would benefit from accounting for this variability. The current work sets the stage for such development by identifying the variability in multi-cue integration relationships and showcasing a method for quantifying it.

References

Anderson, N. H. (1971). Integration theory and attitude change. *Psychological Review, 78*, 171–206.

Asch, S. E. (1946). Forming impressions of personality. *Journal of Abnormal and Social Psychology*, *41*, 258–290.

Axt, J. R., & Lai, C. K. (2019). Reducing discrimination: A bias versus noise perspective. *Journal of Personality and Social Psychology, 117*, 26–49.

Axt, J. R., Nguyen, H., & Nosek, B. A. (2018). The Judgment Bias Task: A flexible method for assessing individual differences in social judgment biases. *Journal of Experimental Social Psychology*, *76*, 337–355.

Becker, D. V., Kenrick, D. T., Neuberg, S. L., Blackwell, K. C., & Smith, D. M. (2007). The confounded nature of angry men and happy women. *Journal of Personality and Social Psychology*, *92*, 179–190.

Bodenhausen, G. V., & Lichtenstein, M. (1987). Social stereotypes and information-processing strategies: The impact of task complexity. *Journal of Personality and Social Psychology, 52*, 871–880.

Bodenhausen, G. V., & Macrae, C. N. (1998). Stereotype activation and inhibition. In R. S. Wyer, Jr. (Ed.), *Stereotype activation and inhibition* (pp. 1–52). Lawrence Erlbaum Associates Publishers.

Brewer, M. B. (1988). A dual process model of impression formation. In T. K. Srull & R. S. Wyer, Jr. (Eds.), *A dual process model of impression formation* (pp. 1–36). Lawrence Erlbaum Associates, Inc.

Bruner, J. S. (1957). On perceptual readiness. *Psychological Review, 64*, 123–152.

Cloutier, J., Mason, M. F., & Macrae, C. N. (2005). The perceptual determinants of person construal: Reopening the social-cognitive toolbox. *Journal of Personality and Social Psychology*, *88*, 885–894.

Crisp, R. J., & Hewstone, M. (2007). Multiple social categorization. *Advances in Experimental Social Psychology*, *39*, 163–254.

Deschamps, J.-C., & Doise, W. (1978). Crossed category memberships in intergroup relations. In H. Tajfel (Ed.), Differentiation between social groups (pp. 142–158). London, UK: Academic Press.

Fiske, S. T., & Neuberg, S. L. (1990). A continuum of impression formation, from category based to individuating processes: Influences of information and motivation on attention and interpretation. *Advances in Experimental Social Psychology*, *23*, 1–74.

Freeman, J. B., Ambady, N., Rule, N. O., & Johnson, K. L. (2008). Will a category cue attract you? Motor output reveals dynamic competition across person construal. *Journal of Experimental Psychology: General*, *137*, 673–690.

Freeman, J. B., & Ambady, N. (2011). A dynamic interactive theory of person construal. *Psychological Review*, *118*, 247–279.

Freeman, J. B., Penner, A. M., Saperstein, A., Scheutz, M., & Ambady, N. (2011). Looking the part: Social status cues shape race perception. *PLOS ONE*, *6*, e25107.

Freeman, J. B., Stolier, R. M., & Brooks, J. A. (2020). Dynamic interactive theory as a domain-general account of social perception. *Advances in Experimental Social Psychology*, *61*, 237–287.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology*, *74*, 1464–1480.

Hutchings, R. J., Freiburger, E., Sim, M., & Hugenberg, K. (2024). Racial prejudice affects representations of facial trustworthiness. *Psychological Science*, *35*, 263–276.

Heck, D. W., Arnold, N. R., & Arnold, D. (2018). TreeBUGS: An R package for hierarchical multinomial-processing-tree modeling. *Behavior Research Methods*, *50*, 264–284.

Hogg, M. A., Abrams, D., Otten, S., & Hinkle, S. (2004). The social identity perspective: Intergroup relations, self-conception, and small groups. *Small Group Research*, *35*, 246–276.

Hugenberg, K., Young, S. G., Bernstein, M. J., & Sacco, D. F. (2010). The categorization-individuation model: an integrative account of the other-race recognition deficit. *Psychological Review*, *117*, 1168–1187.

Klauer, K. C. (2010). Hierarchical multinomial processing tree models: A latent-trait approach. *Psychometrika*, *75*, 70–98.

Klauer, K. C., Hölzenbein, F., Calanchini, J., & Sherman, J. W. (2014). How malleable is categorization by race? Evidence for competitive category use in social categorization. *Journal of Personality and Social Psychology*, *107*, 21–40.

Klein, S. A., & Sherman, J. W. (2024). Measuring the impact of multiple social cues to advance theory in person perception research. *Psychological Review*.

Klein, S. A., & Todd, A. R. (2024). Emotion expression salience and racially biased weapon identification: A diffusion modeling approach. *Psychonomic Bulletin & Review*, *31*, 2767–2775.

Kozlik, J., & Fischer, R. (2020). When a smile is a conflict: Affective mismatch between facial displays and group membership induces conflict and triggers cognitive control. *Journal of Experimental Psychology: Human Perception and Performance*, *46*, 551–568.

Kunda, Z., & Sinclair, L. (1999). Motivated reasoning with stereotypes: Activation, application, and inhibition. *Psychological Inquiry*, *10*, 12–22.

Kunda, Z., & Thagard, P. (1996). Forming impressions from stereotypes, traits, and behaviors: A parallel-constraint-satisfaction theory. *Psychological Review*, *103*, 284–308.

Kurzban, R., Tooby, J., & Cosmides, L. (2001). Can race be erased? Coalitional computation and social categorization. *Proceedings of the National Academy of Sciences*, *98*, 15387–15392.

Lee, M. D., & Wagenmakers, E. J. (2014). *Bayesian Cognitive Modeling: A Practical Course*. Cambridge University Press.

LoBue, V., & Thrasher, C. (2015). The Child Affective Facial Expression (CAFE) set: Validity and reliability from untrained adults. *Frontiers in Psychology*, *5*, 1532.

Ma, D. S., Correll, J., & Wittenbrink, B. (2015). The Chicago face database: A free stimulus set of faces and norming data. *Behavior Research Methods*, *47*, 1122–1135.

Macrae, C. N., Bodenhausen, G. V., & Milne, A. B. (1995). The dissection of selection in person perception: Inhibitory processes in social stereotyping. *Journal of Personality and Social Psychology*, *69*, 397–407.

Maurer, D., Le Grand, R., & Mondloch, C. J. (2002). The many faces of configural processing. *Trends in Cognitive Sciences*, *6*, 255–260.

Navon, M., & Bar-Anan, Y. (2025). The effects of group affiliation versus individuating information on direct and indirect measures of the evaluation of novel individual group members. *Psychological Science*, *36*, 130–142.

Navon, M., Shechter, A., & Bar-Anan, Y. (2021). The effect of group membership and individuating information on automatic and deliberate evaluation of well-known people. *Journal of Personality and Social Psychology*, *121*, 498–523.

Oosterhof, N. N., & Todorov, A. (2009). Shared perceptual basis of emotional expressions and trustworthiness impressions from faces. *Emotion*, *9*, 128–133.

Paulus, A., & Wentura, D. (2014). Threatening joy: Approach and avoidance reactions to emotions are influenced by the group membership of the expresser. *Cognition & Emotion*, *28*, 656–677.

Petsko, C. D., & Bodenhausen, G. V. (2020). Multifarious person perception: How social perceivers manage the complexity of intersectional targets. *Social and Personality Psychology Compass*, *14*, e12518.

Petsko, C. D., Rosette, A. S., & Bodenhausen, G. V. (2022). Through the looking glass: A lens-based account of intersectional stereotyping. *Journal of Personality and Social Psychology*, *123*, 763–787.

Röver, C. (2020). Bayesian random-effects meta-analysis using the bayesmeta R package. *Journal of Statistical Software*, *93*, 1–51.

Rubinstein, R. S., Jussim, L., & Stevens, S. T. (2018). Reliance on individuating information and stereotypes in implicit and explicit person perception. *Journal of Experimental Social Psychology*, *75*, 54–70.

Sherman, J. W., Gawronski, B., Gonsalkorale, K., Hugenberg, K., Allen, T. J., & Groom, C. J. (2008). The self-regulation of automatic associations and behavioral impulses. *Psychological Review, 115*, 314–335.

Singmann, H., Heck, D. W., Barth, M., Erdfelder, E., Arnold, N. R., Aust, F., ... & Groß, J. (2024). Evaluating the robustness of parameter estimates in cognitive models: A meta-analytic review of multinomial processing tree models across the multiverse of estimation methods. *Psychological Bulletin*, *150*, 965–1003.

Tajfel, H., & Turner, J. C. (1986). The social identity theory of intergroup behavior. In S. Worchel and W.G. Austin, Eds., *Psychology of Intergroup Relations* (pp. 7–24). Hall Publishers, Chicago.

Todd, A. R., Johnson, D. J., Lassetter, B., Neel, R., Simpson, A. J., & Cesario, J. (2021). Category salience and racial bias in weapon identification: A diffusion modeling approach. *Journal of Personality and Social Psychology*, *120*, 672–693.

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D. & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Oxford: Blackwell

Wentura, D., Gurbuz, E., Paulus, A., & Rohr, M. (2023). Emotional face expressions and group membership: Does affective mismatch induce conflict? *Journal of Experimental Psychology: Human Perception and Performance*, *49*, 1395–1406.

Wickham, H. (2016). Data analysis. In *ggplot2: elegant graphics for data analysis* (pp. 189–201). Cham: Springer International Publishing.