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Kevin D. Cassidy, Luc Boutsen, Glyn W. Humphreys & Kimberly A. Quinn

School of Psychology, University of Birmingham, Birmingham, UK

School of Life and Health Sciences, Aston University, Birmingham, UK

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Ingroup categorization affects the structural encoding of other-race faces: Evidence from the N170 event-related potential

Kevin D. Cassidy¹, Luc Boutsen², Glyn W. Humphreys¹, and Kimberly A. Quinn¹

¹School of Psychology, University of Birmingham, Birmingham, UK
²School of Life and Health Sciences, Aston University, Birmingham, UK

The current research examined the influence of ingroup/outgroup categorization on brain event-related potentials measured during perceptual processing of own- and other-race faces. White participants performed a sequential matching task with upright and inverted faces belonging either to their own race (White) or to another race (Black) and affiliated with either their own university or another university by a preceding visual prime. Results demonstrated that the right-lateralized N170 component evoked by test faces was modulated by race and by social category: the N170 to own-race faces showed a larger inversion effect (i.e., latency delay for inverted faces) when the faces were categorized as other-university rather than own-university members; the N170 to other-race faces showed no modulation of its inversion effect by university affiliation. These results suggest that neural correlates of structural face encoding (as evidenced by the N170 inversion effects) can be modulated by both visual (racial) and nonvisual (social) ingroup/outgroup status.

Keywords: Other-race effect; Cross-race effect; Own-race bias; Ingroup/outgroup categorization; Configural/holistic processing; Structural encoding; N170 event-related potential.

People are better at recognizing faces from their own racial group than from other racial groups—a phenomenon with wide-ranging implications, from social embarrassment to eyewitness misidentification (Brigham, Bennett, Meissner, & Mitchell, 2007). The importance of this “other-race effect” (ORE) has motivated numerous attempts to identify its causes, with perceptual expertise, feature selection, and social categorization emerging as the most likely candidates (e.g., Brigham & Malpass, 1985; Hugenberg, Young, Bernstein, & Sacco, 2010; Levin, 1996, 2000).

Recently, Hugenberg et al. (2010) proposed a Categorization–Individuation Model of the ORE that integrates these factors and asserts that the ORE has its roots in both perceptual experience and motivated processing. Consistent with evidence that own-race faces are processed more configurally¹ than other-race faces (i.e., with increased sensitivity to the spatial relationships between features; e.g., Rhodes, Brake, Taylor, & Tan, 1989; or processing them more as a perceptual “whole” or gestalt; e.g., Michel, Rossion, Han, Chung, & Caldara, 2006), the model asserts that the ORE derives from the tendency to attend selectively to identity-diagnostic information (e.g., configurations of features) in ingroup faces but to category-diagnostic information (e.g., skin tone, other specific features) in outgroup faces. Experience with de facto segregation tends to dictate that own-race faces are

¹We recognize that there is an ongoing debate as to the nature of “configural” face processing and that many researchers prefer the term “holistic.” We use the term “configural” in this paper because of its compatibility with the language of the Categorization–Individuation Model.
perceived as ingroup faces and other-race faces as outgroup faces, but the model also assumes that any form of ingroup categorization will motivate identity-driven processing and any form of outgroup categorization will motivate category-driven processing. In support of this model, Bernstein, Young, and Hugenberg (2007) demonstrated that when participants are directed to remember faces at encoding, outgroup (vs. ingroup) categorization undermines later recognition of own-race faces. Moreover, Hugenberg and Corneille (2009) demonstrated that outgroup (vs. ingroup) categorization reduces configural processing of own-race faces.

Our own research (Cassidy, Quinn, & Humphreys, 2011) has also examined the interaction of perceptual experience and social categorization (defined as racial category membership and university affiliation). We asked White participants to perform a simultaneous matching task on upright and inverted faces (i.e., faces rotated by 180°) that were either own-race (White) or other-race (Black), and from their own university (ingroup status) or another university (outgroup status). For other-race faces, the data suggested greater configural processing following own-university than other-university labeling, as indexed by larger face-inversion costs (i.e., slower or less accurate responding to inverted than upright faces; Yin, 1969). In contrast, own-race faces showed strong configural processing irrespective of university labeling. We interpret this pattern as reflecting the mutual constraint of experience and motivation: Ingroup categorization of faces along nonracial dimensions motivates perceivers to engage in configural processing, regardless of race, whereas outgroup categorization undermines motivation and allows different default strategies (more configural and less featural processing for own- than other-race faces) to drive processing.

THE CURRENT RESEARCH

The research reviewed above has relied on behavioral measures (response times (RTs), error rates) that reflect the outcomes of face processing (perceptual discrimination, recognition accuracy). Such measures may be limited in their ability to support theoretical clarification of the Categorization–Individual Model, which assumes the operation of intermediate processing stages (e.g., feature analysis, configural/structural encoding) that occur on a finer-grained time scale than can be easily assessed in behavioral RTs. In the current research, we examined the electrophysiological correlates of own-race and other-race face processing and assessed event-related potentials (ERPs), an approach that supports the chronometric assessment and functional characterization of different stages of face perception (Bentin, Allison, Puce, Perez, & McCarthy, 1996). Indeed, ERP studies of face perception have related distinct perceptual stages to distinct ERP components (for a review, see Schweinberger, 2011). We examined the effects of racial and nonracial ingroup/outgroup categorization on the ERP response to faces, to provide converging evidence on whether ingroup/outgroup categorization affects the perception of facial features, the analysis of feature configurations, or both. We measured EEG over occipito-temporal electrode positions during face perception and examined three major components of the resulting ERP waveform that typically appear in chronological succession: the P100, N170, and P200.

Here, we report on the effects for the N170 component.2 The N170 occurs approximately 150–200 ms post-stimulus onset and is a negative deflection that appears bilaterally (though often favoring the right hemisphere) over occipito–temporal sites (Bentin et al., 1996; Rossion et al., 1999). The N170 shows face-sensitivity in that its peak amplitude is larger in response to face-like compared to nonface-like stimuli. The N170 is also generally thought to reflect the later stages of structural encoding (e.g., Bentin et al., 1996; Eimer, 2000a, 2000b, 2000c), and has been shown to be sensitive to configural information in faces (e.g., Boutsen, Humphreys, Praamstra, & Warbrick, 2006; Liu, Harris, & Kanwisher, 2010; Vizzioli, Foreman, Rousselet, & Caldara, 2010), as well as to basic (category-level) and subordinate (within-category) levels of expertise (e.g., Scott, Tanaka, Sheinberg, & Curran, 2006). The N170 is also susceptible to inversion effects, such that inverted faces yield larger and/or delayed N170s relative to upright faces (e.g., Eimer, 2000a; Itier & Taylor, 2002). Given that inversion is known to disrupt face recognition (Maurer, Le Grand, & Mondloch, 2002), the susceptibility of the N170 to inversion effects underscores its role in face individuation and perhaps particularly its sensitivity to face configurations. Its role as a neural marker of specific perceptual

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2 We also examined the P100 and P200 components, seeking to determine whether own-university/other-university categorization would affect the initial processing of facial features (P100) and/or recruit slower-acting attentional processes (P200). The results were inconclusive; this may not be surprising, given the less consistent relationship of these components to inversion effects and own-versus other-race status shown in past research. For the reader’s interest, however, we report the results for P100 and P200 in Supplementary Materials.
processes is further underlined by the observation that the N170 is not modulated by purportedly higher-order derived information such as face familiarity (Bentin & Deouell, 2000; Eimer, 2000a), identity (Gosling & Eimer, 2011), or emotional expression valence (Bobes, Martin, Olivares, & Valdés-Sosa, 2000; Eimer & Holmes, 2002, 2007).

Of critical importance, or magnitude differences for own-race versus other-race faces (e.g., Caldara et al., 2003; Caldara, Rossion, Bovet, & Huart, 2004; Gajewaki, Schlegel, & Stoerig, 2008; Ito & Urland, 2003, 2005; Ofan, Rubin, & Amodio, 2011; Stahl, Wiese, & Schweinberger, 2008, 2010; Vizioli et al., 2010; Wiese, Stahl, & Schweinberger, 2009). Although there is some inconsistency across studies, the general pattern is for delayed and/or enhanced ERP components for other-versus-own race faces, making this component a plausible candidate for the in-group/out-group categorization effects proposed in the Categorization–Individuation Model.

In the current experiment, we analyzed the ERPs of White participants who performed a sequential matching task on White (own-race) and Black (other-race) face pairs that were labeled students from either the same or another university (henceforth labeled own-university or other-university faces, respectively). We predicted that the own-university/other-university categorization effects that we have observed previously (e.g., Cassidy et al., 2011) would be reflected in the N170 based on (1) the N170 being susceptible to differences in structural encoding reflected in the effects of inversion (Bentin et al., 1996; Eimer, 2000a, 2000b, 2000c), and (2) inversion effects typically being larger for own- than other-race faces (e.g., Rhodes et al., 1989). Indeed, recent evidence supports a general effect of own-university/other-university categorization on the N170 (Ratner & Amodio, 2012). Our predictions, however, were more specific, in that we expected the N170 to parallel our behavioral results and demonstrate that the effects of own-university/other-university categorization depend on target race (and race was not included as a factor in Ratner and Amodio’s experiment). Our previous behavioral data (Cassidy et al., 2011) indicate that, for own-race faces, configural processing should be engaged equally for own-university and other-university faces; as a result, the effects of inversion should be present on the N170 component for both own-university- and other-university-categorized own-race faces. A different prediction arises for other-race faces, however. For these faces, configural processing should be engaged to a greater extent for own-university than other-university targets; thus, the effects of inversion on the N170 component should be larger for faces categorized as own-university members. This would provide converging evidence for own-university categorization of other-race faces affecting configural processing.

**METHOD**

**Participants and design**

Sixteen White undergraduate students from the University of Birmingham (15 female, M_age = 19.8 years) participated for course credit. The experiment used a 2 (Race: own/other) × 2 (University: own/other) × 2 (Orientation: upright/inverted) × 2 (Trial Type: same/different) within-participants design.

**Materials**

The materials included university primes and face stimuli. The university primes were color images depicting the University of Birmingham and University of Nottingham names and official crests; the images measured 191 × 50 pixels and 209 × 50 pixels in size, respectively. The face stimuli were 160 images depicting 80 Black and 80 White male faces, in forward pose with neutral expressions (from Eberhardt, Davies, Purdie-Vaughns, and Johnson (2006), Minear and Park (2004), Shriver, Young, Hugenberg, Bernstein, and Lanter (2008)). The images were standardized to be grayscale and sized 236 pixels vertically. An inverted version of each face was also created, resulting in a set of 320 face images. Face pairs were created by combining faces of the same race at the same orientation, and matching them subjectively for luminance, contrast, and head/hair shape, resulting in 160 unique pairs at each orientation, with each face pair appearing twice (once upright, once inverted). There were 320 pairs in total, with 20 pairs allocated to each of the Trial Type × University × Race × Orientation conditions. Further, each face appeared as an own-university target for some participants but an other-university target for others, and appeared on a “same” trial for some participants but a “different” trial for others.

**Procedure**

Prior to the EEG experiment, participants completed a questionnaire to enhance their identification with/self-categorization as students at the University of
Birmingham (adapted from Haslam, Oakes, Reynolds, & Turner (1999)). Specifically, participants received a survey, allegedly from Student Services, with the following instructions:

As a member of the University of Birmingham you’ve joined one of the most exciting academic communities in the country. For over a hundred years the university has contributed to the advancement of knowledge and its application. The University of Birmingham has around 26,000 students from the UK and all over the world, and it’s a great place to study. As part of our continuing effort to understand what motivates our students and makes our community unique, we would be grateful if you could take a few minutes and think about the University of Birmingham’s identity, and the ways in which you are like your fellow University of Birmingham students. When you have done this, please write down your thoughts.

These instructions were followed by five blank lines, numbered 1–5. (Participants were not instructed to fill all five lines.)

Next, following preparation for the EEG recording, participants learned that in the target task, they would see faces of University of Birmingham and University of Nottingham students, indicated by the university logo at the start of each trial. Participants learned further that, following the university logo, two faces would be presented sequentially, and that their task was to indicate as quickly and as accurately as possible whether the second (test) face was identical (had the same identity) as the first (study) face. On “same” trials, the face images were always visually identical.

Stimulus presentation, interfaced with the EEG system, and response collection were controlled by purpose-written programs using E-Prime 2.0 Professional (Psychology Software Tools, 2009). Stimuli were viewed from a distance of approximately 80 cm and were presented on a 15-inch CRT screen in a 1024 × 768 graphics mode (with a vertical refresh rate of 60 Hz) and driven by a Pentium PC running an ATI RAGE PRO 128-MB graphics card. Each trial sequence contained the following centrally presented events (Figure 1): fixation cross (300 ms), group prime (1500 ms), study face (500 ms), and test face (500 ms).

To minimize preparatory activity in the EEG signal, the durations of the blank intervals between the group prime and the study face, and between the study and test faces, were randomized between 900, 1000, and 1100 ms. A valid response was accepted as soon as the test face appeared. Each response was followed by an inter-trial interval of 1500 ms. The 320 trials were presented in four blocks (of 80 trials per block), lasting for approximately 45 min. Including EEG preparation, (de)briefing and breaks, each EEG recording session lasted approximately 90 min.

**EEG recording, offline processing, and component detection**

EEG was continuously recorded using 128 Ag/AgCl scalp electrodes, arranged according to the 10–5 electrode system (Oostenveld & Praamstra, 2001) using a nylon cap. Vertical and horizontal eye movements were monitored by two unipolar electrodes placed at the infraorbital area below each eye, and at the outer canthus of the right eye. EEG and electro-oculogram signals were amplified with a band-pass of 0–128 Hz by BioSemi Active-Two amplifiers (BioSemi, Amsterdam, Netherlands) and sampled at 512 Hz. The raw EEG was re-referenced to the average activity from left and right mastoid electrodes.

The EEG data for the individual trials were segmented offline using BrainVision Analyzer 1.0 (Brain Products, Munich, Germany). Each segment was 800-ms long, starting 200 ms before the onset of the test face (which defined the baseline activity), and lasted for 600 ms after its onset. All channels in all segments were manually inspected for ocular and noise artifacts during the presentation of the university logo, study and test faces. Ocular artifacts (voltage steps exceeding 100 µV) occurring at the unipolar and Fpz electrodes during these parts of the trial resulted in rejection of the trial. In addition, trials containing noise artifacts in individual channels (voltage steps exceeding 150 µV) led to rejection of those channels.
Following artifact detection, the remaining segments were band-pass-filtered (0.5–30 Hz) and corrected to the 200-ms pre-stimulus baseline.

Before averaging, the number of segments retained after artifact detection was determined for each participant in each of the 16 conditions (Race [own/other] × University [own/other] × Orientation [upright/inverted] × Trial Type [same/different]). The data of one participant were excluded due to a high proportion (74%) of artifacts. The data of the remaining 15 participants had an average of 14.46 (out of 20; SD = 3.26) segments per condition. For each participant, segments corresponding to each Race × University × Orientation condition were averaged; the resulting means were then averaged across participants, creating grand-average ERP waveforms.

Scalp topographical distributions of the ERP waveforms (across participants and conditions) were inspected to identify electrode locations representing foci of maximum activity of the P100, N170, and P200 components; these are presented in Figure 2. ERP waveforms per condition were created by pooling activity from three pairs of electrode pools, one for each component and in the left and right hemispheres: The P100 was sampled from two pools of four electrodes each at medial locations (O1, O2, I1, I2, O1h, O12h, POO9h and POO10h). The N170 was sampled from two pools of five electrodes each at lateral occipito–temporal locations (P7, P8, PO7, PO8, P9, P10, PO9, PO10, PPO9h, and PPO10h), and the P200 was averaged from two pools of five electrodes each at occipito–parietal locations (O1, O2, PO5h, PO6h, PO7, PO8, POO9h, POO10h, PPO9h, and PPO10h).

The peak latency and amplitude of each ERP component sampled from its corresponding electrode pools were determined through automatic peak detection of local maxima in time windows of 80–120 ms (P100), 140–200 ms (N170) and 220–250 ms (P200), followed by manual verification and correction if required. Peak latency (in milliseconds, ms), and amplitude (in microvolts, µV, averaged within a 20-ms window centered on the amplitude at peak latency) were then extracted for each participant in each condition and for each component, for statistical analysis.

RESULTS

Behavioral results

Speed and accuracy of responses were analyzed using Race × University × Orientation repeated-measures analyses of variance (ANOVAs) from 14 of the 15 participants whose data were included in the EEG analysis; the behavioral data of one participant were lost due to human error. Proportions of correct and incorrect responses were converted to psychophysical measures \( d' \) and \( c \) to determine discrimination sensitivity and response bias, respectively. RTs (ms) were analyzed for correct trials, after discarding 2.91% outlier RTs (defined as correct RTs faster than 200 ms or slower than 2.5 SD of the participant’s mean RT). Table 1 presents discrimination sensitivity, response bias, and RT for each condition.

Discrimination sensitivity and response bias

The overall accuracy was 92.05%. From the proportion of hits (“different” responses on “different” trials) and false alarms (“different” responses on...
TABLE 1
Mean discrimination sensitivity ($d'$), response bias ($c$), and RT (ms) to test faces as a function of race, university, and orientation

<table>
<thead>
<tr>
<th></th>
<th>Own university (Birmingham)</th>
<th>Other university (Nottingham)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Upright</td>
<td>Inverted</td>
</tr>
<tr>
<td>Sensitivity ($d'$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Race (White)</td>
<td>2.4 [2.3, 2.6]</td>
<td>2.0 [1.8, 2.2]</td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>2.3 [2.1, 2.5]</td>
<td>1.9 [1.7, 2.0]</td>
</tr>
<tr>
<td>Bias ($c$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Race (White)</td>
<td>-.02 [-.14, .10]</td>
<td>.26 [.14, .38]</td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>.05 [-.07, .17]</td>
<td>.23 [.11, .36]</td>
</tr>
<tr>
<td>RT (ms)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>656 [644, 668]</td>
<td>688 [676, 700]</td>
</tr>
</tbody>
</table>

Note: Numbers in brackets represent 95% confidence intervals.

“same” trials) per participant per condition, we calculated the discrimination index $d'$ (with $d' = 0$ indicating chance performance), and response bias $c$ (where $c > 0$ when miss rates exceed false alarm rates, and vice versa when $c < 0$) (Macmillan & Creelman, 2005).

A Race × University × Orientation ANOVA on $d'$ values revealed a reliable effect of race ($F(1, 13) = 8.00$, $MSE = .10$, $p = .014$, $\eta_p^2 = .38$), with discrimination being better for own-race than other-race faces ($d' = 2.22$ vs. 2.06, respectively). Face orientation also had a reliable effect ($F(1, 13) = 32.64$, $MSE = .15$, $p < .001$, $\eta_p^2 = .72$), with better discrimination for upright than inverted faces ($d' = 2.35$ vs. 1.93, respectively). There was no reliable effect of university ($F < 1$), and there were no interactions (all $F_s < 1$).

The Race × University × Orientation ANOVA on $c$ values yielded only a main effect of face orientation ($F(1, 13) = 15.36$, $MSE = .10$, $p = .002$, $\eta_p^2 = .54$), such that participants were more biased to respond “same” on trials with inverted than upright faces ($c = .25$ vs. 0.02, respectively). There were no reliable main or interaction effects of university ($F_s < 1$), and no effects of race (main effect, $F < 1$; Race × Orientation, $F(1, 13) = 2.77$, $p = .12$).

**Reaction times**

A Race × University × Orientation × Trial Type ANOVA revealed a main effect of trial type ($F(1, 13) = 14.57$, $MSE = 15.030.6$, $p = .002$, $\eta_p^2 = .53$), with faster responses on “same” than “different” trials ($M = 633$ vs. 696 ms). There was also a reliable effect of orientation ($F(1, 13) = 30.40$, $MSE = 3328.1$, $p < .001$, $\eta_p^2 = .70$), with faster responses to upright than inverted faces ($M = 612$ vs. 654 ms). Although responses were numerically faster to own-race than other-race faces ($M = 654$ vs. 669 ms), this effect was not reliable ($F(1, 13) = 3.24$, $MSE = 3984.4$, $p = .094$). There was no effect of university ($F < 1$) and there were no interactions ($F < 2.84$, $p > .115$); inspection of Table 1 confirms that responses to own-university and other-university faces were very similar (664 vs. 659 ms, respectively).

**ERP results**

The goal of the ERP analysis was to examine the effects of face inversion as a function of race and university on the peak parameters of the three components of interest, with a special focus on the facesensitive N170. Effects of race, university, and orientation were evaluated using three-way ANOVAs across hemispheres; the ERP waveforms in these conditions are shown in Figure 3. In addition to the across-hemisphere analyses, we conducted the same ANOVAs per hemisphere for the N170 (reported here) and P200 (reported in supplementary material) components. We did this because the topographical distribution of these components across condition appeared to be lateralized, with stronger activity over the right-hemisphere pools (Figure 2); this observation was confirmed by four-way ANOVAs showing reliable main effects of hemisphere on the N170 amplitude ($F(1, 14) = 5.15$, $MSE = 41.1$, $p = .040$, $\eta_p^2 = .27$), and a marginally reliable effect on the P200 amplitude ($F(1, 14) = 3.33$, $MSE = 27.1$, $p = .089$, $\eta_p^2 = .19$). Finally, where reliable effects involving inversion (main or interaction) were observed, we conducted paired $t$-tests (with Bonferroni adjustment of $a$ for multiple comparisons; $a = .0125$) for conditions of interest. Average latencies and amplitudes are reported with 95% confidence intervals, which were computed for repeated-measures designs (Hollands & Jarmasz, 2010).
Amplitudes and latencies per condition are presented in Figure 4A and B (across hemispheres) and in Table 2 (per hemisphere). In addition to the presentation of amplitudes and latencies, Figure 5 presents scalp topographical distributions of the inversion effects by subtracting ERPs to inverted faces from ERPs to upright faces in each Race × University condition and averaging the resulting activity within a 50-ms time window including the N170.

**Amplitude**

N170 peak amplitude (Figure 4A) was larger to own-race than to other-race faces ($M = -3.85 \mu V$ [-5.18, 2.52], vs. -3.14 \mu V [-4.47, -1.81]), $F(1, 13) = 10.48$, MSE = 1.4, $p = .006$, $\eta^2_p = .43$). There were no effects of university or orientation, and no interactions ($F$s < 2.22, $p$s > .15). Analyses per hemisphere yielded no reliable effects.

**Latency**

Inspection of the latencies (Figure 4B) indicates that the N170 peaked later for inverted than upright faces for each Race × University combination. Further, with own-race faces, the size of this inversion effect was twice as large when these faces were labeled other-university rather than own-university (costs of 12.7 and 6.6 ms, respectively; Figure 4B). With other-race faces, however, the difference between inversion effects for other-university versus own-university conditions was reduced (6.6 vs. 4.6 ms, respectively).

An ANOVA to evaluate the above observations showed a reliable effect of orientation, ($F(1, 13) = 22.12$, MSE = 79.8, $p < .001$, $\eta^2_p = .61$), but no main effects of race or university ($F$s < 1). However, there was a marginal University × Orientation interaction ($F(1, 13) = 3.59$, MSE = 34.1, $p = .079$, $\eta^2_p = .20$). While the N170 was delayed by inversion both for own-university ($t(14) = 3.43$, $p = .004$) and other-university faces ($t(14) = 4.38$, $p < .001$), this delay was marginally larger for other-university ($M = 9.7 \text{ ms [5.2, 14.2]}$) than for own-university faces ($M = 5.7 \text{ ms [1.1, 10.2]}$), $t(14) = 1.89$, $p = .078$.

There was also a marginal Race × University interaction ($F(1, 13) = 3.99$, MSE = 28.7, $p = .066$, $\eta^2_p = .22$). Here, the own-university versus other-university factor exerted opposite influences on latencies to own-race and other-race faces.

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**Figure 3.** Event-related brain potential waveforms to upright and inverted test faces as a function of race and university. Waveforms are sampled from the N170 electrode pools and averaged across hemispheres and trial type. Per-hemisphere ERP waveforms can be viewed in Figure S3 (supplementary materials).

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3 Our primary analyses focused on the ERPs averaged across “same” and “different” trials and across hemispheres. However, as behavioral performance in our task was influenced in a general way by response type, and because same/different judgments can affect ERP components across a wide spatio-temporal range (e.g., Barrett, Rugg, & Perrett, 1988), we conducted parallel peak analyses on “same” and “different” trials separately through Race × University × Orientation ANOVAs. These analyses are presented in in Supplementary Materials.
each race separately, however, were not statistically reliable (own-race faces, \( M = 1.6 \text{ ms} \ [\text{−2.9, 6.1}] \), \( t < 1 \); other-race faces, \( M = −2.8 \text{ ms} \ [−7.0, 1.3] \); \( t(14) = 1.30, p = .212 \)).

Inspection of the topographical distributions of inversion effects coinciding with the N170 (Figure 5) reveals larger effects of inversion for own-race than other-race faces, and larger effects over the right than left hemisphere electrode pools. In order to evaluate these hemispheric differences, we conducted three-way ANOVAs on the N170 latencies separately for the left and right hemisphere electrode

![Figure 4](image)

**Table 2**

<table>
<thead>
<tr>
<th></th>
<th>Own university (Birmingham)</th>
<th>Other university (Nottingham)</th>
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<tbody>
<tr>
<td></td>
<td>Upright</td>
<td>Inverted</td>
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<tr>
<td><strong>LATENCY (ms)</strong></td>
<td></td>
<td></td>
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<tr>
<td>Left Hemisphere</td>
<td></td>
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</tr>
<tr>
<td>Own Race (White)</td>
<td>159 (3.5)</td>
<td>164 (2.8)</td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>159 (3.7)</td>
<td>161 (3.1)</td>
</tr>
<tr>
<td>Right Hemisphere</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Race (White)</td>
<td>154 (3.8)</td>
<td>163 (2.5)</td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>159 (3.6)</td>
<td>166 (4.0)</td>
</tr>
<tr>
<td><strong>AMPLITUDE (µV)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Left Hemisphere</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Race (White)</td>
<td>−2.3 (0.8)</td>
<td>−3.2 (0.8)</td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>−2.6 (0.6)</td>
<td>−2.4 (0.8)</td>
</tr>
<tr>
<td>Right Hemisphere</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Race (White)</td>
<td>−4.7 (1.1)</td>
<td>−5.2 (1.4)</td>
</tr>
<tr>
<td>Other Race (Black)</td>
<td>−4.0 (1.1)</td>
<td>−3.8 (1.2)</td>
</tr>
</tbody>
</table>

*Note: Numbers in parentheses represent the standard error of the mean.*
pools; these data are presented in Table 2. The Race × University interaction was reliable over the right hemisphere (F(1, 13) = 6.87, MSE = 33.5, p = .020, η² = .33) but not over the left hemisphere (F <1). Over the right hemisphere, the N170 to own-race faces peaked later for other-university than own-university faces (M = 1.1 ms [-3.4, 5.6]), whereas the N170 to other-race faces peaked earlier for other-university than own-university faces (M = -4.4 ms [-8.9, 0.1]; Table 2).

The right-hemisphere N170 also showed a reliable Race × University × Orientation interaction, F(1, 13) = 4.82, MSE = 40.2, p = .046, η² = .26. As can be observed from Table 2, for own-race faces, the inversion effect was marginal for own-university faces (M = 8.8 ms [3.8, 13.8]; t(14) = 1.99, p = .065) and reliable for other-university faces (M = 15.7 ms [10.8, 20.7]; t(14) = 2.39, p = .031). For other-race faces, a larger inversion effect was observed for own-university (M = 7.1 ms [2.1, 12.1]) than other-university faces (M = 3.8 ms [-1.12, 8.8]). As predicted, the inversion effect was reliable for own-university (t(14) = 4.04, p = .001), but not for other-university faces (t(14) = 1.60, p = .13).

**DISCUSSION**

In this study, we examined the electrophysiological correlates of ingroup/outgroup categorization (based on university affiliation) on the perceptual processing of own-race and other-race faces by measuring the effect of face inversion on visually evoked potentials in a sequential face matching task. We found evidence that the N170 component, which is modulated by visual facial dimensions such as race and orientation, can also be modulated by nonracial information such as a social category label (in this case, denoting own vs. other university). This effect was expressed as differences in size of the inversion effects (here, the delay in N170 peak latency evoked by inverted faces), depending on the race and social category associated with the target face. Specifically, we demonstrate that nonracial ingroup (vs. outgroup) categorization induced configural processing of other-race faces but exerted less influence on the processing of own-race faces, and that this pattern was evident in the face-specific N170 component of the ERP waveform. To the best of our knowledge, this is the most direct empirical demonstration to date that experience and motivation interact sufficiently early in the visual perception of faces.
processing of faces to affect their structural encoding, going beyond the outcome-focused behavioral measures that have been used in past research.

**Social categorization affects structural encoding**

Among our ERP components of interest, our findings suggest that ingroup/outgroup categorization (here, university affiliation) exerts clearest influence on the N170 component. When evoked by faces, the N170 component is known to be sensitive to spatial configurational distortions, including inversion, which has led to its interpretation in the literature as a neural index of configural or holistic perceptual face processing (Rossion, 2008). Given this perceptual interpretation, the finding that the face-evoked N170 can be modulated by non-perceptual factors such as university affiliation labeling may be surprising, in particular when considering that the N170 may not be sensitive to other face-related dimensions such as emotional expression (for a review on this point, see Rellecke, Sommer, and Schacht (2013)). A critical question, then, is what may cause the modulatory effect on N170 activity by social category information.

Starting from the assumptions that the face inversion effect reflects a disruption to a default (i.e., configural/holistic) processing strategy applied normally to upright faces (Maurer et al., 2002) and that the modulation of the N170 latency (and/or amplitude) by inversion reflects some form of interference in this processing (e.g., Bentin et al., 1996; Eimer, 2000a), we propose that the likelihood of default configural processes being applied to a face stimulus will depend on its familiarity on both visual and nonvisual dimensions—orientation and race, but also, for example, ingroup/outgroup category labeling. This would mean that upright, own-race (White) faces—the most familiar orientation and type—would most likely and most rapidly trigger the default processing required to make the visual judgment required in our matching task. Other-race (Black) faces, however, might be less efficient in activating default face processes because of their reduced familiarity; other-race faces may also reduce the motivation to apply normal face processing strategies (Hugenberg et al., 2010). Likewise, face inversion, which alters the configural information available (Maurer et al., 2002; Yin, 1969), incurs a cost in time and resources to extract (encode) the relevant facial information. We propose that when the visual familiarity of a face is reduced (e.g., with inverted White faces, or with upright or inverted Black faces), the delay in the activation of default face processing may enable nonvisual factors such as social category labeling to exert their influence.

In our right-hemisphere N170 latency results, the size of the inversion effects for own-race and other-race faces differed as a function of whether the faces were labeled own-university (ingroup) or other-university (outgroup). Consistent with Cassidy et al. (2011), for other-race faces, the inversion effect was reliable only for own-university-labeled faces and not for other-university-labeled faces, presumably reflecting motivational differences as a function of nonracial ingroup/outgroup status (Hugenberg et al., 2010); without the motivational “boost” of ingroup categorization, other-race faces did not receive the configural processing that is a hallmark of optimal face perception (Maurer et al., 2002). For own-race faces, in contrast, the inversion effect emerged for both own-university and other-university faces. This is consistent with our previous behavioral work (Cassidy et al., 2011).

**Implications for the Categorization–Individuation Model**

In a recent ERP study, Zheng and Segalowitz (2013) reported that after participants learned to associate own-race faces with two independent social category dimensions (own vs. other nationality and own vs. other university), their N170 evoked by own-race target faces was significantly delayed when these faces had been associated as outgroup on both dimensions (i.e., other-nationality and other-university labels), compared to when they were labeled ingroup on both dimensions. Our results are largely consistent with this work, and point to the processing strategy differences that are associated with both racial and nonracial ingroup/outgroup categorization (i.e., the extent to which configural processing is recruited during face perception). Our work highlights the separate contributions of categorization-induced motivation and default processing strategies to own-race and other-race face processing, consistent with the Categorization–Individuation Model.

In another sense, however, our results might seem at odds with the behavioral data presented by Hugenberg and colleagues. In particular, Bernstein et al. (2007) have demonstrated that when participants are directed to remember faces at encoding, outgroup (vs. ingroup) categorization undermines later recognition of own-race faces but has no effect on other-race faces. In contrast, we demonstrated that nonracial ingroup/group status influenced the processing of other-race faces more than own-race faces. Hugenberg and Corneille (2009) also demonstrated that outgroup (vs. ingroup)
categorization reduces configural processing of own-race faces—and yet we have argued that own-race faces are processed configurally regardless of nonracial ingroup/outgroup status. These seeming inconsistencies likely stem from methodological differences. Elsewhere, we have presented evidence that encoding context moderates nonracial ingroup/outgroup effects. We have demonstrated that ingroup/outgroup status affects configural processing of own-race faces when those faces are presented in intra-racial contexts (as in Hugenberg and Corneille (2009)) but not inter-racial contexts (Cassidy et al., 2011), presumably because inter-racial contexts (such as in the current research, where own-race and other-race faces are intermixed) make race salient and thereby undermine the impact of nonracial categorization on the fluent configural processing of own-race faces. Thus, the differences between the current results and those reported by Hugenberg and colleagues may simply highlight additional factors that would enhance the predictive utility of the Categorization–Individuation Model.

It is important to note that, in the current experiment, race and university affiliation represented different types of ingroup/outgroup information. Race was a visually accessible facial cue, whereas university affiliation was a verbal label that was associated only arbitrarily with the faces. Interestingly, the Categorization–Individuation Model (Hugenberg et al., 2010) is agnostic on the question of whether visually accessible versus non-accessible ingroup/outgroup categorization should be accorded differential status. Although the two forms of ingroup/outgroup categorization exerted their effects at similar processing stages in the current experiment (i.e., the N170), the nonvisual university dimension most consistently modulated the N170, whereas the visually accessible race dimension demonstrated extended (earlier and later) impact (see the “Supplementary Materials” section). This pattern suggests that not all forms of ingroup/outgroup status have equal weight in processing. Admittedly, our manipulation of nonracial ingroup/outgroup categorization may have had little emotional impact on participants and, in real-world settings, salient or important nonracial identities may be less prone to decaying activation. The relative impact of racial and nonracial categorization on face processing thus remains to be clarified.

Caveats

Several caveats warrant mention. First, the behavioral Race × University × Orientation interaction was not statistically reliable and did not replicate our own past research (Cassidy et al., 2011). There may be several reasons why we did not observe behavioral effects. First, performance in the matching task may have been relatively easy, increasing the likelihood of ceiling effects and thereby masking the effects of categorization—and categorization along nonvisual dimensions such as university affiliation, in particular. Further, we had a relatively small sample (14 observers), which might have reduced the power of our study. It should also be noted that a relatively large time period (~2 s) separated the social category (university) prime from the test face from which we measured evoked responses. It is possible that such delays might have reduced the likelihood of the social category prime influencing behavior response-related processes. A final possibility is that the ERP effects observed may reflect influences on specific processes that may be too small to result in detectable changes to behavioral responses (which operate at a more coarse temporal scale and which encompass a wider range of cognitive processes).

Second, we analyzed ERPs in response to the test face stimulus only (i.e., the second of two faces presented on each trial). We chose to focus on the test face rather than the study face because this was the stimulus that triggered the computation and execution of a motor response (i.e., the “same” or “different” response). However, since we used a sequential matching task, analysis of the ERPs during the presentation of the study face might reveal further information about the role of our variables of interest, and in particular, about the influence of the social prime. Specifically, because the study face should trigger visual encoding and commitment to (working) memory (given the task requirements), these processes might be sensitive to motivational states that influence face processing in general. Because responses to the study faces may also reflect other, potentially confounding factors that we did not seek to test here (e.g., potential expectancies about the race of the face that would follow an own-university vs. other-university prime), we elected not to include this analysis. A speculative hypothesis, to be tested elsewhere, is that if motivational status influences the propensity or readiness to process faces configurally, then similar effects should be observed during pure encoding stages (i.e., the study phase) as during response computation (test phase).

Third, we relied on inversion effects to index configural processing, and there is some debate about whether inversion truly undermines configural processing (e.g., Richler, Mack, Palmeri, & Gauthier, 2011; Sekuler, Gaspar, Gold, & Bennett, 2004). It is...
important to note, however, that the face–composite effect—a clear marker for configurual/holistic processing (Maurer et al., 2002)—is reduced or even abolished by face inversion (e.g., Rossion & Boremanse, 2008; Young, Helawell, & Hay, 1987). Moreover, from our perspective, the question of whether inversion completely disrupts or merely compromises configurual processing is less important than our findings that inverted faces were processed less efficiently than upright faces. This relative loss of efficiency for configurual versus featural information would enable feature-based representations to have a greater influence on the processing of inverted faces than would be seen with upright faces, consistent with our reasoning.

Finally, all of our participants were White and our other-race faces were Black. A complete ERP investigation of the ORE would require comparisons of ERP components of interest with non-White participants (e.g., see Dickter & Bartholow, 2007; Wiese, Kaufman, & Schiweinberger, 2012) and with faces drawn from a range of races. It should be noted, however, that crossover interactions in own-race and other-race face processing as a function of participant race are not always observed (e.g., Lindsay, Jack, & Christian, 1991; Tanaka, Kiefer, & Bukach, 2004; Walker & Hewstone, 2006), perhaps because of differential other-race exposure and familiarity. Attempts to replicate the current findings with non-White participants would need to acknowledge this factor. We also point out that the current effects of ingroup/outgroup categorization might be particularly strong for the contrast between White and Black faces, given that Black faces have elsewhere been associated with strong emotion-related responses in White participants (Lieberman, Hariri, Jarche, Eisenbergre, & Bookheimer, 2005) and may be susceptible to changes in the participant’s motivational state as a consequence. This may also explain why variations in the effects of inversion on ERPs have not always been observed when, for example, White and Asian faces have been contrasted (e.g., Wiese et al., 2009).

Conclusion

The current research demonstrates that ingroup/outgroup categorization has different effects on the processing of own-race versus other-race faces, and that these effects emerge early in visual processing at the stage of structural encoding. Ingroup (vs. outgroup) categorization prompts more configural processing of other-race faces, but has less impact on the processing of own-race faces. These patterns reflect shifts in processing strategy as a function of racial and non-racial ingroup/outgroup status (with own-race and ingroup faces prompting greater reliance on configural processing, relative to other-race and outgroup faces) and highlight the importance of considering both experience and motivation in own-race and other-race face processing.

Supplementary material

Supplementary material (Figures S1–S3/Tables S1 and S2/Supplemental Analyses) is available via the “Supplementary” tab on the article’s online page (10.1080/17470919.2014.884981).

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