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Ingroup and outgroup differences in face detection

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Abstract

Humans show improved recognition for faces from their own social group relative to faces from another social group. Yet before faces can be recognized, they must first be *detected* in the visual field. Here, we tested whether humans also show an ingroup bias at the earliest stage of face processing – the point at which the presence of a face is first detected. To this end, we measured viewers' ability to detect ingroup (Black and White) and outgroup faces (Asian, Black, and White) in everyday scenes. Ingroup faces were detected with greater speed and accuracy relative to outgroup faces (Experiment 1). Removing face hue impaired detection generally, but the ingroup detection advantage was undiminished (Experiment 2). This same pattern was replicated by a detection algorithm using face templates derived from human data (Experiment 3). These findings demonstrate that the established ingroup bias in face processing can extend to the early process of detection. This effect is 'colour blind', in the sense that group membership effects are independent of general effects of image hue. Moreover, it can be captured by tuning visual templates to reflect the statistics of observers' social experience. We conclude that group bias in face detection is both a visual *and* a social phenomenon.

KEYWORDS
colour, face detection, group processing, ingroup bias, other-race effect, template-matching

INTRODUCTION

Our membership within social groups not only influences how we think and behave but also affects how we perceive other people and events (see Xiao et al., 2016). For instance, our affiliations with different cultural groups, sports teams, or political parties can change how we perceive visual illusions (Henrich et al., 2010), football matches (Hastorf & Cantril, 1954), or inauguration crowd sizes (Schaffner & Luks, 2018). One well-known example of intergroup perceptual bias is the other-race effect (ORE; also called the own-race bias or cross-race effect), in which humans, from a variety of cultures, show improved recognition memory for faces from their own ethnic group, when compared with faces from other ethnic groups (see Meissner & Brigham, 2001; Zhou et al., 2021). While the specific mechanisms underlying the ORE are still debated (see Young et al., 2012), the visual categorisation of faces according to group membership (in this case by ethnicity) is thought to be a fundamental component (Bernstein et al., 2007; Hugenberg et al., 2010; MacLin & Malpass, 2001, 2003). Yet before a face can be recognized, or even categorized by group, its presence must first be *detected* in the visual field. Here we ask whether group membership might affect this early step.

There are multiple stages at which group membership could bias face identification – from the allocation of attentional resources during the encoding of different facial identities into memory (Hugenberg et al., 2007; Kawakami et al., 2014), to the retrieval of identity information at recognition (Valentine, 1991; Valentine et al., 2016). These processes are unified, however, by the need to individuate faces, so that it is possible to separate the facial appearance of one person from that of another. The demands of face detection are different, as detection must rely on visual information that is common to all faces rather than specific to an individual. This characteristic separates face detection from face recognition, identity matching, and other tasks in which other-race effects have been demonstrated.

Previous work has shown that face detection is a rapid perceptual process (Crouzet et al., 2010; Kelly et al., 2019; Nakano et al., 2013; Rousselet et al., 2003) that is highly robust to natural variability in the appearance of different faces (Fletcher-Watson et al., 2008; Hershler & Hochstein, 2005; see Lewis & Ellis, 2003). If this generalisability extends to faces from different ethnic groups, then an ingroup bias for face detection may not exist.

On the other hand, face detection is necessarily sensitive to general visual properties of faces such as colour and shape (Bindemann & Burton, 2009; Burton & Bindemann, 2009; Nakano et al., 2013; Pongakkasira & Bindemann, 2015; Simpson et al., 2019). For example, when veridical skin colour information is removed from faces or they are rendered in unnatural colour tones (e.g., blue; Bindemann & Burton, 2009), or the aspect ratio is distorted (Pongakkasira & Bindemann, 2015), detection performance suffers. Such findings suggest that face detection might operate via matching to a template that combines diagnostic colour and shape information. They also raise the question of whether a detection template could also be tuned to represent more specific qualities of faces (Gobbini et al., 2013; Prunty et al., 2020; Stein et al., 2014), such as the features common to one's own ethnic ingroup. Borrowing from perceptual expertise accounts of the ORE (see Meissner & Brigham, 2001; Tanaka et al., 2013), the template used for face detection could be shaped by visual experience to reflect the range of facial appearance that we encounter.

There is some evidence that ethnic group membership can influence speed of processing for faces in dot-probe (e.g., Trawalter et al., 2008), flash-suppression (e.g., Stein et al., 2014), and visual search tasks (e.g., Chiao et al., 2006). For instance, other-race faces displayed amongst own-race faces can be located quicker than own-race faces amongst other-race faces (Levin, 1996, 2000; Sun et al., 2013), although findings are inconsistent across studies (Chiao et al., 2006; Lipp et al., 2009). According to the categorisation-individuation model of the ORE (see Hugenberg et al., 2007), ingroup and outgroup faces are attended in qualitatively different ways. That is, identity-relevant features are attended more readily for ingroup faces (hence improved identification in recognition memory tasks), while category-relevant features are preferentially attended for outgroup faces (hence improved categorisation speed in search tasks). However, the task of searching for a face amongst other faces is qualitatively different to that of detection. To find a specific face amidst face-like distractors requires a slow serial search, in which it is difficult to dissociate the influence of the target face from that of the distractors (Brown et al., 1997; Kuehn & Jolicoeur, 1994; Nothdurft, 1993). Whereas *detection* – that is, noting the presence or absence of faces – is a rapid automatic process that is largely independent of the number of non-face distractors in the display (Hershler & Hochstein, 2005, 2006). In essence, tasks that require participants to locate faces from one ethnic group amongst faces from another ethnic group are investigating 'race detection', not face detection. Furthermore, when faces are displayed on a blank background without non-face distractors, as is the case in dot probe and flash suppression paradigms, the problem of detection is essentially solved by the mode of presentation itself (Bindemann & Lewis, 2013). It is thus unclear from this literature if group biases would extend to the level of face detection, which must logically precede both recognition and categorisation.

In the current study, we test whether group affiliation affects face detection by measuring participants' ability to detect ingroup and outgroup faces when these are embedded in natural scenes. To focus specifically on faces, we present these stimuli without body cues. Even though bodies occupy more space than faces, previous research has shown that face detection is not guided by the body (Bindemann et al., 2010), and variability in clothing and pose makes them poor search targets. Conversely, face patterns can capture attention even when disembodied (e.g., Johnson et al., 1991; Kelly et al., 2019; Wardle et al., 2020). More importantly for this task, presenting faces without bodies eliminates the potential influence of clothing cues to perceived group membership (Gurung et al., 2021). Considering the ingroup biases that have been observed consistently in face recognition (see Meissner & Brigham, 2001), if early perceptual processing during detection is also sensitive to differences between faces, then faces from the participants' own ethnic group should be detected with greater speed and accuracy relative to faces from other ethnic groups. However, considering that detection does not require the individuation of faces, and logically precedes the categorisation and recognition tasks in which group biases are typically found, it is also possible that ingroup and outgroup faces are detected with comparable efficacy.

EXPERIMENT 1

In the first experiment, we aimed to establish whether humans detect the presence of faces from their own ethnic group with greater speed and accuracy compared with faces from other ethnic groups. We recruited Black and White participants resident in majority Black (South Africa: 79.2% Black African; Statistics South Africa, 2011) and majority White countries (United Kingdom: 92.2% White British; Office for National Statistics, 2011) to ensure that differences in detection performance would reflect group membership, rather than face race per se. Participants' detection performance was then recorded for Black and White faces embedded in a variety of naturalistic scenes. To provide further evidence that we are measuring group identity bias, we also presented Asian outgroup faces to provide an additional comparison condition. We reasoned that if group membership underlies the predicted effects, these Asian faces should perform similarly to *both* Black and White outgroup faces, despite visual differences between sets.

METHODS

Participants

We recruited 120 participants online using Prolific (Prolific, 2021); 60 from the United Kingdom (30 females; Age $M = 36.18$, $SD = 12.55$) and 60 from South Africa (30 females; Age $M = 25.57$, $SD = 6.53$). All UK participants identified as White, and all SA participants identified as Black. To check that participants' face exposure was indeed biased towards ingroup faces, they were asked to complete a social contact questionnaire after completing the detection task (Wong et al., 2020). A difference index based on participants' questionnaire scores (ingroup minus outgroup) indicated that both White ($M = 2.51$, $SD = 0.90$) and Black ($M = 2.42$, $SD = 0.89$) participant groups showed contact biases for ingroup members. Participants were also pre-screened and only deemed eligible if between the ages of 18 and

60, spoke and read fluent English and reported normal or corrected-to-normal vision. We checked participants' English proficiency using the LEAP-Q questionnaire (Marian et al., 2007). Non-native English speakers rated their proficiency in reading English as 7 ('very good') or above on a 1 to 10 scale ($M = 9.00$, $SD = 0.91$). In total, the experiment run time was approximately 30 minutes, and participants were awarded a small fee upon completing the study (£6.40 per hour).

The experiment was conducted online using Inquisit 6.1 (Inquisit, 2020). As stimuli were displayed on participants' personal computers, we included a screen calibration procedure to ensure that they would be presented at a standard size (21 × 15.75 cm), by asking participants to adjust a set of onscreen lines to the dimensions of a credit card. Additionally, to monitor data quality, we also included 12 catch trials to measure participants' attention. For these trials – which were inverted face-absent scenes requiring participants to press 'Spacebar' – we set an inclusion threshold of 75% (nine out of 12) correct responses. An additional 61 participants were thus excluded prior to analysis for either failing attention checks ($N = 11$), or for failing to correctly complete screen calibration ($N = 50$). After initial analyses, we excluded a further five outlying participants with an average detection performance (median = 5.56%) considerably lower than chance (i.e., 50%), which suggests that they misunderstood the task instructions (final $N = 115$; Black SA $N = 57$, White UK $N = 58$).

Design and stimuli

To investigate whether humans demonstrate an ingroup bias in face detection, participants were presented with 288 scene images, 144 of which contained a face. These faces varied according to race: Asian, Black, or White (48 of each). Within each of these categories, an equal number of male and female faces were presented (24 of each, see Figure 1). When combined with the observer's race (i.e., Black or White), scenes with either Black or White faces were coded as either 'ingroup' or 'outgroup' trials accordingly. Scenes containing Asian faces were consistently coded as 'other-outgroup' trials across all participants.

Face stimuli were selected from a set of front-facing, ambient face photos, originally sourced from an online face generator (thispersondoesnotexist.com; see Karras et al., 2017, 2019). To validate the race and gender assignments for generated faces, we selected 20 faces at random from each of the six face categories (120 faces were rated in total) and asked 60 independent observers to classify the intermixed faces according to their perceived race ($N = 30$), or gender ($N = 30$). We found high concordance between observers' classifications and our category assignments for race ($M = 97.61\%$, $SD = 1.83\%$), and gender ($M = 91.64\%$, $SD = 5.32\%$).

Scene images were sourced from online image repositories (e.g., Unsplash.com, Pexels.com) that provide freely usable images (CC0 licence). Scenes pictured a variety of cluttered, natural environments, corresponding to six broad categories: child-centred (e.g., classrooms, playgrounds), garage, home, office, restaurant, and shop scenes (see Figure 2 for examples). Twenty-four scenes from each scene category were randomly selected to contain a face. Faces (143 × 214 pixels) were then cropped to remove the image background, and embedded in the scenes (2000 × 1500 pixels). The locations of the faces were determined by a 4 × 3 grid of 12 regions (500 × 500 pixels each). Locations were counterbalanced across participants by rotating around three region groupings (top, middle, and bottom) such that each of the six face categories (see Figure 1) had an equal chance of appearing in each scene region. This manipulation, of presenting disembodied faces in scenes, removes confounding contextual cues (e.g., bodies, clothing) that might influence detection (see Bindemann et al., 2010; Bindemann & Lewis, 2013; Wolfe & Horowitz, 2017) and elicit prejudiced stereotypes (Gurung et al., 2021).

Procedure

After the screen calibration procedure, scene stimuli (144 face present and 144 face absent) were displayed at 21 × 15.75 cm for all participants (visual angle of 19.85° × 14.96° assuming a 60 cm viewing

FIGURE 1 Examples from the six face categories used in Experiment 1, which vary according to race: Asian (left), Black (middle), and White (right), and gender: male (top) and female (bottom).

distance), regardless of their screen size or resolution. Within face-present scenes, faces were displayed at 1.5×2.25 cm ($1.43° \times 2.2°$). Participants were instructed to press 'P' (present) if they thought the scene contained a face, and 'A' (absent) if they thought it did not contain a face as quickly and as accurately as possible. The 12 attention check trials, consisting of inverted scenes, were presented at pseudo-random intervals. When participants encountered an inverted scene, they were instructed to press 'Spacebar'. Experimental trials were presented in a fully randomized order, with the option of a break every 72 trials.

RESULTS

Face detection

Response speed and accuracy were used as indicators of face detection performance. For each participant, we calculated the proportion of correctly classified trials as an indicator of detection accuracy, and median response times (RTs) for correct trials as an indicator of detection speed. As a first

FIGURE 2 Examples of detection stimuli representing each of the six face categories (Asian male and female, Black male and female, and White male and female) and six scene categories (child-centred, restaurant, garage, shop, home, and office) used in Experiment 1.

check, we compared detection performance for face present and face absent trials separately. As would be expected (e.g., see Eckstein, 2011), participants showed reduced accuracy for face present trials, $t(114) = 4.28$, $p < .001$, $d = .40$, as they were more likely to miss faces that were present (M = 90.95%, SD = 17.56%) than find faces that were absent (M = 97.83%, SD = 2.99%). Furthermore, participants showed faster responses for face present trials (M = 876 ms, SD = 253 ms) compared with face absent trials (M = 1748 ms, SD = 780 ms), as any search for a face is terminated once it is found, $t(114) = 13.80$, $p < .001$, $d = 1.28$.

The data of primary interest comprised of participants' accuracy and response times towards ingroup, outgroup, and other-outgroup (i.e., Asian) faces and are summarized in Figure 3. Consistent with our counterbalanced design, the data are presented collapsed across participant group, but separate analyses by observer race are available in the Appendix S1. Inspection of Figure 3 suggests that participants showed improved detection performance for ingroup faces. To confirm this observation, we conducted one-way repeated-measures ANOVAs across Face Group (ingroup, outgroup, and other-outgroup) for detection accuracy and speed. For accuracy, a main effect of Face Group was found, $F(2,228) = 9.02$, $p < .001$, $\eta_p^2 = .07$, with pairwise comparisons (Benjamini-Hochberg) indicating greater accuracy for ingroup (M = 95.29%) relative to outgroup (M = 93.70%) and other-outgroup (M = 93.30%) faces, both $ts > 3.2$, $ps < .003$, $ds > .30$. Accuracy for outgroup and other-outgroup faces did not differ significantly, $t(114) = 0.84$, $p = .403$, $d = .08$. For detection speed, a main effect of Face Group was also found, $F(2,228) = 4.48$, $p = .012$, $\eta_p^2 = .04$, indicating faster responses for ingroup (M = 848 ms) compared with outgroup (M = 868 ms) and other-outgroup (M = 879 ms) faces, both $ts > 2.1$, $ps < .05$, $ds > .20$. Similar to accuracy, the difference in detection speed between outgroup and other-outgroup faces was not significant, $t(114) = 0.98$, $p = .329$, $d = .09$.

Sensitivity analysis

To estimate the minimum effect size that could be reliably detected by our sample, we conducted a sensitivity analysis using *G*Power* (Faul et al., 2009). A one-way repeated measures ANOVA (Face Group) with 115 participants and 80% power ($\alpha = .05$) would reliably detect effect sizes of $\eta_p^2 = .014$ ($d = .24$) or greater. Our sample was therefore sufficient to detect even small effect sizes.

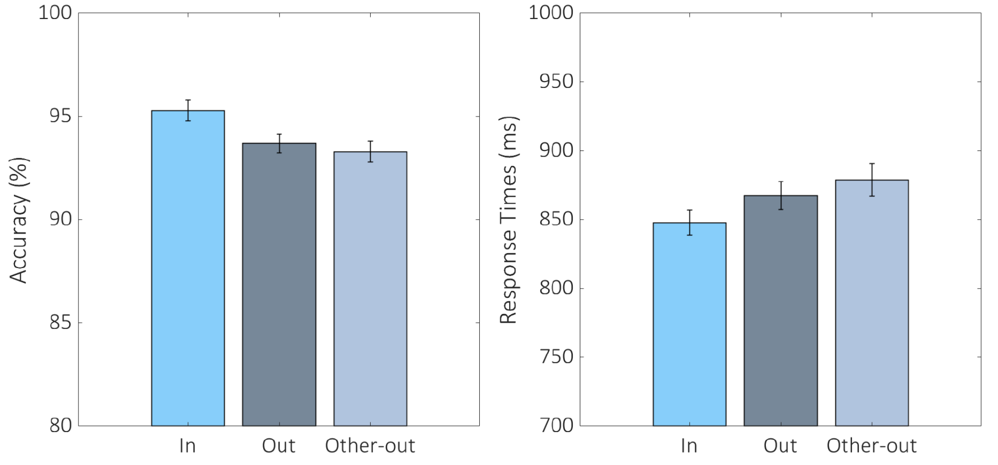

FIGURE 3 Mean detection accuracy and response times for ingroup (In), outgroup (Out) and other-outgroup (Other-out) faces in Experiment 1. Error bars represent within-subjects variability via 95% Cousineau-Morey confidence intervals (see Baguley, 2012).

DISCUSSION

Experiment 1 shows that humans detect ingroup faces with greater speed and accuracy relative to outgroup faces. This finding demonstrates that group processing biases can affect even the most basic stage of face processing; the point at which the presence of a face is registered in the visual environment. With a counterbalanced design that required White participants from the United Kingdom and Black participants from South Africa to detect Black and White faces, we have shown that this ingroup detection bias is cross-cultural and applies to multiple ethnic groups. Despite visual differences, Asian 'other-outgroup' faces also showed similarly reduced detection performance to Black and White outgroup faces. Together, our results suggest that group biases in detection are not driven by low-level properties of faces per se, but that the visual information guiding detection is related to the observer's prior experience with faces.

Nevertheless, the specific visual properties of faces underlying the ingroup detection bias remain unclear. A possible mediating factor is colour, which has a powerful influence on face detection (Bindemann & Burton, 2009) and on visual search more generally (D'Zmura, 1991; see Wolfe & Horowitz, 2004), and which is also a relevant factor in race category judgements (Stepanova & Strube, 2009, 2012). In Experiment 2, we attempt to replicate the results from Experiment 1, while also investigating whether colour information is necessary for detection biases to emerge.

EXPERIMENT 2

Colour is a powerful low-level cue that can induce rapid visual pop-out of search targets (Treisman & Gelade, 1980; Wolfe, 1994). It also facilitates detection of human faces when these are presented in veridical skin-colour tones compared with unnatural skin colours (Bindemann & Burton, 2009). Experiment 2 therefore investigates whether differences in skin colour can also explain the ingroup face detection advantage that was observed in Experiment 1. For this purpose, we selectively manipulated colour information in faces, scenes, and the entire stimulus display (faces *and* scenes) by removing hue to create greyscale conditions. There are several aspects of faces that influence race category judgements, including facial physiognomy, skin tone, and hue (Stepanova & Strube, 2009, 2012). Although group biases in own- and other-race face processing are routinely investigated using greyscale faces (e.g., Brigham & Barkowitz, 1978; Levin, 2000), previous work suggests that the colour presentation mode of face images (i.e., colour vs. greyscale) also plays an important role in race category judgements

(Stepanova & Strube, 2009). Moreover, given the importance of colour in visual search (Carter, 1982; Treisman & Gormican, 1988; Wolfe & Horowitz, 2004), group biases in *detection* may depend on the colour information inherent within faces and scene backgrounds. Consequently, face detection should be impaired generally, and the ingroup face detection advantage of Experiment 1 should be attenuated, when faces are presented in greyscale, irrespective of the colour information in the scene background.

Participants, stimuli, and procedure

To investigate the role of stimulus hue in face detection, we again used Prolific to recruit 128 participants: 64 White UK residents (32 females; Age M = 36.56, SD = 12.21) and 64 Black SA residents (32 females; Age M = 27.97, SD = 6.74) using the same eligibility criteria as Experiment 1. Once again non-native English speakers rated their reading proficiency as 7 ('very good') or higher (M = 9.09, SD = 0.90). Difference scores computed from the social contact questionnaire suggest that an ingroup contact bias was present for both White (M = 2.21, SD = 0.80) and Black (M = 1.82, SD = 0.85) participant groups. The experiment and screen calibration were again conducted online via Inquisit. For this experiment, we simplified the screen calibration procedure with the aim of reducing data loss. To confirm correct calibration, participants were now asked to compare their credit card to a rectangle, rather than a series of lines. Consequently, three additional participants were excluded prior to analysis for failing to produce 75% correct responses on attention-check trials, but all participants successfully completed calibration.

As in Experiment 1, participants were presented with 288 upright scenes in a fully randomized order, 144 of which contained a face. To accommodate the manipulation of colour with these stimulus numbers, Experiment 2 included ingroup and outgroup faces only. Faces were therefore either Black or White (72 of each), and contained equal numbers of male and female faces. Half of the face items in each face category (18 items) were converted to greyscale. Similarly, the same scenes were also used in this experiment as in Experiment 1, but half of the scenes (both face present and face absent) were converted to greyscale. Hue was removed from faces and scenes systematically to create four colour categories: full colour, greyscale face in colour scene, colour face in greyscale scene, and full greyscale (see Figure 4 for examples). As in Experiment 1, face locations were again counterbalanced across participants to ensure each face category appeared an equal number of times in each of the 12 scene regions. However, we also included additional counterbalanced conditions to ensure each stimulus image appeared an equal number of times within the four colour categories, forming eight counterbalanced conditions in total. The experimental procedure was identical to Experiment 1.

RESULTS

Face detection

We first compared participants' detection performance for face present and face absent trials, and found the expected pattern of greater detection accuracy for face absent trials (M_{FP} = 94.30%, M_{FA} = 96.12%), $t(127)$ = 1.98, p = .050, d = .18, and greater detection speed for face present trials (M_{FP} = 830 ms, M_{FA} = 1765 ms), $t(127)$ = 16.90, $p < .001$, d = 1.49. We then focused our analysis on face present trials, and compared participants' ability to detect ingroup and outgroup faces within each of the four colour categories (i.e., full colour, grey face, colour face, full greyscale). These data are illustrated in Figure 5 and were analysed with two 2 (Face Group: ingroup and outgroup) × 2 (Scene Colour: colour and greyscale) × 2 (Face Colour: colour and greyscale) repeated-measures ANOVAs for detection accuracy and RTs. For clarity, the ANOVA results are displayed in Table 1.

For accuracy, a main effect of Face Group was found, $F(1,127)$ = 10.98, p = .001, η_p^2 = .08, reflecting more accurate responses for ingroup (M = 94.97%) compared with outgroup faces (M = 93.63%). Main effects of Face Colour, $F(1,127)$ = 59.22, $p < .001$, η_p^2 = .32, and Scene Colour, $F(1,127)$ = 27.11, $p < .001$, η_p^2 = .18, were also observed, indicating greater detection accuracy for colour faces

FIGURE 4 Examples of the additional colour categories for detection stimuli in Experiment 2. Alongside full colour images, this included colour scenes with greyscale faces (left), greyscale scenes with colour faces (middle), and full greyscale images (right). Examples include a Black male face (top row) and White female face (bottom row).

(M_{Col} = 96.29%, M_{Grey} = 92.31%) and for greyscale scenes (M_{Col} = 93.24%, M_{Grey} = 95.36%). These main effects were qualified by an interaction between Face and Scene Colour, $F(1,127) = 16.95$, $p < .001$, $\eta_p^2 = .12$. Pairwise comparisons across Scene Colour (Benjamini-Hochberg) indicated that greyscale scenes only facilitated detection when they contained colour faces, $t(255) = 8.15$, $p < .001$, $d = .51$, but not when faces were also rendered in greyscale, $t(255) = 1.86$, $p = .064$, $d = .12$. Conversely, colour faces improved detection in both colour, $t(255) = 5.72$, $p < .001$, $d = .36$, and greyscale scenes, $t(255) = 9.17$, $p < .001$, $d = .57$. Face and Scene Colour did not interact with Face Group, both $Fs < 0.4$, $ps > .58$, and a three-way interaction between factors did not reach significance, $F(1,127) = 2.99$, $p = .086$, $\eta_p^2 = .02$.

For RTs, the same analysis also uncovered a main effect of Face Group, $F(1,127) = 28.12$, $p < .001$, $\eta_p^2 = .18$, indicating faster detection of ingroup (M = 831 ms) compared with outgroup faces (M = 860 ms). There were again main effects of Face Colour, $F(1,127) = 224.67$, $p < .001$, $\eta_p^2 = .64$, and Scene Colour, $F(1,127) = 106.13$, $p < .001$, $\eta_p^2 = .46$, reflecting faster detection for colour faces (M_{Col} = 787 ms, M_{Grey} = 904 ms) and greyscale scenes (M_{Col} = 881 ms, M_{Grey} = 810 ms). These main effects were again qualified by an interaction between Face and Scene Colour, $F(1,127) = 36.44$, $p < .001$, $\eta_p^2 = .22$. There was a larger difference between colour and greyscale faces for scenes rendered in greyscale (M_{Diff} = 148 ms, $d = 1.11$), compared with colour scenes (M_{Diff} = 86 ms, $d = .56$), though corrected comparisons indicated that both reached significance, $ts > 8.9$, $ps < .001$. Further, there was a greater advantage for greyscale scenes when faces were in colour (M_{Diff} = 102 ms, $d = .92$), rather than in greyscale (M_{Diff} = 40 ms, $d = .26$), though both comparisons were also significant, $ts > 4.2$, $ps < .001$. Once again, Face and Scene Colour did not interact with Face Group, both $Fs < 0.6$, $ps > .44$, and a three-way interaction was not found, $F(1,127) = 0.29$, $p = .589$, $\eta_p^2 < .01$.

Sensitivity analysis

To estimate the minimum effect size that could be reliably detected by our sample in Experiment 2, we again conducted a sensitivity analysis using *G*Power* (Faul et al., 2009). A 2 (Face Group) x 2 (Scene Colour) × 2 (Face Colour) repeated measures ANOVA with 128 participants and 80% power ($\alpha = .05$) would reliably detect effect sizes of $\eta_p^2 = .007$ ($d = .17$) or greater. Our sample was therefore sufficient to detect even small effect sizes.

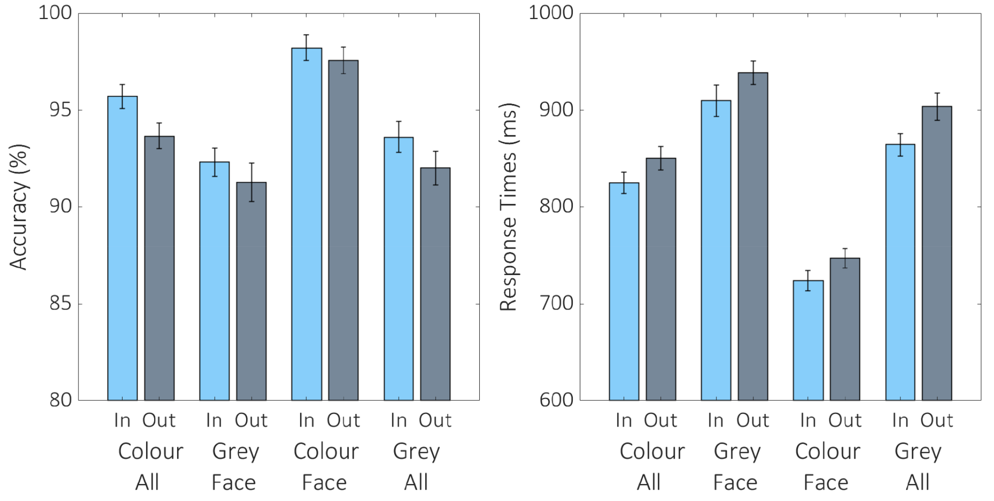

FIGURE 5 Mean detection accuracy and response times in Experiment 2 for the Colour All condition (colour faces and colour scenes), the Grey Face condition (greyscale faces in colour scenes), the Colour Face condition (colour faces in greyscale scenes), and the Grey All condition (greyscale faces and scenes). Blue bars represent ingroup (In) faces, and grey bars represent outgroup (Out) faces. Error bars represent within-subjects variability via 95% Cousineau-Morey confidence intervals (see Baguley, 2012).

TABLE 1 The effect of Face Group, Face Colour, and Scene Colour on detection accuracy and response times in Experiment 2

	df	*F*	*p*	η_p^2
Accuracy				
A. Face group	1, 127	10.98	.001	.08
B. Face colour	1, 127	59.22	<.001	.32
C. Scene colour	1, 127	27.11	<.001	.18
A × B	1, 127	<0.01	.977	<.01
A × C	1, 127	0.31	.581	<.01
B × C	1, 127	16.95	<.001	.12
A × B × C	1, 127	2.99	.086	.02
Response times				
A. Face group	1, 127	28.12	<.001	.18
B. Face colour	1, 127	224.67	<.001	.64
C. Scene colour	1, 127	106.13	<.001	.46
A × B	1, 127	0.60	.443	<.01
A × C	1, 127	0.14	.713	<.01
B × C	1, 127	36.44	<.001	.22
A × B × C	1, 127	0.29	.589	<.01

Note: Results from two 2 (Face Group: ingroup, outgroup) × 2 (Face Colour: colour, grey) × 2 (Scene Colour: colour, grey) repeated measures ANOVAs.

DISCUSSION

Experiment 2 replicated the ingroup detection advantage for faces in accuracy and response times. The experiment also shows that detection is moderated by the colour information in faces and scenes. Faces rendered in colour on greyscale scene backgrounds were detected far easier than any of the other face-scene colour combinations. This effect is likely driven by the salience of hue on a background that has a dissimilar, but homogenous colour (i.e., grey) causing the face to 'pop out' – a well-known phenomenon in visual search (Carter, 1982; Treisman & Gormican, 1988; Wolfe & Horowitz, 2004). However, colour faces were also detected faster and more accurately within colour scenes than greyscale faces. Moreover, detection was slower for greyscale faces in colour scenes than it was for fully greyscale stimuli. This contrast highlights the importance of face hue in detection (Bindemann & Burton, 2009), and demonstrates that hue forms an important component of the cognitive template for face detection. Critically, however, neither face colour nor scene colour interacted with group membership. Thus, ingroup faces were detected more effectively than outgroup faces, and colour faces more effectively than greyscale faces, but these effects were independent. This indicates that, while hue is important for face detection, the hue of faces of different races does not explain the ingroup detection advantage, despite the salience that this information is often attributed (for example, when labelling faces according to race).

EXPERIMENT 3

Experiments 1 and 2 provide evidence that the human detection template is not only sensitive to general properties of faces, such as colour or shape (Bindemann & Burton, 2009; Pongakkasira & Bindemann, 2015; Simpson et al., 2019), but that it is also tuned towards *specific* properties common to groups of faces, such as the features common to one's own ethnic group. Thus far, however, we have been inferring the nature of the face detection template from participants' detection performance. That is, we assume that the more similar faces are to the observer's template, the faster and more accurately they should be detected. Our aim in Experiment 3 is to model strict template matching for the same scenes, thereby providing a comparison for the observed human performance.

To this end, we simulated human face detection using a template-matching algorithm (Kroon, 2021; see also Viola & Jones, 2004). This algorithm examines the visual information within an image and locates the region of the image that best matches a given template. To model individual participants, we constructed separate participant-specific templates by averaging together Black and White faces in the ratio determined by each participant's social contact score in Experiment 2. The algorithm then scans the scenes presented in Experiment 2, using each template in turn. This process is of course different to that of human observers, however, our goal here is not to directly compare human and algorithm performance per se (i.e., which is more accurate overall), but to compare the *pattern* of performance across groups (i.e., ingroup versus outgroup). If this procedure recreates the group membership effects seen in Experiment 2, it would show that individual differences in face templates are sufficient to generate such effects. If the group membership effects do not emerge, it would show that additional factors are necessary.

METHODS

Template-matching algorithms are routinely used in automated systems to perform object recognition and image registration. To simulate human face detection, we used a template-matching algorithm (Kroon, 2021) to determine the location of a face within a larger scene image. The algorithm uses the Sum of Squared Differences (SSD; see Di Stefano & Mattoccia, 2003) and Normalized Cross Correlation (NCC; see Kaso, 2018) to identify the region of an image most similar to a template. For each scene image, if the algorithm was able to correctly identify the location of the face, we recorded a 'hit', otherwise we recorded a 'miss'. The scene stimuli used in this simulation were identical to the face-present scenes in Experiment 2 (see Figure 4), and included the four colour categories.

To simulate the face detection performance of each participant in Experiment 2, we used InterFace (Kramer et al., 2017) to construct a corresponding average face template (Figure 6). Each template (N = 128) was formed by morphing 10 face images into a single average identity. Faces were selected at random from a larger pool of 64 faces (32 females), but participants' mean scores on the social contact questionnaire were used to calculate the ratio of Black to White faces within each template.[1] Templates were 143 × 214 pixels, the same size as the faces in scenes, but to minimize the influence of the image background on the matching process, each image was cropped to the face outline, and the remaining background was filled with gaussian noise (see Figure 6). The template-matching algorithm then compared each template to the 144 face-present scenes used in Experiment 2, and the proportion of hits to misses for each template was recorded. Face location and colour category were also counterbalanced across template 'participants' as in the previous experiment.

RESULTS

Analogous to the analysis of Experiment 2, we compared the template-matching algorithm's ability to accurately locate faces in scenes across each of the four colour categories. As the template images were constructed to represent participants' own cognitive detection templates, Black and White faces in scenes were coded as either ingroup or outgroup faces, relative to the race of participants in Experiment 2. The algorithm's mean accuracy for the detection simulation closely resembles participants' accuracy data in Experiment 2 and is illustrated in Figure 7.

A 2 (Face Group: ingroup and outgroup) × 2 (Scene Colour: colour and greyscale) × 2 (Face Colour: colour and greyscale) repeated-measures ANOVA of the detection simulation data revealed a main effect of Face Group, $F(1,127) = 61.22$, $p < .001$, $\eta_p^2 = .33$, reflecting greater accuracy for ingroup (M = 52.56%) relative to outgroup faces (M = 34.56%). In addition, a main effect of Face Colour was found, $F(1,127) = 176.69$, $p < .001$, $\eta_p^2 = .58$, as colour faces (M = 48.63%) were more accurately located compared with greyscale faces (M = 38.49%). A main effect of Scene Colour was also present, $F(1,127) = 24.54$, $p < .001$, $\eta_p^2 = .16$, due to the enhanced detection of faces in greyscale (M = 44.90%) compared with colour scenes (M = 42.22%). These main effects were qualified by an interaction of Face Colour and Scene Colour, $F(1,127) = 6.55$, $p = .012$, $\eta_p^2 = .05$. Pairwise comparisons (Benjamini-Hochberg) showed that colour faces were located with greater accuracy than greyscale faces in colour scenes, $t(255) = 11.75$, $p < .001$, $d = .73$, and in greyscale scenes, $t(255) = 9.67$, $p < .001$, $d = .61$. In contrast, greyscale faces were detected more accurately in greyscale scenes, $t(255) = 4.72$, $p < .001$, $d = .30$, but detection performances for colour faces did not differ significantly for greyscale and colour scene contexts, $t(255) = 1.62$, $p = .107$, $d = .10$. However, Face Colour and Scene Colour did not interact with FaceGroup, both $Fs < 1.1$, $ps > .30$, and a three-way interaction between factors was not found, $F(1,127) < 0.01$, $p = .936$.

DISCUSSION

This experiment recreated the main findings from Experiment 2 using a template-matching algorithm. Specifically, we found an 'ingroup bias' in detection performance, as well as improved detection for colour over greyscale faces. In contrast to the behavioural data of Experiments 1 and 2, in which the nature of the face detection template was inferred from human performance, the simulations in Experiment 3 were based on templates that were constructed from human social contact data. This provides direct evidence that individual differences in detection templates can produce an ingroup detection advantage, and that this effect is dissociable from effects of image hue on face detection.

[1]The race contact questionnaire used a 5-point scale, thus ingroup-outgroup difference scores ranged from −4 to 4. Difference scores were converted to a 0 to 1 scale by adding 4 and dividing by 8. This proportion was then used to determine the number of Black or White faces within each template by multiplying by the image number (10) and rounding to the nearest integer.

FIGURE 6 Examples of average face templates used to simulate the human detection template in Experiment 3. Average faces were comprised of 10 identities, and the ratio of Black to White faces varied according to Experiment 2 participants' scores on the race contact questionnaire. Examples of templates from Black South African participants (top row) and White United Kingdom participants (bottom row) are displayed. Image backgrounds were cropped to the face region and filled with gaussian noise.

GENERAL DISCUSSION

An extensive body of research demonstrates group biases in person identification, whereby faces of one's ingroup are stored and recognized more effectively than outgroup faces (for a review, see Meissner & Brigham, 2001; Xiao et al., 2016). In this study, we investigated whether the ingroup bias in face memory extends to the earliest stage of face processing – the point at which the presence of a face is first detected in visual scenes. In Experiment 1, ingroup faces were detected faster and more accurately than outgroup faces, demonstrating a clear group bias. This was observed with a counterbalanced design incorporating observers from predominantly Black and White ethnic cultures, and was replicated with an additional category of outgroup faces (Asian). Experiment 2 extended these findings by systematically examining the role of image hue. Detection performance was enhanced when faces were displayed in veridical skin tones compared with when these were rendered in greyscale, but this effect was independent from the observed group biases. These behavioural findings suggest that the cognitive template for face detection could be tuned by our visual experience with faces, but do not show that such template tuning is sufficient to produce an ingroup effect. To test the sufficiency of template tuning, we constructed separate detection templates based on each participant's self-reported experience with ingroup and outgroup faces. We then simulated their detection performance with a standard face detection algorithm (Experiment 3). This simulation replicated the pattern seen in Experiment 2 by producing an ingroup advantage that was dissociable from effects of image hue.

Several theoretical implications emerge from these findings. Foremost, we show that group biases in face perception extend to earlier processes than encoding of identity and recognition memory.

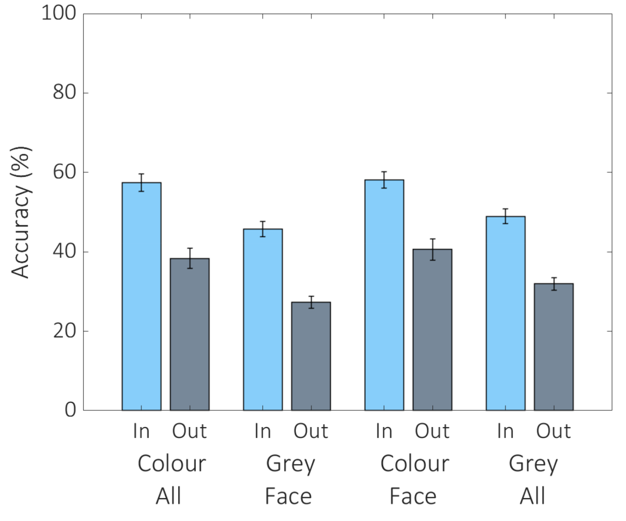

FIGURE 7 Mean simulated detection accuracy for ingroup and outgroup faces within each colour category in Experiment 3 for the Colour All condition (colour faces and colour scenes), the Grey Face condition (greyscale faces in colour scenes), the Colour Face condition (colour faces in greyscale scenes) and the Grey All condition (greyscale faces and scenes). Error bars represent within-subjects variability via 95% Cousineau-Morey confidence intervals (see Baguley, 2012).

Specifically, they extend to the detection stage. This observation suggests that a person's face detection template may reflect the distribution of facial appearance encountered in that person's everyday life. Furthermore, it opens the door for future work to consider whether detection biases are present for other demographic ingroups, such as age or gender. Our findings also demonstrate that, while detection performance benefits generally when faces are presented in their natural colour, group biases emerge whether faces are presented in colour or greyscale. This observation is remarkable considering the salience of face colour in explicit race categorisation (Stepanova & Strube, 2009, 2012), and the widespread use of colour words to refer to people from different groups. Although image colour influences face detection generally, detection of faces from different ethnic outgroups is apparently 'colour blind', in the sense that effects of group membership are orthogonal to effects of image hue.

The reproduction of the same effects in our simulation study (Experiment 3) suggests that visual processes are sufficient to generate them. Recent motivational accounts of group biases in face recognition have emphasized the role of non-visual group processing alongside perceptual expertise (Hugenberg et al., 2010, 2013; Levin, 2000; Sporer, 2001). For example, there is evidence to suggest that social categorisation alone can produce an ingroup advantage in face recognition by signalling the need to individuate faces (Bernstein et al., 2007; MacLin & Malpass, 2001, 2003; Shutts & Kinzler, 2007; Van Bavel & Cunningham, 2012). Although it is conceivable therefore that group biases in detection might be driven by similar high-level properties of faces, such as their group status, the findings from our simulation suggest that motivational influences on perception are not required to produce these effects. Nevertheless, future research could directly test this by investigating whether detection biases are present for arbitrary ingroups, such as those used within 'minimal groups' paradigms (e.g., Bernstein et al., 2007; Van Bavel & Cunningham, 2012).

On the other hand, our observers self-reported clear differences in social contact with ingroup and outgroup faces, and our detection simulation, based on templates that reflect these differences, replicated the behavioural effects closely. Consequently, our findings resonate with perceptual expertise accounts of the ORE in face recognition (O'Toole et al., 1991; Rhodes et al., 1989; Tanaka et al., 2013; Valentine et al., 2016), which emphasize the role of experience in the tuning of face representations. Although the simulations in the current study were based on visual information alone, there is also a social component. The detection templates were constructed to reflect the statistics of each participant's social experience, and accordingly showed similar biases to the human participants. In a similar manner, recent work has shown that modern face recognition algorithms also show an 'other-race effect', as they demonstrate better recognition accuracy for the majority race in their training set (Phillips et al., 2011). In this sense, the group biases in human face detection are both a visual *and* a social phenomenon, as detection templates are likely tuned to reflect the asymmetrical experience of ingroup and outgroup faces in daily life.

A bias towards detecting ingroup faces is also contrary to what one might predict from previous work in visual search, which has reported shorter search times for *outgroup* faces (Levin, 1996, 2000; Sun et al., 2013), although findings have been mixed (Chiao et al., 2006; Lipp et al., 2009). One reason for this is that the task of searching for a face of one race amongst faces of another race is qualitatively different to that of detection (see Bindemann & Lewis, 2013). Such visual search tasks are slow, effortful processes, requiring the categorisation of individual faces before the target can be identified. Contrastingly, detection is a fast, parallel process that must logically occur *prior* to categorisation (Hershler & Hochstein, 2005, 2006). It is thus perhaps unsurprising that that these tasks might yield different results.

The finding that preferential processing of ingroup faces extends to such an early stage has practical implications too. If ingroup members are systematically prioritized for detection in real-world scenarios, then outgroup members might be overlooked, suggesting that intergroup social interactions may be disadvantaged from the outset. Although group effects in face perception are known to be small (Zhou et al., 2021), statistical effect size is not the same as social importance. We suggest that future work should consider the downstream consequences of early detection biases for intergroup relations.

AUTHOR CONTRIBUTIONS

Jonathan Prunty: Conceptualization; data curation; formal analysis; investigation; software; visualization; writing – original draft; writing – review and editing. **Rob Jenkins:** Conceptualization; funding acquisition; supervision; validation; writing – review and editing. **Rana Qarooni:** Writing – review and editing. **Markus Bindemann:** Conceptualization; funding acquisition; project administration; resources; supervision; validation; writing – review and editing.

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CONFLICT OF INTEREST

All authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available on the Open Science Framework at https://osf.io/jfkbd.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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