Investigating the other-race categorization advantage within the context of learning.

By

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Abstract

It is well established that people process own-race and other-race faces differently. When required to *recognise* or *differentiate between* specific facial identities, better performance is achieved with own-race faces compared to other-race faces, a finding termed the other-race effect (ORE). However, when asked to *categorize* faces, performance is better for other-race faces than for own-race faces, a finding termed the other-race categorization advantage (ORCA).

This work explored how these race effects might vary as a function of face familiarity. A race categorization task was chosen in which stimuli were covered with two-dimensional Gaussian noise and participants were required to classify faces as Asian or Caucasian. Two experiments were conducted. In Experiment 1, the signal (face) alpha level on each trial was gradually increased to modulate the visibility of the target face such that the faces emerged from noise. Participants ended the trial by making a response as soon as possible. Faces were repeated across blocks to include face familiarity. The ORCA was present in the task in both accuracy data and levels of alpha, with participants responding more accurately for other-race faces as well as requiring less visible face to categorize other-race faces. Despite the repetition of faces, no learning took place in this task.

In Experiment 2, the alpha levels of the face within the dynamic noise were predetermined, providing 4 possible levels (0.5, 0.6, 0.7 and 0.8) of visibility. Participants were required to respond as quickly as possible, with reaction time (RT) being the main dependent measure. Faces were again repeated across blocks. The ORCA was present in both accuracy and RT data. A learning effect for own-race faces was obtained such that RT to categorize own-race faces decreased while the RT to categorize other-race faces increased. A follow- up control experiment presented a new set of faces in each block and concluded that the learning effect obtained in Experiment 2 was due to the individuation of the faces presented during the task, not more general task or race-template learning.

Taken together these results suggest that the ORCA is a robust phenomenon that can be consistently measured in novel, online tasks. The results of Experiment 2 further suggest that with repetition of faces, faster individuation of own-race faces takes place, reducing the influence of the ORCA and leading to patterns of performance more consistent with the ORE.

Keywords: other-race categorization advantage, face categorization, face familiarity, face individuation

Chapter 1

The theme of this thesis is to explore how we process own-race and other-race faces, particularly within the context of learning. After reviewing the literature, two empirical studies that address this from different angles will be presented.

Faces

Faces hold a powerful place in human psychology, revealing a variety of characteristics including gender, age, expression, identity and race (Todorov et al., 2005; Willis & Todorov, 2006). A number of distinct but interrelated activities make up human face processing, including the detection of faces within the visual environment, categorization of faces from objects, discrimination between face stimuli, recognition of familiar faces as well as individuation, and memory of identities (Oruc et al., 2019).

Early research on faces

Research on faces dates back to the mid-1980s, and was based on careful reasoning, neuropsychological observations of single cases as well as experiments using photographs and slide projectors (Young & Bruce, 2011).

It was during this period that models of face perception were being developed. Nevertheless, some of these models remain influential to this day. For instance, Bruce & Young (1986) used converging evidence and arrived to a face perception model proposing that following initial perceptual encoding, identity and emotions are processed independently. This model has proved surprisingly resilient (Schweinberger & Burton, 2011). As the field of neuroanatomy improved, Haxby et al. (2000) integrated behavioural and neuropsychological evidence and supported the model by Bruce and Young (1986). Although this model needs revision in some areas (Calder et al., 2011, Freiwald et al., 2016), it also remains influential and suggests that a core system of regions is involved in the processing of faces, which comprises of the lateral fusiform gyrus, inferior occipital gyri and posterior superior temporal sulcus (STS). The model also presents distinct neural pathways for processing the invariant facial proprieties and the variant facial aspects. Invariant components of face identities are examined through one channel (using the lateral fusiform gyrus), while more variable aspects and social messages are extracted through another route (particularly via the posterior STS). Functional magnetic resonance imaging (fMRI) research using adaptation or multivoxel analysis of the patterns of activation have also found activations in the same regions (Andrews & Ewbank, 2004; Flack et al., 2019; Kovács, 2020). However, it is not clear which of these areas are involved in perceiving faces (Freiwald et al., 2016; Kovács, 2020; Yovel, 2016).

Research since the 1980s

Since the 1980s, the field of face perception research has relied on different tasks and paradigms to further understand such an important area of human cognition, often times relying on accuracy scores that fall within the range of a control group, reaction time measures and cognitive subtraction (Bruce & Young, 2012).

Amongst the many tasks developed for face perception research are the alternative forced-choice tasks, categorization tasks, same/different tasks, old/new recognition tasks and face matching tasks (Oruc et al., 2019). In alternative forced-choice tasks, observers are required to indicate which interval contained the face. For instance, Dalrymple & Duchaine (2016) revealed that slower reaction times were obtained by prosopagnosia patients when asked to indicate whether or not a face is present from display arrays of 25 images. Alternative forced-choice tasks have also been used to investigate individuation of faces (Peterson & Eckstein, 2012). In categorization tasks, participants are required to classify a face as a forming part of a particular category, for example own race vs other race (Zhao & Bentin, 2008). Same/different tasks have been used to assess discrimination ability. For instance, Oruc et al. (2018) used morphed stimuli to investigate the discrimination ability to face expressions in individuals with autism spectrum disorder. Participants were presented with two faces, having the same level of expressions (e.g., 5% happy and 5% angry) and were to determine which of the faces was “happier” or “angrier”. The results revealed difficulties within face perception amongst individuals with autism spectrum disorder. Furthermore, old/new recognition paradigms have been used to assess memory. In these tasks, a set of faces are initially viewed. The participants are then presented with a face and are to decide whether the face is among those viewed before (Hancock & Rhodes, 2008).

In addition, human error has revealed a lot about the field of face perception. Errors in eyewitness testimonies occur often, even when the witnesses are confident that they are right. In an attempt to address this, Kemp et al. (1997 as cited in Bruce & Young, 2012) investigated the usefulness of photos on credit cards as a way to reduce fraud. When presented with a genuine photo, cashiers challenged shoppers on 10% of occasions. Face matching tasks are a useful tool to investigate such errors. A face matching task, in which a target face was to be chosen from an array of photographs, revealed a 30% error rate when matching an unfamiliar face image to 10 possible photos (Bruce et al., 1999). White et al. (2014) revealed that despite years of experience, passport officers tend to have similar performance as the rest of the population. In addition to this study, Papesh (2018) recruited over 800 notaries and 70 bank tellers. Using a face matching task, she revealed that individuals who are exposed to frequent image matching at their job, do not perform better than inexperienced student controls.

Other widely used paradigms in the field of face research include priming (manipulations that result in a benefit of the task, such as, repetition of stimulus) and interference (which often results in an impairment in the task) (Bruce & Young, 2012). For instance, Bruce & Valentine (1985) revealed that priming with Clint Eastwood's face resulted in better recognition of the face, however, this was not the case when priming was done using his name. An example of interference is the composite task (Young et al., 1987 as cited in Bruce & Young, 2012), in which participants must evaluate whether two identical top halves are the same (Goffaux & Rossion, 2006; Le Grand et al., 2004; McKone, 2008). Difficulty is often encountered when the two top halves are paired with different bottom halves. Furthermore, the alternating dual task experiment by Furubacke et al. (2020) serves as another example of interference. This task was used to investigate if the processing of words and faces interfere with one another. Subjects were presented with alternating stimuli and were to determine whether the stimulus was the same or different to a stimulus viewed two trials before. Their results showed that interference occurred when the attributes used for the trial were processed in the same hemisphere.

Finally, several tests have also been developed such as tests of face comparison (e.g., the Glasgow face Matching Test (GFMT)) (Burton et al., 2010), face memory tests (e.g., the Cambridge Face Memory test (CFMT)) (Duchaine & Nakayama, 2006) and familiar face recognition tests (e.g., Before They Were Famous" (BTWF)) (Bruce et al., 2018).

Stimuli used for face research

Throughout the years of face research, there has been a tendency to use highly standardized face stimuli; using controlled lighting conditions, showing stimuli in frontal view or even editing out certain features (e.g. hair) to ensure that only the central features of the faces are visible (Dawel et al., 2021). Furthermore, models used for the stimuli were often asked to pose, which often results in stimuli that are perceived as having fake emotions (Dawel et al., 2017). Though this has led to excellent control within experiments, it limits the knowledge on how people respond to faces in real life. In fact, Burton (2013) argued that despite the extensive research, progress has been slow when it comes to identification. Burton (2013) suggests that the use of controlled stimuli as opposed to real faces may even jeopardize the theoretical knowledge of the situation. More recently, the field has seen an increase in the use of ambient images in addition to standardized images (Burton, 2013; Jenkins et al., 2011; Sutherland et al., 2013). In their survey on face stimuli, Dawel et al. (2021) argue that research should combine the use of both naturalistic images as well as standardized ones.

With the use of technology, there have been great advances within this field, especially related to image manipulation techniques (Sutherland et al., 2017) such as morphing (Armann & Bülthoff, 2012; Michel et al., 2007; Oruc et al., 2018) and caricaturing facial images (Andrews et al., 2016). These techniques have enabled the investigation of consequences when changing certain facial aspects. New image averaging methods have allowed for further manipulation of facial images, for instance, creating an average between two races (Thornton et al., 2019). Burton et al. (2005) revealed that when images of famous faces were averaged, participants were faster at recognising the identities of averaged images rather than individual images. Furthermore, the more images used in the average, the better the performance. The study showed that averaging preserves useful information of identity while removing irrelevant variation. In a recent study, Bülthoff & Zhao (2021) investigated how the process of face averaging influences our ability to differentiate between these faces. They combined the use of 3D-face averaging, eye-movement tracking as well as the computation of image-based face similarity. The results revealed that the number of faces averaged influences the performance. When two faces were averaged, the performance was near-ceiling level, however the visual system seems to have a limit such that when 80 faces were mixed, the performance dropped to chance level. This study also discovered that fixations increase when discrimination becomes difficult, but with the same distribution of fixations across features.

Some other approaches have incorporated the use of 3D shapes (Vetter & Walker, 2011) as well as the use of dynamic face stimuli or movement (Dobs et al., 2018). Furthermore, technology has allowed researchers to generate virtual faces. Research on virtual faces have revealed an increased difficulty to remember virtual faces (Balas & Pacella, 2015) with less neural activations when compared to human faces (Kätsyri et al., 2020; Schindler et al., 2017) and have shown reduced other-race effects (Craig et al., 2012; Crookes et al., 2015).

Faces as interesting stimuli but are they special?

Research on faces has revealed that faces are special functionally, especially when it comes to social situations (Noyes et al., 2017; Oruc et al., 2019), however, the debate in the literature on whether faces are special has referred to visual processing mechanisms related to faces. Evidence that faces are special includes the innateness of face representations which is not present for objects (Taubert et al., 2011), the holistic or configural processing of faces as well as the presence of specific neural representations for faces.

Innateness of face representations

From the first moments of life, new-borns show a preference towards human faces over any other stimulus (Pascalis & Kelly, 2009), tracking face like patterns for a longer period of time than non-face patterns (Farroni et al., 2005; Goren et al., 1975; Johnson et al., 1991). In fact, it has been suggested that an innate representation of a face is present at birth (Morton & Johnson, 1991), with new-borns being able to discriminate between highly similar faces even when the faces have never been viewed before, when hair is removed as well as when subjected to viewpoint changes between the habituation and test (Turati et al., 2006, 2008). In addition, a process known as perceptual narrowing (Nelson, 2001) takes place during infancy, which can also be taken as evidence for the presence of innate representations. This preference for faces also remains throughout adulthood (Crouzet et al., 2010).

Face processing: holistic and configural processing

Face recognition involves a specific processing style, which also suggests that faces are special. Facial features are integrated into a gestalt whole, termed holistic face processing (Farah et al., 1998; McKone et al., 2007). Support for this claim is found with classic paradigms; the composite effect, the part-whole effect and the face inversion effect (FIE). As already mentioned, the composite task reveals that when asked to assess whether two identical top halves are the same (Goffaux & Rossion, 2006; Le Grand et al., 2004; McKone, 2008), individuals frequently struggle when the two top halves are coupled with different bottom halves. This implies that the entire face context influences perception of the identity of features in the top half. The part-whole effect characterizes the difficulty in recognizing familiar faces from isolated features (Donnelly & Davidoff, 1999; Tanaka & Farah, 1993; Tanaka & Sengco, 1997). These two effects suggest the integration of facial features when processed. The FIE (Rossion & Gauthier, 2002; Valentine, 1988) suggests that when faces are upright, small changes in the space between facial features are easily detectable, however, such changes tend to go unnoticed with inverted faces (Collishaw & Hole, 2000; Freire et al., 2000; Rhodes et al., 1993; Rossion & Boremanse, 2008; Van Belle et al., 2010). This effect suggests that we are unable to process inverted faces holistically (Rossion, 2008, 2009). Evidence for the holistic processing also comes from single cell analysis (Freiwald et al., 2009) as well as event-related potentials (ERP) (Jacques et al., 2007).

Neural representations

Finally, neural representations also hint to faces being special stimuli. A specific neural representation for faces is present. fMRI studies present selective neurons appearing clustered together, creating an area of the visual cortex specific to face processing: Occipital Face Area (OFA), the Fusiform Face Area (FFA), and the posterior Superior Temporal Sulcus (pSTS) (Visconti di Oleggio Castello et al., 2017). Transcranial magnetic stimulation (TMS) has revealed a triple dissociation between face, body and object recognition (Pitcher et al., 2009). Furthermore, face selective ERPs reveal that the N170 is specific to faces. These results suggest that in typical situations, faces are special.

Are we face experts?

Human faces reveal at least two levels of information. The basic features of every face (eyes, nose and mouth) provide the first order information which allows us to distinguish between other visual objects. Second order information, refers to the variability that exists between faces (e.g. size of lips, distance between nose and mouth) which enables us to discriminate between faces (Freire et al., 2000). The ability to competently recognize and categorize different faces can have social consequences (Noyes et al., 2017), such as allowing us to distinguish between individuals, recall behaviours of particular individuals, sense emotions and recognize group members within and outside the group (Pascalis et al., 2014). Face recognition occurs in three stages (Maurer et al., 2002); detection of faces based on first order information, followed by holistic processing, and finally second order information is used for face detection. Using the face inversion task, Taubert et al. (2011) revealed that holistic processing takes place on whole upright faces irrespective of the level or information that is extracted first, suggesting that holistic processing might occur at a stage before discrimination to enable rapid detection of faces in visual scenes. Other studies further support this claim (Jacques & Rossion, 2006; Rossion, 2008, 2009; Rossion et al., 2011).

Although behavioural, eye movement, and electrophysiological studies in humans have shown that widely variable natural stimuli are interpreted as faces remarkably precisely (within 100 milliseconds), and automatically (without intentionality) (Hershler et al., 2010; Noyes et al., 2017), suggesting that neurotypical human adults tend to be experts with respect to faces, one must consider the challenges of individual face perception. Face processing capabilities develop over childhood (de Heering et al., 2012) and reach a peak in adulthood (Germine et al., 2011). However, this dimension of human cognition (Wilmer et al., 2010) is not constant across the population. At one extreme are the super-recognizers who are exceptionally good at remembering faces (Noyes et al., 2017; Tardif et al., 2019) and at the other extreme, the prosopagnisics, who are unable to recognize even familiar faces (Duchaine & Nakayama, 2006). A continuous distribution of abilities can be found between these two extremes (Bowles et al., 2009; Davis et al., 2011; Richler et al., 2015; Wilhelm et al., 2010; Wilmer et al., 2010).

In a sorting task, Jenkins et al. (2011) involved the use of multiple everyday photographs (ambient images) as opposed to the more commonly found experiments which relied on a single photograph under standardized conditions. In the sorting task, participants were to sort different faces into piles of different identities. Participants sorted 40 photographs into 9 piles, despite there being only two identities. This task hinted at the difficulties encountered when processing faces. Different properties characterize identification of familiar and unfamiliar faces (Hancock et al., 2000; Johnston & Edmonds, 2009). Information about facial identity is experienced on a continuum with familiar and unfamiliar faces at separate extremes (Bindemann & Johnston, 2017).

For instance, recognition of familiar faces tends to be quick and accurate (Bruce et al., 1998; Bruce & Valentine, 1985) and can be done without conscious awareness or explicit memory. Factors such as viewing partial images (Brunas et al., 1990; Johnston et al.,1996 as cited in Bindemann & Johnston, 2017), degraded (Demanet et al., 2007; Lander et al., 2001) and distorted images (Bindemann et al., 2008; Hole et al., 2002) do not seem to influence familiar face recognition, revealing the robustness of familiar face recognition. Alternatively, unfamiliar face identification is less robust and quite error prone, even under good conditions. For instance, performance is error prone in an identification task from a line-up of ten possible faces (Bruce et al., 1999, 2001) as well as in a simple pairwise comparison, in which observers are required to decide whether the same or different people are depicted (Bindemann et al., 2012; Burton et al., 2010). Difficulty is also shown when using moving images (Davis & Valentine, 2009) or when matching a person seen live to a photo (Kemp et al., 1997; Megreya & Burton, 2009; White et al., 2014). Furthermore, unfamiliar face identification is difficult under optimized conditions, suggesting that we might only be face experts when it comes to familiar faces. Jenkin's sorting task also revealed that differences between images can be mistaken for differences in identity, suggesting that there are constraints on our face expertise (Young & Burton, 2017; Young & Burton, 2018).

Another factor that raises the question of whether humans are face experts is race. It is evident that there are differences when processing own-race and other-race faces. For instance, own-race faces tend to be processed holistically/configurally whereas other-race faces are processed in a feature-based manner. Studies on the FIE suggest that other-race faces are less effected by the FIE than same-race faces (Hancock & Rhodes, 2008; Sangrigoli & De Schonen, 2004). However, it is important to note that conclusions are mixed with other studies obtaining inverse results (Valentine, 1991; Valentine & Bruce, 1986), or else similar FIE for own-race and other-race faces (Buckhout & Regan, 1988). Several behavioural studies based on the Thatcher effect (Rhodes et al., 2006), the whole-versus-part superiority effect (Tanaka et al., 2004), and the face composite effect (Tanaka et al., 2004) provide additional evidence for the claim that own-race and other-race faces are processed differently (Michel, Caldara, et al., 2006; Michel, Rossion, et al., 2006).

The other-race effect

When required to *recognize or distinguish* between specific facial identities, performance is *worse* for other-race faces than own-race faces. This has been termed the other-race effect, (ORE), the other-race recognition disadvantage, own-race recognition advantage or the cross-race effect (Meissner & Brigham, 2001; Young et al., 2012). As discussed, face recognition tends to be quite hard in some circumstances, for instance when presented with a card sorting task involving numerous photos of an unspecified number of people, difficulty is shown in sorting the images, often times resulting in putting images of the same identity in different piles (Jenkins et al., 2011), or overestimating the number of unique identities within the deck of cards (Laurence et al., 2016). This is even more evident when other-races are involved. Laurence et al. (2016) asked participants to sort multiple images of own-race and other-race faces. Images of other-race faces (both celebrities and non-celebrities) were classified into more identities than photographs of own-race faces. These findings show that some of the ORE may be related to a lack of image variation tolerance when seeing a face of a different race.

The ORE has been extensively studied and the robustness of the effect has been generalized across different tasks and dependent variable measures. The effect has been found in old/new recognition tasks (Golby et al., 2001; Wright et al., 2003), eyewitness line-up paradigms (Evans et al., 2009; Jackiw et al., 2008; Meissner et al., 2005) as well as perceptual matching tasks (Meissner et al., 2013; Meissner et al., 2013; Mondloch et al., 2010). The ORE has also been found using different dependent variable measures (e.g. accuracy and reaction times) (Meissner & Brigham, 2001). In addition, the ORE is evident across several racial and ethnic groups (Meissner & Brigham, 2001). It arises at the age of three months (Sangrigoli & De Schonen, 2004) and is also observed in non-typically developing populations (Wilson et al., 2011; Yi et al., 2016).

The collection of faces encountered on a day-to-day basis, termed the ‘face diet’ (Rhodes et al., 2003) influences the expertise that one has with faces. The ORE is modulated by the experience that one has with a particular race. A reduced ability in face identification due to a limited face diet is also seen with individuals living in sparsely populated regions (Balas & Saville, 2017) as well as in autism spectrum disorder where the low social motivation results in less social interactions and consequently less encounters with faces (Oruc et al., 2018). Kelly et al. (2005) showed that Caucasian infants do not show signs of ORE from birth. Similarly, Bar-Haim et al. (2006) found that 3-month-old Africans showed no preference when presented with Caucasian and African faces. Whereas adults of Korean origin that were adopted in France between 3 and 9 years of age showed a reversed ORE such that they were significantly better at recognizing Caucasian than Asian faces (Sangrigoli et al. 2005). In addition, training studies suggest that providing infants, children and adults with video, picture book or image-based experience of the other race can prevent or remove the ORE (Anzures et al., 2012; Heron-

Delaney et al., 2011; Lebrecht et al., 2009; Tanaka & Pierce, 2009). However, another study by De Heering et al. (2010) showed that the ORE can be modulated but not completely reversed. A recent study by Tham et al. (2017) investigated the influence of a multicultural environment on the ORE. They tested British and Malaysian children on their recognition of Chinese, Malay, Caucasian, and African faces. British children showed the ORE, however Malaysian children showed an own-race advantage for Chinese and Malay faces compared to African faces, suggesting that experience with another race, as a result of a multicultural environment, may result in more malleable face representations.

Although, some studies support the idea that the ORE seems to be reversible as a function of the visual environment (Bar-Haim et al., 2006; Sangrigoli et al., 2005), the timing of exposure is crucial such that the there is a developmental window up to 12 years of age for simple acquisition of other-race faces (McKone et al., 2019), after which, during adolescence and adulthood, the ORE appears to be less malleable (Zhou et al., 2019) and even social contact, over many years, does not result in reduced ORE (McKone et al., 2019).

The other-race categorization advantage

Contrary to the ORE, individuals tend to be better at categorizing faces from other-races (Levin, 1996; Valentine & Endo, 1992) with less time required to categorize other-race faces, and often times showing better accuracy with other races (Caldara et al., 2004; Ge et al., 2009; Levin, 1996; 2000; Valentine & Endo, 1992; Zhao & Bentin, 2008), a phenomenon termed the other-race advantage (ORA) or the other-race categorization advantage (ORCA) (Levin, 1996; Valentine & Endo, 1992). The presence of the ORCA has been found with several face stimuli and across different racial groups. This has been found using race-based categorization tasks or simple visual search tasks (Ge et al., 2009). While much has been found about the ORE, the ORCA has received much less attention.

There is limited research on the development of the ORCA. Anzures et al. (2010) investigated the ability of 6- and 9-month-old Caucasian infants to categorize faces based on race. Their results showed that 9-month-old infants were able to form discrete categories for own-race and other-race faces, however 6-month-olds were not yet able. The study also revealed that both age groups were able to discriminate between different faces within their race category, however, they were not able to differentiate between Asian faces. The researchers concluded that the asymmetry could be linked to the experience with own-race and other-race faces, influencing face processing abilities. Quinn et al. (2016) also investigated the formation of other-race categories during infancy. Their results showed that Caucasian 6-month-olds were sensitive to the perceptual differences between African and Asian faces, however the 9-month-olds grouped Asian and African faces as the other-race. In addition, it has been shown that consistent sensitivity to multiracial faces is only found after 10 years of age, suggesting a protracted period of development when it comes to the categorization of face race (Roberts & Gelman, 2015). Furthermore, it has also been reported that while adults rely on physiognomic features to categorize face race, children as old as 9 years focus more on skin tone (Dunham et al., 2015).

A study by Woo et al. (2020) investigated the ORCA in children and adults from a multicultural society. Malay and Chinese children and adults showed quicker categorization responses for Caucasian faces followed by Chinese faces and Malay faces. The classic ORCA was not found in Chinese children and adults since they responded to Chinese faces as an intermediate between other-race Caucasian and other-race Malay faces. In addition, children presented with a greater accuracy for Caucasian faces relative to Chinese and Malay faces.

Malay children responded to Chinese faces as own-race faces. Similarly, Chinese children responded to the Malay faces as own-race. Woo et al. (2020) argue that a threshold of experience needs to be surpassed for faces to be identified as own race. Accuracy in categorizing faces was greater for Caucasian and Chinese faces relative to Malay faces. The results for the Malay adults support the ORCA, however, Chinese adults responded to own-race Chinese faces more as low-frequency other-race Caucasian faces than as high-frequency own-race faces. This is another aspect of the data that contradicts the ORCA's usual structure.

The ORCA was also obtained in a study by Zhao & Bentin (2008), whereby using Chinese and Israeli participants, the effect was greater for faces with distorted inner components than normal faces. This result was linked to the configural/holistic processing of own-race faces and feature-based processing of other-race faces. Holistic/configural processing would have resulted in a slower response in the race categorization task for own-race faces (Zhao & Bentin, 2008). An EEG study by Caharel et al. (2011) revealed that when Caucasians were asked to categorize upright and inverted faces of own-race and other-race, a stronger FIE on N170 amplitudes was obtained for Caucasian faces than other-race Asian and African faces, supporting more holistic/configural processing for own-race faces. In addition, using a set of racially ambiguous morphed faces in a composite task, Michel et al. (2007) presented how the holistic processing of own-race only happened after the face had been classified as own-race, as seen from a greater face composite effect in the own-race condition than the other-race condition.

Relation between ORE and ORCA

The ORE and the ORCA were believed to be based on different information and accessed by distinct processing mechanisms whereby in a recognition task, an identity specific semantic code needs to be extracted from the face, while in the categorization task, a category specific semantic code needs to be extracted (Bruce & Young, 1986). However, more recent evidence supports a single route hypothesis that enables the interaction between the two processes (Bruyer et al., 2004; Ganel & Goshen-Gottstein, 2002, 2004). This view suggests that a trade-off and competition take place between processing individual identity and category facial information.

Ge et al. (2009) compared recognition and categorization of own-race and other-race faces in both Caucasian and Chinese participants. Other-race faces were detected less precisely and slowly, but categorized more quickly, providing support for the single route hypothesis. Brain behaviour correlation analyses revealed a negative correlation between the response difference for own-race faces against other-race faces in the left FFA and classification accuracy between own-race and other-race faces. An increased neural activity meant less categorization accuracy. The researchers argue that the higher neural activity for own-race faces and the poor categorization for own-race faces might be related to the neural resources that were employed to process own-race faces. The additional neural resources might have been used to individuate own-race faces during categorization, whereas, individuation did not occur for other-race faces (Ge et al., 2009). Similar results were obtained in a recognition task by Golby et al. (2001). The results showed a positive correlation between the activation difference of own-race and other-race faces in the left FFA and superior memory for own-race relative to other-race faces. Thus, a greater neural activity for own-race faces occurs with better recognition for these faces. An ERP study by Vizioli et al. (2010) showed that neural activity is sensitive to the identity of own-race faces but not to the identity of other-race faces and occurs as early as the perceptual stage. In addition, increased experience results in a shift in processing from basic level to individual level, i.e., from processing “is it a face?” to processing “is it Mark?” (Tanaka & Taylor, 1991). Feng et al. (2011) also investigated the neural correlates of the ORCA using fMRI. Their behavioural results confirmed the ORCA. They also found greater FFA activations when participants categorized own-race faces. Feng et al. (2011) argued that the results of enhanced activations could be attributed to the extensive experience when processing own-race faces. Furthermore, their analysis also revealed that when participants categorized own-race faces as opposed to other-race faces, greater activations in the bilateral OFA were obtained. This was also found by Natu et al. (2011). This activation might also be attributed to individuals' expert-level capacity to retrieve feature information from their own-race faces. To sum up, these studies suggest that increased activations of the left FFA results in better recognition of own-race faces and better categorization for other-race faces, explaining the paradoxical behavioural effects of the ORE and ORCA.

Nelson (2001) proposes that initially infants are born with a general face processing mechanism which by time becomes more fine-tuned to human faces depending on the input received in the early months of life. This account can be better explained by addressing the influential framework of the multidimensional face space model proposed by Valentine (1991). This model suggests that faces tend to be represented as memory points in a multidimensional space, with each facial feature being represented by a dimension. Faces are encoded based on the deviation from the prototypical average, such that dimensions of similar facial features tend to be closer to each other (Krumhansl, 1978). Nelson (2001) argues that at birth, these dimensions are broad and unspecified, however a process known as “perceptual narrowing” occurs based on the face diet during infancy. The features that the infant is exposed to will become the basic features of the prototype. People forming part of a particular race share apparent phenotypical similarities with distinctive features based on their race (Bruce & Young, 2012; Rossion & Michel, 2011). These features form the prototype and thus enables people to recognise faces from own-race as opposed to other-race. Initially infants are able to identify both own-race and other-race faces, however, this eventually becomes fine-tuned such that ability to distinguish other-race faces no longer holds (Kelly et al., 2007; Pascalis et al., 2002). This multidimensional face space model is also a good explanation for the interaction between the ORE and the ORCA. Experience enables one to capture subtle differences between faces. Given that people are more experienced with own race, faces from other races form a denser neighbourhood, making each individual easily confused with the neighbour, explaining the ORE. However, since other-race faces are denser in space, one exemplar will likely activate other exemplars, thus making it easier to categorize other-race faces, explaining the ORCA (Valentin, 1991).

Theoretical accounts

Several models and hypothesis have been presented to explain the ORE and the ORCA. Though it may appear that other races have comparable facial characteristics, the rationale for the differences in processing own-race and other-race faces is tied to the perceiver's perceptual and cognitive processes (Hayward et al., 2016).

Perceptual expertise accounts suggest that recognizing faces from other ethnicities is a skill that improves with practice. For instance, the contact hypothesis suggests that with experience, that is, frequent exposure, people become better tuned to recognize individual faces within their own-race (Furl et al., 2002). Races have different race specifying features (Deregowski et al., 1975; Shepherd & Deregowski, 1981). As mentioned previously, people forming part of a particular race share apparent phenotypical similarities, and encompass a combination of shape differences across facial features and surface differences in skin hue and brightness (Bruce & Young, 2012; Rossion & Michel, 2011). Face processing systems become more adapted to recognize own-race faces after repeated encounters (Rhodes et al., 2006; Tanaka et al., 2004; Valentine, 1991), since the individual becomes aware of the distinguishing traits that should be employed to detect faces. Whereas, individuals that lack experience with a particular race tend to focus on the wrong discriminating features (Lucas et al., 2011). Evidence from neural activation studies suggest that when individuals experience other races more intimately rather than more frequently, less difference in the N170 amplitude is visible when viewing own-race and other-race faces, whereas a greater disparity and disruption is visible in individuals with less experience with other-race faces (Walker et al., 2008). The perceptual expertise model may also account for the stronger holistic coding of own-race faces that was mentioned previously (Tanaka et al., 2004).

On the other hand, motivational accounts argue that the other-race effect arises because people are not motivated to recognize other-race faces (Hugenberg et al., 2007; Levin, 2000; Sporer, 2001). Levin (1996; 2000) established the feature selection hypothesis, which was based on the contact hypothesis and suggests that we have an automatic tendency to focus on individuating information for own-race and on race specifying information for other-race. For instance, to classify an individual as black or white, the decision is based on the presence or absence of the marker features of the race. Shorter time is needed to determine the presence of marker features of other-race faces (Levin, 1996). This was further supported in the literature (Bernstein et al., 2007; Hugenberg et al., 2010). In addition, Sporer (2001) proposed an in-group/out-group model. This model holds that same-race faces are processed in a configural manner since in addition to the in-group status, individuals tend to be experts towards same race. On the other hand, other-race faces are detected as an out-group and categorized as such. Another hypothesis, the differential processing hypothesis holds that an initial judgment of whether the face is own-race or other-race is first made followed by different processing strategies based on this judgment. The point at which the ORCA occurs differs between the feature selection hypothesis and the differential process hypothesis. According to the racial feature theory, the ORCA occurs during categorization, however the differential processing hypothesis argues that the ORCA happens after race categorization (Li et al., 2018).

The different processing between own-race and other-race faces seems to occur at very early stages of face processing. Li et al. (2018) investigated the ORCA in a binary response race categorization task, in which the response could be own-race and other-race and a tertiary response task in which there were three possible races: own-race and two other-races. Their results revealed that other-race faces (Caucasian and Indian) were classified faster than own-race (Chinese) faces in the binary response task, however, consistent ORCA was not obtained in the tertiary response task. The researchers argue that these findings could not be fully supported by the race-feature hypothesis or the differential processing hypothesis, suggesting that automatic and controlled processing drives race categorization.

Finally, the categorization-individuation model is focused on selective attention being directed to category level or identity level face characteristics, such that, when viewing a face from another race, attention would be drawn to category level features rather than individuating information (Correll et al., 2017). This account holds that it is possible, with perceptual experience to individuate faces of other races, however, a lot of effort is required (Hugenberg et al., 2010). Some argue that a boost in motivation would result in a decrease in the other-race effect (Hugenberg et al., 2007; Young et al., 2010; Young & Hugenberg, 2012). However, Rossion & Michel (2011) presented a competing argument, that the default level of motivation for own-race and other-race might be the same, therefore increasing the participant's motivation for other-race may result in motivation being higher than that of own-race faces.

Some studies show that when participants are given instructions to focus on individuating information, a decrease in the ORE is obtained, however this is stronger when they have more experience with other-race (Pica et al., 2015; Young & Hugenberg, 2012). Tanaka & Pierce (2009) trained participants to identify African American and Hispanic faces at either the basic level of race or the subordinate level of the individual. Their results revealed that training led to an improvement in recognition, with more improvement for the individuated race. However, competing results are also found in the literature. For instance, Wan et al. (2015) found that although individuating instructions resulted in more reported effort to individuate other-race, this did not result in better memory for other-race faces. Furthermore, Crookes & Rhodes (2017) and Tullis et al. (2014) used self-paced learning and found that increased effort did not reduce the ORE. These studies suggest that increasing drive is insufficient to overcome a lack of familiarity with people of various races.

However, Tüttenberg & Wiese (2021) used ERPs to examine the neural mechanisms underlying own-race and other-race face learning. Participants were randomized to one of two groups (standard instruction, individuation instruction). The ORE was explained to participants in the individuation instruction group, in which they were instructed to pay special attention to other-race faces during encoding, while the standard instruction group did not receive this information. While their EEG was being recorded, participants conducted an old/new recognition task with own-race and other-race face stimuli. Instructions eliminated the own-race bias and led to more processing resources being allocated to other-race faces during encoding, to compensate for the reduced experience with the race group.

The current study

Although researchers have been interested in the ORE and the ORCA, there is limited research focusing on the effects when learning faces. The purpose of this thesis is to further investigate the ORCA, by addressing how this race effect interacts with face familiarity, or more specifically what happens to the ORCA when faces become familiar.

Familiar faces were at one point unfamiliar and became familiar through learning, which results in a transformation in the cognitive representations, though this process remains poorly understood (Dowsett et al., 2016). Learning has been addressed in terms of the ORE (Hayward et al., 2016; Tüttenberg & Wiese, 2019; Cavazos et al., 2018; Matthews & Mondloch, 2018). For instance, Hayward et al. (2016) used a face learning strategy to investigate the ORE in a naturalistic way by utilizing name learning. Learning took place faster for own race, with less time taken to memorize names of own-race faces and with better identification of own-race persons. Using a five-day training paradigm, Matthews & Mondloch (2018) explored the efficacy of multi-image training for Caucasian participants when learning other-race faces (Black individuals). The researchers chose photos that demonstrated the inherent variation in the look of each identity. In one experiment, participants were exposed to six different identities using a variety of photos. Participants in a second experiment were shown the same image repeatedly while being exposed to 12 distinct identities. The results showed that training with many photos enhanced recognition accuracy when compared to training with single repeated images. Furthermore, their findings revealed that training benefits are particular to the faces encountered during training and do not transfer.

Tüttenberg and Wiese (2019) investigated how people learn own-race and that of others. A sorting exercise was given to the participants for them to learn faces. After that, participants were instructed to complete a matching task or an old/new recognition task with naturally varying images. Caucasians did better in classifying their own-race faces versus other-race faces, while East Asians performed similarly in both categories. Own-learning effects were quantitatively larger in Caucasian participants than in other races, but the results were not statistically significant. East Asian participants, on the other hand, showed larger learning effects. According to Tüttenberg & Wiese (2019), the similarity of East Asian stimuli may have made learning East Asian faces difficult for both Caucasian and East Asian individuals.

Cavazos et al. (2018) studied how image variability (many variable images vs single repeated images) and learning context (distributed i.e., seeing varying images randomly interspersed vs contiguous i.e., seeing many photos of the same person in series) affect identification accuracy for own-race and other-race faces. The first experiment presented multiple images randomly or in a sequence. Asian and Caucasian participants learned these faces. Their findings revealed a strong ORE. In addition, distributed learning did not result in higher accuracy than contiguous learning. In the second experiment, they addressed learning from single repeated images when presented in a contiguous or distributed context. The results of the second experiment showed that when single-repeated images were employed, recognition accuracy was higher for own-race faces than for other-race faces (Cavazos et al., 2018, Experiment 2). Their study concluded that distributed learning results in better recognition accuracy when the same image is repeated, however, when multiple images are used, the presentation type does not play a role. The benefits of distributed learning are only present when the images are viewed as a unique identity, which could be explained by the multiple trace theory (Crowder 1976 as cited in Cavasos et al., 2018). According to this idea, scattered presentation produces many traces of the experience of seeing a face, whereas contiguous presentation produces a single episodic memory trace. Their findings also revealed that multi-image learning improves detection of other-race faces. Similarly, Zhou et al. (2018) found that a higher degree of variability was required to learn other-race faces. There have also been perceptual training studies based on children (Xiao et al., 2015) and adults (Tanaka & Pierce, 2009). Xiao et al. (2015) revealed that when trained to individuate other race, pre-schoolers were less likely to categorize an angry racially ambiguous face as the other race, in this case African American.

This thesis took a different approach by focusing on the perceptual learning of faces. Gold et al. (1999) presented participants with faces emerging from noise to investigate whether people can pick up faces over time. By being repeatedly exposed to faces emerging from noise, participants were able to learn the individual faces. Since people are able to individuate faces emerging from noise, this study further investigates how this individuation in turn influences race effects.

To investigate what happens to the ORCA when faces become familiar, a two-forced choice race categorization task was chosen, in which participants were required to classify faces as Asian or Caucasian. The task used the main principal from the face learning paradigm in Gold et al's (1999) study, such that the stimuli were covered with two-dimensional Gaussian noise. The consequences on performance were investigated when faces change from unfamiliar to familiar upon repetition. The study comprised of two experiments as well as a control condition.

The following chapter presents the first experiment in which participants were presented with faces emerging from noise and were given control over the viewing conditions. The third chapter presents the second experiment in which the stimuli were experimentally controlled.

Chapter 4 presents the final discussion, proposes some future directions as well as concludes the thesis.

Chapter 2

It is well established that people process own-race and other-race faces differently. Two race effects have been identified. The ORE refers to the better performance achieved with own-race faces compared to other-race faces when required to *recognise* or *differentiate between* specific facial identities (Meissner & Brigham, 2001; Young et al., 2012). The ORCA refers to the better performance for other-race faces than own-race faces when asked to *categorize* faces (Caldara et al., 2003; Ge et al., 2009; Levin, 1996, 2000; Valentine & Endo, 1992; Zhao & Bentin, 2008). These effects have been extensively studied and their robustness has been generalized across different racial groups, different tasks as well as when using different dependent measures (Meissner & Brigham, 2001). The purpose of the work described in the current chapter is to explore how the ORCA might vary as a function of face familiarity.

Information about facial identity is experienced on a continuum with familiar and unfamiliar faces at separate extremes (Bindemann & Johnston, 2017). Extensive research on face familiarity has shown that familiar faces and unfamiliar faces are processed differently (Hancock et al., 2000; Johnston & Edmonds, 2009), with familiar face recognition being quick, accurate and robust across different factors (Bruce et al., 1998; Bruce & Valentine, 1985), whereas unfamiliar face recognition requires more effort and is more error-prone, even under optimised conditions (Bindemann et al., 2012; Bruce et al., 1999, 2001; Burton et al., 2010; Jenkins et al., 2011).

Through learning, and a transformation in cognitive representations (Dowsett et al., 2016), unfamiliar faces become familiar. Other-race effects and learning have been explored using different methods. For instance Tüttenberg & Wiese (2019) investigated whether other-race faces are more difficult to learn than own-race faces. In their study, participants learned own-race and other-race faces by means of a sorting task. A matching task and an old/new recognition task were then used to investigate learning. Overall, their results revealed that own-race faces are easier to learn. However, this advantage was only observed in Caucasian participants, while East Asian participants were able to learn both races. While their results revealed an ORE in the sorting task in Caucasian participants, they found limited support that learning is pronounced for own-race identities in Caucasian participants in the matching task, however, the old/new recognition task revealed an ORE when learning faces. Another study by Cavazos et al. (2018) investigated the effects of image variability and learning context on the identification accuracy for own-race and other-race faces. In the first experiment, participants were required to learn faces from multiple images presented randomly or in sequence. This led to a strong ORE. In the second experiment they used single repeated images and the results revealed a higher recognition accuracy for own-race than other-race faces. The study concluded that when the same images are used, distributed learning results in better recognition accuracy, nevertheless, the presentation type does not influence the results when multiple images are used. Their results also showed that multi-image learning improves recognition for other-race faces. Similarly, Zhou et al. (2018) found that a higher degree of variability was required to learn other-race faces. Hayward et al. (2016) used reaction time and accuracy measures in learning names of own-race and other-race and found that learning occurs faster for own-race than other-races. However, this task focused on name-learning, therefore, the reduced performance could be due to difficulty associating the name with the faces.

These results can be explained using the multidimensional face space model proposed by Valentine (1991). Racial groups share phenotypical similarities (Bruce & Young, 2012; Rossion & Michel, 2011). These similar features form a prototype which enables people to recognise own-race faces. Faces are encoded in space based on the deviation from the prototypical average (Krumhansl, 1978). Experience with own-race faces results in these faces being more spaced out in the multidimensional space, resulting in a recognition or discrimination advantage on own-races whereas other-race faces tend to form denser neighbourhoods, resulting in a categorization advantage for other-race faces since one exemplar likely activates other exemplars (Valentine, 1991). One hypothesis, the single route hypothesis, suggests that a trade-off and competition occurs between these two phenomena when processing individual identity and category facial information (Bruyer et al., 2004; Ganel & Goshen-Gottstein, 2002, 2004). An increase in experience results in a shift in processing from basic level to individual level (Tanaka & Taylor, 1991) and a shift from a categorical response to an identity level response may take place. Thus, with experience (or learning), as one becomes more familiar with faces, the faces should spread out in the multidimensional space, reflecting the sensitivity to the details of faces.

This chapter investigates how the ORCA interacts with face familiarity, more specifically what happens to this race effect when faces become familiar. A race categorization task was chosen to explore these two phenomena. Participants were presented with Asian or Caucasian faces emerging from two-dimensional Gaussian noise and were required to classify faces as Asian or Caucasian. Two questions guide this experiment:

1. Can the ORCA be measured online?
2. Do changes occur in the patterns of race effects when faces are repeated?

In order to include face familiarization, 6 blocks were used and a set of 12 faces (6 Asian and 6 Caucasian), randomly selected from a set of 96 photographs, were repeated in all 6 blocks. A unique set of 12 faces was randomly selected for each participant.

It was predicted that initially, the ORCA would play a role such that other-race faces would be categorized faster than own race faces (i.e., requiring less facial detail/ alpha level to categorize other-race faces). It was expected that with repetition of faces, participants would become familiar with the faces and consequently a change in performance would take place. Based on the ORE, it was predicted that participants would become familiar with own-race faces faster than other-race faces, thus showing an improvement in performance to classify own-race faces. In other terms, less facial detail (alpha level) would be required to categorize own-race faces. Furthermore, it was hypothesized that this improvement in performance would only occur for own-race faces, with the performance for other race-faces remaining almost the same.

Method

Participants

Twenty-five (25) adult, Caucasian participants (18 Female; Left Hand = 2; M_age = 19.45, SD = 1.25) from the Department of Psychology at the University of Novi Sad, Serbia, took part in this study for partial course credit. All procedures followed the research ethics and data protection (REDP) guidelines of the University of Malta for conducting online studies. Ethical approval from the Department of Psychology at the University of Novi Sad, Serbia, was also obtained. All participants were provided with written instructions (translated into Serbian) and explicitly confirmed their consent online, prior to data collection. Refer to Appendix A for original and translated information sheets and on-screen instructions.

Sample Size

Sample size was determined prior to data collection and was based on three previous experiments that explored the ORCA using explicit responses to single images (Li et al., 2018, Experiments. 1a & 1b; Zhao & Bentin, 2011, Experiment 1). These studies used N= 20, 20 & 24 participants, and had reported effects sizes (η_p^2) of 0.42, 0.72 and 0.22, respectively, for their significant main effects of face race. An *a priori* power analysis carried out in G*Power 3 (Faul et al., 2009) – using the most conservative of these effect sizes, $\eta_p^2 = 0.22$, together with an alpha value of 0.05 and 1-beta of 0.8 – indicated that a minimum of 12 participants should be sufficient to replicate this main effect. However, given the online nature of the data collection, and the additional learning factor in the current work, it was decided to more closely match the sample used in the original papers.

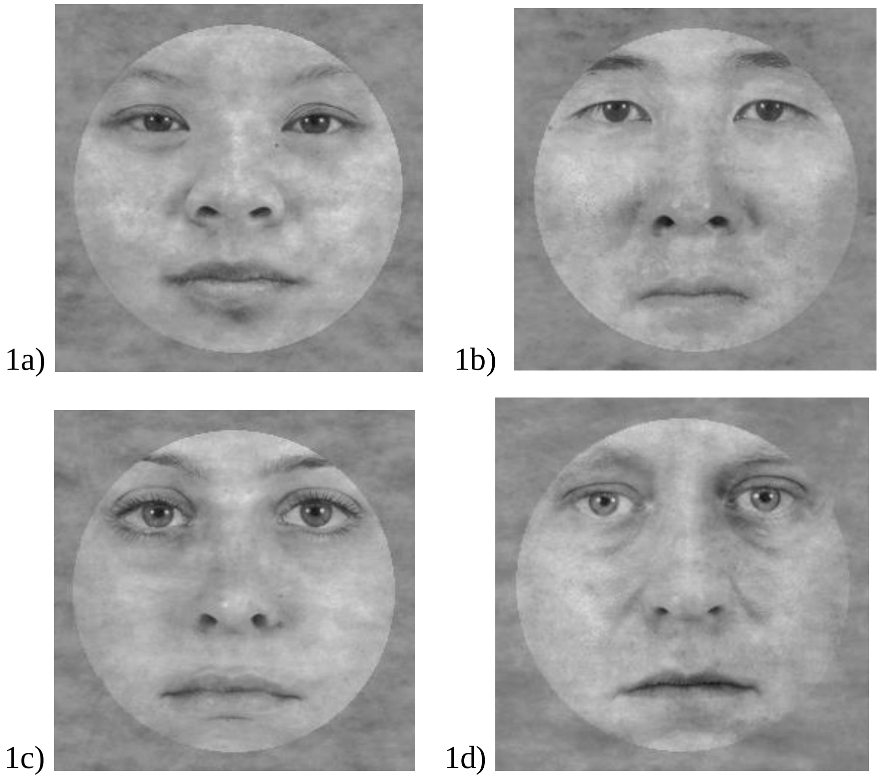


Figure 1 - Examples of the edited face image stimuli. 1a is an example of an Asian female. 1b is an example of an Asian male. 1c is an example of Caucasian female. 1d is an example of Caucasian male.

Stimuli

A total of 96 photographs; 24 male Caucasian faces, 24 female Caucasian faces, 24 male Asian faces and 24 female Asian faces were extracted from freely available academic databases. The photographs were extracted from the Chicago face database (Ma et al., 2015) and Tsinghua facial expression database (Yang et al., 2020). The original images were cropped using a round aperture to remove details of head shape and hair, leaving visible only the internal features of the face. The images were then equated in terms of mean luminance and frequency using the default parameters of the SHINE Matlab Toolbox (Willenbockel et al., 2010). The faces had a neutral face expression and a forward gaze. Figure 1 presents example stimuli, while Appendix B shows the complete image sets used in this study.

Equipment and online protocol

The study was conducted online using custom written HTML, JavaScript and PHP routines that were hosted directly on the https://maltacogsci.org secure server. Participants were provided with an experimental link that presented instructions, confirmed consent, and then allowed them to complete the task via a standard browser on their own equipment. Viewing conditions were not controlled. Anonymous performance data was sent directly to the server for analysis.

A demonstration of the task can be found at https://maltacogsci.org/RaceCat/Task1Demo/

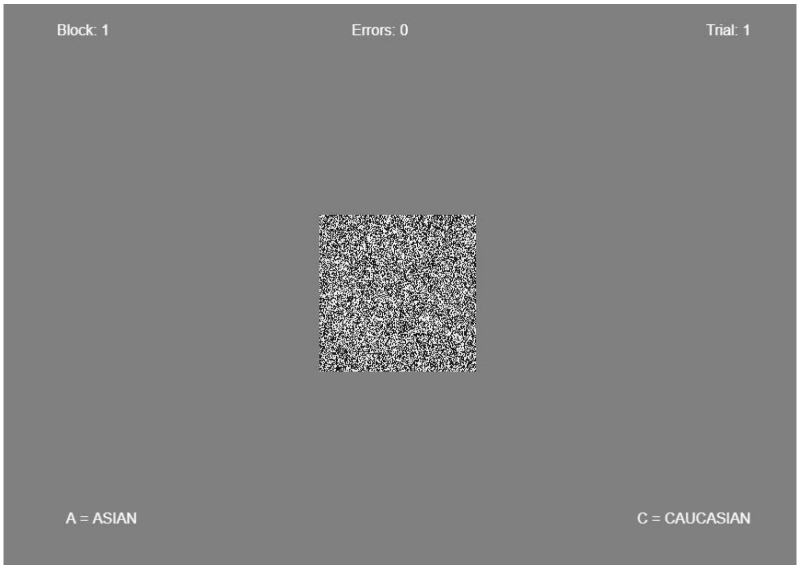
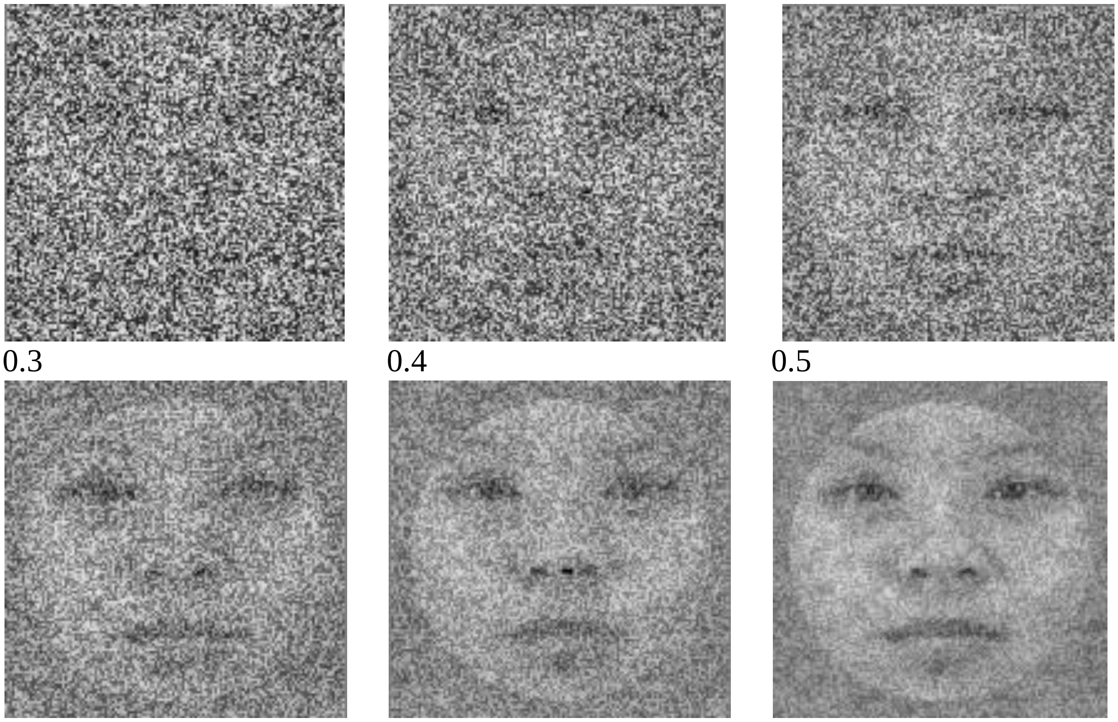


Figure 2 - The display layout of trials in Experiment 1.



0.3 0.4 0.5

0.6 0.7 0.8

Figure 3 - Example of Asian female from alpha 0.8 to alpha 0.3. See appendix C for other an example of Asian male, Caucasian female, Caucasian male.

Task & Display Description

The task on each trial was to categorize a face as either Asian or Caucasian using an assigned key on a standard keyboard. The display layout is shown above in Figure 2. The browser window was set to full screen mode, with a uniform, middle grey background. An 800 x 600 pixel display area was centred in the middle of the screen, with trial information presented on the upper and lower borders. At the very centre of the display was a 170 x 170 pixel patch of dynamic noise flickering at approximately 30 Hz. A target face with the same dimensions was embedded within the noise and slowly emerged during a maximum display period of 25 seconds. The signal (face) alpha level was gradually increased to modulate the visibility of the target face.

When Alpha = 1 the face was fully visible whereas when Alpha = 0 the face was not present in the mask. The face alpha was set at 0.008 and the noise was set at 0.992 at the start of each trial. The face alpha was increased in steps of 0.008 on every 15th screen refresh (approximately 250 ms), until a final display balance of face = 0.8, mask = 0.2 was reached if no response was made. Thus, the face slowly emerged from the noise. An example of a face emerging from noise can be found in Figure 3. Responses were made using assigned keys, with hints displayed on screen. Participants received feedback after each trial. The unmasked face was shown in full for 500 ms. A red square surrounded the stimuli if the response was incorrect, and a green square surrounded the stimuli if the response was correct. There was a 1000 ms ITI, and the next trial started automatically.

Procedure and experimental design

Each participant was allowed some time to get familiar with the experimental set up prior to the actual trials. They were given 4 practice trials. They then completed 6 experimental blocks of 12 trials. Breaks could be taken between blocks. For each participant, a fixed set of 12 faces (6 Asian and 6 Caucasian) were randomly selected from the available 96 images and repeated in all the sic blocks. The order of stimuli within a block was randomized.

Data Analysis

The final level of alpha signal – the visibility of the face – was the main dependent variable. This was analysed using a 2 (Race: own/other) x 6 (Block: 1-6) repeated measures analysis of variance (ANOVA). Although accuracy was expected to be close to ceiling, initial examination indicated that responses to Asian faces (M = 91.0, SE = 0.02) were significantly higher than responses to Caucasian faces (M = 76.0, SE = 0.03), $t(23) = 6.06$, $p < 0.001$. Further analysis of this apparent ORCA for accuracy is presented in Appendix D, but since there were no main effects of interactions involving Block, this measure will not be discussed further in the main text.

For the main analysis of alpha levels, incorrect responses were filtered out. One participant was excluded from the data analysis since there was a technical issue and a significant proportion of data was missing. Analysis was thus conducted on N=24 datafiles. The practice block was also excluded from the analysis. When Sphericity violations were detected, Greenhouse-Geiser correction was used.

Results

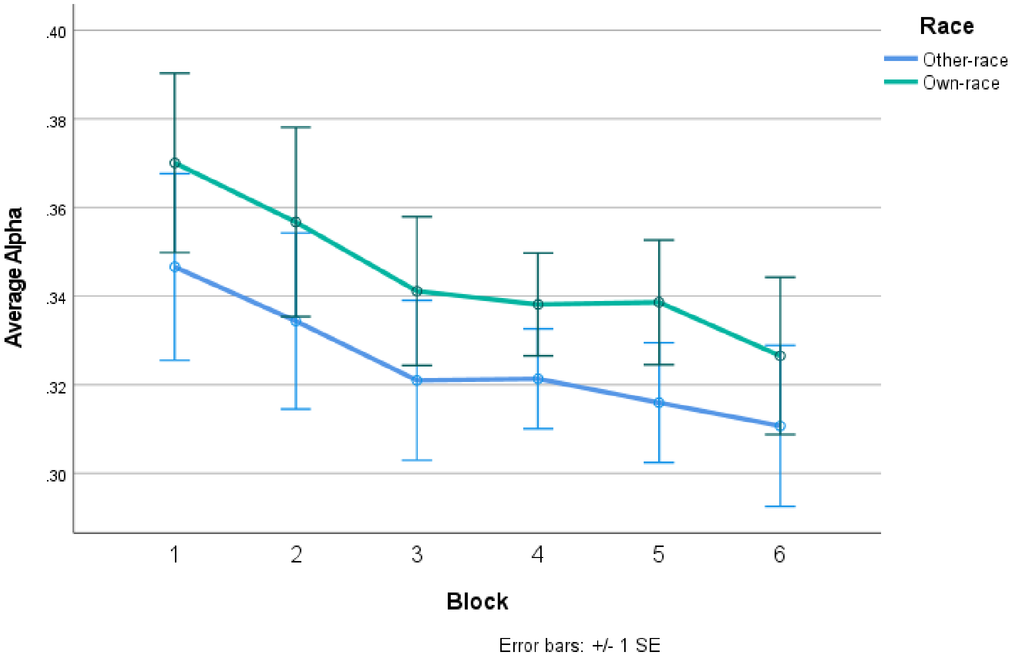


Figure 4 - Graph showing the average alpha for both races across blocks. Error bars +/- 1 SE.

Figure 4 summarizes the pattern of alpha values for correct responses as a function of both Race and Block. The first point to note is that participants were able to accurately categorize the faces with quite some level of noise. As shown above in Figure 3, alpha levels between 0.3 and 0.4 are quite hard to interpret out of the dynamic context. This suggests that responses were being made using fairly degraded images, where limited facial detail would be available, an issue discussed further below.

The second pattern of interest is the clear separation of the two lines. Participants required less visible face when categorizing other-race faces (M_Asian = 0.33, SD = 0.01) compared to own-race faces (M_Caucasian = 0.35, SD = 0.01), giving rise to a significant main effect of Race, $F(1,23) = 23.50$, $p < 0.001$, MSE = 0.03, $\eta_p^2 = 0.51$, supporting the ORCA.

Finally, although Figure 4 shows that the average alpha decreased throughout the experiment, indicating a trend for learning, this was not supported by statistical analysis. Neither the main effect of Block, *F*(1.82, 41.77) = 1.53, p = 0.23, MSE = 0.03, η_p^2 = 0.62, nor the Race x Block interaction, *F*(2.80, 64.40) = 0.216, p = 0.87, MSE = 0.00, η_p^2 = 0.01, were significant.

To further probe for possible learning effects, an "early vs late" analysis was conducted in which the first 3 blocks were grouped as the early phase of the experiment and the last 3 blocks were grouped the late phase of the experiment.

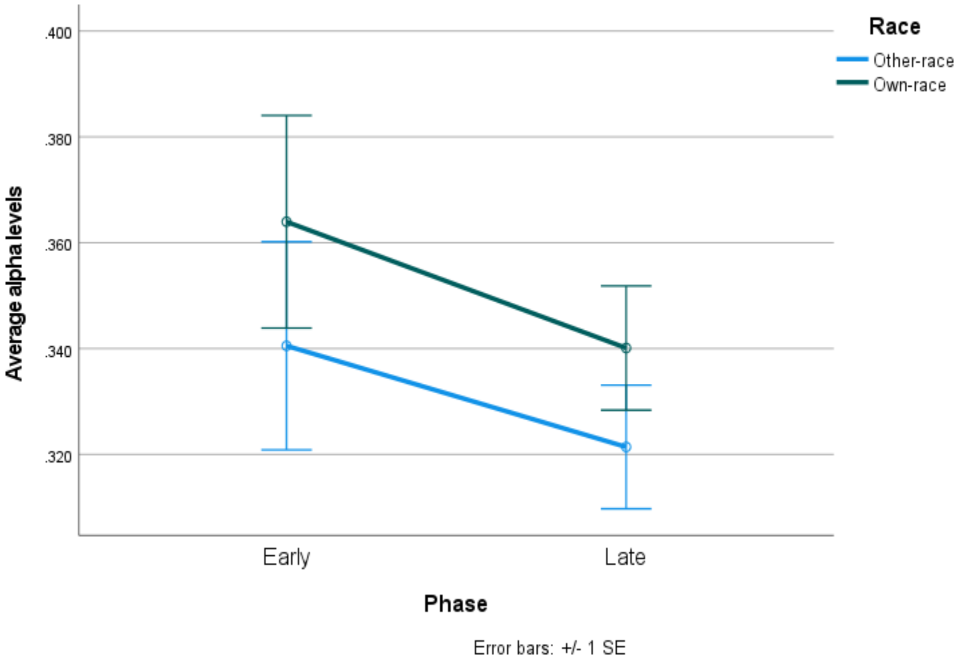


Figure 5 - Graph showing the average alpha for own-race and other-race from the early to the late phase of the experiment. Error bars +/- 1 SE.

Figure 5 shows how the average alpha from the early to the late phase varied as a function of race. To explore these patterns, 2 (Race: own/other) x 2 (Phase: early/late) repeated measures ANOVA was conducted. As expected, there was a main effect of Race, *F*(1,23) =

17.62, $p < 0.001$, MSE = 0.01, $\eta_p^2 = 0.43$. However, again despite the apparent trend in Figure 5, the main effect of Phase was not significant, $F(1,23) = 1.89$, $p = 0.18$, MSE = 0.01, $\eta_p^2 = 0.08$. The Race x Phase interaction was also not significant, $F(1,23) = 0.57$, $p = 0.46$, MSE = 0.00, $\eta_p^2 = 0.02$.

Discussion

This chapter investigated how the ORCA might interact with face familiarity. More specifically, it investigated this race effect and the consequences on performance when faces become familiar. A race categorization task was used in which face stimuli emerged from two-dimensional Gaussian noise. In this experiment participants were given control over the signal strength before making a race categorization decision. Participants were presented with 6 blocks in which a set of 12 stimuli were repeated across blocks.

Two research questions guided this experiment. The first question asked whether the ORCA can be measured online. Consistent with the predictions, there was a difference when categorizing other-race and own-race faces, with participants requiring less face signal to categorize other-race faces, supporting the ORCA.

The second question asked whether changes occur in the patterns of race effects when faces are repeated. It was predicted that learning would take place across blocks such that alpha levels (i.e., the amount of face needed to categorize the face) would decrease from the beginning to the end of the experiment. It was also predicted that an initial ORCA would be present at the start of the experiment, however as faces become familiar, the ORE would play a role such that participants learn own-race faces faster than other-race faces.

The initial ORCA was present; however, performance did not improve throughout the experiment and there were no changes in race effects. From the first block of trials, participants seem to be responding accurately to low resolution faces i.e., between 0.3 and 0.4 alpha levels (see Figure 3). Although participants were able to judge the category of the face, the low resolution of faces might not provide enough detail to learn faces.

The following chapter presents a reaction time (RT) experiment in which alpha levels were predetermined. In this experiment, higher levels of alpha were chosen to ensure that enough facial detail is presented to facilitate learning of faces.

Chapter 3

This chapter further investigates what happens to the ORCA faces become familiar. The previous chapter presented a race categorization task in which participants were given control over the viewing conditions (alpha levels). This task revealed that the ORCA influenced responses when categorizing faces, however there was no improvement throughout the experiment and consequently there were no changes in race effects. Furthermore, participants accurately categorized faces at low resolutions (alpha level between 0.3 and 0.4). Although these alpha levels might provide enough information to categorize the faces by race, they might not provide sufficient detail to enable face learning.

This chapter presents a second experiment which further investigates what happens to race effects when faces become familiar. More specifically:

1. Can the ORCA be measured in the task?
2. Do changes occur in the patterns of race effects and RT when faces are repeated?

The same race categorization task was chosen in which participants were presented with Asian and Caucasian faces covered with two-dimensional Gaussian noise. However, the signal (face) and noise alpha levels were experimentally controlled, using the method of constant stimuli, presenting participants with four possible levels (0.5, 0.6, 0.7, 0.8). RT was chosen as the dependent measure.

In this experiment, higher levels of alpha were chosen to ensure that enough facial detail was presented to facilitate learning of faces, ensuring that participants responded carefully rather than guessed the race. Pilot testing was used to determine a maximum time window that would allow accurate responses but would reduce RT variability. Thus, a response window of 1200ms was set up. A lack of response within this time frame resulted in a repetition of the trial. Six experimental blocks were used and a set of 8 faces (4 Asian and 4 Caucasian), randomly chosen from the available set of faces, were repeated in all 6 blocks.

It was predicted that initially, the ORCA would influence responses such that participants would respond more quickly (i.e., with less RT) when categorizing other-race faces compared to own-race faces. It was expected that a change in performance would occur as faces are repeated, such that participants would become familiar with own-race faces faster than other-race faces because of the ORE. It was expected that this improvement in performance (or a decrease in RT) would take place for own-race faces, with the performance of other-race faces remaining almost the same.

In addition to this main experiment (learning condition), a control experiment was conducted in which the same race categorization task was used. However, rather than presenting participants with repeated faces, a total of 6 experimental blocks were used and each block presented a new set of 8 faces (4 Asian and 4 Caucasians) per participant. The dependent measure was again chosen to be RT. The goal of this control condition was to separate general task learning effects from learning of specific identities as well as to specify the cause of the learning effect. The following research question guided the control experiment:

Is the learning effect caused by specific learning of individual faces through familiarisation or is the learning effect caused by a fine-tuning for the own-race category template?

Any learning observed in the control condition could either be due to basic task learning or some form of template refinement that occurs more rapidly for own race than other race. If the same interaction is observed between the learning condition and the control condition, this would indicate that the learning observed in main experiment cannot be due to individuation. In any event, the main prediction would be for an ORCA that remains constant across blocks.

Method

Participants

Participants were recruited from an online participant website (Prolific. Co). In the learning condition, twenty-four (24) adult participants (11 Female; Left Hand = 0; M_age = 27, SD = 6.12) were recruited. In the control condition, a separate set of twenty-four (24) adult participants (12 Female; Left Hand = 0; M_age = 25, SD = 4.74) were recruited. Participants were selected (mainly through geographical location) to be Caucasian in ethnic origin.

All procedures followed the research ethics and data protection (REDP) guidelines of the University of Malta for conducting online studies. All participants were provided with written instructions and explicitly confirmed their consent online, prior to data collection. See Appendix A for information sheet and on-screen instructions

Sample size

The sample size was determined in the same way as in Chapter 2. See page 39 for details.

Stimuli

The basic images were exactly the same as the previous experiment. See page 40 for details. The only difference was the noise. In the first experiment, the faces emerged from two-dimensional Gaussian noise. In Experiment 2, the stimuli were experimentally controlled using the method of constant stimuli such that stimuli with fixed noise levels were presented to participants. Alpha levels 0.5, 0.6, 0.7 and 0.8 were chosen and were presented in a random order.

Experiment and online protocol

The experiment and online protocols were the same as in Experiment 1, except that the participants in Experiment 2 (both the learning condition and the control condition) were recruited from Prolific.co. As described below, the task itself is different. A demonstration of the task can be found at https://maltacogsci.org/RaceCat/Task2Demo/

Task and Display Description

Similar to Experiment 1, the task on each trial was to categorise a face as either Asian or Caucasian using an assigned key on a standard keyboard. The same display layout was used in the learning condition and the control condition (see Figure 2). At the very centre of the display was a 170 x 170 pixel patch of dynamic noise flickering at approximately 30 Hz. A target face with the same dimensions was embedded within the noise. In contrast to Experiment 1, in which the signal (face) alpha level was gradually increased to modulate the visibility of the target face, giving participants control over the stimuli, in these two conditions, the alpha levels were predetermined providing four possible alpha levels: 0.5, 0.6, 0.7 and 0.8. Stimuli with Alpha = 0.8 were the easiest stimuli since the face was most visible, whereas stimuli with Alpha = 0.5 were the hardest stimuli since the faces were least visible. The stimuli were randomised and on each trial, participants saw only one of the four possible alpha levels.

Responses were made using assigned keys, with hints displayed on screen. Participants received feedback after each trial. The stimuli were kept on screen for 1200ms. If no response was made within this time, a feedback screen indicated that the response was too slow, and the trial had to be repeated. If a response was made, a red square surrounded the stimuli if the response was incorrect and a green square surrounded the stimuli if the response was correct. There was a 1000 ms ITI, and the next trial started automatically.

Procedure and experimental design

Each participant was allowed some time to get familiar with the experimental set up prior to the actual trials. They were given 10 practice trials with no response window. Followed by another block of 10 trials with a fixed response window. They then completed 6 experimental blocks of 32 trials. Breaks could be taken between blocks.

The only difference between the learning condition and the control condition was that in the learning condition, each participant was presented with a fixed set of 8 unique faces (4 Asian and 4 Caucasian) which were randomly selected from the possible 96 images and repeated in all the 6 blocks. The order of stimuli within a block was randomized. Whereas, in the control condition a new set of 8 faces, randomly selected from the stimuli set were presented in each block.

Data Analysis

RT was the main dependent variable. This was analysed using a 2 (Race: own/other) x 6 (Block: 1-6) repeated measures ANOVA. Accuracy was expected to be close to ceiling. Initial examination of the accuracy scores in the learning condition indicated that responses to Asian faces (M = 95.0, SE = 0.01) were significantly higher than responses to Caucasian faces (M = 90.0, SE = 0.02), $t(22) = 3.69$, $p < 0.001$. In the control condition, accuracy was overall very good (M_Caucasian = 0.914, SE = 0.01 and M_Asian = 0.913, SE= 0.01). As in Experiment 1, a full analysis was carried out, however since there were no main effects or interactions involving block, this will not be discussed further in the main text. Full analysis can be found in Appendix D. For the main analysis of RT, incorrect responses were filtered out. Due to a technical issue, one participant was excluded from the data analysis in the experimental condition. Analysis was thus conducted on N=23 datafiles in the experimental condition and N= 24 datafiles in the control condition. The practice blocks were also excluded from the analysis.

Results

Learning condition

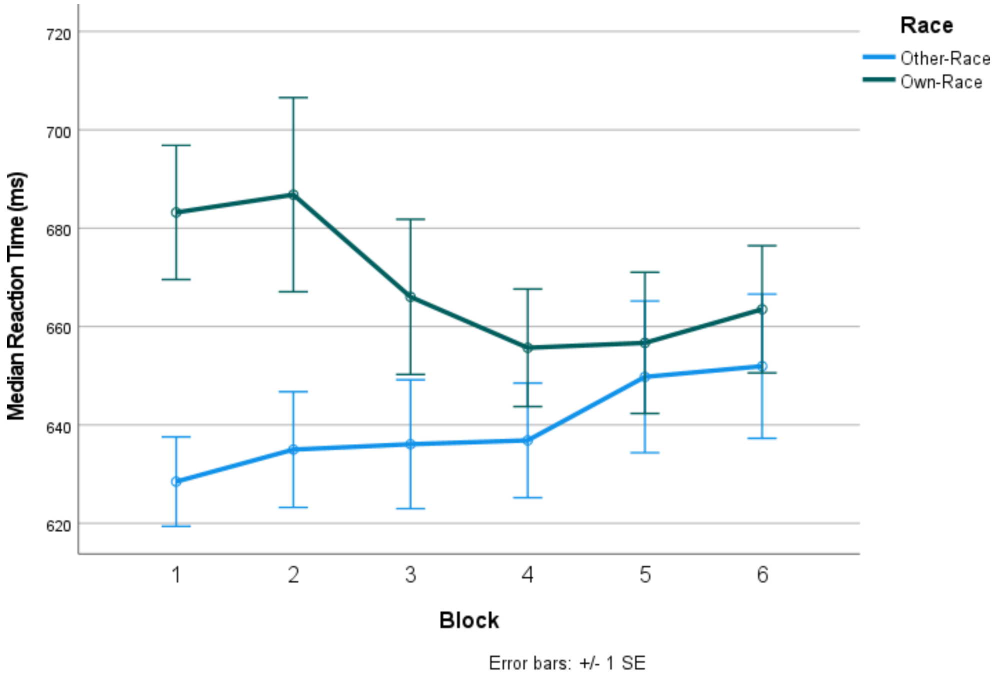


Figure 6 - Graph showing the median RT for both races across blocks for the learning condition. Error bars +/- 1 SE.

Figure 6 summarises the pattern of median RT for correct responses as a function of both Race and Block for the experimental condition

The first point to note is the clear separation of the two lines during the earlier blocks. Participants were quicker to categorize other-race faces (M_Asian = 639.70, SD =10.13) compared to own-race faces (M_Caucasian = 668.67, SD = 11.77), giving rise to a significant main effect of Race, *F*(1,22) = 22.60, p < 0.001, MSE = 57913, η_p^2 = 0.51, supporting the ORCA.

The second point of interest is the convergence of the two lines. Specifically, there was an improvement in performance for own-race faces, indicating a trend for learning for own-race faces. There was a decrease in performance for other-race faces. This was supported by statistical analysis, with a significant interaction between Race and Block, $F(5,110) = 3.06$, $p = 0.01$, MSE $= 4783.44$, $\eta_p^2 = 0.12$.

Finally, the main effect of Block was not significant, $F(5,110) = 0.50$, $p = 0.78$, MSE $= 1230.40$, $\eta_p^2 = 0.02$.

A further “early vs late” analysis was conducted in which the first 3 blocks were grouped as the early phase of the experiment and the last 3 blocks were grouped as the late phase of the experiment.

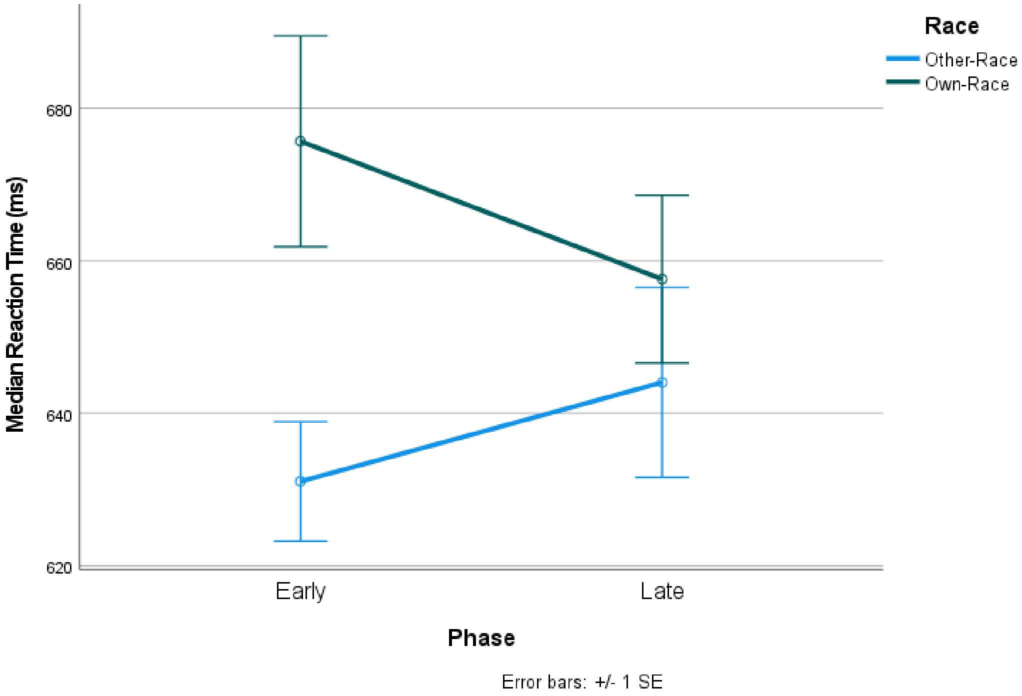


Figure 7 - Graph showing the median RT for own-race and other-race from the early to the late phase of the experiment. Error bars +/- 1 SE.

Figure 7 summarises the median RT across phase. To explore these patterns, a 2 (Race: own/other) x 2 (Phase: early/late) repeated measures ANOVA was conducted. As expected, there was a main effect of Race, $F(1,22) = 19.01$, $p < 0.001$, MSE = 19488.27, $\eta_p^2 = 0.46$. Furthermore, as revealed by the trend in Figure 7, the Race x Phase interaction was significant, $F(1,22) = 8.64$, $p = 0.008$, MSE = 5556.79, $\eta_p^2 = 0.28$. A pairwise comparison for the interaction between race and phase shows a difference of 44.65 (SE = 10.81) between own-race and other-race faces in the early phase of the experiment. In the late phase the difference between own-race and other-race was 13.57 (SE = 5.32). Finally, the main effect of Phase was not significant, $F(1,22) = 0.14$, $p = 0.71$, MSE = 148.79, $\eta_p^2 = 0.01$.

Summary

The aim of the task was to investigate how the ORCA interacts with face familiarity. More specifically, it addressed whether the ORCA and RT change when faces become familiar through repetition. A race categorization task was used in which face stimuli were covered by two-dimensional Gaussian noise. Participants were presented with one of 4 possible alpha signal strengths before making a race categorization decision. There were 6 blocks in which a set of 8 stimuli were repeated across blocks.

Two research questions guided this experiment. The first question asked whether the ORCA can be measured in the task. Consistent with the predictions, there was a difference when categorizing other-race and own-race faces, with participants being quicker (less RT) to categorize other-race faces.

The second question asked whether changes occur in the patterns of race effects and RT when faces are repeated. It was predicted that initially ORCA would influence responses with participants responding quicker (less RT) for other-race faces, compared to own-race faces. It was predicted that the ORE would influence responses at the later stages of the task resulting in performance gains for own race. Consistent with this prediction, RT data revealed that participants were initially quicker to categorize other-race faces, thus the ORCA influenced performance. A learning effect for own-race faces was obtained, with a decrease in RT over time to categorize own-race faces. Performance for other-race faces decreased, with an increase in RT over time to categorize other-race faces.

The difference in the pattern between own-race and other-race indicates that the learning effect is not due to simple task learning but rather there is something specific to race. This learning effect could be due to learning the specific individual faces through familiarisation. Alternatively, it could be that participants have a bias towards their own-race template which becomes fine-tuned as faces are repeated.

Control condition

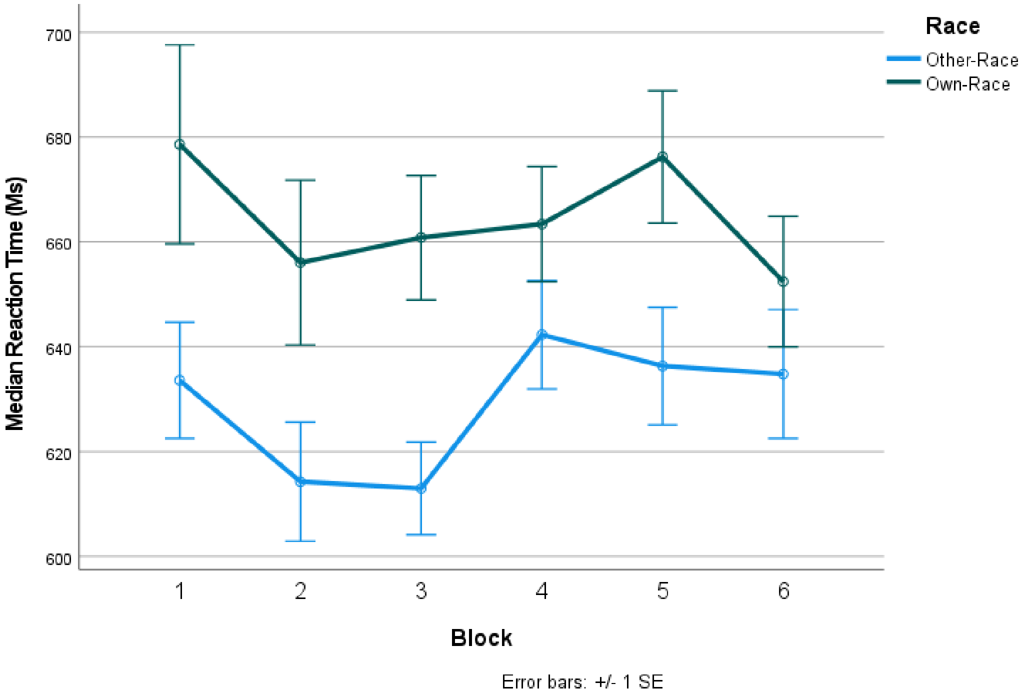


Figure 8 - Graph showing the median RT for both races across blocks for the control condition. Error bars +/- 1 SE.

Figure 8 summarises the median RT for correct responses as a function of Race and Block for the control condition. As expected, participants were quicker to categorize other-race faces (M_Asian = 629.05, SD = 8.34) compared to own-race faces (M_Caucasian = 664.59, SD = 10.46), giving rise to the main effect of Race, $F(1,23) = 56.44$, $p < 0.001$, MSE = 91022.22, $\eta_p^2 = 0.71$, supporting the ORCA. The important point to note is the parallel pattern of the two lines. There was no main effect of Block, $F(5,115) = 1.87$, $p = 0.10$, MSE = 4387.60, $\eta_p^2 = 0.08$ and no Race x Block interaction, $F(5,115) = 1.23$, $p = 0.30$, MSE =1989.71, $\eta_p^2 = 0.05$. Thus, there is no evidence of learning. This suggests that the pattern seen in the learning condition was due to item specific learning of own-race faces.

Summary

The purpose of this control condition was to further investigate the learning effect for own-race obtained in the learning condition. This learning effect could be due to learning specific individual faces through familiarisation or learning something about the own-race Caucasian category, where the template for Caucasian faces changes. A race categorization task was used in which face stimuli were covered by two-dimensional Gaussian noise. Participants were presented with one of 4 possible alpha signal strengths before making a race categorization decision. There were 6 blocks, and each block presented a new set of 8 faces (4 Asian, 4 Caucasian).

Similar to the learning condition, the results revealed an ORCA whereby participants were quicker to categorize other-race faces. There was no general task learning. Furthermore, the results revealed that the learning effect obtained for own-race in the learning condition was due to the specific learning of the own-race identities.

Discussion

This chapter investigated how the ORCA interacts with face familiarity, using a RT experiment in which participants were required to make a race categorization decision when presented with one of 4 possible alpha signal strengths. The chapter described two conditions. The learning condition presented participants with a race categorization task in which participants were presented with repeated stimuli. This experiment revealed an initial ORCA as well as a learning effect for own-race. A follow-up control condition used the same task, however, stimuli were presented only once. This control condition did not show any general task learning, however, revealed that the learning effect observed when faces were repeated in the learning condition was a result of an individuation of the specific faces presented during the task.

The following chapter concludes the thesis by presenting the final discussion of results as well as some recommendations for future research.

Chapter 4

This thesis set out with the aim to further investigate the ORCA. More specifically, the goal was to establish what happens to the ORCA when faces become familiar. Two online experiments were conducted to address the following research questions:

1. Can the ORCA be measured online?
2. Do changes occur in the patterns of race effects when faces are repeated?
3. Is the learning effect caused by specific learning of individual faces through familiarisation or is it caused by a fine-tuning for the own-race category template?

This chapter presents the experiments individually and discusses what their findings mean in terms of the research questions as well as presents some further recommendations for future research.

Summary of findings

Experiment 1

In Experiment 1, a race categorization task was used in which participants were presented with Asian or Caucasian faces and were required to classify faces based on race. The target face was embedded within two-dimensional Gaussian noise and slowly emerged from noise. In order to include face familiarisation, 6 blocks were used and a set of 12 faces (6 Asian and 6 Caucasian) were repeated in all 6 blocks.

A very clear ORCA was found. This is consistent with findings from other studies. For instance, Caharel et al. (2011) found the ORCA in Caucasian participants when asked to categorize Caucasian, Asian and African faces. Ge et al. (2009) found that Caucasian and Chinese participants classified other-race faces more rapidly. Studies on other populations also reveal similar results. Li et al. (2018) found that Chinese participants classified other-race

Caucasian and Indian faces faster than own-race Chinese faces. Zhao & Bentin (2011) also found the ORCA with Israeli and Chinese participants using Israeli and Chinese faces, with both races classifying other-race faces more quickly and accurately. Thus, the finding from this study further supports the ORCA research, adding to the robustness of the ORCA as well as supporting the effect's generalisation to a new task.

However, there was no evidence that race effects changed as people became more familiar with the faces. The most likely explanation is that people were responding very early in the noise sequence, more specifically between 0.3 and 0.4 facial alpha (see Figure 3). Thus, they might not have examined the image enough to obtain sufficient facial information to become familiar with the faces and individuate the faces.

Research on categorization of faces reveals that people are able to make categorization decisions using different types of features, without requiring a full individuation of the face prior to making the decision. For instance, gender discrimination research revealed that people tend to look at local features such as eyes, chin and mouth (Brown & Perrett, 1993; Russell, 2003; Schyns et al., 2002), or alternatively look at more global properties such as face shape (Baudouin & Humphreys, 2006; Stevenage & Osborne, 2006) or skin tone (Nestor & Tarr, 2008) when required to make some form of gender discrimination decision. Dupuis-Roy et al. (2009) recently established that observers can use a range of cues depending on the information provided in a given presentation, the time restrictions and constraints of a certain task. Specifically, that people use and respond quickly to colour information in the mouth region, however when colour is not present, they rely on the more robust but slower luminance information in the eye-eyebrow region. Similarly, when it comes to categorization by race, Fiset et al. (2012) revealed that Caucasian participants focus mainly on the nose and mouth for African faces, the eyes and mouth for Asian faces and the eyes, region between the eyes and the mouth for Caucasian faces. When categorizing between Caucasian and African faces, the main focus seems to be the skin colour and other facial features such as nose shape, lip fulness, hair texture and hair quality (Blair & Judd, 2010; Stepanova & Strube, 2012). Furthermore, Bülthoff et al. (2021) used Asian and Caucasian stimuli and revealed that when exchanging features of a race with that of another race, eyes and texture influence the race categorization decision while contour, nose and mouth have less of an influence on race perception.

Given that in this experiment the stimuli were cropped such that only the internal features of the face were visible, and were controlled for luminance and frequency, it is possible that participants focused on individual features – possibly the eye region – when making the race categorization decision since the texture was not available, and thus did not obtain enough facial detail to be able to individuate faces.

As will be discussed shortly, the second experiment addressed this issue by experimentally varying the signal (face) and noise alpha levels providing 4 fixed levels. However, another way to address this, while also keeping the participants in control of alpha levels, would be to use a face matching task in which participants would have to match a face emerging from noise to one of two faces on either side of the stimulus. This would force participants to extract more information from the stimulus emerging from noise, thus enabling learning and face individuation.

Experiment 2 - Learning Condition

In Experiment 2, the extent of facial detail available on each trial was increased. Specifically, the alpha levels were predetermined, providing 4 possible levels (0.5, 0.6, 0.7 and 0.8) of visibility. A total of 6 experimental blocks were used with 32 trials per block in each condition. The same 8 stimuli (4 Asian, 4 Caucasian) were repeated across blocks. The ORCA was found once again. More importantly, a learning effect was found. RT to categorize own-race faces decreased while the RT to categorize other-race faces increased (Figure 7). Before addressing what this means in terms of the relationship between familiarity and race effects, the following section will summarise a control condition, which was conducted to test for general task learning, and further investigated whether the learning effect for own-race obtained in the learning condition of Experiment 2 was a result of individuation or a result of a refinement for the own-race category template.

Experiment 2 – Control Condition

In the control condition of Experiment 2, the same race categorization task was used in which participants were presented with Asian and Caucasian faces covered with two-dimensional Gaussian noise. Once again, the alpha levels were predetermined. However, rather than presenting participants with repeated faces, a total of 6 experimental blocks were used and each block presented a new set of 8 faces (4 Asian and 4 Caucasians). This experiment revealed that the learning effect for own-race observed when faces were repeated (learning condition of Experiment 2), was a result of an individuation of the specific faces presented during the task.

The following sections discuss the results in terms of the research questions.

Can the other-race categorization advantage be measured online?

Given the results from the experiments, the ORCA can clearly be measured. In Experiment 1, less visible facial detail (alpha level) was required when other-races were presented, giving rise to the ORCA. In Experiment 2 faster RT responses to categorize other-race faces were present in both conditions. In addition to these main dependent measures, the ORCA was also evident in accuracy scores for both Experiment 1 & 2 (learning condition), with participants being more accurate to categorize other-race faces than own-race faces.

Do changes occur in the patterns of race effects when faces are repeated?

While research on face familiarity and race effects have presented extensive information including the accuracy and robustness of familiar face recognition and the lack thereof unfamiliar face recognition (Bindemann & Johnston, 2017) as well as the differences in recognition and categorization of own-race and other-race faces (Young et al., 2012), the bridge between the two is unclear. This thesis specifically addressed the interaction between these two phenomena.

Repetition of faces resulted in a decrease in RT to categorize own-race faces and an increase in RT to categorize other-race faces (Experiment 2, learning condition). The difference in pattern for own-race and other-race faces suggests that the changes obtained throughout the experiments were not attributable to general task learning. Further exploration revealed that the observed learning effect was most likely the result of the individuation of the faces presented in the task – rather than tuning of race-specific templates – as performance did not change across blocks that introduced novel faces (Experiment 2, control condition).

A possible explanation for the observed learning effect in Experiment 2, relates to a proposed antagonistic relationship between individuation and categorization (Ge et al., 2009). Face categorization efficiency may suffer as a result of increased face individuation efficiency during early stages of face processing due to the allocation of resources towards individuation. When an individual is experienced with a category of faces (own-race faces), individuating information is automatically encoded first followed by encoding of categorical information. On the other hand, when experience with a category is limited (other-race faces), encoding categorical information precedes encoding of individuating information (Levin, 1996, 2000). This was shown at the beginning of the experiment where the lack of experience with the stimuli explains the lower RT to categorize other-race faces.

However, as faces became familiar, both races were individuated, as seen from the similar patterns obtained in the control condition of Experiment 2. Despite this, the individuation of own-race faces took place faster, since the participants are generally more experienced with own-race. Thus, as a result of familiarisation with the faces, the influence of the ORCA declined, and the pattern of performance were more consistent with the ORE.

A further explanation can be extracted from the multidimensional face space model (Valentine, 1991; Valentine & Endo, 1992). According to this model, faces are represented as nodes in a multidimensional space, with the distance between nodes being inversely proportional to their resemblance. A summation of the total activation of nodes is required to classify a face. Other races form a denser neighbourhood thus are easier to classify since the spread of activation across all nodes is easier. Whereas own-race faces are more spaced apart, thus, are easier to individuate. When faces are new to the participant, an easier classification of other-race takes place, however, as faces become familiar through repetition, faces become individuated, with a faster individuation for own-race since the nodes are more spaced out in space.

Taken together, the experiments reveal the presence of the initial ORCA. A repetition of faces, leads to an individuation of the faces presented in the task, which occurs faster for own-race faces than other-race faces, resulting in a decrease in the influence of the ORCA and pattern of results more consistent with the ORE.

Recommendations and future directions

It is important to consider that the images used in this study were manipulated such that they were cropped to show the main facial features and aligned based on eye position. This made sense since having features such as hair would have made it easier to categorize the faces based on race. In addition, the images were matched for mean luminance and frequency. Although this provided some guarantees and control in the experiments, it does not necessarily reflect what happens in the real world, since faces are seen in natural setting and contain variability (Oruc et al., 2019). Thus, the results should be interpreted with caution. One possibility to address this is to repeat the experiment with two different conditions; manipulated images and naturalistic images. This will give a better understanding of what happens in the real world.

The current work also opens up interesting issues for further investigation.

Firstly, it would be useful to further test the replicability of the findings by using a different set of stimuli. Additionally, further behavioural tests should be carried out to ensure that participants individuated own-race faces better than other-race faces. An old/new recognition task could be used in which participants are presented with previously viewed images of faces as well as new faces and would be required to decide if the face presented has been viewed before. If own-race faces are individuated better than other-race faces, as suggested by the results from Experiment 2 (learning condition), then a higher accuracy in responses for own-race faces and quicker response times would be expected for own-race faces compared to other-race faces.

As discussed in previous chapters, face processing capabilities are not a constant across the population (Duchaine & Nakayama, 2006, Noyes et al., 2017; Tardif et al., 2019) and individuals show a distribution of abilities, (Bowles et al., 2009; Davis et al., 2011; Richler et al., 2015; Wan et al., 2017; Wilhelm et al., 2010; Wilmer et al., 2010). Thus, another issue that needs further investigation is the individual differences related to this task. By obtaining the magnitude of the ORCA in individuals, it would be interesting to investigate whether the learning effect is constant or whether there is a relationship between the magnitude of the ORCA and the slope of learning.

Finally, the participants recruited for this study were selected to be Caucasian in ethnic origin, thus making use of only one race to investigate the ORCA. In many previous studies, participants from more than one race have been involved to generalise the findings (Ge et al., 2009; Tüttenberg & Wiese, 2019; Woo et al., 2020). It would thus be useful to extend the current study to incorporate participants from other ethnicities. It would be expected that once again the participants would initially be quicker to categorize other-race faces, however throughout the task, they would become familiar with own-race faces faster than other-race, such that upon familiarisation, they become quicker to categorize own-race faces.

If the task is extended to Asian populations (given the current stimulus set), it is expected that the results would produce similar results for Asian and Caucasian participants, with a switch in the exact pattern depending on face-race. More specifically, it is expected that Asian participants would be better at categorizing Caucasian (other-race) faces. However, upon familiarisation, they would show an improvement in categorizing Asian (own-race) faces, with the performance for Caucasian (other-race) faces becoming worse.

It should be noted however, that previous research that has used multiple races found an asymmetry between them. For instance, Tüttenberg & Wiese (2019) revealed that Caucasian participants found learning own-race faces easier than other-race faces, however, this advantage was not present in East Asian participants who were able to learn both races. Furthermore, Woo et al. (2020) discovered that Malay and Chinese children and adults displayed faster categorization reactions for Caucasian appearances, followed by Chinese faces and Malay faces in a mixed community. The traditional ORCA was not detected in Chinese children and adults because they perceived Chinese faces as a bridge between other-race Caucasian and other-race Malay faces. The results for Malay adults confirm the ORCA, however, Chinese adults saw own-race Chinese faces as low-frequency other-race Caucasian faces rather than high-frequency own-race faces. Similarly, Ge et al. (2009) found that Chinese participants were faster in own-race recognition than own-race categorization, whereas Caucasian were faster in categorizing both races than recognizing them. Thus, the current study can be extended on Asian societies as well as multicultural societies to investigate whether the changes in race effects with face familiarity obtained in this study can be generalised to other populations.

Conclusion

This thesis set out to investigate how we process own-race and other-race faces within the context of learning, by addressing the interaction between race effects (specifically the ORCA) and face familiarity. A novel race categorization task was used in which Asian and Caucasian faces were embedded within two-dimensional Gaussian noise and participants were required to classify faces as Asian or Caucasian. Two experiments investigated whether any changes occur within race effects when faces become familiar through repetition. In the first experiment, participants were given control over viewing conditions, such that the signal (face) alpha levels were systematically varied to modulate the visibility of the face, while in the second experiment the signal (face) alpha levels were fixed. The thesis concludes that the ORCA can be measured online, which was clearly evident through accuracy scores, alpha levels as well as RT measures. Furthermore, it also concludes that as faces become familiar through repetition, an improvement in the task for own-race faces takes place. This improvement is a result of individuation of the faces presented in the task, which occurs faster for own-race faces than other-race faces. While the ORCA dominated performance in the early stages of the task, the ORE also played a role, such that own-race faces were individuated more quickly than other-race faces. Thus, as faces become familiar, the influence of the ORCA appeared to diminish, and patterns of results were more consistent with the ORE.

These findings contribute to the growing literature on race effects and familiarity by bridging the gap between the two, providing an understanding of what happens to race effects when faces become familiar.

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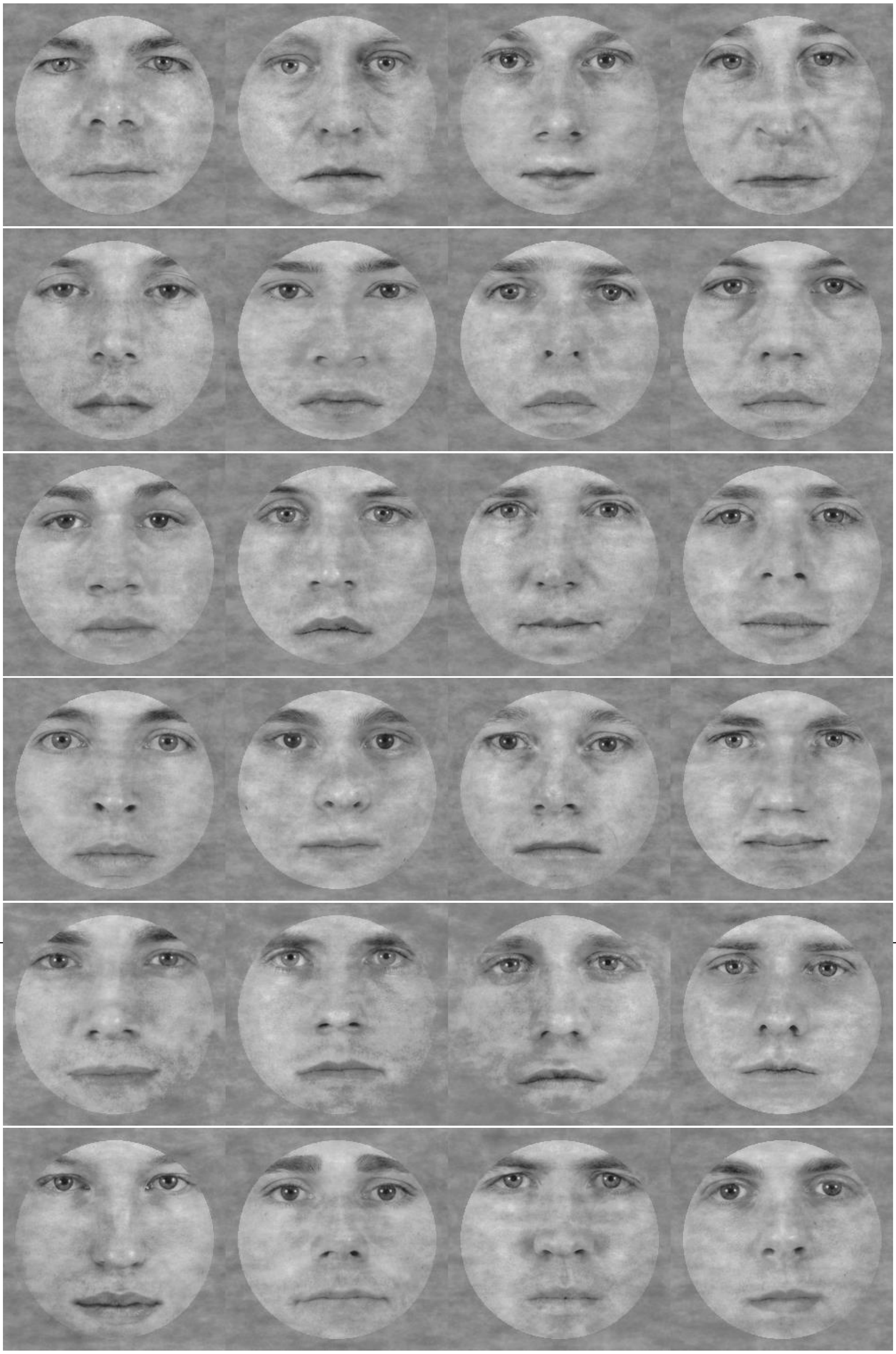
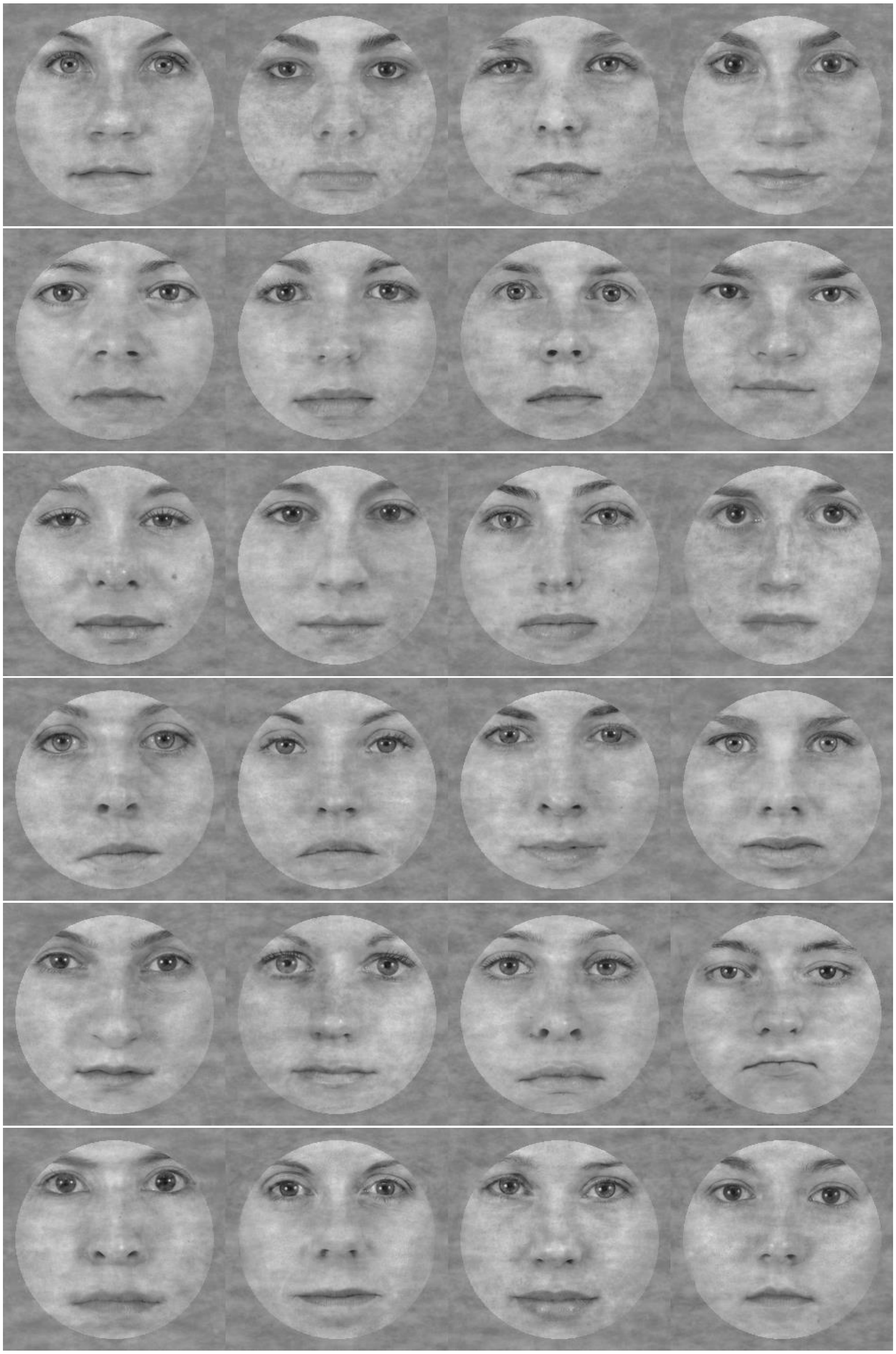
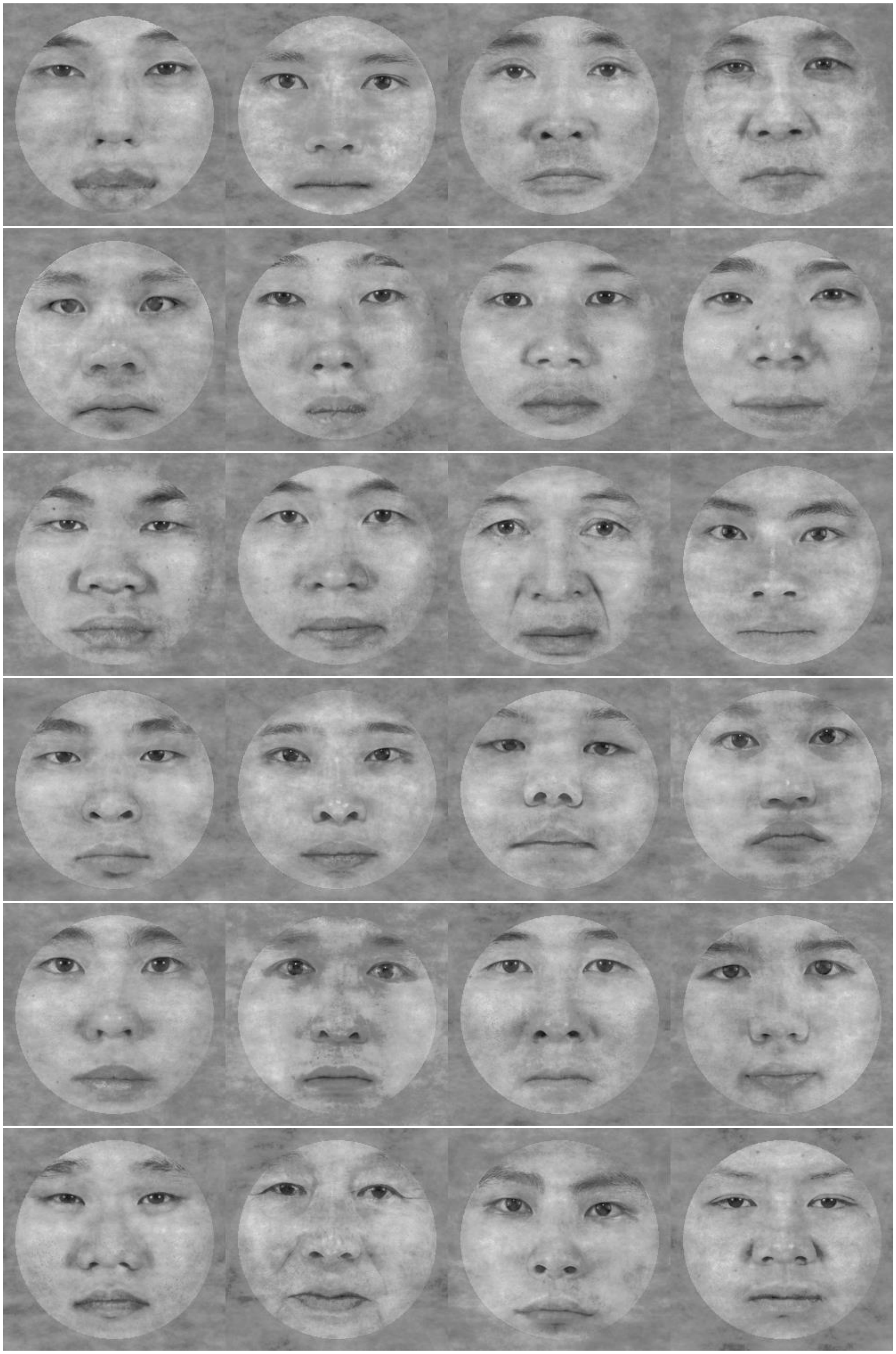
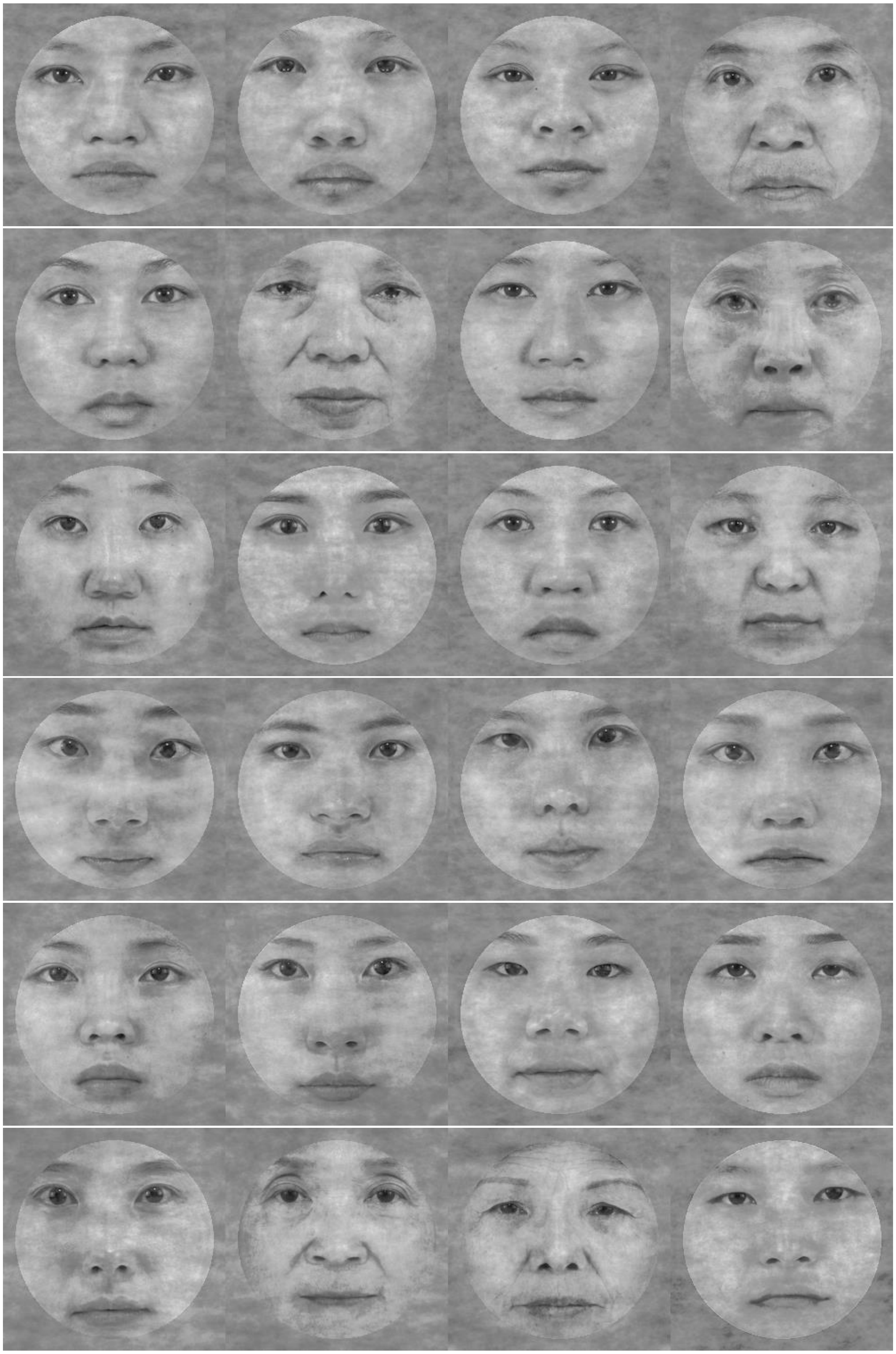
Appendix A: Images used in the study





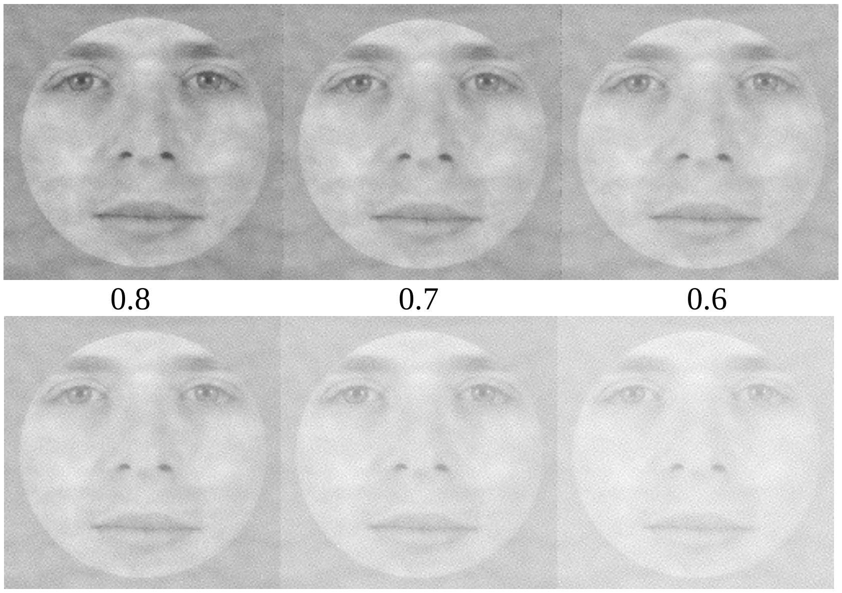




.

Appendix B – Examples of images ranging from 0.8 to 0.3 alpha levels

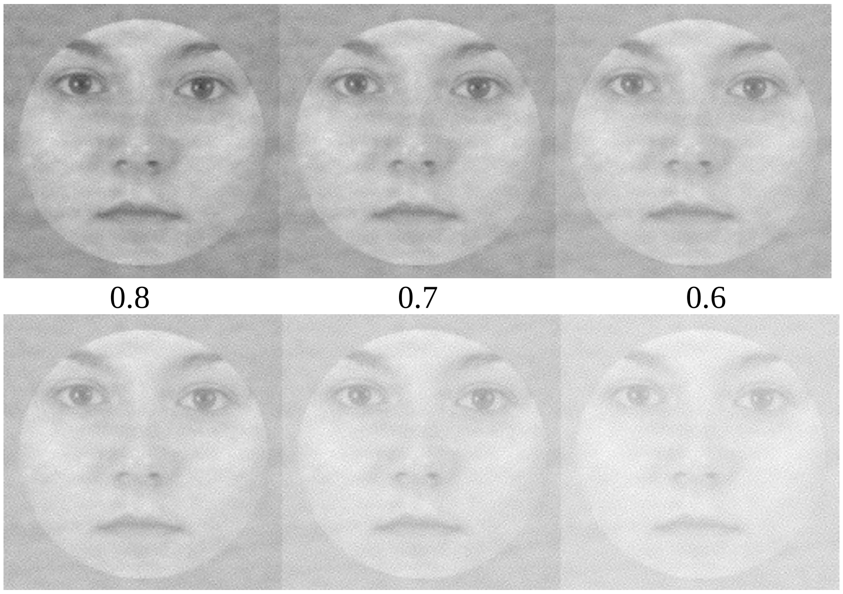
Example of Caucasian male from alpha 0.8 to alpha 0.3



0.8 0.7 0.6

0.5 0.4 0.3

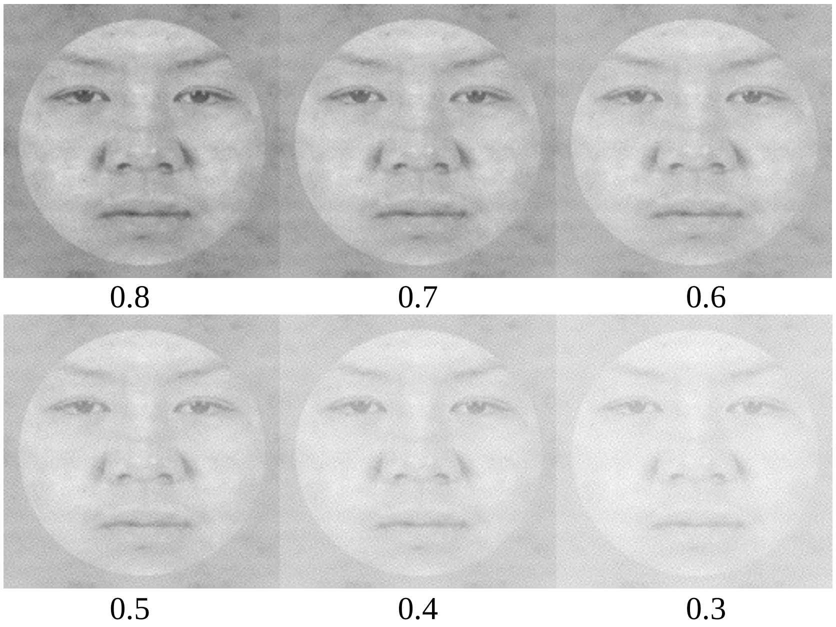
Example of Caucasian female from alpha 0.8 to alpha 0.3



0.8 0.7 0.6

0.5 0.4 0.3

Example of Asian male from alpha 0.8 to alpha 0.3



Appendix C – Accuracy analysis

The tasks used in this thesis were designed to produce performance levels that were close to ceiling in terms of accuracy, maximizing the power of the respective alpha-level and RT dependent measures. However, as noted during the respective results sections, examination of the accuracy data revealed robust ORCAs, both in Exp1 and the experimental condition of Exp2.

The purpose of this supplemental analysis was to explore whether there were any hidden learning effects in the accuracy data. Given the binary nature of the accuracy scores, the repeated measures ANOVA approach used for alpha-level and RT in the main text were not appropriate. Instead, a binomial generalized linear mixed model was specified using the *lmerTest* (Kuznetsova et al., 2017) package in R4.0.4 (Team, 2020)

The same basic model, specifically

Accuracy = Race*Block + (1+ Race*Block | Participants)

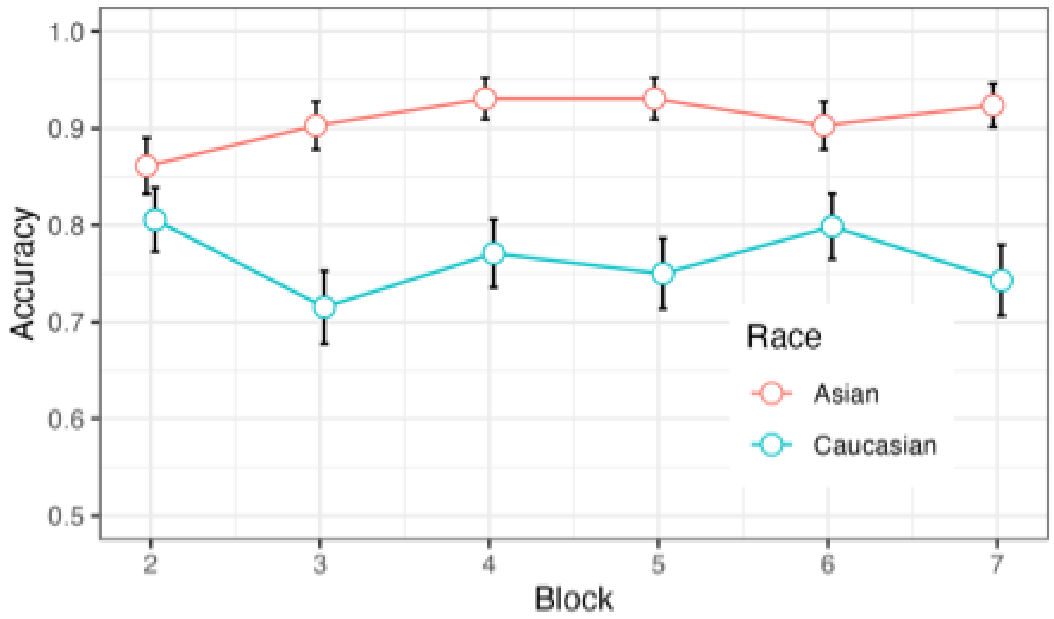
with Race and Block as fixed effects and Participants as a random effect, was applied to all three datasets. The full R syntax for the *glmer* call was

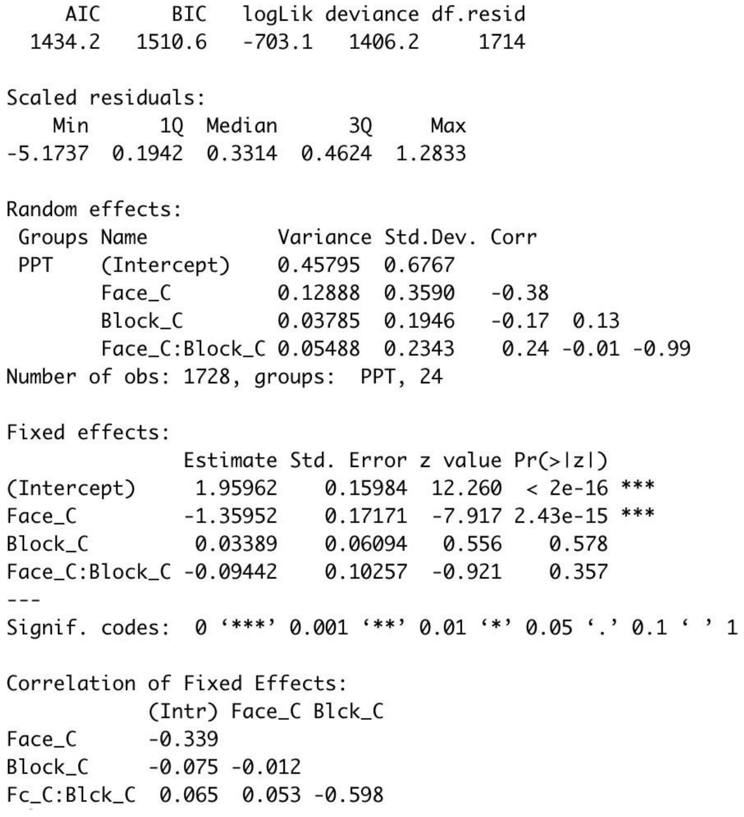
```
Exp_X_accuracyAnalysis = glmer(Accuracy ~ Race *Block + (1+ Race *Block_|PPT), data =
                                   Exp_X_InputData, family = binomial)
```

(Note that random slopes and intercepts were not included in the model as the exact items selected was not constant across participants).

On the following pages, the patterns of accuracy plus the outcome of the respective likelihood-ratio tests are presented in detail. In summary, however, while there was a clear effect of face Race in the experimental conditions of both experiments, there was no change across Block. In the control condition of Experiment 2, the accuracy scores did not vary at all across any of the factors. It can thus be concluded that accuracy levels were not modulated as a function of learning.

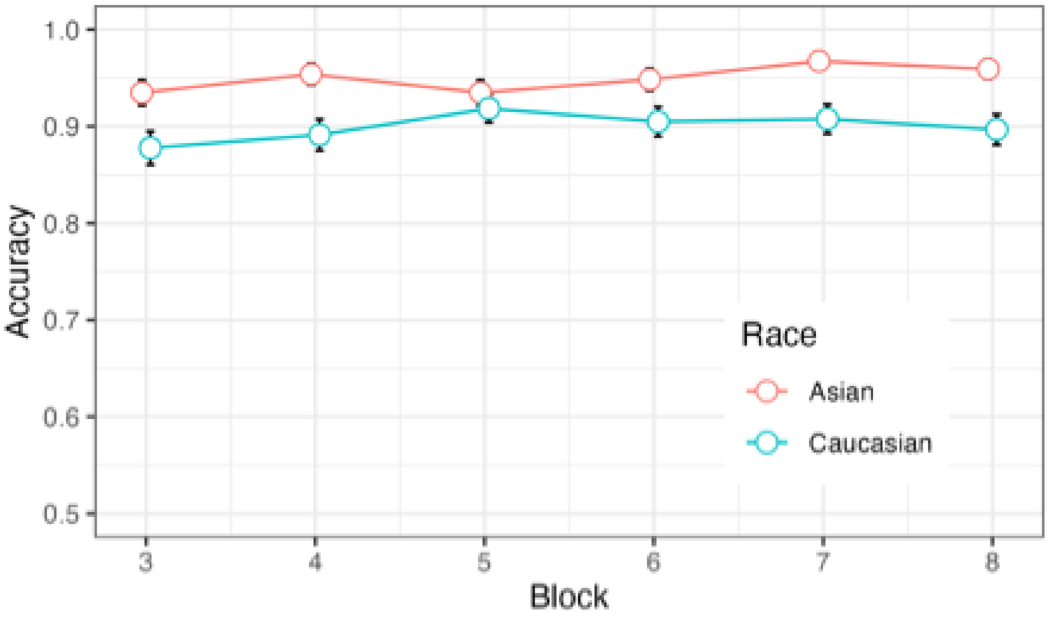
Experiment 1





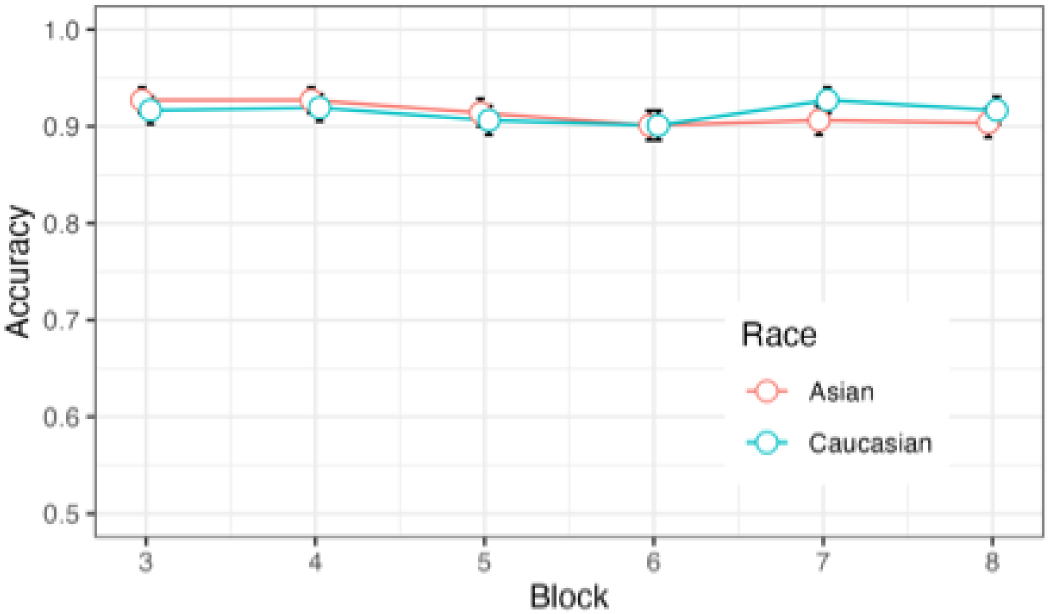
```
      AIC      BIC   logLik deviance df.resid
   1434.2   1510.6   -703.1   1406.2     1714

Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.1737  0.1942  0.3314  0.4624  1.2833

Random effects:
 Groups Name          Variance Std.Dev. Corr
 PPT    (Intercept)   0.45795  0.6767
        Face_C        0.12888  0.3590   -0.38
        Block_C       0.03785  0.1946   -0.17  0.13
        Face_C:Block_C 0.05488  0.2343    0.24 -0.01 -0.99
Number of obs: 1728, groups:  PPT, 24

Fixed effects:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)     1.95962    0.15984  12.260  < 2e-16 ***
Face_C         -1.35952    0.17171  -7.917 2.43e-15 ***
Block_C         0.03389    0.06094   0.556    0.578
Face_C:Block_C -0.09442    0.10257  -0.921    0.357
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) Face_C Blck_C
Face_C      -0.339
Block_C     -0.075 -0.012
Fc_C:Blck_C  0.065  0.053 -0.598
```

Experiment 2 – Learning Condition



```
     AIC      BIC   logLik deviance df.resid 
  2216.5   2306.0  -1094.3   2188.5     4402 

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-8.3869  0.1625  0.2316  0.3080  0.7542 

Random effects:
 Groups Name           Variance Std.Dev. Corr           
 PPT    (Intercept)    0.59045  0.7684                  
        Face_C         0.23693  0.4868    0.12          
        Block_C        0.01438  0.1199   -0.24  0.60    
        Face_C:Block_C 0.04358  0.2088   -0.65  0.64  0.78
Number of obs: 4416, groups:  PPT, 23

Fixed effects:
               Estimate Std. Error z value Pr(>|z|)    
(Intercept)     2.85528    0.17536  16.282  < 2e-16 ***
Face_C         -0.70456    0.16532  -4.262 2.03e-05 ***
Block_C         0.07591    0.04514   1.682   0.0927 .  
Face_C:Block_C -0.11199    0.08644  -1.296   0.1951    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) Face_C Blck_C
Face_C      -0.016              
Block_C     -0.090  0.165       
Fc_C:Blck_C -0.348  0.314  0.045
```

Experiment 2 – Control Condition



```
     AIC      BIC   logLik deviance df.resid
  2616.8   2706.9  -1294.4   2588.8     4594

Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.9885  0.1984  0.2549  0.3408  0.6938

Random effects:
 Groups Name             Variance Std.Dev. Corr
 PPT    (Intercept)      0.45103  0.6716
        Face_C           0.16444  0.4055    0.08
        Block_C          0.01074  0.1036    0.61 -0.20
        Face_C:Block_C 0.08337  0.2887   -0.32 -0.20  0.54
Number of obs: 4608, groups:  PPT, 24

Fixed effects:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)     2.591787   0.149702  17.313   <2e-16 ***
Face_C          0.071289   0.139949   0.509    0.610
Block_C        -0.005227   0.038778  -0.135    0.893
Face_C:Block_C  0.027001   0.088732   0.304    0.761
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) Face_C Blck_C
Face_C       0.053
Block_C      0.315 -0.049
Fc_C:Blck_C -0.199 -0.094  0.234
```