Modulation of Mood on Eye Movement and Face Recognition Performance

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Abstract

In face recognition, looking at the eyes has been associated with engagement of local attention, as well as better recognition performance. As recent research has suggested negative mood facilitates local attention while positive mood facilitates global attention, negative mood changes may lead to more eyes-focused eye movement patterns and consequently enhance recognition performance. Here we test this hypothesis using mood induction. Through Eye Movement analysis with Hidden Markov Models (EMHMM), we discovered eyes-focused and nose-focused eye movement strategies in the participants, and the eyes-focused strategy was associated with better recognition performance. During the recognition phase, participants with a negative mood change had increased eye movement pattern similarity to the eyes-focused strategy, and participants' mood change was correlated with eye movement pattern similarity change. Nevertheless, mood change did not significantly change participants' eye movement strategy classification despite changes in eye movement pattern similarity, and the eye movement pattern similarity change did not modulate recognition performance. These results suggest that mood changes through mood induction lead to slight changes in eye movement pattern that may not be sufficient to modulate recognition performance. Thus, individuals may have preferred eye movement strategies in face recognition impervious to transitory mood changes. This finding is consistent with a recent speculation on limited plasticity in adult face recognition, and suggests that eye movements in face recognition may provide reliable information about an individual's cognitive abilities.

Keywords: eye movements; face recognition; Hidden Markov Model; mood induction

Introduction

In the literature on face recognition, it has been widely accepted that faces are primarily recognized based on global or holistic information, and holistic processing has been considered a hallmark of face processing (e.g., Bartlett and Searcy, 1993; Barton, Keenan, and Bass, 2001; Bruce, 1998; Freire, Lee, & Symons, 2000; Kemp, McManus, & Piggot, 1990; Rakover & Teucher, 1997; Searcy & Bartlett, 1996). Evidences for holistic face processing come from various classical effects in face perception, including the composite face effect (Goffaux and Rossion, 2006; Le Grand, Mondloch, Maurer, & Brent, 2004; McKone, 2008) and the part-whole effect (Davidoff & Donnelly, 1990, Donnelly & Davidoff, 1999, Tanaka & Farah, 1993, Tanaka & Sengco, 1997). The composite face effect refers to the phenomenon that two identical top half faces are perceived as different when they are paired with different bottom half faces, whereas in the part-whole effect, participants have higher accuracy when identify a face part in a whole-face context than when identifying it alone. However, more recent studies demonstrate that both holistic and part-based information are important in face processing (Burton et al., 2015; Cabeza & Kato, 2000; Hayward, Crookes, Rhodes, 2013). For example, Hayward, Rhodes, and Schwaninger (2008) showed that the own-race effect in face recognition (better recognition of own-race than other-race faces) could be observed in both blurred face (intact configural information with featural information removed) and scrambled face conditions (intact featural information without configural information), indicating both holistic and feature-based processes contribute to accurate face recognition. This observation has been robustly replicated (e.g. Mondloch et al., 2010; Rhodes et al., 2009). Consistent with these findings, a significant link between holistic processing and face recognition ability has not been consistently reported in the literature (Konar, Bennett, & Sekuler, 2010; Rezlescu et al., 2017; Richler, Cheung, & Gauthier, 2011; Richler, Floyd, & Gauthier, 2015; Verhallen et al., 2017; Wang, Li, Fang, Tian, & Liu, 2012; Yovel, Wilmer, & Duchaine, 2014).

The importance of local/part-based information in addition to global/holistic information in face recognition is further supported by evidence from eye movement studies. For example, Sekiguchi (2011) showed that people with high face memory made more eye movement transitions between the two eyes compared with those with lower face memory. Davis et al. (2017) reported that more looking at the eyes during face recognition is associated with better face memory. Since global face processing has been associated with fixations at the face center whereas local face processing with fixations on the eyes and the mouth (Bombari, Mast, Lobmaier, 2009; Miellet, Caldara, and Schyns, 2011), these results suggested the benefit of incorporating local/part-based processing on face memory. Another study by Chuk, Crookes, Hayward, Chan, and Hsiao (2017) used the Eye Movement analysis with Hidden Markov Models (EMHMM; Chuk, Chan, & Hsiao, 2014) approach to model each individual participant’s eye movement data using a hidden Markov model (HMM) and cluster them into three distinct groups based on similarities between the individual models. One group, labeled as holistic strategy, consisted of fixations that focus on the face center. Left-eye-biased analytic strategy involved frequent eye fixations switching between the two eyes in addition to the face center, with a slightly higher probability to start a trial by looking at the left eye than the right eye. Lastly, right-eye-biased analytic strategy had fixations mainly on the right eye and the face center. The researchers discovered that participants implementing left-eye biased analytic strategy outperformed the other two groups in face recognition. That is, those who focused at both the local/feature-based (fixations at the two eyes) and global/holistic (fixations at the face center) information displayed the best performance.

The above findings suggested that although faces are processed holistically in general, additional attention to local features (i.e., the individual eyes) to the global information (through looking at the face center) is beneficial for face recognition. Thus, the enhancement of local selective attention may induce more eye fixations to the eyes during face recognition, which may consequently enhance face memory. To investigate this possibility, Cheng, Chuk, Hayward, Chan, and Hsiao (2015) used hierarchical letter patterns to prime participants to engage local or global attention during face recognition. They found that compared with a no-priming baseline condition, local priming significantly increased participants' eye movement pattern similarity to a more eyes-focused strategy, but did not enhance participants' recognition performance. This result may be because in the local priming condition, participants had to perform both the priming and the face recognition tasks, in contrast to the no-priming condition. Thus, the cognitive demand of the priming task may have offset the potential enhancement of face memory due to engagement of local attention.

In addition to using an attention priming task, attention engagement can be modulated by emotion/mood. Indeed, mood has an overarching effect on the way we perceive the world, process information, as well as behave (Chepenik, Cornew, & Farah, 2007). A popular theme in the literature is that sad mood promotes local focus, characterized by attention to individual features, and that happy mood promotes global focus, with greater reliance on global/holistic processing (Kimchi and Palmer, 1982; Gasper and Clore, 2002). In the context of face processing, Curby, Johnson, and Tyson (2012) used a composite face task to show that sad mood, but not neutral or happy mood, significantly decreased holistic face processing. This finding suggested sad mood may enhance local selective attention in face processing, which may consequently enhance face memory. Consistently with this speculation, mood has been found to affect how well people remember things – specifically, negative mood may enhance memory. Bless and Fielder (2006) postulated that different moods serve different adaptive functions and thus recruit different processing styles. Negative mood signals a novel or challenging situation and requires greater attention to external stimuli, thus recruiting a more focused, bottom-up processing. In contrast, positive mood calls for assimilative, top-down processing and greater reliance on heuristics. As a result, people in negative mood can more effectively encode information about a stimulus. Consistently, Forgas, Goldenberg, and Unkelbach (2008) found that shoppers had significantly better recall memory about the interior of a shop when they were having a negative mood than a positive mood. Also, Вдuml and Kuhbandner (2007) found that participants with a negative mood experienced less memory interference and showed better memory. Similar observations were made with regards to eyewitness testimony (Thorley et al., 2016).

So far, we have made three important points: first, negative mood promotes local/part-based processing and positive mood global/holistic processing; second, part-based processing of the features (i.e. the eyes) in addition to global/holistic processing has an advantageous effect in face recognition as compared with a purely global/holistic processing style; third, negative mood might benefit memory, possibly by recruiting a more focused, attentive processing style. It can thus be inferred that negative mood might boost local/part-based processing of faces (indicated by more fixations on the individual eyes), which might in turn lead to better recognition memory.

However, some recent studies have argued that an individual's face recognition ability is a rather fixed, or even inherited. Given that we have abundant experience in face recognition in daily life, adult face recognition may have reached a capacity limit, with little plasticity for improvement. For example, twin studies point out that face recognition ability is highly determined by genes, and that environmental factors play little role (Wilmer, et al., 2010; Shakeshaft & Plomin, 2015; Zhu et al., 2010). In addition, extensive face drawing training did not lead to better face recognition performance (Zhou, Cheng, Zhang, & Wong, 2012; Tree et al., 2017; Devue and Barsics, 2016). Thus, it remains unclear whether sad mood can indeed bolster face recognition performance.

Here we aim to answer the question whether a relative shift in attentional focus that enhances local processing of faces in addition to global processing due to a mood change, as reflected in eye movement pattern, would result in differences in face recognition performance. Participants completed two face recognition blocks, one without (pre-induction block) and one with mood induction (post-induction block). They were induced with either positive, neutral, or negative mood by watching video clips. Their eye movements were recorded and analyzed using the EMHMM method (Chuk et al., 2014), as EMHMM allows us to quantitatively measure eye movement pattern change due to mood change and assess its relationship with mood change and face recognition performance change. Through EMHMM, Chuk et al. (2014) discovered eyes-focused (analytic) and nose-focused (holistic) strategies in face recognition, and eyes-focused strategies were associated with better recognition performance (e.g., Chan, Chan, Lee, & Hsiao, 2018; Chuk, Chan, & Hsiao, 2017).

Accordingly, we expected to discover ‘eyes-focused’ and ‘nose-focused’ strategies from our participants. If negative mood indeed promotes local/part-based processing that is advantageous for face memory, participants with a negative mood change would show an increased eye movement pattern similarity to the eyes-focused strategy as well as enhanced recognition performance after mood induction as compared with the pre-induction baseline. In contrast, those with a positive mood change may show increased similarity to the nose-focused strategy as well as decreased recognition performance. In contrast, if face recognition ability is indeed not malleable, we would observe an effect of mood on visual processing style that does not extend to differences in recognition performance. Specifically, negative mood change might make a participant’s eye movement pattern more eyes-focused, and positive mood change more nose-focused, without significant changes in recognition performance.

Methods

Participants

Participants were 90 Asian undergraduate students from The University of Hong Kong (54 females, 17-26 years, M = 20.5 years). All reported normal or corrected-to-normal vision. They were randomly allocated to receive either positive (n = 30, 21 females), neutral (n = 30, 16 females), or negative (n = 30, 17 females) mood induction. The sample size was consistent with a prior study by Curby et al. (2012) that also examined the effect of mood induction on face processing (the study had 93 participants with approximately 30 participants in each mood induction condition). In addition, a power analysis indicated that a sample of 54 participants would be needed to detect a medium effect size (f = .25) in within-between interaction using ANOVA with 95% power, alpha at .05.

Materials

The stimuli consisted of 80 color frontal-view Asian face images (half females) from a face database developed in Professor William Hayward's lab at the University of Hong Kong (Chuk et a., 2014; Chan et al., 2018). All faces had a neutral expression, had no extraneous features such as glasses or facial hair, and were unfamiliar to the participants. All face photographs were taken under a consistent lighting condition and were rescaled and aligned to maintain the same interpupil distance. The face images were cropped around the chin and the ears and were placed on top of a black background. The face images subtended 8° of visual angle horizontally, about the size of a real face at a distance of 100 cm, a typical distance in normal conversations (Hsiao & Cottrell, 2008).

An Affect Grid (Russell, Weiss, & Mendelsohn, 1989) was used to measure mood. It is a simple, easy tool that directly measures valence and arousal. It is composed of 9 x 9 boxes, in which each box represents a combination of valence (1 = extremely unpleasant, 9 = extremely pleasant) and arousal (1 = sleepy, 9 = high arousal). Our study measured a participant's mood multiple times throughout the procedure. The affect grid is an appropriate method as it could be used rapidly and repeatedly. In the first mood check, a participant was given an instruction sheet along with verbal general instructions about the Affect Grid. Once he/she understood the instructions, he/she was given an Affect Grid and was instructed to mark the position in the grid that best reflects how he/she feels "right now, at this moment".

Note that although the Affect Grid is a self-report method and thus may be subject to individual differences in the interpretation of the magnitude of each square, it has been argued that mood is inherently subjective, and thus its measurement should be straightforward and have face validity (Hammersley, Reid, Atkin, 2014). In this regard, the Affect Grid is an appropriate tool for the current study which requires a quick and easy measurement that can be repeatedly used. Indeed, the Affect Grid has been used in many studies with a similar purpose in the literature (e.g., Curby et al., 2011; Eich, Macauley, & Ryan, 1994; Deaver, Miltenberger, Smyth, Meidinger, & Crosby, 2003).

Video clips were used to induce either positive (a funny animation), negative (a documentary about suffering animals), or neutral (an instructional video about pottery making) affective states. Of the various mood induction procedures developed for use in a laboratory setting, the presentation of video clips with affective content is considered one of the most effective and widely used methods (Gerrard-Hesse et al., 1994; Westermann et al., 1996). Each video was approximately 5 minutes long. We used 3 videos with different valence contents to ensure a relatively even distribution of valence changes among the participants in the examination of the relationship between mood change and eye movement pattern/recognition performance change.

Design

Participants performed two face recognition blocks: a pre-induction block with no mood induction to obtain baseline mood state and behavior, and a post-induction block with a mood induction procedure before the face recognition task. The post-induction block took place at least one week after the pre-induction block to avoid possible practice effects. Participants' mood change was defined as the difference in valence rating between the pre- and post-induction blocks as assessed using the Affect Grid immediately before the recognition tests. We examined the effect of mood change on recognition performance and eye movement pattern using a linear mixed-effects model with repeated measures with block, valence change, and the interaction between block and valence change as fixed effects and intercepts for subjects as a random effect. Analyses were performed using the lme4 package (Bates, Maechler, Bolker, & Walker, 2015) in R (R Core Team, 2019). P-values were obtained with the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017). Visual inspection of residual plots did not reveal any obvious violations of homoskedasticity or normality.

Procedure

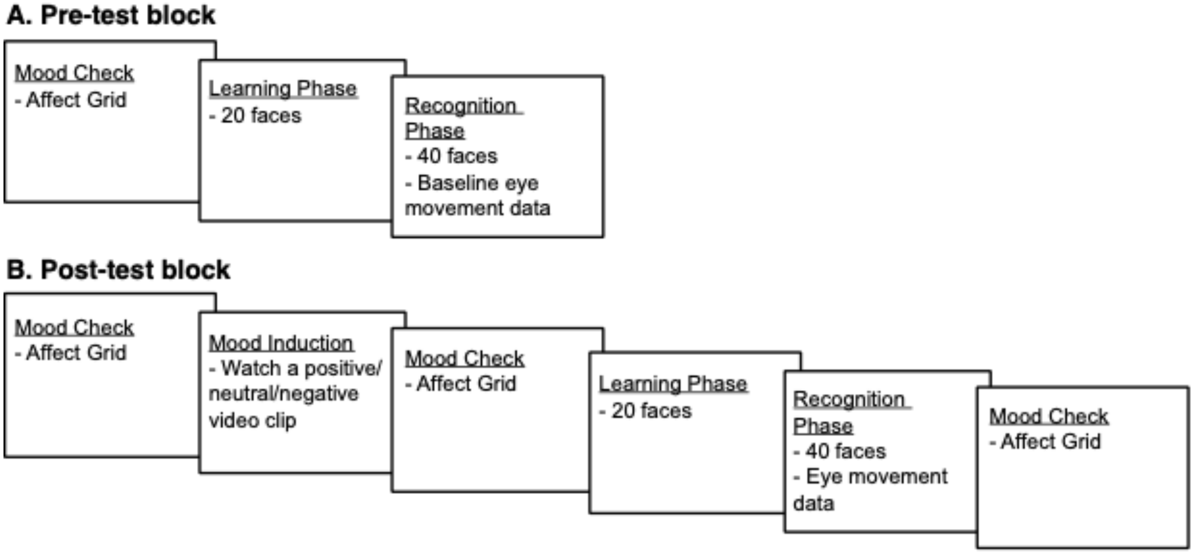


Figure 1. (A) Procedure of the pre-induction block. (B) Procedure of the post-induction block. There was at least one-week break between the two blocks.

In the pre-induction block, participants filled in the Affect Grid for a baseline mood check before the face recognition task. The task consisted of a learning phase and a recognition phase. In the learning phase, participants were presented with 20 face images, one at a time (10 male and 10 female), each for 5 s, and instructed to remember the faces. In the recognition phase, they were presented with the 20 old faces together with 20 new faces, one at a time, and asked to judge whether they saw the face during the learning phase; the face stayed on the screen until their response. Each trial began with a fixation dot at the center of the screen for drift correction; when the participant's eye fixation coincided with the dot, the experimenter pressed a button to initiate image presentation. The image was presented at one of the four quadrants of the screen in a random order until response. In the post-induction block, they filled in the Affect Grid, received either a positive, neutral, or negative mood induction by watching video clips, and then filled in the Affect Grid again. This was followed by the face recognition task with a different set of faces from the pre-induction block. After the task, they completed a final mood check with the Affect Grid. The images used in the pre- and post-induction blocks, as well as those used as old (i.e., presented during the learning phase) and new (i.e., distractor faces used in the recognition phase) faces, were counterbalanced across participants. The procedure is outlined in Figure 1. The study was approved by Human Research Ethics Committee at University of Hong Kong.

Participants' eye movements were recorded using an EyeLink 1000 eye tracker with a desktop mount. A chinrest was used to minimize head movements. Pupil and corneal reflection tracking mode were used with a sampling rate of 1000Hz. EyeLink default settings for cognitive research were used for data collection, i.e. saccade motion threshold of 0.1 degree of visual angle, saccade acceleration threshold of 8000 degree/square second, and saccade velocity threshold of 30 degrees. Before each learning and recognition phase, a nine-point calibration procedure was performed. Re-calibration took place whenever drift correction error exceeded 1° of visual angle. The EMHMM toolbox (Chuk et al., 2014; http://visal.cs.cityu.edu.hk/research/emhmm/) was used to analyze eye movement data, as introduced below. The data that support the findings of this study are openly available at http://doi.org/10.17605/OSF.IO/GHXQ3.

Eye Movement analysis with Hidden Markov Models (EMHMM)

Recent studies have reported substantial individual differences in eye movement in cognitive tasks (e.g., Peterson & Eckstein, 2013; Kanan, Bseiso, Ray, Hsiao, & Cottrell, 2015; Mehoudar, Arizpe, Baker, & Yovel, 2014). The EMHMM approach aims to reflect these individual differences in eye movement data analysis. It is based on the assumption that current eye fixation in a visual task is conditioned on previous fixations; thus, eye movements may be considered a Markovian stochastic process, which can be better understood using hidden Markov models (HMMs). Each person's eye movement pattern is summarized in terms of both person-specific ROIs and transitions among the ROIs in an HMM, with the parameters estimated from the individual's data using the Variational Bayesian Expectation Maximization (VBEM) algorithm (Bishop, 2006). The ROIs are estimated as Gaussian emissions, and the number of ROIs is automatically determined from a pre-set range through a variational Bayesian approach. Individual HMMs can be clustered according to their similarities using the variational hierarchical expectation maximization (VHEM) algorithm (Coviello, Chan, & Lanckriet, 2014) to reveal common strategies. Similarity between an individual pattern and a common strategy can be quantitatively assessed by estimating the likelihood of the pattern being generated by the strategy HMM. Thus, EMHMM takes individual differences in both temporal and spatial dimensions of eye movements into account, and provides quantitative measures of eye movement pattern similarities among individuals (For more details about the EMHMM methodology, please refer to Chuk et al., 2014, and Chuk, Crookes, et al., 2017). Here, we used one HMM to summarize a participant's eye movement pattern in a face recognition task. Thus, each participant had two HMMs, with each corresponding to eye movement pattern in the pre-induction and post-induction recognition phase respectively. We then clustered all HMMs into two representative strategies, and then calculated the log-likelihood of each individual's eye movement pattern (in the pre- and post-induction recognition phase separately) being generated by the representative strategy HMMs as the eye movement pattern similarity measures. This allowed us to quantitatively measure the amount of eye movement pattern change and assess its relationship with mood change and face recognition performance change.

Following previous studies, in the analysis we included only the first three eye fixations on the face area (e.g., Chan et al., 2018; Chuk et al., 2014, 2017; Zhang, Chan, Lau & Hsiao, 2019), as early fixations in a trial have been shown to play a more important role in face recognition performance (Hsiao & Cottrell, 2008; Chuk et al., 2017). When training individual HMMs, we used 1 to 6 ROIs as the pre-set range. Each individual model with a specific number of ROIs was trained for 200 times, and the resulting model with the highest data log-likelihood was used in the analysis. In previous studies implementing the EMHMM method, individual models for face recognition typically had a median of 3 (e.g. Chan et al., 2017; Chuk, Crookes et al., 2017; Zhang et al., 2019) or 4 (e.g. Chuk, Chan et al., 2017) ROIs. We selected a range of 1 to 6 ROIs to ensure the algorithm covered variations in individual data. When we clustered individual HMMs, since the VHEM algorithm for clustering HMMs (Coviello et al., 2014) requires a predefined number of clusters and ROIs for generating representative HMMs of the clusters, following previous studies (e.g., Chuk, Chan et al., 2017; Chan et al., 2018; Zhang et al., 2017), we set the number of clusters to two and used the median number of ROIs among the individual models. The clustering algorithm was run for 200 times with a different initialization, and the result with the highest data log-likelihood was used in the analysis.

Results

Mood Induction Manipulation Check

To check whether the participants had comparable baseline moods between the pre- and post-induction blocks, we used a Wilcoxon signed-rank test. The results showed that the participants did not have a significant difference in baseline valence rating between the two blocks, $Z = -1.29$, $p = 0.20$.

To check the effectiveness of mood induction procedure, we conducted a one-way ANCOVA to compare mood ratings collected after mood induction of the three mood induction groups (positive vs. neutral vs. negative mood induction) whilst controlling for mood ratings collected before mood induction. There was a significant difference in mood ratings after mood induction between the mood induction groups, $F(2, 86) = 71.57$, $p < .001$, $\eta_p^2 = .63$. Post-hoc tests showed that positive mood induced participants had a significantly higher mood ratings compared with neutral mood induced participants, $t = 2.97$,

$p = .011$, $d = .69$, as well as compared with negative mood induced participants, $t = 11.53$, $p < .001$, $d = 2.55$, after mood induction. In addition, negative mood induced participants had a significantly more negative mood rating compared with neutral mood induced participants, $t = 8.56$, $p < .001$, $d = -1.89$, after mood induction.

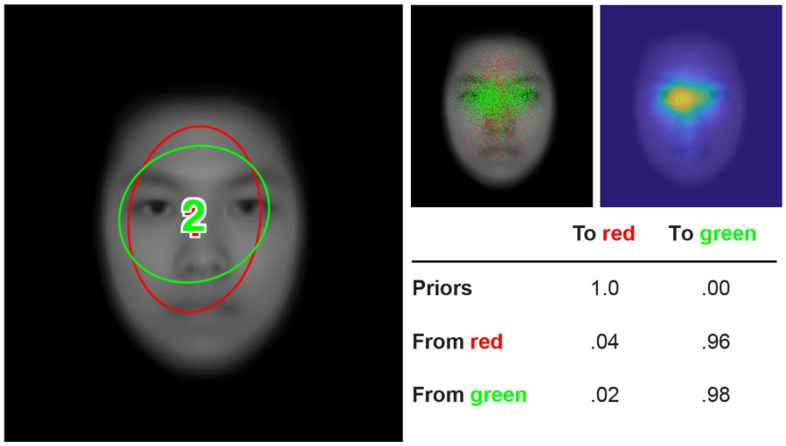
To check whether the induced moods were sustained throughout the face recognition task, we conducted a Wilcoxon Signed-rank test to compare valence ratings collected after mood induction (and before the face recognition task) with those collected after the face recognition task. Participants receiving negative mood induction showed an increase in valence rating after the task ($M = -0.50$, $SD = 1.50$), $Z = -3.36$, $p < .001$, $r = .75$, and those receiving positive mood induction showed a decrease in valence rating after the task ($M = 1.07$, $SD = 1.34$), $Z = 3.34$, $p < .001$, $r = .75$. Thus, participants' moods were neutralized during the face recognition task. However, an ANCOVA with mood ratings collected before mood induction as a covariate showed that the three groups still had significantly different mood ratings after the recognition task, $F(2, 86) = 15.34$, $p < .001$, $\eta_p^2 = .26$. Post-hoc tests showed that participants who received negative mood induction had significantly more negative valence ratings than those who received neutral, $t = 4.11$, $p < .001$, $d = -.83$, and positive mood induction, $t = 5.28$, $p < .001$, $d = 1.10$; however, those who received positive mood induction did not differ significantly in their valence rating after the recognition test from those who received neutral mood induction, $t = 1.17$, $p = .47$, $d = .30$.

Eye Movement Strategies

Learning phase. Each participant's eye movements during the learning phase was summarized using an HMM, separately for the pre- and post-induction blocks. Thus, we had 90 HMMs for pre-induction block, and 90 for post-induction block, summing up to

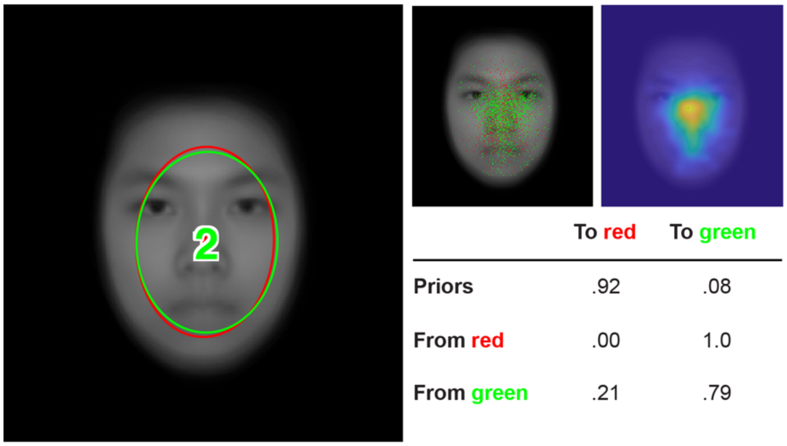
180 HMMs in total. The individual HMMs were then clustered into two groups to discover common strategies across participants. Following previous studies, we pre-specified the number of ROIs of the representative strategies as two, which was the median number of ROIs among the individual HMMs (the number of ROIs in each individual HMM was estimated using a variational Bayesian approach, and thus individual HMMs may have different numbers of ROIs). The clustering result is shown in Figure 2.

A. Eyes-focused strategy



	To red	To green
Priors	1.0	.00
From red	.04	.96
From green	.02	.98

B. Nose-focused strategy



	To red	To green
Priors	.92	.08
From red	.00	1.0
From green	.21	.79

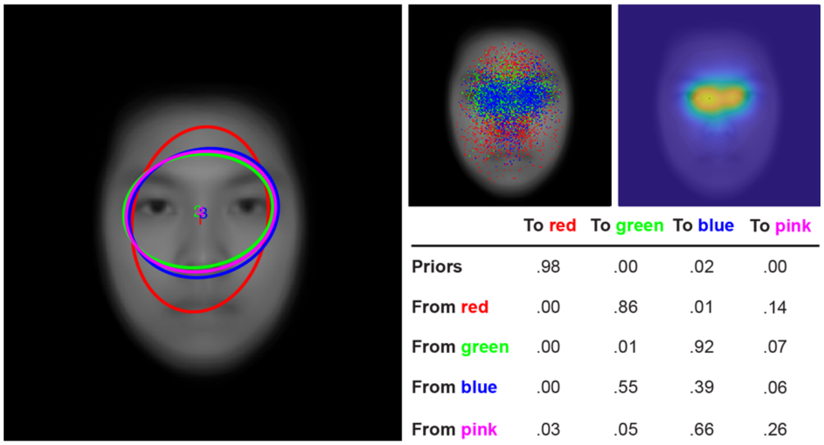
Figure 2. The two representative strategies in the learning phase. The ellipses show ROIs as Gaussian emissions with the border of the ellipses showing two standard deviations from the mean. The small images to the right show the distribution of actual fixations with the

color representing assignment to the ROI with the highest likelihood, and a corresponding heatmap, respectively. The table shows transition probabilities among the ROIs; priors show the probabilities that a fixation sequence starts from the ROI.

The eyes-focused strategy consisted of relatively more compact ROIs that centered around the midpoint between the eyes. All initial fixations occurred at the red region, which covers both the eyes and the nose. The subsequent fixations occurred at a narrower region around the eyes (red to green, p = .96). Participants were most likely to remain in this region (green to green, p = .98). The fixation plot shows a greater density of fixations around the eyes. This group consisted of 117 HMMs. In contrast, the nose-focused strategy consisted of two bigger ROIs centering at the middle of the nose. This group had 63 HMMs.

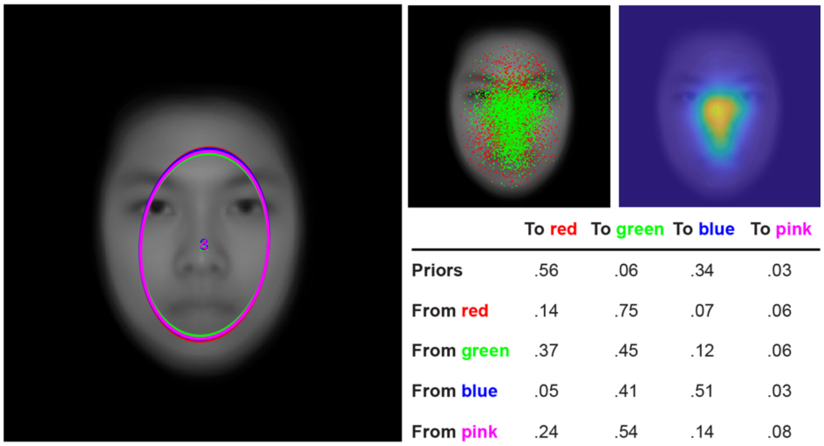
Recognition phase. we summarized each participant’s eye movements during the recognition phase into an HMM, separately for the pre- and post-induction blocks. Then the individual HMMs were clustered into two groups. The number of ROIs for the representative HMMs was set to 4, which was the median number of ROIs among the individual HMMs. Consistent with the learning phase eye movement data, we found an eyes-focused strategy and a nose-focused strategy. As shown in Figure 3, in the eyes-focused strategy, all ROIs centered around the midpoint between the eyes. Most initial fixations were located at the red region (prob. = 0.98), which covers a wider area around the eyes and the nose. The subsequent fixations converged at a narrower region around the eyes. This strategy is comparable to the analytic eye movement strategy discovered in previous studies (e.g. Chuk et al., 2014; Chuk et al., 2017), which also consisted of fixations around the eyes in addition to the face center. This group had 101 HMMs. In contrast, the nose-focused strategy had four, nearly identical ROIs centering at the middle of the nose. It is analogous to the holistic eye movement strategy discovered in previous studies (e.g. Chuk et al., 2014; Chuk et al., 2017). This group had 79 HMMs. Note that for both learning and recognition phases, both strategies had fixations across the face center; however, we labeled them as eyes-focused and nose-focused to highlight relative differences in the density of fixations on the eyes versus the nose. According to the clustering results, each participant's eye movement pattern during the pre- and post-induction blocks could be classified into either the eyes-focused or the nose-focused strategy.

A. Eyes-focused strategy



	To red	To green	To blue	To pink
Priors	.98	.00	.02	.00
From red	.00	.86	.01	.14
From green	.00	.01	.92	.07
From blue	.00	.55	.39	.06
From pink	.03	.05	.66	.26

B. Nose-focused strategy



	To red	To green	To blue	To pink
Priors	.56	.06	.34	.03
From red	.14	.75	.07	.06
From green	.37	.45	.12	.06
From blue	.05	.41	.51	.03
From pink	.24	.54	.14	.08

Figure 3: The two representative strategies in the recognition phase. The ellipses show ROIs as Gaussian emissions with the border of the ellipses showing two standard deviations from the mean. The small images to the right show the distribution of actual fixations with the color representing assignment to the ROI with the highest likelihood, and a corresponding heatmap respectively. Note that some ROIs with very low probability of being used may not show any fixation in the fixation plot. The table shows transition probabilities among the ROIs; priors show the probabilities that a fixation sequence starts from the ROI.

In addition to participants' eye movement strategy classification, we also quantitatively assessed participants' eye movement pattern similarities using the EMHMM method. To do so, for each participant's eye movement data, its log-likelihoods of being generated by the representative HMMs of the eyes-focused and the nose-focused strategy were calculated. The log-likelihood indicates how similar one's eye movement pattern is to the common strategy. To quantitatively assess individual patterns' similarities along the eyes-focused and nose-focused strategy dimension, following previous studies (Chan et al., 2018), we defined the eyes-nose scale as below:

$$\text{Eyes-Nose Scale} = (E-N) / (|E| + |N|)$$

where E stands for the log-likelihood of being generated by the eyes-focused strategy HMM, and N for the log-likelihood of being generated by the nose-focused strategy HMM. A more positive eyes-nose scale value indicates greater resemblance to the eyes-focused strategy, and a more negative value indicates greater similarity to the nose-focused strategy. We calculated the eyes-nose scale separately for the learning phase and the recognition phase eye movement data. We used the eyes-nose scale as a measure of participants' eye movement pattern and examined its relationship with mood change and recognition performance.

Effect of mood change on recognition performance and eye movement pattern within participants

Table 1.

Linear mixed effects analysis by valence change and block.

Parameter	β	SE	95% CI [LL, UL]	t	p
Learning phase eyes-nose scale					
Valence change	0.00028	0.0011	[-.0019, .0024]	1.02	0.23
Block	0.0022	0.0028	[-.0034, .0078]	0.26	0.80
Interaction	-0.00068	0.0010	[-.0027, .00014]	-0.66	0.51
Recognition phase eyes-nose scale					
Valence change	0.0015	0.0013	[-.0010, .0041]	1.21	0.23
Block	0.0055	0.0026	[.00035, .011]	2.12	0.037
Interaction	-0.0019	0.00094	[-.0038, -.000071]	-2.06	0.043
Recognition task performance					
Valence change	0.023	0.027	[-.029, .076]	0.881	0.38
Block	-0.18	0.068	[-.32, -.050]	-2.72	0.0078
Interaction	-0.039	0.025	[-.088, .0097]	-1.59	0.12

Learning phase eye-nose scale. The linear mixed-effects model analysis on learning phase eyes-nose scale did not show a significant main effect of block, β = .0022, 95% CI [-.0034, .0078], t(90) = .44, p = .80, nor a significant interaction between block and valence change, β = -.00068, 95% CI [-.0027, .00014], t(90) = -.66, p = .51. Main effect of valence change was also not significant, β = .00028, 95% CI [-.0019, .0024], t(138.10) = .26, p = .80

(Table 1)[1]. These results suggest that mood change was not associated with changes in eye movement pattern in the learning phase. Consistently, valence change across blocks was not correlated with learning phase eyes-nose scale change across blocks, r(88) = .070, p = .51, 95% CI [-.27, .14] (Figure 5A).

Recognition phase eyes-nose scale. A similar linear mixed-effects model analysis on recognition phase eyes-nose scale yielded a significant main effect of block, β = .0055, 95% CI [.00035, .011], t(90) = 2.12, p = .037, and a significant interaction between block and valence change, β = -.0019, 95% CI [-.0038, -.00071], t(90) = -2.057, p = .042 (Table 1)[2]. A correlation analysis revealed a significant negative correlation between valence change and eye movement pattern change, r(88) = -.21, p = 0.045, 95% CI = [-.40, -.0050] (Figure 5B): the more negative the valence change, the larger the increase in eyes-nose scale. These results

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[1] In a separate analysis, we classified participants into two groups - those with a positive valence change (n = 40, 27 females; 24 received positive mood induction, 12 neutral mood induction, and 4 negative mood induction) and those with a negative valence change (n = 36, 20 females; 25 received negative mood induction, 9 neutral mood induction, and 2 positive mood induction) across the blocks. A 2 (pre- vs. post-induction block) x 2 (positive vs. negative mood change group) ANOVA showed similar results: no main effect of block, F(1, 74) = 1.02, MSE < .001, p = .32, main effect of valence change group, F(1, 74) = .29, MSE = .001, p = .59, or interaction between block and mood change group, F(1, 74) = 2.02, MSE < .001, p = 0.16.

[2] Similar results were obtained using ANOVA: a significant main effect of block, F(1, 74) = 6.03, MSE < .001, p = .016, , 90% CI for = [.0076, .18], and a significant interaction between block and mood change group, F(1, 74) = 5.35, MSE < .001, p = 0.023, , 95% CI for = [.0048, .17]: the negative mood change group had a significant increase in eyes-nose scale, t(35) = -3.08, p =.004, d = -.36, 95% CI for d = [-.61, -.12], whereas the positive mood change group did not have a significant change, t(39) = -.11, p = 0.91. Note that the negative and positive mood change groups did not differ significantly in eyes-nose scale in the pre-induction block, t(69.07) = -1.24, p = .22, suggesting that the difference between the two groups was not due to a difference in baseline eye movement behavior in the pre-induction block.

were consistent with our hypothesis that participants with a negative mood change would have increased similarity to the eyes-focused strategy due to increased local attention engagement (See also Figure 4).

Recognition task performance. A similar linear mixed-effects model analysis was conducted on recognition performance. The results revealed a main effect of block, β = -.18, 95% CI [-.32, -.050], t(90) = -2.72, p = .0078. Participants performed worse in the post-induction block as compared with the pre-induction block. There was no main effect of valence change, β = .023, 95% CI [-.029, .076], t(135.49) = .88, p = .38, or interaction effect between block and valence change, β = -.039, 95% CI [-.088, .0097], t(90) = -1.59, p = .12 (Table 1)[3]. These results showed that the positive and negative mood change groups did not differ significantly in either overall recognition performance or performance change between the pre- and post-induction blocks, in contrast to the results in eye movement pattern. Consistent with this finding, there was no correlation between participants' valence change and performance change, r(88) = -.16, p =.12, 95% CI [-.36, .044] (Figure 5C).

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[3] Similar results were obtained using ANOVA: a main effect of block, F(1,74) = 10.18, MSE = .21, p = .002, , 90% CI for = [.028, .24], and no main effect of mood change group, F(1, 74) = .16, MSE = .82, p = .69, or interaction effect between block and mood change group, F(1, 74) = .94, MSE = .21, p = .34.

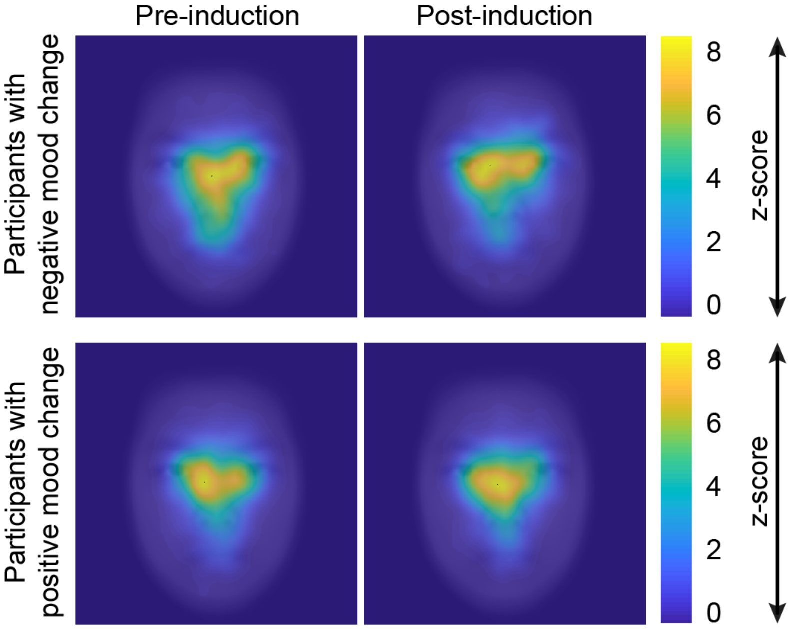

Figure 4. Heatmaps of recognition phase eye movement in pre- vs. post-induction blocks of negative and positive mood change groups.

The findings presented above suggest that mood change modulates eye movement patterns in face recognition; however, this change in eye movement pattern does not lead to a change in recognition performance. This result is in contrast to those from previous studies, where more eyes-focused eye movement patterns were associated with better recognition performance across participants (e.g., Davis et al., 2017; Chuk et al., 2017; Chuk, Crooke, Hayward, Chan, & Hsiao, 2017; Chan et al., 2018). To examine whether this association could also be observed in the current data, we examined the correlation between recognition performance (D') and eye movement pattern (eyes-nose scale) across the pre- and post-induction blocks. Consistent with previous studies, the result showed a significant positive correlation, r(178) = .17, p = .026, 95% CI [.020, .20] (Figure 6B; similarly for eye movement pattern during the learning phase; Figure 6A): the more eyes-focused the eye movement pattern, the better the recognition performance. Thus, while a significant correlation between eye movement pattern and recognition performance was observed across participants, within-participant changes in eye movement pattern due to mood changes do not seem to modulate recognition performance[4]. Indeed, changes in eye movement pattern between the pre- and post-induction blocks did not correlate significantly with changes in recognition performance, for both the learning phase, r(88) = .04, p = .71, 95% CI [-.17, .25] (Figure 6C)[5], and the recognition phase, r(74) = -.002, p = .99, 95% CI [-.21, .21] (Figure 6D)[6].

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[4] In a separate analysis, we tested the mediation effect of recognition phase eye movement pattern change between mood change and recognition performance change. The regression analysis showed that the mediator, recognition phase eye movement pattern change, was not a significant predictor of recognition performance change when controlling for mood change, b = -1.00, t(73) = -.36, p = .72. Also, mood change was not a significant predictor of recognition performance change when controlling for the mediator eye movement pattern change. Thus, although mood change predicted changes in recognition phase eye movement pattern, it did not predict recognition performance change and the relationship was also not mediated by recognition phase eye movement pattern change.

[5] The correlations were also not significant when we only included the negative mood change group, r(34) = .13, p = .44, 95% CI [-.21, .44], or only the positive mood change group, r(38) = .11, p = .49, 95% CI [-.21, .41].

[6] Consistently, the correlations were not significant among the negative mood change group, r(34) = -.049, p = .78, 95% CI [-.28, .37], or the positive mood change group, r(38) = -.14, p = .40, 95% CI [-.43, .18].

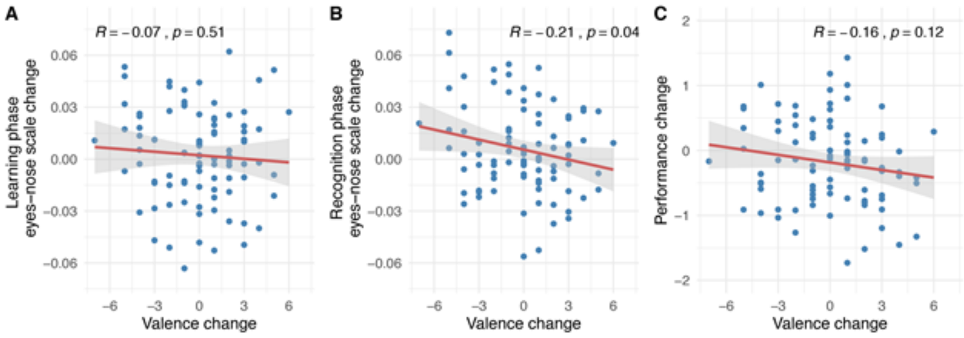

Figure 5: Correlation between valence change and (A) study phase eye movement change, (B) recognition phase eye movement change, and (C) performance change. The grey area indicates 95% confidence interval.

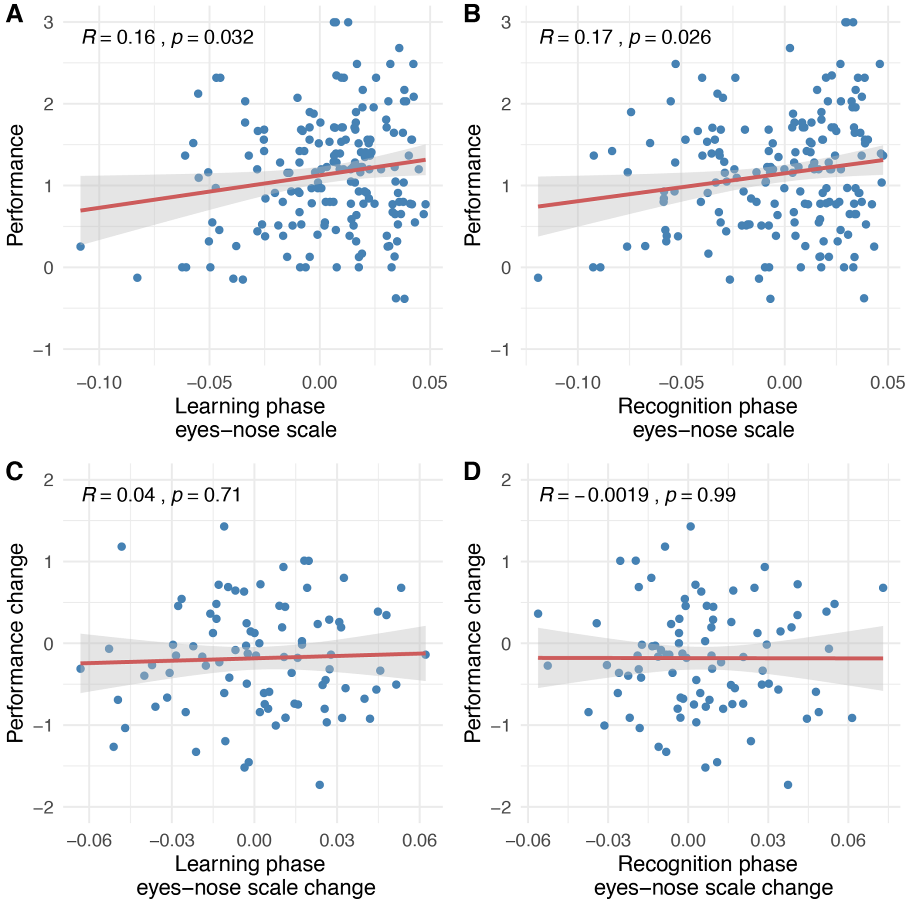

Figure 6: (A, B) Correlation between face recognition performance and eye movement pattern across participants, with eye movement data from (A) the learning phase, and (B) the recognition phase. (C, D) Correlation between within-participant changes in eye movement pattern and recognition performance with eye movement data from (C) the learning phase, and (D) the recognition phase. The grey area indicates 95% confidence interval.

The results above showed that participants' eye movement pattern similarity during the recognition phase changed as a result of their mood change. We further examined whether this eye movement pattern similarity change significantly changed their eye movement strategy classification (i.e., eyes-focused or nose-focused; Table 2). We found that across the pre- and post-induction blocks, significantly more participants used the same eye movement strategy (86.84%) than a different strategy (13.16%; $\chi^2(1) = 40.88$, $p < .001$). A similar result was observed when we only examined participants with a negative mood change, among whom a significant change in eye movement pattern similarity was observed (80.6% used the same strategy; $\chi^2(1) = 14.77$, $p < .001$). This result suggested that although mood changes may lead to some degree of changes in eye movement pattern similarity, the changes were not sufficient to significantly change their eye movement strategy classification.

Table 2.

Pre-test * Post-test Cross-tabulation of Recognition Phase Eye Movement Group

Post-induction Eye Movement Pattern

		Eyes-focused	Nose-focused	Total
Pre-induction Eye Movement Pattern	Eyes-focused	38	4	42
	Nose-focused	6	28	34
Total		44	32	76

Discussion

Previous research has shown that looking more at the eyes, which is related to the engagement of local face processing (Miellet et al., 2011), predicts better face memory (e.g., Davis et al., 2017; Chuk et al., 2017). This finding suggests that engaging local attention may induce more eye fixations to the eyes during face recognition and consequently lead to better face recognition performance. Here we examined how mood change modulates eye movement pattern and performance in face recognition, as negative mood has been reported to promote local attention (e.g., Gasper & Clore, 2002; Curby et al., 2012) and enhance memory (e.g., Forgas et al., 2008). We hypothesized that a negative mood change would lead to increased eye movement pattern similarity to an eyes-focused strategy due to heightened local attention, and this eye movement pattern change would consequently lead to better recognition performance. We used EMHMM to analyze eye movement data because it provides quantitative measures of eye movement pattern similarity, which is required for assessing eye movement pattern changes.

Through clustering individual eye movement HMMs, we discovered two representative strategies among our participants, namely the eyes-focused and nose-focused strategy, during both face learning (Figure 2) and face recognition (Figure 3). Interestingly, participants' mood change significantly modulated eye movement pattern during face recognition, but not during face learning. Specifically, consistent with our hypothesis, participants with a negative mood change showed increased similarity to the eyes-focused strategy during face recognition, while those with a positive mood change showed no change. In addition, there was a significant correlation between mood change and eye movement pattern change: the more negative the mood change, the more the increase in eye movement pattern similarity to the eyes-focused strategy. In contrast, these effects were not observed during face learning. This result suggested that the effect of mood change on eye movement pattern may depend on take requirements. Indeed, recent studies have suggested that eye movement patterns during visual tasks are related to executive function/planning ability (e.g., Chan et al., 2018; Zhang, Yeh, & Hsiao, 2019; Hsiao, Chan, Du, & Chan, 2019). Thus, it is possible that modulation effects of mood change on eye movement pattern would be better observed in tasks that involve more executive control, such as active extraction of diagnostic information required in face recognition as compared with passive viewing during face learning. Consistent with this speculation, whereas modulation effects of mood were observed in tasks that involve selective attention to specific information such as the composite face task (Curby et al., 2012) and visual search tasks (e.g., Grubert, Schmid, & Krummenacher, 2012), mood did not modulate performance in a change detection task (Bendall & Thompson, 2015), where participants did not have a specific target in mind.

Further research is needed to better understand what type of visual tasks is more susceptible to mood modulation.

Although we observed significant eye movement pattern change due to mood change during face recognition, this eye movement pattern change was not followed by a significant performance change, in contrast to the literature showing an advantage of the eyes-focused strategy in face recognition performance (e.g., Chan et al., 2018; Chuk et al., 2017; Chuk, Crookes, et al., 2017; Davis et al., 2017). More specifically, although previous studies have suggested facilitation effects of negative mood on memory performance, here participants with a positive or a negative mood change did not differ significantly in performance change. In addition, there was no correlation between either mood change and recognition performance change, or eye movement pattern change (during either face learning or face recognition) and performance change. Perhaps, the eye movement pattern similarity change during face recognition due to mood change by the mood induction procedure was not strong enough to modulate performance. Indeed, the correlation between valence change and eye movement changes ($r = -0.21$) indicated a weak relationship. A cross-tabulation analysis revealed that according to participants' eye movement strategy classification from the EMHMM clustering results, the majority of the participants with mood changes adopted an identical eye movement strategy (eyes-focused or nose-focused) after mood induction (84.2%; Table 2). Even for those with a negative mood change, who showed a significant change in eye movement pattern similarity, the majority of them used the same strategy (80.6%). These findings suggested that within-individual mood changes to an extent similar to the mood induction, i.e., watching video clips with emotional contents that are not self-relevant, resulted in slight alterations in eye movement pattern but not a fullblown shift to a different strategy. Although it remains unclear whether a more dramatic mood change would lead to changes in eye movement strategy and recognition performance, the current results suggested that individuals may have preferred processing strategies that are relatively resistant to temporary mood changes, since face recognition is an essential skill that people use on a daily basis.

Indeed, recent research has reported a significant genetic contribution to face recognition ability (Wilmer et al., 2010; Shakeshaft & Plomin, 2015; Zhu et al., 2010), suggesting limited plasticity in adult face recognition performance (Tree et al., 2017). Our results further suggested that this limited plasticity is reflected in eye movement behavior: in the context of face recognition, although negative mood through mood induction promoted local attention to the eyes, it elicited limited changes in eye movement pattern, and consequently the change was not sufficient to modulate face recognition performance. The EMHMM method provides quantitative measures of eye movement pattern change, allowing us to reveal the cognitive mechanism underlying limited plasticity in adult face recognition. This limited plasticity in eye movement planning behavior may be due to adults' abundant experience in face recognition, which may have led to an optimal eye movement strategy given an individual's cognitive capacity limit. Consistent with this speculation, recent research has suggested that eye movement behavior in face processing reflects individual differences in cognitive capacity. For example, Chan et al. (2018) reported that eye movement patterns in face recognition predicted older adults' cognitive decline, especially in executive function and visual attention ability. Zhang et al. (2019) showed that eye movements in facial expression recognition reflected deficits in attention control in those with insomnia symptoms.

These findings suggest the possibility of using eye movements in face processing for cognitive deficit screening purposes.

Note that in the current study, whereas participants with a negative mood change showed a significant increase in eye movement pattern similarity to the eyes-focused strategy, those with a positive mood change did not have a significant change in eye movement pattern. This finding was in contrast to previous research suggesting that a positive mood change would promote global attention engagement (e.g., Gasper & Clore, 2002), which could result in a decrease in similarity to the eyes-focused strategy. A similar phenomenon has been reported in holistic face processing: a negative mood change through mood induction significantly decreased holistic processing, whereas no significant change in holistic processing was observed after a positive mood change (Curby et al., 2012). The null modulation effect of positive mood change may be related to the global precedence effect, which refers to the phenomenon that the global form of a visual stimulus is unavoidably recognized before local features (Navon, 1977). Thus, participants may tend to engage global processing first in a trial, leaving less room for further enhancement in global processing due to a positive mood change through mood induction. Alternatively, Huntsinger, Clore, and Bar-Anan (2010) proposed that positive mood may empower whatever strategy that is more momentarily available. In their study, for participants primed with words related to global focus, positive mood induction increased the usage of global processing, whereas for those primed with a local focus, positive mood induction promoted attending to local details. Similarly, Bless and Fiedler (2006) postulated that negative mood signals a novel or challenging situation that requires a more focused, bottom-up processing, whereas positive mood calls for a top-down processing with greater reliance on existing heuristics. Accordingly, in the current study, participants with a negative mood change might have been prompted to shift their processing to be more local/analytic, whereas those with a positive mood change simply continued using their dominant processing style.

In the current study, we did not observe any modulation effect of mood change on face recognition performance. This result is consistent with Hills, Werno, and Lewis (2011), in which participants with different mood states did not differ significantly in face recognition performance. In addition, we found that participants performed worse in the post-induction block than the pre-induction block regardless of their mood changes, suggesting that mood induction through video viewing may have increased cognitive load for visual processing and consequently impaired subsequent recognition performance (e.g. Moreno & Mayer, 1999). Note however that in Hills et al. (2011), mood was found to influence recognition performance under an incidental learning condition where participants were instructed to rate the faces in distinctiveness during the learning phase without knowing about the recognition phase. Perhaps using a rating/judgment task during face learning could better engage participants' attention, making it more susceptible to mood modulation. Alternatively, the null effect of mood change on recognition performance, as well as the small effect size of the mood modulation on eye movement pattern, may be related to the dwindled mood induction effect during the recognition phase (e.g., Mokhtari & Buttle, 2015). Future work will examine these possibilities.

To conclude, here we showed that within-subject changes in mood through mood induction modulate eye movement pattern but not performance in face recognition. Although a negative mood change due to mood induction led to increased eye movement pattern similarity to an eyes-focused strategy, and the eyes-focused strategy was found to be linked with better recognition performance across participants, the amount of change in eye movement pattern similarity due to the mood change did not seem to significantly modulate recognition performance. As the mood change did not significantly change participants' eye movement strategy classification despite a significant change in eye movement pattern similarity, the amount of eye movement pattern change due to the mood change may not be sufficient to significantly change recognition performance. These results suggest that while mood changes may modulate eye movement patterns due to changes in attention engagement, individuals may have preferred eye movement strategies for face processing that are impervious to the influence of transitory mood changes, at least to an extent similar to the mood induction. This finding is consistent with the recent speculation on limited plasticity in adult face recognition performance due to adults' expertise in face recognition and the high heritability of face recognition ability. It also suggests that eye movement patterns in face recognition may provide reliable information about an individual's cognitive abilities.

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References

Bartlett, J. C., & Searcy, J. (1993). Inversion and configuration of faces. *Cognitive Psychology*, 25, 281-316.

Barton J. J., Keenan J. P., Bass T. (2001). Discrimination of spatial relations and features in faces: effects of inversion and viewing duration.' *British Journal of Psychology*, *92*, 527 – 549.

Вдuml, K., & Kuhbandner, C. (2007). Remembering Can Cause Forgetting—but Not in Negative Moods. *Psychological Science, 18(2)*, 111-115. doi:10.1111/j.1467-9280.2007.01857.x

Bless, H., & Fiedler, K. (2006). Mood and the regulation of information processing and behavior. In J. P. Forgas (Ed.), *Affect in social thinking and behavior*. New York, NY, US: Psychology Press.

Bombari, D. , Mast, F. W. , Lobmaier, J. S. (2009). Featural, configural, and holistic face-processing strategies evoke different scan patterns. *Perception, 38(10),* 1508–1521.

Bruce, H. L. V. (1998). Local and relational aspects of face distinctiveness. *The Quarterly Journal of Experimental Psychology: Section A, 51(3),* 449–473.

Burton, A. M., Schweinberger, S. R., Jenkins, R., & Kaufmann, J. M. (2015). Arguments against a configural processing account of familiar face recognition. *Perspectives on Psychological Science, 10(4)*, 482-496.

Cabeza, R., & Kato, T. (2000). Features are also important: Contributions of featural and configural processing to face recognition. *Psychol. Sci.,11(5)*, 429-433.

Chan, C. Y., Chan, A. B., Lee, T. M., & Hsiao, J. H. (2018). Eye-movement patterns in face recognition are associated with cognitive decline in older adults. *Psychonomic Bulletin & Review, 25*(6), 2200-2207.

Cheng, Z., Chuk, T., Hayward, W. G., Chan, A. B., & Hsiao, J. H. (2015). Global and local priming evoke different face processing strategies: evidence from an eye movement study. *Journal of Vision, 15*(12), 154.

Chepenik, L. G., Cornew, L. A., & Farah, M. J. (2007). The influence of sad mood on cognition. *Emotion, 7(4),* 802-811.

Chuk, T., Chan, A. B., & Hsiao, J. H. (2017). Is having similar eye movement patterns during face learning and recognition beneficial for recognition performance? Evidence from hidden Markov modeling. *Vision Research, 141*, 204-216.

Chuk, T., Chan, A. B., & Hsiao, J. H. (2014). Understanding eye movements in face recognition using hidden Markov models. *Journal of Vision*, 14(11), 1–14.

Chuk, T., Crookes, K., Hayward, W. G., Chan, A. B., & Hsiao, J. H. (2017). Hidden Markov model analysis reveals the advantage of analytic eye movement patterns in face recognition across cultures. *Cognition*, 169, 102-117.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Coviello, E., Chan, A. B., & Lanckriet, G. R. (2014). Clustering hidden Markov models with variational HEM. *Journal of Machine Learning Research*, 15(1), 697–747.

Curby, K. M., Johnson, K. J., & Tyson, A. (2012). Face to face with emotion: Holistic face processing is modulated by emotional state. *Cogn. Emot.,* 26(1), 93-102.

Davidoff, J., & Donnelly, N. (1990). Object superiority effects: Complete versus part probes. Acta Psychologica, 73, 225–243.

Davis, J., McKone, E., Zirnsak, M., Moore, T., O'Kearney, R., Apthorp, D. & Palermo, R. (2017). Social and attention-to-detail subclusters of autistic traits differentially predict looking at eyes and face identity recognition ability. *British Journal of Psychology*, *108*(1), 191-219.

Deaver, C. M., Miltenberger, R. G., Smyth, J., Meidinger, A., & Crosby, R. (2003) An evaluation of affect and binge eating. *Behavior Modification, 27*, 578-599.

Devue, C., & Barsics, C. (2016). Outlining face processing skills of portrait artists: Perceptual experience with faces predicts performance. *Vision Research, 127*, 92–103.

Donnelly, N., & Davidoff, J. (1999). The mental representations of faces and houses: Issues concerning parts and wholes. Visual Cognition, 6(3/4), 319–343.

Bates, D., Maechler, M. Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67(1)*, 1-48. doi:10.18637/jss.v067.i01.

Eich, E., Macauley, D., & Ryan, L. (1994) Mood dependent memory for events of the personal past. *Journal of Experimental Psychology: General, 123*, 201-215.

Forgas, J. P., Goldenberg, L., & Unkelbach, C. (2009). Can bad weather improve your memory? An unobtrusive field study of natural mood effects on real-life memory. *Journal of Experimental Social Psychology, 45(1)*, 254-257. doi:10.1016/j.jesp.2008.08.014

Freire A., Lee K., Symons L. A. (2000). The face-inversion effect as a deficit in the encoding of configural information: direct evidence. *Perception, 29,* 159 – 170.

Gasper, K., &amp; Clore, G. L. (2002). Attending to the big picture: Mood and global versus local processing of visual information. *Psychol. Sci.,13(1),* 34-40.

Gerrard-Hesse, A., Spies, K., and Hesse, F. W. (1994). Experimental inductions of emotional states and their effectiveness: a review. Br. J. Psychol. 85, 55–78.

Goffaux, V., & Rossion, B. (2006). Faces are "spatial" – Holistic face perception is supported by low spatial frequencies. Journal of Experimental Psychology: Human Perception and Performance, 32, 1023–1039.

Hammersley, R., Reid, M. & Atkin, S.L. (2014). How to measure mood in nutrition research. *Nutrition Research Reviews. 27*, 284–294.

Hayward, W. G., Crookes, K., & Rhodes, G. (2013). The other-race effect: Holisticcoding differences and beyond. *Visual Cognition, 21*, 1224–1247

Hayward, W. G., Rhodes, G., & Schwaninger, A. (2008). An own-race advantage for components as well as configurations in face recognition. *Cognition, 106*, 1017-1027.

Hills, P. J., Werno, M. A., & Lewis, M. B. (2011). Sad people are more accurate at face recognition than happy people. *Conscious. Cogn.*, 20(4), 1502-1517.

Hsiao, J. H., Chan, K. Y., Du, Y. & Chan, A. B. (2019). Understanding individual differences in eye movement pattern during scene perception through hidden Markov modeling. In A.K. Goel, C.M. Seifert, & C. Freksa (Eds.), *Proceedings of the 41st Annual Conference of the Cognitive Science Society* (pp. 3283). Montreal, QB: Cognitive Science Society.

Hsiao, J. H., & Cottrell, G.W. (2008). Two fixations suffice in face recognition. *Psychol. Sci., 19*(10), 998-1006.

Huntsinger, J. R., Clore, G. L., & Bar-Anan, Y. (2010). Mood and global–local focus: Priming a local focus reverses the link between mood and global–local processing. *Emotion, 10*(5), 722-726.

Kanan, C., Bseiso, D. N., Ray, N. A., Hsiao, J. H., & Cottrell, G. W. (2015). Humans have idiosyncratic and task-specific scanpaths for judging faces. *Vision Research,108*, 67-76.

Kemp R., McManus C., Piggot T. (1990). Sensitivity to the displacement of facial features in negative and inverted images. *Perception, 19,* 531 - 543

Kimchi, R., & Palmer, S. E. (1982). Form and texture in hierarchically constructed patterns. *Journal of Experimental Psychology: Human Perception and Performance, 8(4),* 521-535. doi:10.1037//0096-1523.8.4.521

Konar, Y., Bennett, P. J., & Sekuler, A. B. (2010). Holistic processing is not correlated with face-identification accuracy. *Psychological Science, 21(1),* 38–43.

Kuznetsova A., Brockhoff P. B., & Christensen R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software, 82(13)*, 1-26. doi:10.18637/jss.v082.i13.

Le Grand, R., Mondloch, C. J., Maurer, D., & Brent, H. P. (2004). Impairment in holistic processing following early visual deprivation. Psychological Science, 15, 762–768.

McKone, E. (2008). Configural processing and face viewpoint. Journal of Experimental Psychology: Human Perception and Performance, 34, 310–327.

Mehoudar, E., Arizpe, J., Baker, C. I., & Yovel, G. (2014). Faces in the eye of the beholder: Unique and stable eye scanning patterns of individual observers. *Journal of Vision, 14*(7), 6.

Miellet, S., Caldara, R., & Schyns, P. G. (2011). Local Jekyll and Global Hyde The Dual Identity of Face Identification. *Psychol. Sci.,* 22(12), 1518-1526.

Mokhtari, S., & Buttle, H. (2015). The Effect of Observers' Mood on the Local Processing of Emotional Faces: Evidence from Short-Lived and Prolonged Mood States. Advances in Cognitive Psychology,11(1), 14-21. doi:10.5709/acp-0165-3

Mondloch, C. J., Elms, N., Maurer, D., Rhodes, G., Hayward, W. G., Tanaka, J. W., & Zhou, G. (2010). Processes underlying the cross-race effect: An investigation of holistic, featural, and relational processing of own- vs other-race faces. *Perception, 39*, 1065-1085.

Moreno, R. & Mayer, R. (1999). "Cognitive principles of multimedia learning: The role of modality and contiguity". Journal of Educational Psychology. 91 (2): 358–368.

Navon D. (1977). Forest before trees: The precedence of global features in visual perception. *Cognitive psychology*, 9(3), 353–83.

Peterson, M. F., & Eckstein, M. P. (2013). Individual Differences in Eye Movements During Face Identification Reflect Observer-Specific Optimal Points of Fixation. *Psychological Science, 24*(7), 1216-1225.

R Core Team (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Rakover, S. S. & Teucher, B. (1997). Facial inversion effects: part and whole relationship. Perception & Psychophysics, 59, 752-761.

Rakover, S. S. & Teucher, B. (1997). Facial inversion effects: part and whole relationship. Perception & Psychophysics, 59, 752-761.

Rezlescu, C., Susilo, T., Wilmer, J. B., & Caramazza, A. (2017). The inversion, part-whole, and composite effects reflect distinct perceptual mechanisms with varied relationships to face recognition. *Journal of Experimental Psychology: Human Perception and Performance, 43(12)*, 1961– 1973.

Richler, J. J., Cheung, O. S., & Gauthier, I. (2011). Holistic processing predicts face recognition. *Psychological Science, 22(4)*, 464–471.

Richler, J. J., Floyd, R. J., & Gauthier, I. (2015). About-face on face recognition ability and holistic processing. *Journal of Vision, 15*, 1–12.

Rhodes, G., Ewing, L., Hayward, W. G., Maurer, D., Mondloch, C. J., & Tanaka, J. W. (2009). Contact and other-race effects in configural and component processing of faces. British *Journal of Psychology, 100*, 717-728.

Russell, J. A., Weiss, A., & Mendelsohn, G. A. (1989). The affect grid: A single-item scale of pleasure and arousal. *J. Pers. Soc. Psychol.*, 57, 493-502.

Schmid, P. C., Mast, M. S., Bombari, D., Mast, F. W., & Lobmaier, J. S. (2011). How mood states affect information processing during facial emotion recognition: An eye tracking study. *Swiss Journal of Psychology*, *70*(4), 223–2.

Searcy, J. H., & Bartlett, J. C. (1996). Inversion and processing of component and spatial–relational information in faces. Journal of Experimental Psychology: Human Perception and Performance, 22(4), 904.

Sekiguchi, T. (2011). Individual differences in face memory and eye fixation patterns during face learning. *Actapsychologica, 137(1)*, 1–9.

Shakeshaft, N. G., & Plomin, R. (2015). Genetic specificity of face recognition. PNAS Proceedings of the National Academy of Sciences of the United States of America, 112, 12887–12892. http://dx.doi.org/10.1073/pnas.1421881112

Tanaka, J. W., & Farah, M. J. (1993). Parts and wholes in face recognition. The Quarterly Journal of Experimental Psychology A, 46, 225–245.

Tanaka, J. W., & Sengco, J. A. (1997). Features and their configuration in face recognition. Memory and Cognition, 25, 583–592.

Thorley, Craig, Dewhurst, Stephen A., Abel, Joseph W., and Knott, Lauren M. (2016) Eye-witness memory: the impact of a negative mood during encoding and/or retrieval upon recall of a non-emotive event. *Memory, 24 (6)*, 838-852.

Tree, J. J., Horry, R., Riley, H., & Wilmer, J. (2017). Are portrait artists superior face recognizers? Limited impact of adult experience on face recognition ability. *Journal of Experimental Psychology - Human Perception and Performance, 43(4),* 667-676.

Verhallen, R. J., Bosten, J. M., Goodbourn, P. T., Lawrance-Owen, A. J., Bargary, G., & Mollon, J. D. (2017). General and specific factors in the processing of faces. *Vision Research, 141,* 217– 227.

Wang, R., Li, J., Fang, H., Tian, M., & Liu, J. (2012). Individual differences in holistic processing predict face recognition ability. *Psychological Science, 23(2),* 169–177.

Westermann, R., Spies, K., Stahl, G., and Hesse, F. W. (1996). Relative effectiveness and validity of mood induction procedures: a metaanalysis. Eur. J. Soc. Psychol. 26, 557–580.

Wilmer, J. B., Germine, L., Chabris, C. F., Chatterjee, G., Williams, M., Loken, E.,... Duchaine, B. (2010). Human face recognition ability is specific and highly heritable. *Proceedings of the National Academy of Sciences*, USA, 107, 5238 –5241. http://dx.doi.org/10.1073/pnas. 0913053107.

Yovel, G., Wilmer, J. B., & Duchaine, B. (2014). What can individual differences reveal about face processing? *Frontiers in Human Neuro-science, 8*, 562.

Zhang, J., Chan, A. B., Lau, E. Y. Y., & Hsiao, J. H. (2019). Individuals with insomnia mis-recognize angry faces as fearful faces while missing the eyes: An eye-tracking study. *Sleep*, *42*(2), zsy220.

Zheng, Y., Ye, X., & Hsiao, J. H. (2019). Does video content facilitate or impair comprehension of documentaries? The effect of cognitive abilities and eye movement strategy. In A.K. Goel, C.M. Seifert, & C. Freksa (Eds.), *Proceedings of the 41st Annual Conference of the Cognitive Science Society* (pp. 1283-1289). Montreal, QB: Cognitive Science Society.

Zhou, G., Cheng, Z., Zhang, X., & Wong, A. C. (2012). Smaller holistic processing of faces associated with face drawing experience. *Psychonomic Bulletin & Review, 19*, 157–162. http://dx.doi.org/10.3758/s13423-011-0174-x

Zhu, Q., Song, Y., Hu, S., Li, X., Tian, M., Zhen, Z., . . . Liu, J. (2010). Heritability of the specific cognitive ability of face perception. *Current Biology, 20*, 137–142. http://dx.doi.org/10.1016/j.cub.2009.11.067=