Appears in Proceedings of the Annual Meeting of the Cognitive Science Society, 2016 (CogSci 2016)

Mind reading: Discovering individual preferences from eye movements using switching hidden Markov models

Tim Chuk (u3002534@connect.hku.hk)
Department of Psychology, The University of Hong Kong, Pokfulam Road, Hong Kong
Antoni B. Chan (abchan@cityu.edu.hk)
Department of Computer Science, City University of Hong Kong, Tat Chee Avenue, Kowloon Tong, Hong Kong
Shinsuke (Shin) Shimojo (sshimojo@caltech.edu)
Division of Biology and Biological Engineering, 1200 East California Boulevard, Pasadena, CA 91125.
Janet H. Hsiao (jhsiao@hku.hk)
Department of Psychology, The University of Hong Kong, Pokfulam Road, Hong Kong

Abstract

Here we used a hidden Markov model (HMM) based approach to infer individual choices from eye movements in preference decision-making. We assumed that during a decision making process, participants may switch between exploration and decision-making periods, and this behavior can be better captured with a Switching HMM (SHMM). Through clustering individual eye movement patterns described in SHMMs, we automatically discovered two groups of participants with different decision making behavior. One group showed a strong and early bias to look more often at the to-be chosen stimulus (i.e., the gaze cascade effect; Shimojo et al., 2003) with a short final decision-making period. The other group showed a weaker cascade effect with a longer final decision-making period. The SHMMs also showed capable of inferring participants' preference choice on each trial with high accuracy. Thus, our SHMM approach made it possible to reveal individual differences in decision making and discover individual preferences from eye movement data.

Keywords: hidden Markov model; gaze preference; eye movement; face recognition.

Introduction

Gaze plays a crucial role in our social lives because it helps to signify the target of one's attention and interest in a complex environment. For example, studies have shown that gaze is an important cue for infants to infer what adults mean and therefore a precursor to their language development (Brunet, 1985). Gaze also has been shown to be an indicator of people's preferences. The phenomenon of preferential looking (Franz, 1964) suggested that the liked stimuli are usually looked at for longer time. Some researchers argue that gaze not only reflects individual attentions and preferences, it also helps to shape them. Shimojo et al. (2003) conducted a two-alternative-forced-choice (2AFC) preference task, in which participants were required to look at two face images and then to decide which one they liked more. The two face images were shown on the left and the right side of the screen. Their results showed that the participants spent significantly more time on the side that they were about to choose, starting from about 800ms before they made and indicated their decisions. They coined the term "gaze cascade effect" to distinguish it from the mere exposure effect, which suggested that people tend to prefer things that they are familiar with (Zajonc, 1968). Shimojo et al., (2003) argued that gaze shifts are essential to shaping preferences. In other words, it is not exposure to the stimuli alone that shaped the mere exposure effect; gaze shifts have to be involved (Shimojo et al., 2011).

In order to experimentally demonstrate this argument, in one of their follow-up studies (Simion & Shimojo, 2006), they adopted the same 2AFC settings but forced the participants to look at a fixation point located at the center of the screen. The participants' eye movements were therefore constrained. The two face images were sequentially superimposed in the foveal region for different time lengths. They found no bias that favored the longer-exposed images over the shorter ones, which argued for the role of gaze shifts in actively shaping one's preferences.

Although these studies discovered the role of gaze in reflecting and shaping preferences, the finding was based on group-level analysis and thus was not able to address individual differences in preference decision-making behavior. Some studies have shown that participants' eye movements in preference decision-making tasks may to some extent reflect their traits. For instance, it was found that when faced with happy faces and angry faces, old participants paid more attention toward the happy faces, while young participants paid more attention toward the angry faces (Isaacowirz, 2006). It was also found that when participants were shown unpleasant images, the optimistic participants paid significantly less attention toward the images than their pessimistic counterparts.

Studies have shown that people have substantial and persistent differences in their eye movements in cognitive tasks. For example, Castelhano and Henderson (2008) found that fixation durations and saccade amplitudes were highly consistent within-individuals. Participants showed similar fixation patterns when viewing different types of image. Peterson and Eckstein (2013) found that when looking at human faces, people had different preferred fixation locations and that these individual differences persisted over time and tasks.

In our previous studies (Chuk et al., 2014; Chan et al., 2015), we used hidden Markov models (HMMs) to address individual differences in eye movements. We conducted face recognition studies and found that individual differences in eye movements were useful indicators of participants' performance. We used an HMM to summarize the fixation locations and the scan-paths of an individual. We then clustered the individual HMMs into groups according to their similarities and found that while some people preferred to look at specific facial features (i.e. the analytic eye movement pattern), others preferred to look at the center of the faces (i.e. the holistic eye movement pattern). We found that people who showed analytic eye movement patterns performed significantly better than those who showed holistic eye movement patterns (Chuk et al., 2014). We also found that old people were significantly more likely to use holistic eye movement patterns than young people, and the more holistic their patterns, the lower their cognitive abilities (Chan et al., 2015). These findings were not possible with other existing methods that do not take individual differences into account.

The above findings suggested that one's eye movement pattern could be used to infer one's recognition performance, which also implied the possibility of using one's eye movement pattern to infer one's preference in decision-making tasks. Our HMM approach is more capable of capturing individual differences because it takes into account the spatial (i.e., fixation locations) and temporal (i.e., scan paths) information of one’s eye movement simultaneously, when many of the alternatives only focus on the spatial information.

In this study, we try to read participants’ mind through their eye movements. We aim to infer participants' preferences in a preference decision-making task by modeling their eye movements using HMMs. However, the standard HMMs may not be suitable for the purpose of this task. The gaze cascade effect showed that in these tasks, participants might go through at least two mental periods during a trial: exploration and decision-making. During the exploration period, they may switch their gaze between the two sides equally; during the decision-making period, they may look more often at the images to-be-chosen (Shimojo et al., 2003). This finding suggests that participants' patterns of switching their gazes between the two images could be different during the two periods. The standard HMM with one set of hidden states and a transition matrix is unable to capture this. Therefore, instead of using a standard HMM, we create a ‘switch’ for two HMMs, such that a high-level HMM consists of two low-level HMMs, each representing gaze patterns of a particular mental period (Figure 1).

Here we train the SHMMs on individual fixation data and cluster the models. The analysis separates participants into groups based on their eye movement differences. This helps to reveal common eye movement patterns when they make decisions, and in turn allows us to examine whether different patterns are associated with different decision-making behavior. We then use the models to infer their preferences on each trial and examine the models’ accuracy.

Method

Materials and Procedure

We performed our analysis using the data collected in a preference decision-making study (Shimojo et al., 2011). A total of 12 participants were recruited for the 2AFC task. There were in total 60 trials. On each trial, two face images, one on the left and one on the right, were shown on the screen for the participants to make their choices. There was no time limit. Participants were allowed to move their eyes to compare the two images. They were told to press a button to indicate which image (left or right) they preferred once they had made their decisions. Eye movements were recorded using an Eyelink 2 eye tracker.

Switching hidden Markov model

A standard hidden Markov model (HMM) contains a vector of prior values, a transition matrix, and a Gaussian emission for each hidden state. The prior values indicate the probabilities of the time-series data to begin with the specific hidden states; the transition matrix indicates the transition probabilities between any two hidden states; the Gaussian emissions indicate the probabilistic associations between the time-series data and the hidden states. In our current context, the hidden states correspond to the regions of interest (ROIs), which were learned from the fixation locations, and the emissions are the fixation locations.

In contrast to a standard HMM, a switching HMM (SHMM) contains two levels of HMMs; the high-level HMM indicates the transitions between the low-level HMMs (Figure 1). In our implementation, the high-level hidden states represent the current gaze strategy (i.e., exploration or decision-making), whereas the low-level hidden states correspond to ROIs over the stimuli. Each high-level state has its own low-level prior values and transition matrix. The low-level states (ROIs) are shared among the high level states (gaze strategies). The high-level HMM has its own transition matrix, which governs the switching between gaze strategies. The high-level state sequences and the low-level state sequences are both 1st-order Markov chains.

In practice, the SHMM can be turned into a standard HMM by combining the high-level and the low-level hidden state variables into a single hidden state variable, whose values are the Cartesian product of the low- and high-level state values. In the current case, since the low-level states are shared among the high level states, the number of low-level states (K) is the same for each high-level state. Hence, the equivalent HMM has S*K hidden states, where S is the number of high-level hidden states; the transition matrix has block structure. Because the Gaussian emissions are shared among the high-level hidden states, they are independent from the high-level switches and are only attached to the low-level hidden states (Figure 1).

We performed the EM algorithm to estimate the SHMM parameters. In the E-step, the responsibilities were calculated using the standard forward-backward algorithm with the block transition matrix, initial state vector, and emission densities. In the M-step, the prior and pairwise responsibilities were summed over the high-level and the low-level states respectively to yield the parameter updates for both the high-level states and the low-level states.

For instance, the prior responsibilities were summed over the low-level hidden states for each of the high-level state in order to yield the parameter updates for the low-level states, and then they were summed over the high-level states to yield the parameter updates for the high-level states. Similarly, the pairwise responsibilities were summed over the low-level hidden states for each high-level state to yield the transition matrix updates for each transition matrix, and then were summed over the high-level hidden states to yield the updates for the switching matrix.

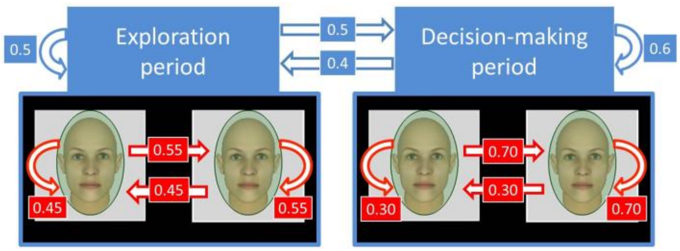

Figure 1: An illustration of the SHMM used in the current study. The high-level HMM states consisted of two gaze strategies: exploration and decision-making. The blue arrows indicate the transitions between them, and the numbers indicate transition probabilities. Eye movements within each period were modeled with a low-level HMM. The red arrows represent transitions between ROIs. The two periods have the same ROIs but different transition probabilities.

Training and clustering individual SHMMs

For each participant, we trained an SHMM using the fixation locations collected from all trials. In order to simplify the analysis, we used only two Gaussian emissions per model; one on each side. This helped to focus the analyses on the transition information between the two face stimuli (Figure 1). The advantage of using Gaussian rather than discrete emissions is that it can be easily extended to analyses that explore the ROIs on each face. We used two high-level hidden states to reflect that the participants may switch between exploration and decision-making periods during a trial.

For SHMM estimation, we initialized the transition matrices based on the actual data. The exploration period usually happened at the beginning of a trial and the decision-making period usually happened at the end of a trial. Therefore, we initialized the exploration and the decision-making transition matrices based on the first 5 and the final 5 fixations of each trial.

Since participants’ exploration and decision-making may influence each other during a trial (e.g., Shimojo et al., 2003), here we assumed that participants may switch back to exploration after decision making before they made the final decision. To reflect this, the high-level transitions between the exploration and the decision-making periods were set to [0.5, 0.5; 0.4, 0.6] (Figure 1). That is, once the participant had switched from the exploration period to the decision-making period, the chance of switching back to the exploration period (0.4) was slightly lower than the chance of him or her staying in the decision-making period (0.6).

To reveal a common eye movement pattern shared by all individuals during the exploration period, we created an HMM using the exploration transition matrix and Gaussian emissions for each individual, and clustered these HMMs into a group using the VHEM algorithm (Coviello et al., 2014). To reveal whether participants had different fixation patterns when they were making decisions, we clustered their HMMs for the decision-making period into two groups and examined their differences.

To infer when the participants were in the exploration or decision-making period, we used the Viterbi algorithm to find the most likely hidden state sequence for each trial. In this sequence, a change in the value of the high-level hidden state indicated a switching point. Next, we examined whether SHMMs can be used to infer individual preferences on each trial. We used only the fixations in the last decision-making period to perform our inferences. That is, the inference was performed using only the fixations after the final switch from exploration to decision-making. We split the trials into two sets: one for all the trials on which the left side images were chosen, and one for all the trials on which the right side images were chosen. For each set, we used all but one trial to train an SHMM and used the held-out trial for testing. If, for example, on the test trial, the participant selected the image on the right, the SHMM trained on the trials in which the right image was chosen should fit the trial better than the SHMM trained on the left-selected trials. To test this, we compared the log-likelihoods generated by the two SHMMs (Chuk et al., 2014). We hypothesized that the SHMM for the right-selected trials should produce a higher log-likelihood than the SHMM for the left-selected trials. This was repeated over all the trials and all the participants. The accuracy of our inferences was evaluated using one-sample t-tests. We hypothesized that we can infer participants' decisions at a level that is significantly above chance.

Results

Categorization of individual SHMMs

First, we clustered the 12 participants' exploration HMMs into one representative HMM using the VHEM algorithm. The output showed that participants did not look more often at the side that they were going to choose during the exploration period. This is evident from the fact that both the not-chosen images and the chosen images had a prior value of roughly 0.5. The transition probabilities were also around the chance level for both sides, indicating that at the exploration stage of the trials, participants paid roughly equal attention to the two images. Table 1 below shows the transitional information of the representation HMM.

For the decision-making period, we clustered their decision-making HMMs into two groups. The two groups had an equal number of participants. Each participant had a probability of being associated with each group. The probabilities showed a clear-cut division between the two groups, indicating that the two groups were clearly separated, t (11) = 3.32, p = .007. Tables 2 and 3 below show the representative transition matrices of the two groups generated by the VHEM algorithm. Participants in group A showed apparent fixation bias toward the side that they were about to choose, whereas those in group B showed only mild bias. Although participants in group B also paid more attention to the images that they were about to choose, the transition matrices suggested that their fixation pattern were not that different from the exploration period.

Table 1: The exploration period for all the participants

	to not-chosen	to chosen
Priors	.50	.50
from not-chosen	.55	.45
from chosen	.53	.47

Table 2: The decision-making period for group A.

	to not-chosen	to chosen
from not-chosen	.32	.69
from chosen	.32	.69

Table 3: The decision-making period for group B.

	to not-chosen	to chosen
from not-chosen	.44	.56
from chosen	.43	.57

Cascade plots

In order to visually compare the two groups in terms of the magnitude of their gaze cascade effects, we generated the gaze cascade plots as that seen in Shimojo et al. (2003). The plots show the proportion of time that the participants spent on looking at the chosen images, and span 2.5 seconds (see Figure 2). It can be seen from the plot generated from all participants that as it got closer to the end, participants spent more time on inspecting the side that they were about to choose. The proportion of time spent on the chosen sides went from about chance level (0.5) steadily up until it reached almost 0.9. Chi-square test showed that the trend began at around 900 ms before the end of the trials, $\chi^2(1) = 3.92$, p = .05. The plots of the two groups show some more interesting differences. It can be found that although the general trend was shared between the two groups, participants in group A showed a more stable gaze cascade effect. Chi-square test showed that the cascade effect occurred at around 1100 ms before the end of the trials, $\chi^2(1) = 4.74$, p = .03, which was earlier than the general trend. The proportion of time on the chosen image reached about 0.95 by the end, which was also higher than the general trend. Group B, however, showed a decrease in the proportion of time spent on the chosen images between 1.5 seconds and 1 second.

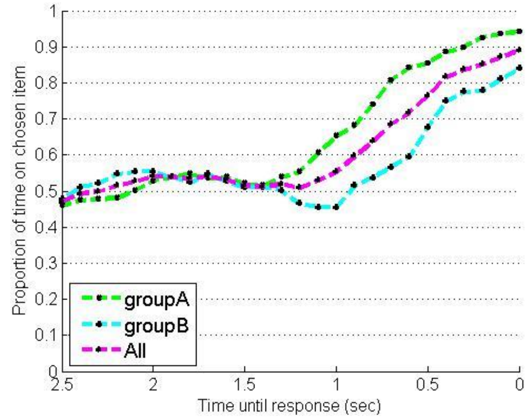

Figure 2: The cascade plots.

Chi-square test showed that the cascade effect occurred at around 600 ms before the end of the trials, $\chi^2(1) = 6.51$, p = .01, The proportion of time on the chosen image then accumulated continuously to about 0.85, which was lower than the general trend. Although both groups showed the gaze cascade effect, neither their magnitudes nor their onset times were the same. However, the observation that the two groups did not show qualitative differences in eye movement pattern suggests that there may be a continuum between the two groups.

Inference of individual preferences

We performed the inference of individual preferences using the fixations after the last time that the participant switched from the exploration to the decision-making period. The inference was done on every trial for every participant. The accuracy of the inferences is shown in Table 4 below.

Table 4: Inference of participants' preference.

participant no.	group	accuracies
01	A	.98
03	A	.94
07	A	.97
08	A	1
10	A	.98
11	A	.96
02	B	.78
04	B	.85
05	B	.93
06	B	.58
09	B	.94
12	B	.52

It can be seen that for participants in group A, the inference accuracies were both high and consistent (*M* = 0.97). One sample t-test showed that the inference accuracies were significantly above the chance level, t(5) = 56.6, p < .001. For group B (*M* = 0.77), while for some of the participants the inference accuracy was also high, there was a larger variance within the group. For instance, for participant 6 and participant 12, the models showed only around chance level accuracies, but for participant 5 and participant 9, the models showed a high level of accuracies comparable to that of group A. One sample t-test showed that the inference accuracies of group B were also significantly higher than chance, t (5) = 3.66, p = .01. However, Group A's inference accuracies were significantly higher than that of group B, t(10) = 2.79, p = .02.

In addition, we examined the time length of the final decision-making period for each participant. Table 5 below shows the average time length of the decision-making period and the average number of fixations within the period.

Table 5: Average time length of the final decision-making period

participant	group	time length (sec)	number of fixations
01	A	1.32	4.76
03	A	1.39	4.89
07	A	1.78	5.88
08	A	1.89	5.5
10	A	6.09	17.22
11	A	2.79	7.17
02	B	2.93	9.14
04	B	3.87	9.75
05	B	3.71	12.72
06	B	4.82	16.95
09	B	3.92	12.52
12	B	5.26	13.2

It can be seen that on average, the participants switched to the final decision-making period at about 9.97 fixations prior to the end of the trials. The average duration of the period was 3 seconds. This was earlier than what the cascade plots showed, which suggested that our SHMM analysis was able to detect participants' preferences at an earlier stage. The final decision-making period for group B (4.09 secs) was longer than that for group A (2.54 secs). The difference between the two groups was marginal, t(10) = 2.12, p = .06. Note that the clustering of the two groups was completely based on the eye movement data, and thus the group difference in inference accuracy and in length of the final decision period emerged naturally as the results of the clustering.

Discussion

In this study, we revealed individual differences in decision-making behavior from their eye movements and also successfully inferred participants' preferences using their eye movements through the HMM-based approach. More specifically, by assuming a decision process involves an exploration and a decision-making period, and using SHMMs to model these two periods, we discovered two participant groups with different decision-making behavior automatically from the eye movement data. Although all participants showed a tendency of looking more often at the to-be-chosen images by the end of the trials, our SHMMs showed that this tendency was obvious only among 6 of the 12 participants. As shown in Table 2, for group A, the transition matrix showed a strong bias to look at the chosen images. The cascade plot showed that the cascade effect happened early, roughly 1.5 seconds before the end of the trials (Figure 2). They also had a stronger gaze cascade effect: and onset time was about 600 ms before the end of the trials, and the proportion of time spent on the chosen images reached almost 95%. For group B (Table 3), although they also showed the gaze cascade effect, it was both later and less obvious. The cascade plot showed that its onset time was about 1100 ms before the end of the trials, and the proportion of time on the chosen images was about 85%.

The fact that all the 12 participants showed the gaze cascade effect suggests its robustness. However, our SHMM analysis revealed that the 12 participants could be separated into two groups with substantial differences in their fixation patterns for preference decision making. This demonstrated the advantage of our approach: by summarizing participants' fixation patterns using the SHMM, those who had similar fixation patterns could be clustered together. The grouping was done automatically based on eye movement data alone, and participants' differences in decision making behavior emerged naturally as the result of the clustering.

In addition, the SHMM approach allowed us to infer individual preferences with very high accuracies. This was made possible because the structure of the SHMM allowed us to capture the eye movements during the final decision-making period, which were informative for such inferences. Both groups' inference accuracies were significantly above the chance level. The inference accuracy for group A was significantly higher than group B, suggesting that eye movement was a more accurate indicator of preference for participants in group A than those in group B. There was also a much larger individual difference among participants in inference accuracy in group B. It is worth noting that the two groups were discovered from the eye movement data without considering the participants' other behavioral differences. Therefore, although for some participants (e.g., participant 5 and 9), the inference accuracies were high, they were nevertheless clustered into group B because of their eye movement patterns. Having that said, the fact that some of these participants in group B also showed a high level of accuracies suggest that this group could be further divided into sub-groups, so that a more fine-grained categorization should be possible. This could be done in future studies.

The analysis of the time length of the final decision-making period showed a different pattern from the cascade plots (see Tables 2-3 and Figure 2). Our analysis results suggested that the final switch from the exploration period to the decision-making period happened at a much earlier time than that suggested by the cascade plots. The average number of fixations within the period, for all the participants, was 9.97 fixations, which translated to about 3 seconds of time. In contrast, in the cascade plots, the cascade effect emerged at around 900 ms before the trial end. The average time length of the final decision-making period in group B (4.09 secs) was longer than that in group A (2.54

secs; see Table 5). This is possibly because the transition matrix of group B showed a milder tendency towards the to-be-chosen side than group A, and hence it took longer for the gaze cascade effect to become noticeable. For group A, the transition matrix showed a more obvious tendency, so that the cascade effect appeared earlier even though the participants started the decision-making period later than group B.

Note that the cascade plots did not show a turning point which shifted a flat line to a steep slope. The accumulation of the proportion of time on the chosen image was gradual and slow. The accumulation only became apparent by the end of the trials, which therefore suggested that it would be hard to use the cascade plots to determine when the decision-making period had begun. Our analysis showed the advantage of being able to distinguish and isolate the fixations in the final decision-making period, which allowed us to infer participants' preferences with high accuracy using only their eye movements. Note however that the model assumes a separation of the two periods with the possibility to switch between the two periods during the decision-making process. It remains possible that there is an additional period between these two periods, in which exploration and decision making are mixed (e.g., Shimojo et al., 2013). This additional period could be represented by adding an additional high-level state to the SHMM. Future work will examine this possibility.

The finding that some people have a longer final decision period might imply some traits of these individuals. Previous studies demonstrated relationship between personality and response time when making decisions. For instance, extraverts were found to respond slower than introverts (Doucet & Stelmack, 2000). Reflective people have longer response time than impulsive people (Sternberg & Grigorenko, 1997). These findings point to the possibility that the two groups we found might also differ in terms of their personalities. In future studies, this should be explored.

In summary, here we used SHMMs to analyze eye movement data collected from a preference decision-making task. The SHMM assumes an exploration period and a decision-making period during the decision making process. By clustering individual models into groups in a data-driven fashion, we discovered two participant groups with different decision-making behavior: one group had a stronger and longer-lasting gaze cascade effect and a shorter decision-making period than the other group. These group differences emerged naturally as the results of the clustering based on eye movement data alone, demonstrating the power of the HMM approach of eye movement data analysis for the understanding of individual cognitive behavior. We also found that participants' preferences on each trial can be inferred from their fixation patterns with high accuracy. This result thus provides a strong evidence for the possibility of mind reading from eye movement behavior.

Acknowledgments

We are grateful to the Research Grant Council of Hong Kong (project 17402814 to J. H. Hsiao and CityU 110513 & G-CityU109/14 to A. B. Chan) and to JST.CREST (SS).

References

Bruner, J. (1985). Child's talk: Learning to use language. *Child Language Teaching and Therapy*, *1*(1), 111-114.

Castelhano, M. S., & Henderson, J. M. (2008). Stable individual differences across images in human saccadic eye movements. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*,*62*(1), 1.

Chuk, T., Chan, A. B., & Hsiao, J. H. (2014). Understanding eye movements in face recognition using hidden Markov models. *Journal of vision*, *14*(11), 8.

Chan C. Y. H., Chan, A. B., Lee, T. M. C., & Hsiao, J. H. (2015). Eye movement pattern in face recognition is associated with cognitive decline in the elderly. *Proceedings of the 37th Annual Conference of the Cognitive Science Society* (pp. 321-326).

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

Doucet, C., & Stelmack, R. M. (2000). An event-related potential analysis of extraversion and individual differences in cognitive processing speed and response execution. *Journal of personality and social psychology*, *78*(5), 956.

Fantz, R. L. (1964). Visual experience in infants: Decreased attention to familiar patterns relative to novel ones. *Science*, *146*(3644), 668-670.

Isaacowitz, D. M. (2006). Motivated gaze the view from the gazer. *Current Directions in Psychological Science*, *15*(2), 68-72.

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.

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature neuroscience*, *6*(12), 1317-1322.

Shimojo, S., Simion, C., & Changizi, M. A. (2011). Gaze and preference-orienting behavior as a somatic precursor of preference decision. In R, B, Adams (Ed.), *The science of social vision* (pp. 151-163). Oxford: Oxford University Press.

Simion, C., & Shimojo, S. (2006). Early interactions between orienting, visual sampling and decision making in facial preference. *Vision research*, *46*(20), 3331-3335.

Sternberg, R. J., & Grigorenko, E. L. (1997). Are cognitive styles still in style?. *American psychologist*, *52*(7), 700.

Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of personality and social psychology*, *9*(2p2), 1.