Do we know our visual preferences?

Nitzan Guy
Cognitive and Brain Sciences Department, Hebrew University of Jerusalem, Mount Scopus, Jerusalem, Israel
Psychology Department, Hebrew University of Jerusalem, Jerusalem, Israel

Rasha Kardosh
Psychology Department, New York University, New York, NY, USA

Asael Y. Sklar
Edmond & Lily Safra Center for Brain Sciences, Hebrew University of Jerusalem, Jerusalem, Israel
Arison School of Business, Reichman University, Herzliya, Israel

Oryah C. Lancry-Dayan
Psychology Department, Hebrew University of Jerusalem, Jerusalem, Israel

Yoni Pertzov
Psychology Department, Hebrew University of Jerusalem, Jerusalem, Israel

Humans differ in the amount of time they direct their gaze toward different types of stimuli. Individuals' preferences are known to be reliable and can predict various cognitive and affective processes. However, it remains unclear whether humans are aware of their visual gaze preferences and are able to report it. In this study, across three different tasks and without prior warning, participants were asked to estimate the amount of time they had looked at a certain visual content (e.g., faces or texts) at the end of each experiment. The findings show that people can report accurately their visual gaze preferences. The implications are discussed in the context of visual perception, metacognition, and the development of applied diagnostic tools based on eye tracking.

Introduction

Given the distribution of photoreceptors in the retina, most visual information is extracted from a small area around the center of gaze (Osterberg, 1935). Thus, people's gaze position determines which visual information is processed with high acuity and strongly affects the nature of visual experience (Findlay et al., 2003). Although evidence has been recently accumulating that individuals differ in where they direct their gaze (Guy et al., 2019; Haas et al., 2019; Mehoudar et al., 2014), it is still unknown whether people have knowledge about their own visual preferences (i.e., which visual contents tend to attract their gaze compared to others). The goal of the current study is to shed light on this matter.

Visual preferences have been typically assessed by attentional bias paradigms. Early methods included the dot probe task in which participants are required to respond to the appearance of a dot. Importantly, the dot appears in the location of a previously presented stimulus. Thus, response time to the dot was considered to reflect the amount of attention that was directed to the previously displayed stimulus (MacLeod et al., 1986; i.e., faster reaction times reflect more attention to the stimulus). However, criticism of the reliability of the dot probe task (Chapman et al., 2019; Schmukle, 2005) prompted more recent studies to use eye tracking to quantify attentional bias by examining where participants look when multiple distinct images appear simultaneously or when a complex image, which includes various types of items, is displayed. In this setup, visual preference is operationally defined as the duration of time gaze is directed at certain contents out of the overall duration of time gaze is directed at the stimuli (e.g., Sears et al., 2018).

Citation: Guy, N., Kardosh, R., Sklar, A. Y., Lancry-Dayan, O. C., & Pertzov, Y. (2023). Do we know our visual preferences? *Journal of Vision*, *23*(2):9, 1–12, https://doi.org/10.1167/jov.23.2.9.

https://doi.org/10.1167/jov.23.2.9 Received October 19, 2022; published February 17, 2023 ISSN 1534-7362

The empirical literature on the eye tracking–based attentional bias paradigm has revealed tendencies to look at social images (from infancy [see Peltola et al., 2018] to adulthood [see Eizenman et al., 2003]) and to look more at positive content (Pool et al., 2015). Recent studies have generalized the controlled attentional bias task to more complex environments such as scene viewing and reported findings similar to those observed on the controlled attentional bias task (Flechsenhar et al., 2018; Leder et al., 2010). For example, in Leder et al. (2010), participants showed a tendency to look more at attractive faces than less attractive faces, similar to that found in attentional bias tasks (Valuch et al., 2015).

However, it remains unclear whether all individuals manifest the same tendencies. Recent studies have found high variability between individuals in gaze preference paradigms, including attentional bias (Lazarov et al., 2018; Sears et al., 2018) and scene viewing (Guy et al., 2019; Haas et al., 2019). Individual differences in gaze preferences were shown to be stable over time (Guy et al., 2019; Haas et al., 2019; Lazarov et al., 2018), suggesting that these preferences may be perceptual traits. Moreover, some gaze preferences were found to be related to other traits and skills (Dechant et al., 2017; Haas et al., 2019; Lazarov et al., 2018). For example, preference to look at faces was positively correlated with individuals' face recognition skills (Haas et al., 2019).

Even though people rely heavily on vision, they are not necessarily aware of their gaze behavior characteristics (e.g., scanning pattern and visual preferences). Examining whether individuals are aware of their gaze characteristics will not only contribute to the state of the art on visual metacognition processes but may also suggest possible ways to influence (or perhaps enhance) gaze behavior through metacognitive processes. Although no studies have examined the metacognition of visual preferences, several studies have explored whether individuals can recognize their own scanning patterns. Whereas participants were able to distinguish between their own scanning patterns and random ones (Foulsham & Kingstone, 2013), there is mixed evidence as to participants' ability to differentiate between their own scanning patterns and others' (Clarke et al., 2017; Foulsham & Kingstone, 2013; van Wermeskerken et al., 2018; Võ et al., 2016). For example, in one study (Foulsham & Kingstone, 2013), participants memorized complex scenes. Then, the previously displayed scenes were displayed together with two overlaid scanning patterns, one of which was their own and the other was that of another observer or a random sequence. Participants were able to discriminate between their own pattern and the patterns of others. By contrast, in Võ et al. (2016), after viewing several images, participants were asked to mark 12 locations they thought they had just looked at, as well as 12 other locations where they thought another person had looked. The overlap between their own fixations and their reported locations was not significantly different from the overlap with the locations reported for others. Regardless of whether participants are capable or not of identifying their own scanning patterns compared to others, studies concur that the ability to identify one's own fixation locations as compared to others is partial at best (e.g., Võ et al., 2016). Importantly, examining the ability to recognize one's own fixations refers to specific and detailed information about eye movements, but it does not capture the ability to estimate and aggregate information throughout the experiment, which might be more strongly linked to metacognitive awareness.

Most humans (unlike trained vision researchers) typically do not think about where they fixate their gaze but rather what objects or people they are looking at, which may explain variations in ability to distinguish one's fixations from others' by remembering the objects they looked at (Foulsham & Kingstone, 2013; Võ et al., 2016). Thus, even though individuals cannot recognize their own scanning patterns, it is still possible that individuals are able to report more general visual behavior, such as their gaze preferences (i.e., the content they tend to look at). To shed light on this possibility, we conducted three experiments using a variety of visual contents and tasks to ensure generalizability of the findings. Additionally, the stimuli in our experiments became increasingly complex, ranging from attentional bias tasks with two images to viewing complex scenes. The variety in the stimuli and tasks is important for examining the robustness of the findings, but on the other hand, it hampers direct comparison between conditions. In all experiments, participants were presented with multiple images and then, without prior warning, asked to report the amount of time they spent viewing specific visual content (e.g., faces or images with positive valence). Individuals' degree of accessibility to their own preferences was examined by correlating their self-reports (or estimates) of subjective visual preference to their empirical gaze preference, as measured by the eye-tracking system ("gaze preference").

Method

Experiment 1

Neurotypical participants tend to look more at positive stimuli (e.g., Bradley et al., 1997; Pool et al., 2015). In the current experiment, we tested if participants are aware of this tendency.

Participants

Sixty-seven students of the Hebrew University of Jerusalem (53 female, mean age = 24.95, $SD = 4.84$) participated in the experiment in exchange for 20 NIS (∼$5.00) or course credit. Eight participants did not complete the experiment. Four other participants were excluded due to bad data quality (see data preprocessing section for further details), resulting in a final sample size of 55 participants (43 females, mean age = 24.67, $SD = 3.65$). All participants had normal or corrected-to-normal vision and provided informed consent prior to participating in the experiment. The experiment was approved by the local ethics committee of the Hebrew University of Jerusalem and conducted in accordance with the Declaration of Helsinki.

Stimuli

The experiment was composed of three stimulus categories in the form of International Affective Picture System (IAPS) images (Lang, 2005), faces (Chelnokova et al., 2014), and food images (Blechert et al., 2019). There were 27 pairs of IAPS images, each consisting of one of the 30 images with the highest positive valence in the database (mean valence 8.01, $SD = 0.18$) matched with a neutral image (mean valence 5.01, $SD = 0.44$). The facial images consisted of 20 pairs of female faces, each consisting of one of the 30 faces rated as most attractive in the Oslo Face Database (mean attractiveness rating 5.49, $SD = 0.55$) and a face that was rated as one of the 30 least attractive faces (mean attractiveness rating 3.03, $SD = 0.59$). The food stimuli consisted of 30 pairs of images of food items, one from the highest palatability rating (mean palatability rating 79.73, $SD = 3.00$) out of the food images in the Food-Pics_Extended database (Blechert et al., 2019) and one image of rotten food downloaded from Google images.

Apparatus

The experiment was conducted online on the participants' personal computers. The open-source JaveScript package webgazer.js (Papoutsaki, 2015) was used to capture the participants' gaze position. This package was recently compared to high-end eye-tracking systems and was found to be reliable for cognitive tasks that do not require very detailed spatial resolution, such as the attentional bias task used here (Semmelmann & Weigelt, 2018). The calibration procedure included a sequential presentation of 20 squares at different locations on the screen. Participants were instructed to look at the square and click on it with the mouse. To further evaluate the data quality, additional tests were conducted (see data preprocessing). The experiment was run on the Pavlovia website.

Procedure

The experiment consisted of 77 pairs of images depicting three content types: images with a positive and neutral valence (IAPS images; 27 trials), attractive and less attractive faces (attractive faces; 20 trials), and tasty and unappealing food images (food images; 30 trials). Images of the same visual content were presented in the same block in a random order. The order of the blocks was counterbalanced across participants. Each pair of images was displayed for 3 s (see example in Figure 1). Before presenting an image, participants were instructed to look at a fixation point that appeared in the center of the screen for 1 s. At the end of the experiment, participants were asked to estimate on a visual analog scale the amount of time (as a percentage) they looked at the more positive images compared to the less positive IAPS images, the percentage of time they looked at the appealing food compared to unappealing food images, and the percentage of time they looked at the more attractive female faces compared to the less attractive ones.

Data preprocessing

To compensate for between-participant variance in setup-related noise levels, we used the following preprocessing procedure. First, we computed the trial mean horizontal center—that is, the mean horizontal coordinates (x coordinates) of all samples collected during the last 500 ms of the central fixation stage for each trial. Then, for each participant, we defined the participant's standard deviation as the standard deviation of the differences between all samples during the last 500 ms of the central fixation stage and the relevant trial's mean horizontal center across all trials and samples. These differences served to assess the stability of the eye-tracking measures, in which a larger participant's standard deviation was indicative of higher noise levels of the eye-tracking recording. During the presentation of the images, if the horizontal coordinate of the gaze position sample was more than two participants' standard deviations to the right from the trial mean horizontal center, the sample was considered as positioned on the right side of the screen. If the sample's horizontal value was more than two participants' standard deviations from the trial mean horizontal center to the left, the sample was considered as positioned on the left side of the screen. Other samples (not right or left) were considered as samples in the center. Based on this analysis, we computed the visual gaze preference on each trial as the number of samples of a certain content (one side) divided by the total number of samples on both sides.

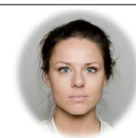
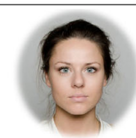
Exp	Task	Content Type	Stimulus Example
#1	Attentional Bias	IAPS Images	 
#1	Attentional Bias	Food Images	 
#1	Attentional Bias	Attractive Faces	 
#2	Estimation	Skin Color	
#2	Estimation	Gender	
#3	Scene Viewing	Faces	
#3	Scene Viewing	Text	

Figure 1. Stimulus examples. Each line represents an example of a specific image content type. The two images in the attentional bias task were presented simultaneously. The size of the illustrated matrix in Experiment 2 was 2 × 2, while the matrices in the experiment were 10 × 10. Matrix was produced with permissions (copyright Center for Decision Center, University of Chicago). Note: due to copyright limitations, the example of "attractive faces" includes the same face twice, rather than two different faces (copyright Leknes Affective Brain lab). The stimulus example of Experiment 3 (taken by Austin Distel—no permission is needed; faces have been blurred to protect people's identity in accordance with copyright regulations) is an illustration of images in the experiment that were not presented in the figure due to copyright limitations.

As a result of using an online eye-tracking procedure, missing samples were not identified. However, samples in which the face of the observer was not identified were marked. The percentage of samples without a face across all participants was 0.03% with a standard deviation of 0.17%. Notably, computing the percentage of time out of the total time gaze was directed to both sides (rather than the overall display time) controls for differences in the acquired number of samples between individuals (which are influenced by the type of personal computer, camera, and data loss) and reduced the noise on the individual level. For example, if a participant had 150 samples on the appealing food and 100 on the unappealing food, the visual gaze preference for appealing food was 60% (150/250). Finally, we computed the overall gaze preference within each category by averaging over trials consisting of the same image category.

In addition to optimizing the signal of each trial and participant, we validated the quality of the data by extracting the median horizontal coordinate for each participant from all the samples taken during the fixation stages (across all trials). If the median horizontal coordinate of a participant was very far from the center of screen (more than 25% of the screen width to the right or left side), this participant was excluded from the analysis (two participants). Participants with a participant's standard deviations of zero (i.e., for whom no eye movements were recorded at all) were also excluded (one participant). Furthermore, we removed trials in which the trial mean horizontal center was far from the center (more than five times the participant's standard deviation) and trials without any samples on one of the sides (13% of trials). Participants with 50% or more excluded trials were excluded from the analysis (one participant). Overall, four participants were excluded in this process.

Experiment 2

Individuals often report that the prevalence of minorities is higher than it is (Kardosh et al., 2022). In the current experiment, we examined if participants are aware of how much they look at faces with specific characteristics, including minorities.

Participants

Thirty-two Hebrew University students (19 females, mean age = 24.91, $SD = 3.58$) participated in the experiment in exchange for 10 NIS (~$2.50) or course credit. One participant did not complete the experiment and was excluded. All participants had normal or corrected-to-normal vision and provided informed consent prior to participating in the experiment. The experiment was approved by the local ethics committee of the Hebrew University of Jerusalem and conducted in accordance with the Declaration of Helsinki.

Stimuli

The experiment consisted of 20 matrices, each displaying of 100 neutral-expression faces previously rated as belonging to either White Americans or Black Americans taken from the Chicago Face Database (Ma et al., 2015; for further details on these stimuli, see Kardosh et al., 2022). The percentage of faces of Black Americans changed between matrices (10%, 20%, 30%, and 40% in equal probability), with overall 25% Black faces. Half of the faces were females and the other half were males. The location of the faces was randomly chosen. The matrix resolution was 750 × 750 pixels, capturing approximately 23 × 23 degrees of visual angle from a distance of 50 cm.

Apparatus

The stimuli were displayed on a 23-in. Syncmaster monitor, with a 120 Hz refresh rate and a 1920 × 1080 screen resolution. Monocular gaze position was tracked at 1000 Hz with an Eyelink 1000+ (SR Research Ltd., Mississauga, Ontario, Canada). Participants' heads were stabilized using a chinrest situated 60 cm from the screen.

Procedure

The second experiment was based on Experiment 2 in the Kardosh et al. (2022) study. Participants viewed 20 matrices of 100 faces with neutral facial expressions while their eye movements were recorded. Before each trial, the participants fixated on a central fixation point, and a drift correction procedure was applied (SR Research Ltd.). After observing each matrix for 2 s, participants were asked to indicate whether the matrix had a majority of females or males. At the end of the experiment, participants were asked to estimate the percentage of Black and White faces across all the matrices. Next, participants evaluated how much time they had looked at female faces compared to males (where 100 indicated that they looked only at females and 0 only at males) and at Black compared to White faces (100 indicated that they looked only at Black faces and 0 only at White faces) on a visual analog scale. Finally, participants were asked about their political orientation. Because the current study examined whether participants were aware of their visual preferences, we only report here responses to the gaze estimates at Black/White faces or female/male faces.

Data preprocessing

To measure gaze preference for female faces, we extracted the amount of time gaze was directed toward female faces and divided it by the total time gaze was directed toward both female and male faces. Then, the gaze preference for female faces was averaged across trials. Gaze preference for Black faces was calculated in a similar manner. Gaze was considered to be directed at a face if it fell within a virtual square of approximately 2.4 × 2.4 degrees of visual angle that included the face. The average rate of missing samples across all participants was 0.86% with a standard deviation of 1.36%. Missing samples were excluded from the analysis.

Experiment 3

Individuals differ in the amount of time they look at semantic contents in complex scenes (Guy et al., 2019;

Haas et al., 2019). Here we tested if they are aware of their tendencies.

Participants

Sixty Hebrew University students (37 female, mean age = 24.13, $SD = 2.9$) participated in the experiment in exchange for 30 NIS or course credit. One participant did not complete the experiment and was excluded from the analysis. All participants had normal or corrected-to-normal vision and provided informed consent prior to participating in the experiment. The experiment was approved by the local ethics committee of the Hebrew University of Jerusalem and conducted in accordance with the Declaration of Helsinki.

Stimuli

The stimuli consisted of a subset of 78 images from the image collection in Xu et al. (2014). Each image in this collection was published together with several heatmaps containing information on the semantic features of the objects. Here, we used the heatmaps that capture information on the locations of faces and texts, in which the center of each face/text has a maximum value (255) and gradually decreases to zero in a Gaussian manner when moving away from the center. Similar to our previous study (Guy et al., 2019), a threshold of 64 was used to indicate whether a fixation was directed at a face/text or not. One third of the images (26 images) contained faces and texts, one third had only faces without text, and one third included text without faces. As in Xu et al. (2014), faces were defined as back, profile, or frontal views of humans' and animals' heads.

Apparatus

Gaze position was tracked using a SMI 250RED (SansoMotoric Instruments, Inc. [SMI], Teltow, Germany), installed on a DELL laptop. Participants were positioned approximately 60 cm from the monitor. Each participant performed calibration and validation sessions for five points (implemented by the experimental software provided by SMI) at the beginning of each session. All the data analyzed here were obtained from recordings with an average absolute global validation error of less than 1 degree of visual angle. The recording sample rate was 250 Hz. The analysis was based on fixations parceled from the data by the software provided by SMI (BeGaze). Fixations were detected using a peak velocity threshold of 40°/s and minimum duration of 50 ms (default SMI implementation). The monitor resolution was 1920 × 1080, and the stimuli covered 1440 × 1080 of the screen (centered), capturing approximately 24 × 18 degrees of the visual field.

Procedure

Participants freely viewed 78 scenes without any instructions or explanations as to the goals of the study. Before each image was presented, the participants were instructed to look at a fixation point that appeared in the center of the screen for 1 s, after which each image was displayed for 3 s. Immediately after the experiment, the participants were asked verbally by the experimenter about their visual preferences for text and faces: "How much time did you look at the faces/text? 100 means that you looked only at faces/text, and 0 that you did not look at all."

Data preprocessing

To measure gaze preference for faces and text, we extracted the percentages of the fixation time directed at each content type out of the total fixation time on the image. This measure was extracted solely for images that contained the relevant content (e.g., face preference was computed only on images that contained faces). Fixations were parceled from the sample data using the software provided by SMI (BeGaze). The average rate of missing samples across all participants was 9.75% with a standard deviation of 16.23%. Missing samples were excluded from the analysis.

General statistical analysis

In all three experiments, we extracted two measures: gaze preference (i.e., the proportion of time gaze was directed at the specific content, measured by the eye-tracking system) and the subjective visual preference (i.e., the participants' reports on the percentage of time they looked at certain content). The first experiment had three types of visual content (food, attractive faces, and IAPS images), the second experiment had two other types of visual content (gender and skin color), and the third had two other types of visual content (faces and text). The participants' ability to report their visual preferences was evaluated by a Spearman correlation between each participant's estimate and acquired gaze preferences for each type of visual content. To examine the overall relation, an omnibus analysis was performed to examine whether the Spearman correlation coefficients are significantly larger than zero across all visual content and experiments. To that end, each Spearman correlation coefficient was transformed to a Pearson correlation coefficient (Rupinski & Dunlap, 1996). Then, a Fisher's r-to-z transformation was carried out on the approximated Pearson correlation coefficients (Silver & Dunlap, 1987). The random-effects model was used to compute the mean correlation coefficient across visual contents without limiting the variability across visual contents. Because the omnibus analysis yields a single measure that is compared to zero, no correction for multiple comparisons was applied. The degree of heterogeneity (i.e., τ^2) was estimated using the Hunter–Schmidt estimator (Hunter & Schmidt, 2004; Viechtbauer, 2005). In addition to the estimate of τ^2, the Q-test for heterogeneity (Cochran, 1954) is reported. Studentized residuals and Cook's distances were used to examine whether the correlation coefficients were outliers and/or influential in the context of the model (Viechtbauer & Cheung, 2010). Correlations with a studentized residual exceeding the $100 \times (1 - 0.05/(2 \times k))$th percentile of the standard normal distribution were considered potential outliers, where k was defined as the number of studies included in the omnibus analysis (i.e., using a Bonferroni correction with a two-tailed $\alpha = 0.05$). Two correlation coefficients were detected as outliers; hence, to validate the results, another omnibus analysis was performed without it. Furthermore, to take the dependency between correlations into account (some correlations were based on the same samples), we performed another omnibus analysis using the sample-wise approach (Hunter & Schmidt, 2004) that considers the averages of the correlation coefficients of each experiment while defining the sample size as the actual number of participants (the number of data points used for one correlation from the experiment and not the sum of all data points). The meta-analysis was performed using the metafor R package (Viechtbauer, 2010).

Results

The first experiment involved an attentional bias task in which two images appeared simultaneously on each trial. The content of the images was either positive and neutral IAPS images, attractive and less attractive faces, or appealing and unappealing food. The correlations between subjective reports and gaze preferences for each content type revealed two significant positive correlations for IAPS images ($\rho = 0.29$, $p = 0.032$) and food ($\rho = 0.66$, $p < 0.001$), reflecting participants' ability to evaluate how much time they looked at more positive images and more appealing food, compared to neutral images and unappealing food, respectively. The correlation between subjective reports and gaze preference for attractive faces was positive but not significant ($\rho = 0.07$, $p = 0.614$). The scatterplots of all correlations (across all experiments and visual contents) are presented in Figure 2.

In the second experiment, participants were asked to estimate whether they looked more at female faces than male faces when viewing matrices of faces and whether they looked more at Black faces than White faces. The correlations between the subjective reports and gaze preferences for skin color ($\rho = 0.41$, $p = 0.02$) and gender ($\rho = 0.26$, $p = 0.163$) revealed two nonsignificant positive correlations.

In the third experiment, participants freely viewed complex scenes that included text and faces without specific instructions. The correlations between the subjective reports and gaze preferences were positive and significant for both faces ($\rho = 0.31$, $p = 0.015$) and text ($\rho = 0.29$, $p = 0.025$).

To evaluate whether the ability to report visual preferences differed across experiments and contents, an omnibus analysis was performed. A total of seven different visual contents were included in the analysis. Fisher's r-to-z transformed correlation coefficients ranged from 0.07 to 0.83, and all estimates were positive. The estimated average Fisher's r-to-z transformed correlation coefficient based on the random-effects model was $\hat{\mu} = 0.37$ (95% CI: 0.2, 0.54). Therefore, the average outcome differed significantly from zero ($z = 4.27$, $p < 0.0001$), which indicates that overall, the correlation between subjective reports and gaze preferences was significant and that people are aware of their visual preferences. A forest plot showing the observed outcomes and the estimates based on the random-effects model is shown in Figure 3. To validate the robustness of the results, two statistical adjustments were performed (removal of outliers and considering the dependencies between samples). These adjustments led to qualitatively similar results (Supplementary Table S1).

Discussion

The current study examined whether individuals are aware of their visual preferences. All the correlations between subjective visual preference (the participants' estimates of how long they looked at certain content) and objective gaze preference (the time they actually spent looking at the content) toward all content types were positive. An omnibus analysis including the seven different types of visual content showed that participants were aware of their visual preferences.

Previous research on individuals' knowledge of their gaze behavior characteristics has focused on the ability to recognize one's own gaze patterns as compared to others (Clarke et al., 2017; Foulsham & Kingstone, 2013; Võ et al., 2016). Here, we focused on a more general measure—namely, visual gaze preferences, which visual content people tend to look at. The findings suggest that participants were aware of their visual preferences for various types of content. Interestingly, although gaze tendencies can be inferred from the specific gaze pattern, the mixed results as to the ability to recognize one's own scanning patterns (Henderson, 2017; Võ et al., 2016) suggest that there may be other ways in which people estimate their visual

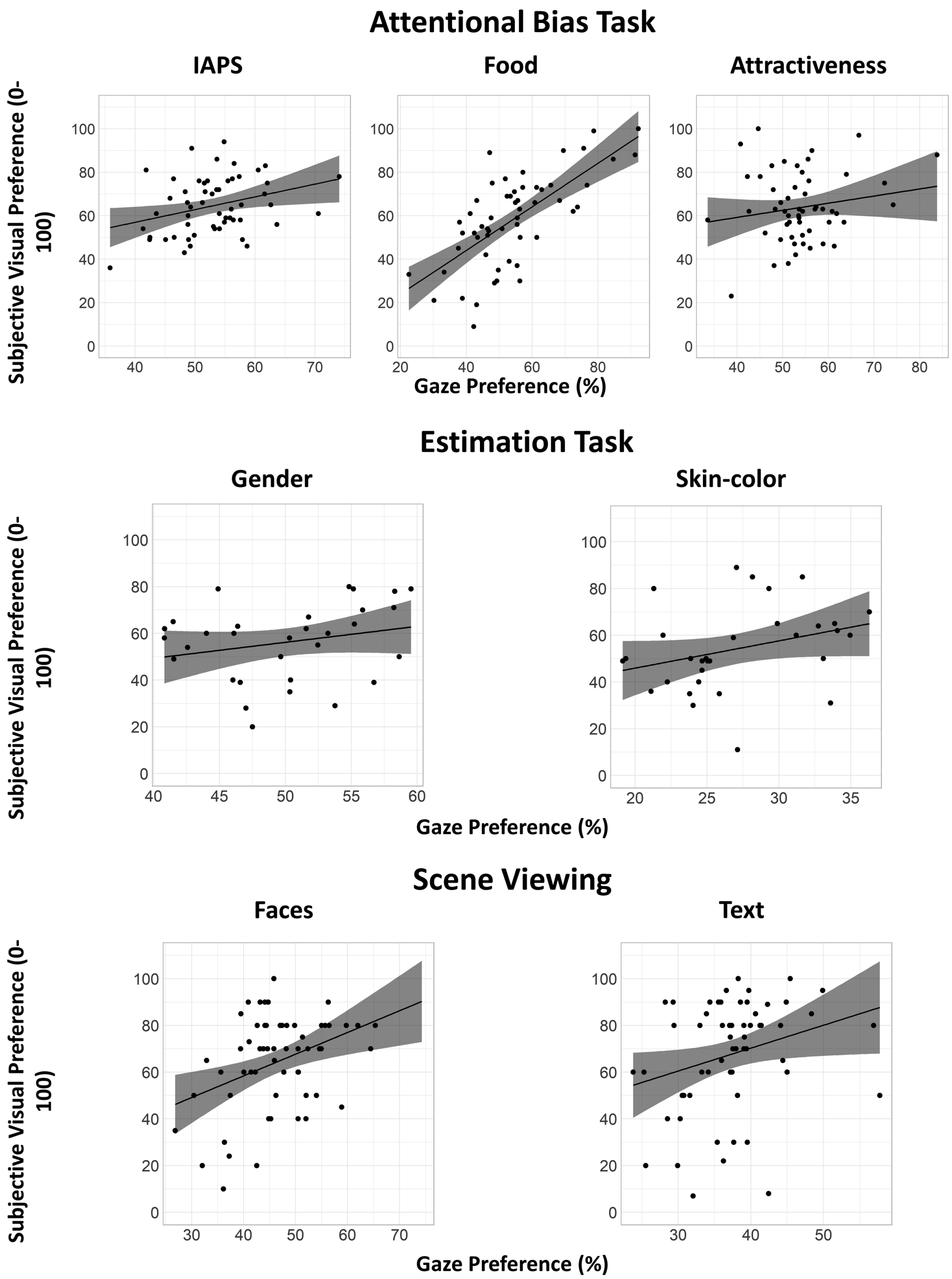


Figure 2. Scatterplots with regression lines of gaze preference and subjective reports of visual preference. Each cell illustrates the scatterplot for visual gaze preference (x-axis), as measured by the eye tracker, and subjective reports of visual preference (y-axis), as reported by the participants after the experiment, for each specific content type.

preferences rather than remembering where exactly they fixated.

Here we suggest three nonmutually exclusive explanations for participants' ability to report their gaze preferences. First, participants might have based their subjective visual preferences reports on their visual memory of the objects they looked at and not their specific gaze positions (Clarke et al., 2017; Foulsham & Kingstone, 2013). Importantly, this explanation assumes that participants remembered many of the objects they looked at across multiple stimuli and were able to evaluate the time they looked at each object. Second, participants might have inferred their subjective visual preference through introspection by

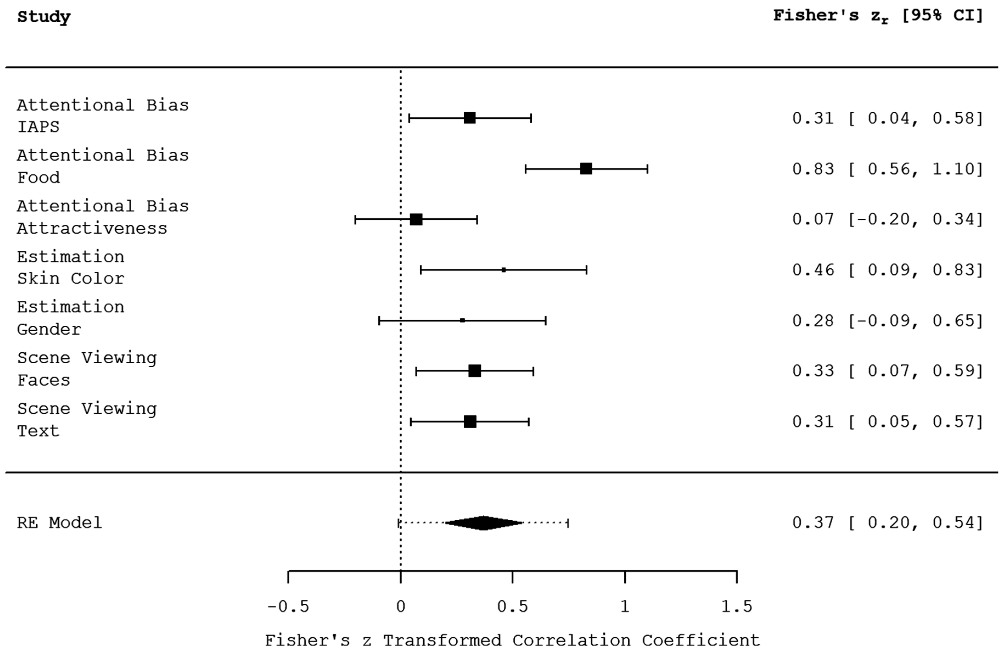


Figure 3. Omnibus analysis forest plot. Each line shows the observed output of visual content. The bottom line indicates the estimate of the random-effects model.

examining internal processes and thoughts (Byrne, 2005). For example, after viewing the IAPS images (neutral and positive images), individuals who felt happier may have inferred that they looked longer at the positive images. Finally, our measure might reflect the declarative knowledge of visual preference—that "knowledge about oneself as a learner and about what factors influence one's performance" (Schraw & Moshman, 1995), which suggests that people generally know their visual preferences and therefore can report them at any given time (and not only after viewing images of specific visual content). Further research is needed to differentiate between these possible explanations.

According to the omnibus analysis, a large proportion of the variances of both measures (gaze and subjective visual preferences) remained unexplained (i.e., not related to the other). Thus, although subjective visual preferences reflect objective gaze preferences (~13% of the variance), they do not fully capture them (~87% of the variance). The unexplained variance suggests that both measures tap additional information that might relate to other cognitive processes. For example, the unexplained variance could be related to individuals' percepts of themselves, which could influence the subjective reports but not gaze preference. If people perceive themselves as optimistic, they might tend to report a more positive visual preference regardless of their gaze preference. Another alternative is related to visual processing abilities. More efficient processing of faces (faster recognition) may shorten the time people look at faces without perceiving this time as shorter, resulting in an overestimation of the subjective reporting of face preference.

The current study has several limitations. First, participants may have been more conscious of their eye movements following the eye-tracking procedures (e.g., calibration), which could either have improved their accuracy in estimating their subjective visual preference or impacted their "natural" visual preference. Future studies could calibrate without the participants' knowledge, for example, by using smooth pursuit calibration (Celebi et al., 2014). Second, we asked participants to report their visual preference for two or three visual contents at a time, so the reports could have influenced each other. Third, the number of trials differed across visual contents, which might have led to underestimating the correlation for cases with fewer trials. This concern also limits the ability to directly compare the awareness level of preference to the different contents. Fourth, in Experiment 2, matrices always contained fewer Black faces compared to White faces. This might lower the range of subjective report values and by product lower the correlation with the real gaze behavior measures. Finally, although some studies generalize gaze preference to the real world (Peterson et al., 2016), it still remains unclear whether all gaze preferences measured in the lab apply to real situations.

Nevertheless, the findings suggest that the participants were aware of which content they looked at. The content types were positive and neutral images (IAPS), appealing and unappealing food images (food), attractive faces and less attractive faces (attractive faces), female and male faces (gender), Black and White faces (skin color), and faces and text in complex scenes. The experiments presented here tested various visual contents, but each content appeared in only one of the experiments, which also differed in terms of their settings. While the different settings mean that any direct comparison between preferences should be treated with cautious, a few interesting observations emerged from the findings. In the second experiment that included two types of visual content, one was related to the task itself (the participants were asked to estimate the percentage of female faces), and the other was unrelated (skin color). Presumably, the relationship to the task should improve participants' ability to estimate their visual preference for female faces. However, the results did not support this hypothesis and instead revealed a stronger correlation for the unrelated visual content. In addition, the omnibus analysis revealed two outliers that reflected a very strong relationship between subjective report and gaze preference when viewing food images (appealing and unappealing) and a weak relationship when viewing attractive and less attractive faces. One possible explanation for the high correlation coefficient observed in the study involving food pictures presenting a contrast between fresh and rotten food is that the definition of freshness and rottenness is relatively objective and not highly influenced by the subjectivity of the participants. In contrast, attractiveness is highly subjective and therefore may lead to a weaker relationship. Besides the extreme values, we still observed a range of coefficients across different visual contents, with a range of $0.26 \leq \rho \leq 0.41$. The cause of this variation is currently unknown, but understanding it may provide insight into metacognitive processes. Nevertheless, the presence of this pattern across multiple stimuli supports the existence of a basic metacognitive process that occurs irrespective of the specific stimulus being presented. Future research is needed in order to better understand what influences the ability to report visual preferences.

The present findings have implications for the development of eye tracking–based diagnostic tools and clinical practice. Since gaze preferences are predictive of mental health states (e.g., Giel et al., 2011; Kellough et al., 2008), the positive correlations observed here between subjective reports and gaze preferences imply that asking individuals about their visual preferences may also be predictive of their mental health states. In addition, the finding that participants were aware of their visual biases and preferences could pave the way to techniques that interfere with (undesirable) preferences in clinical settings. For example, individuals could be trained to look more or less at certain visual content as a function of their biases. Indeed, simply enhancing their awareness of their visual preferences might influence their percepts.

Thus, overall, in three different tasks (attentional bias, estimation, and scene viewing) and across seven types of visual content, participants could accurately report their visual preferences. Individuals' sensitivity to their visual preferences hints at memory and metacognitive mechanisms that allow access to features of gaze behavior. This access has applicative implications for the development of eye tracking–based diagnostic tools and clinical interventions.

Keywords: eye movements, visual cognition, meta cognition, individual differences

Acknowledgments

The authors thank Sharon Livneh and Ron Seinberg for data collection.

Supported by Israeli Science Foundation (ISF) grant 2414/20.

Commercial relationships: none.
Corresponding author: Nitzan Guy.
Email: guynitzan@gmail.com.
Address: Cognitive and Brain Sciences Department, Hebrew University of Jerusalem, Mount Scopus, Jerusalem, Israel.

References

Blechert, J., Lender, A., Polk, S., Busch, N. A., & Ohla, K. (2019). Food-pics_extended—an image database for experimental research on eating and appetite: Additional images, normative ratings and an updated review. *Frontiers in Psychology, 10*, 307.

Bradley, B. P., Mogg, K., Millar, N., Bonham-Carter, C., Fergusson, E., & Jenkins, J. et al. (1997). Attentional biases for emotional faces. *Cognition & Emotion, 11*(1), 25–42, https://doi.org/10.1080/026999397380014.

Byrne, A. (2005). Introspection. *Philosophical Topics, 33*(1), 79–104.

Celebi, F. M., Kim, E. S., Wang, Q., Wall, C. A., & Shic, F. (2014). A smooth pursuit calibration technique. *Proceedings of the Symposium on Eye Tracking Research and Applications,* 377–378, ETRA conference 2000, https://doi.org/10.1145/2578153.2583042.

Chapman, A., Devue, C., & Grimshaw, G. M. (2019). Fleeting reliability in the dot-probe task. *Psychological Research, 83*(2), 308–320, https://doi.org/10.1007/s00426-017-0947-6.

Chelnokova, O., Laeng, B., Eikemo, M., Riegels, J., Løseth, G., Maurud, H., . . . Leknes, S. (2014).

Rewards of beauty: The opioid system mediates social motivation in humans. *Molecular Psychiatry, 19*(7), 746–747.

Clarke, A. D. F., Mahon, A., Irvine, A., & Hunt, A. R. (2017). People are unable to recognize or report on their own eye movements. *Quarterly Journal of Experimental Psychology, 70*(11), 2251–2270, https://doi.org/10.1080/17470218.2016.1231208.

Cochran, W. G. (1954). The combination of estimates from different experiments. *Biometrics, 10*(1), 101–129.

Dechant, M., Trimpl, S., Wolff, C., Mühlberger, A., & Shiban, Y. (2017). Potential of virtual reality as a diagnostic tool for social anxiety: A pilot study. *Computers in Human Behavior, 76*, 128–134, https://doi.org/10.1016/j.chb.2017.07.005.

de Haas, B., Iakovidis, A. L., Schwarzkopf, D. S., & Gegenfurtner, K. R. (2019). Individual differences in visual salience vary along semantic dimensions. *Proceedings of the National Academy of Sciences, 116*(24), 11687–11692, https://doi.org/10.1073/pnas.1820553116.

Eizenman, M., Yu, L. H., Grupp, L., Eizenman, E., Ellenbogen, M., & Gemar, M. et al. (2003). A naturalistic visual scanning approach to assess selective attention in major depressive disorder. *Psychiatry Research, 118*(2), 117–128.

Findlay, J. M., Findlay, J. M., & Gilchrist, I. D. (2003). *Active vision: The psychology of looking and seeing*. Oxford, UK: Oxford University Press.

Flechsenhar, A., Rösler, L., & Gamer, M. (2018). Attentional selection of social features persists despite restricted bottom-up information and affects temporal viewing dynamics. *Scientific Reports, 8*(1), 12555, https://doi.org/10.1038/s41598-018-30736-8.

Foulsham, T., & Kingstone, A. (2013). Where have eye been? Observers can recognise their own fixations. *Perception, 42*(10), 1085–1089, https://doi.org/10.1068/p7562.

Giel, K. E., Friederich, H.-C., Teufel, M., Hautzinger, M., Enck, P., & Zipfel, S. (2011). Attentional processing of food pictures in individuals with anorexia nervosa—an eye-tracking study. *Biological Psychiatry, 69*(7), 661–667, https://doi.org/10.1016/j.biopsych.2010.09.047.

Guy, N., Azulay, H., Kardosh, R., Weiss, Y., Hassin, R. R., & Israel, S. et al. (2019). A novel perceptual trait: Gaze predilection for faces during visual exploration. *Scientific Reports, 9*(1), 1–12, https://doi.org/10.1038/s41598-019-47110-x.

Henderson, J. M. (2017). Gaze control as prediction. *Trends in Cognitive Sciences, 21*(1), 15–23, https://doi.org/10.1016/j.tics.2016.11.003.

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Thousand Oaks, CA: Sage.

Kardosh, R., Sklar, A. Y., Goldstein, A., Pertzov, Y., & Hassin, R. R. (2022). Minority salience and the overestimation of individuals from minority groups in perception and memory. *Proceedings of the National Academy of Sciences, 119*(12), e2116884119, https://doi.org/10.1073/pnas.2116884119.

Kellough, J. L., Beevers, C. G., Ellis, A. J., & Wells, T. T. (2008). Time course of selective attention in clinically depressed young adults: An eye tracking study. *Behaviour Research and Therapy, 46*(11), 1238–1243, https://doi.org/10.1016/j.brat.2008.07.004.

Lang, P. J. (2005). *International affective picture system (IAPS): Affective ratings of pictures and instruction manual*. Gainesville, FL: NIMH, Center for the Study of Emotion & Attention. (Technical Report).

Lazarov, A., Ben-Zion, Z., Shamai, D., Pine, D. S., & Bar-Haim, Y. (2018). Free viewing of sad and happy faces in depression: A potential target for attention bias modification. *Journal of Affective Disorders, 238*, 94–100, https://doi.org/10.1016/j.jad.2018.05.047.

Leder, H., Tinio, P. P. L., Fuchs, I. M., & Bohrn, I. (2010). When attractiveness demands longer looks: The effects of situation and gender. *Quarterly Journal of Experimental Psychology, 63*(9), 1858–1871, https://doi.org/10.1080/17470211003605142.

Ma, D. S., Correll, J., & Wittenbrink, B. (2015). The Chicago face database: A free stimulus set of faces and norming data. *Behavior Research Methods, 47*(4), 1122–1135.

MacLeod, C., Mathews, A., & Tata, P. (1986). Attentional bias in emotional disorders. *Journal of Abnormal Psychology, 95*(1), 15.

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. https://doi.org/10.1167/14.7.6.

Osterberg, G. A. (1935). Topography of the layer of the rods and cones in the human retina. *Acta Ophthalmology, 13*(6), 1–102.

Papoutsaki, A. (2015). Scalable webcam eye tracking by learning from user interactions. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 219–222), John Wiley & Sons Ltd., https://doi.org/10.1145/2702613.2702627.

Peltola, M. J., Yrttiaho, S., & Leppänen, J. M. (2018). Infants' attention bias to faces as an early marker of social development. *Developmental Science, 21*(6), e12687, https://doi.org/10.1111/desc.12687.

Peterson, M. F., Lin, J., Zaun, I., & Kanwisher, N. (2016). Individual differences in face-looking behavior generalize from the lab to the world. *Journal of Vision, 16*(7), 12, https://doi.org/10.1167/16.7.12.

Pool, E., Brosch, T., Delplanque, S., & Sander, D. (2015). Attentional bias for positive emotional stimuli: A meta-analytic investigation. *Psychological Bulletin, 142*(1), 79, https://doi.org/10.1037/bul0000026.

Rupinski, M. T., & Dunlap, W. P. (1996). Approximating Pearson product-moment correlations from Kendall's tau and Spearman's rho. *Educational and Psychological Measurement, 56*(3), 419–429.

Schmukle, S. C. (2005). Unreliability of the dot probe task. *European Journal of Personality, 19*(7), 595–605, https://doi.org/10.1002/per.554.

Schraw, G., & Moshman, D. (1995). Metacognitive theories. *Educational Psychology Review, 7*, 351–371.

Sears, C., Quigley, L., Fernandez, A., Newman, K., & Dobson, K. (2018). The reliability of attentional biases for emotional images measured using a free-viewing eye-tracking paradigm. *Behavior Research Methods, 51*, 2748–2760, https://doi.org/10.3758/s13428-018-1147-z.

Semmelmann, K., & Weigelt, S. (2018). Online webcam-based eye tracking in cognitive science: A first look. *Behavior Research Methods, 50*(2), 451–465, https://doi.org/10.3758/s13428-017-0913-7.

Silver, N. C., & Dunlap, W. P. (1987). Averaging correlation coefficients: Should Fisher's z transformation be used? *Journal of Applied Psychology, 72*(1), 146–148, https://doi.org/10.1037/0021-9010.72.1.146.

Valuch, C., Pflüger, L. S., Wallner, B., Laeng, B., & Ansorge, U. (2015). Using eye tracking to test for individual differences in attention to attractive faces. *Frontiers in Psychology, 6*, 42, https://www.frontiersin.org/articles/10.3389/fpsyg.2015.00042.

van Wermeskerken, M., Litchfield, D., & van Gog, T. (2018). What am I looking at? Interpreting dynamic and static gaze displays. *Cognitive Science, 42*(1), 220–252, https://doi.org/10.1111/cogs.12484.

Viechtbauer, W. (2005). Bias and efficiency of meta-analytic variance estimators in the random-effects model. *Journal of Educational and Behavioral Statistics, 30*(3), 261–293.

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software, 36*(3), 1–48, https://doi.org/10.18637/jss.v036.i03.

Viechtbauer, W., & Cheung, M. W.-L. (2010). Outlier and influence diagnostics for meta-analysis. *Research Synthesis Methods, 1*(2), 112–125.

Võ, M. L.-H., Aizenman, A. M., & Wolfe, J. M. (2016). You think you know where you looked? You better look again. *Journal of Experimental Psychology. Human Perception and Performance, 42*(10), 1477–1481, https://doi.org/10.1037/xhp0000264.

Xu, J., Jiang, M., Wang, S., Kankanhalli, M. S., & Zhao, Q. (2014). Predicting human gaze beyond pixels. *Journal of Vision, 14*(1), 28, https://doi.org/10.1167/14.1.28.