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Individual Differences in Motivated Response and Visual Perception

By

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Abstract

Leong and colleagues (2019) found two dissociable biases in motivated perception: a bias in sensory perception and a bias in a person's reports of what they perceive. Prior research on motivated perception have noted that individuals differ in how susceptible they are to motivated perception (Leong et al., 2019), but they have not examined why these differences exist. The goal of the current study was to assess the relationship between personality traits (i.e. anxiety, depression, impulsiveness and paranoia) and the level of bias towards what a participant is motivated to see. A merged face-scene image task was presented to participants, with a forced-choice between the image as more face-dominant or more scene-dominant. Participants were motivated towards face-dominant images for 4 of 12 blocks, scene-dominant for 12 blocks, and neutral or no motivation for 4 blocks. Survey measures were collected for each participant personality trait. Linear regressions, Drift Diffusion Modeling (DDM), t tests, and psychometric modeling were used to analyze data. Results showed that participants are more likely to see what they are motivated to see, but individual difference findings were not significant. This is likely due to the small sample size, and future research should explore this topic further.

Table of Contents

From a quote by Edgar Allen Poe “believe only half of what you see,” to Ralph Waldo Emerson “people only see what they are prepared to see,” people have understood that perception is not always reality (Emerson, 2013; Poe, 1845). Research has found these observations to be true: people tend to see what they want to see (Leong et al., 2019).

Studies on motivational effects of visual perception can be traced back to the cognitive revolution in the 1950s, when research pursuits in psychology shifted towards the study of unobservable aspects of the mind (e..g, beliefs, goals, desires). In 1954, a case study by Hastorf and Cantril analyzed members of rival schools who witnessed the same game, but had opposing perceptions of the event. Questions arose after Hastorf and Cantril’s initial findings; such as the depth in which motivation, wishes or preferences could impact the mind (1954). Since then, the study of motivated perception supported theories that preferences and wishes impact information processing beyond the conscious mind, and into subconscious processes (Balcetis & Dunning, 2006). Previous work has found that when there is increased ambiguity in a stimulus and an incentive to interpret information for a favored outcome, participants are more likely to report seeing the interpretation they favor, a phenomenon that is often referred to as *motivated perception* (Balcetis & Dunning, 2006).

In recent work, Leong and colleagues (2019) proposed that motivated perception reflects two dissociable biasing mechanisms: a response bias (e.g., a bias in what people report seeing) and a perceptual bias (e.g., a bias in sensory perception). They then mapped the two biases onto two distinct components of a drift diffusion model (DDM). The DDM assumes that perceptual decisions are determined by accumulating sensory information over time, influencing the person towards one decision or the other. When the accumulated evidence reaches a threshold for a decision, a choice is made. Leong and colleagues argued that a bias in the starting point of evidence accumulation reduces that amount of evidence needed to make a response, and can be mapped onto a response bias. In contrast, a bias in the rate of evidence accumulation (i.e. the "drift" rate) reflects a change in how sensory evidence is gathered, and can be mapped onto a perceptual bias. By fitting the model to behavioral data of human participants, Leong and colleagues (2019) found that motivation biased both the starting point and rate of evidence accumulation in favor of the desirable category, providing empirical evidence that motivated perception reflects both response and perceptual biases.

While we have a better understanding of the cognitive components of motivated perception, we know very little about the factors that drive individual differences in the magnitude of motivated perception. Although prior studies on motivated perception have noted that individuals differ in how susceptible they are to motivated perception (Leong et al., 2019), they have not examined why these differences exist. Why do participants in the same age range, participating in the exact same experiment, exhibit different degrees of motivated perception? One possibility is that these differences reflect personality differences. If so, what personality traits are related to motivated perception? The goal of the current set of experiments is to assess the relationship between personality traits and the magnitude of motivated perception. In particular, we assess if inter-individual differences in impulsivity, depression, paranoia and anxiety would be associated with motivated perception. We focus on these four traits because they have been previously associated with suboptimal decision-making (Lee, 2013). In addition, as these traits are also implicated in psychiatric disorders, our work allows us to examine the relationship between motivated perception and psychopathology.

Here, we review the evidence suggesting why these four traits might be related to motivated perception. Impulsiveness and motivation was investigated by Białaszek and colleagues (2015) which showed that impulsive people had a compulsion towards immediate gratification. Similarly, Martin and Potts (2009) found a positive relationship between impulsivity and a bias towards immediate reward. Raio and colleagues (2020) found that people with higher impulsivity also had a tendency to choose faster when under acute stress. This could indicate that impulsive decisions are influenced by outside factors, with the possibility that motivational bias could be one. Together, these studies suggest that impulsivity might increase one's susceptibility to motivational biases. Thus, we predict that impulsive individuals would be more likely to exhibit motivated perception. Savulich and colleagues (2017) found that people with clinical paranoia showed high levels of cognitive bias in interpretation. More recently, Rossi-Goldthorpe and colleagues (2021) found that paranoid individuals are more susceptible to motivated perception. Thus, we expect to replicate these findings in the current study.

Previous studies investigating depression and motivation found that a deficit in motivation was tied to a belief that the proposed reward was not going to provide pleasure (Sherdell et al., 2012). This might lead to a lower bias in depressed individuals because they are not as motivated by reward, as they believe the reward to be less enjoyable. Rude and colleagues (2002) found that people with depression tend to process emotionally ambiguous images as more negative. This could potentially be due to increased attention to negative aspects of the image (Guha et al., 2021). This might suggest that there is an inverse relationship between depression and bias towards reward, meaning that rather than being biased towards the desirable percept, individuals with depression might be biased against the desirable percept. Kornbrot and colleagues (2013) however, found that people with higher depression were more accurate and less biased than people with low depression. Thus, past work would predict a negative or null correlation between depression and motivated perception.

Finally, Richards and colleagues (2002) found that anxious people categorized emotionally ambiguous images of faces with more negativity bias than non-anxious people. Other researchers have found that people with anxiety have increased attentional bias towards negative information when looking at complex images (Rudaizky et al., 2013). From these readings it was expected that when facing ambiguous stimuli in this experiment, people with anxiety would exhibit bias towards negative outcomes. This would predict a negative correlation between anxiety and motivated perception.

In summary, we expect individual differences of anxiety, paranoia, depression and impulsiveness to be correlated with motivated perception. Paranoia and impulsiveness are expected to be positively related to motivated perception, whereas anxiety and depression are expected to be negatively related to motivated perception. In addition to correlating overall levels of motivated perception with the trait measures, we also fit a DDM model to participants' data. We then examined if the bias parameters (e.g., bias in drift rate and bias in starting point) are related to the trait measures.

Methodology

Participants

24 Participants were recruited from The University of Chicago research participation program, with ages between 18 - 25 (8 Male, 15 Female). Sample communities were chosen based on convenience. Participants were recruited with monetary compensation based upon performance, and without demographic targets. All participants provided informed written consent prior to the start of the study. All experimental procedures were approved by the Institutional Review Board at The University of Chicago.

Survey Measures

Individual difference measures were collected through four consecutive surveys: the 18 question Revised Green et al. Paranoid Thoughts Scale (RGPTS) with both parts A and B to evaluate ideas of reference and ideas of persecution (Freeman et al., 2021); the 21 question Beck Depression Inventory II (BDI-II) for generalized depression (Beck et al., 1996); the 40 question State Trait Anxiety Inventory (STAI) with both the Y-1 and Y-2 form to evaluate generalized anxiety over time and momentary anxiety (Spielberger, 1983); and the 30 question Barratts Impulsiveness Scale Version 11 (BIS-11) to evaluate attentional, motor, and non-planning impulsiveness (Patton et al., 1995). Prior to the experiment, each participant was sent an email with an experiment date, a four digit participant ID, and a link to a Qualtrics survey. The surveys were arranged without titles in the order of RGPTS part A, RGPTS part B, BDI-II, STAI Y-1, STAI Y-2, and BIS-11.

Survey measures have been broken into 7 sub-scales. Depression has been measured through the BDI-II scale. The average cut off value for non-clinical samples across literature according to Wang and Gorenstein (2015) for the BDI-II was 11.8, so the cutoff value for this experiment was 12. Impulsiveness has been measured through the BIS-11 scale. Stanford and colleagues (2009) identified scores above 71 to be an ideal cutoff in impulsiveness of participants using the BIS-11 and that score was used in this experiment as well.

Paranoia has been measured in two contexts of a) reference paranoia (RGPTSA) and b) persecutory paranoia (RGPTSB). Cut off values for each survey was based on prior clinical research cut off values. Freeman and colleagues (2021) identified optimal cut off values as the *moderately severe* threshold for nonclinical samples as 11 for the RGPTS-A which evaluates persecutory paranoid thoughts, and 16 for the RGPTS-B which evaluates paranoid thoughts of reference. Participants that meet the cutoff values for either part A or B will be categorized into the paranoid group for analysis, given that the scales were designed to be assessed differently to measure two different types of paranoia (persecutory or reference) (Freeman et al., 2021).

Anxiety has been measured in three contexts; a) momentary or state anxiety within 3 days prior to experiment (STAI-Y1), b) momentary or state anxiety immediately following the experiment (STAI-Y1), and c) generalized anxiety assessed prior to experiment (STAI-Y2). Prior work found the ideal STAI Y1 cut off value as 41, and STAI Y2 cut off value as 44 (Ercan et al., 2015). The analysis for anxiety in comparison to other individual differences will use the STAI-Y2 for generalized anxiety, given that the other individual differences are generalized states rather than momentary fluctuations. State anxiety measures will be compared to each other to understand if fluctuations in state anxiety impact experimental scores, but will not be compared with other individual difference conditions for this experiment.

Stimuli

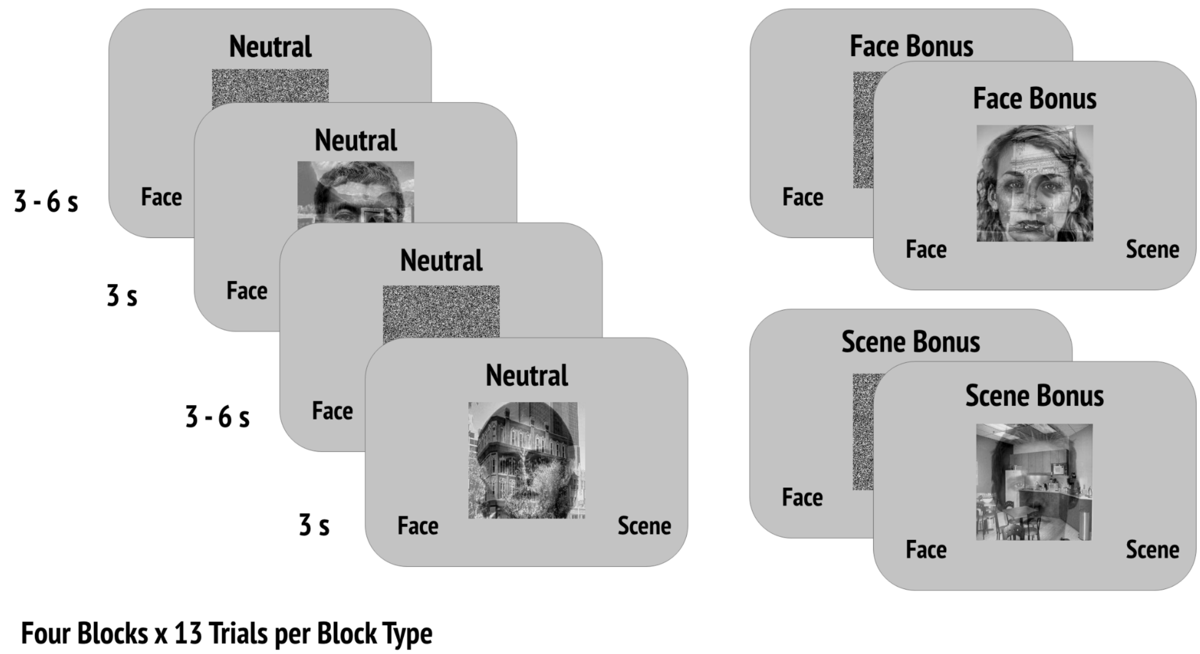
Each participant viewed 12 sets of face-scene stimuli consisting of a face image and scene image merged together. Stimulus sets contained 13 gray-scale images and each image in a set combined face and scene content in different proportions. Images containing less than 48% scene content were considered face dominant, and images containing more than 48% scene content were considered scene dominant. Images were divided into these groups based on a test of the boundaries in which people found a distinction between images as either face-dominant or scene-dominant (Leong et al., 2021). Six stimulus sets had more scene dominant images (0 images at 33% scene, 2 images at 43% scene, 8 images at 48% scene, 2 at 53% scene, and 1 at 63% scene). Six different stimulus sets contained more face dominant images (1 image at 33% scene, 2 images at 43% scene, 8 images at 48% scene, 2 at 53% scene, and 0 at 63% scene). All images of faces were frontal photographs taken from the Chicago Face Database and contained neutral expressions (Ma et al., 2015). Presentations of stimuli were through MATLAB and Psychophysics Toolbox.

Task

Immediately following the stimuli presentation, participants were asked to categorize the image as primarily ‘face’ or ‘scene’ (see Figure 1). In the categorization task there were three types of blocks, one for each motivational condition: a monetary bonus for correctly identifying ‘face’, a monetary bonus for correctly identifying ‘scene’, and a ‘neutral’ condition without a monetary bonus. The experiment consisted of four of each motivation condition, for a total of twelve sets. For face bonus blocks, participants received a bonus of $3.00 if there were more face-dominant images. For scene bonus blocks, participants received a bonus of $3.00 if there were more scene-dominant images. In the neutral blocks, they did not receive a bonus based on the category of images in the block. In all blocks, Participants were rewarded $0.14 for every image that was correctly identified. Thus participants would be motivated to see more face-dominant images in the face-bonus blocks and scene-dominant images in the scene-bonus blocks.

Figure 1

Experimental Task Visualization



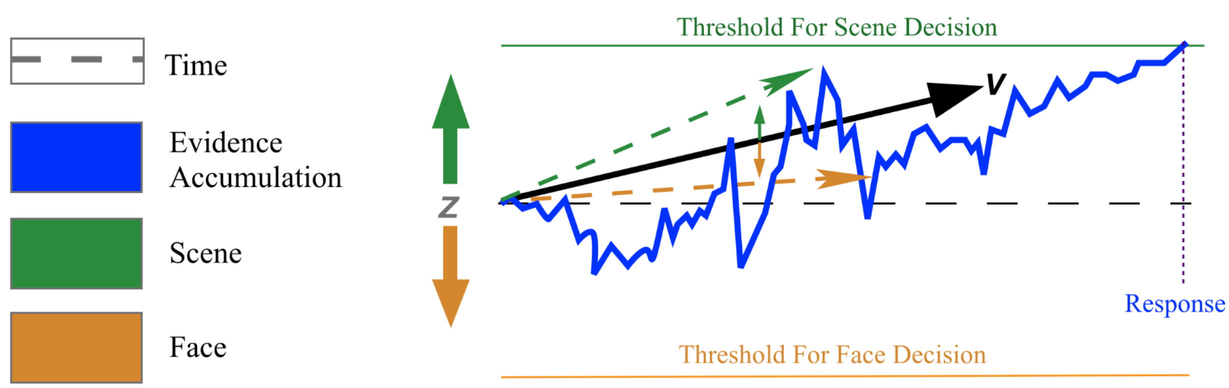
Note. Participants were asked to categorize ambiguous face-scene merged images as either face-dominant or scene dominant, and were awarded \$0.14 for each correct categorization. Bonus blocks awarded \$3.00 if there were more images in the bonuses category (i.e. more face images in face bonus blocks).

Drift Diffusion Model

The Drift Diffusion Model (DDM) is a mathematical model that uses behavioral data to allow for further interpretation about biases. We will fit the DDM to participants' data, and correlate the model parameters with survey results. The DDM models the cognitive process during a 2 choice decision, and assumes that a choice is the result of noisy evidence accumulation towards one decision threshold over the other. A bias in the starting point of evidence accumulation (*z*) reduces the amount of evidence needed to make a response, and can be mapped onto a response bias. A bias in the rate of evidence accumulation, or drift rate (*v*) reflects a change in how sensory evidence is gathered, and can be mapped onto a perceptual bias. A largely positive *v* indicates a bias towards scene images, and a largely negative *v* indicates a bias towards face images.

Figure 2

Schematic Diagram of the Drift Diffusion Model (DDM)



Note. Each choice is modeled as noisy evidence accumulation towards one of two decision thresholds. Motivation biases decision making by biasing the drift rate (*v*) or a starting point (*z*). The dotted lines represent a bias towards scene images (green) or against scene images (orange). An unbiased starting point *z* is shown in black, with solid arrows around *z* representing a starting point bias towards scene images (green) or away from scene images (orange).

Reaction time distributions and participant categorizations were used to estimate model parameters by the HDDM toolbox. Model parameters were estimated by Markov chain Monte Carlo sampling (100,000 samples; burn-in = 10,000 samples; thinning =2). Outliers generated by processes not accounted for in the model (i.e. accidental button press) were accounted for by a mixture model with 5% of trials assumed to be uniformly distributed.

The HDDM package identifies the starting point (z) bound by 0 and 1, with 0.5 representing an unbiased starting point. The inverse logit link function was used to restrict z values between 0 and 1. To incorporate motivational bias in the starting point, we modeled z as follows:

$$z = \frac{1}{1 + \exp(-(\beta_{z1}\ \text{Motivation} + \beta_{z0}))}$$

where motivation represents the motivationally consistent category, represented with +1 when participants were motivated to see more scene images, -1 when participants were motivated to see more face images and 0 when participants were not motivated to see either image. β_{z1} signifies the effect of motivation on the starting point (z bias), and β_{z0} signifies an intercept term denoting an intrinsic response bias towards one of the categories..

We modeled the drift rate as:

$$v = \beta v_1 \text{Motivation} + \beta v_2\,\%\ \text{scene} + \beta v_0.$$

Motivation was coded the same as it was above, with +1 representing trials on which participants were motivated to see more scene images and -1 representing trials on which participants were motivated to see more face images. β_{v1} signifies the effect of motivation on the drift rate (v bias), and β_{v2} signifies the effect of percentage scene on the drift rate. Scene percentage was calculated before putting it into the model so β_{v0} would reflect intrinsic drift rate bias. Bias parameters (z bias and v bias) were used to compute the ratio of posterior samples larger than 0.

Psychometric function

Generalized linear mixed-effects models were used to model participant response data, which allowed for a single model to represent psychometric properties rather than creating a different model for each participant (Knoblauch & Maloney, 2012). Participant choices (i.e. image as scene dominant or face dominant) was modeled as a function of the percentage of scene information and block type. Models were created with the glmer function in the lme4 package in R Studio (Bates et al., 2015). Motivational bias for each participant was estimated by the random effect of block type on responses for that participant.

Individual Difference Analysis

Multiple linear regressions were run for each personality trait (i.e., anxiety, depression, impulsiveness, and paranoia) to understand the relationship between individual difference levels and motivational bias. It was hypothesized that there would be a significant positive relationship between paranoia and motivational bias, as well as impulsiveness and motivational bias. It is hypothesized that there will be a negative relationship between depression and motivational bias as well as anxiety and motivational bias. Two-sample t-tests were run to assess if motivational bias would differ between high-paranoia and low-paranoia participants, high-depression and low-depression participants, high-anxiety and low-anxiety participants, and high impulsiveness and low impulsiveness participants. Bonferroni multiple comparison correction testing was used for correction among findings in regressions and t-tests.

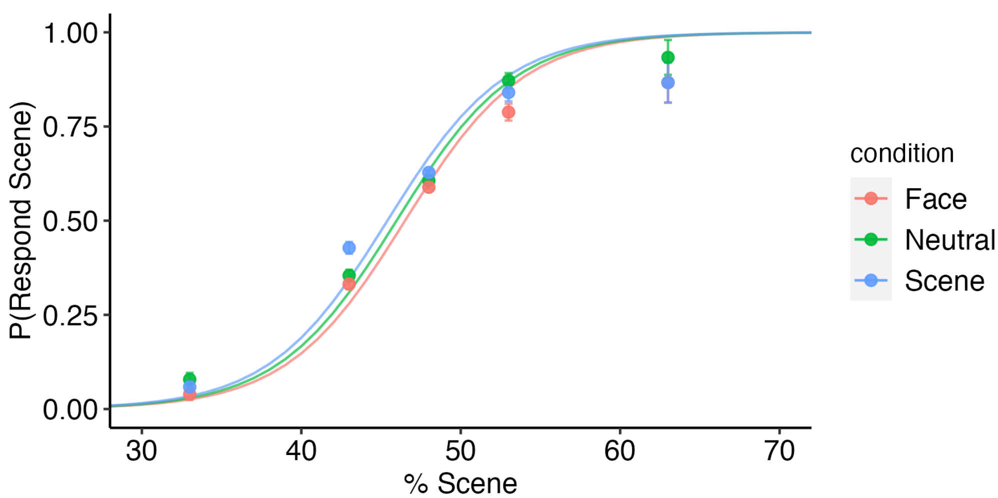
Results

Behavioral Results

Behavioral analysis explored the effects of category bonus on perceptual judgements and estimated differences between each block by using general linear mixed-effect models (Figure 3). Results replicated the findings seen in Leong and colleagues (2021) and showed that participants were more likely to categorize an image as face-dominant in face-bonus blocks and as scene dominant in scene-bonus blocks ($z = 2.12$, $p = .034$, $b = 0.29$, 95% CI = [0.02, 0.56]). In simplest terms, this is evidence that participants are biased to report seeing what we motivated them to see.

Figure 3

Psychometric Curve

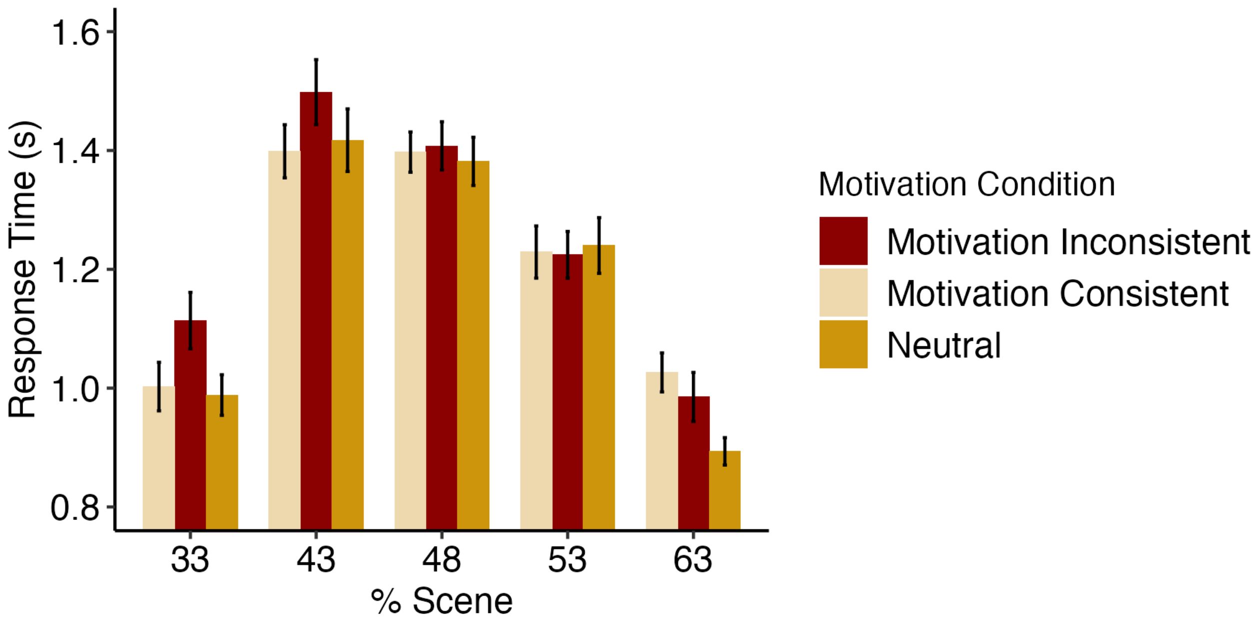


Note. The proportion of trials in which participants reported that the image was more scene dominant (P(Respond Scene)") as a function of the actual percentage of scene in the image (% Scene) and block type (scene-bonus, neutral or face-bonus).

Motivational effects on participant reaction times were explored. Motivation consistent responses were responses where participants categorized an image as the category associated with the category bonus (i.e., categorizing an image as face-dominant in a face-bonus block). Motivation inconsistent blocks were responses in the category that were not associated with the category bonus (i.e. categorizing an image as face-dominant in a scene-bonus block). Response times were not significantly different between motivation consistent and motivation inconsistent responses, $t(21.9) = 1.14$, $p = .27$, $b = 0.032$, 95% CI = [-0.02, 0.09].

Figure 4

Response Times of Behavioral Data



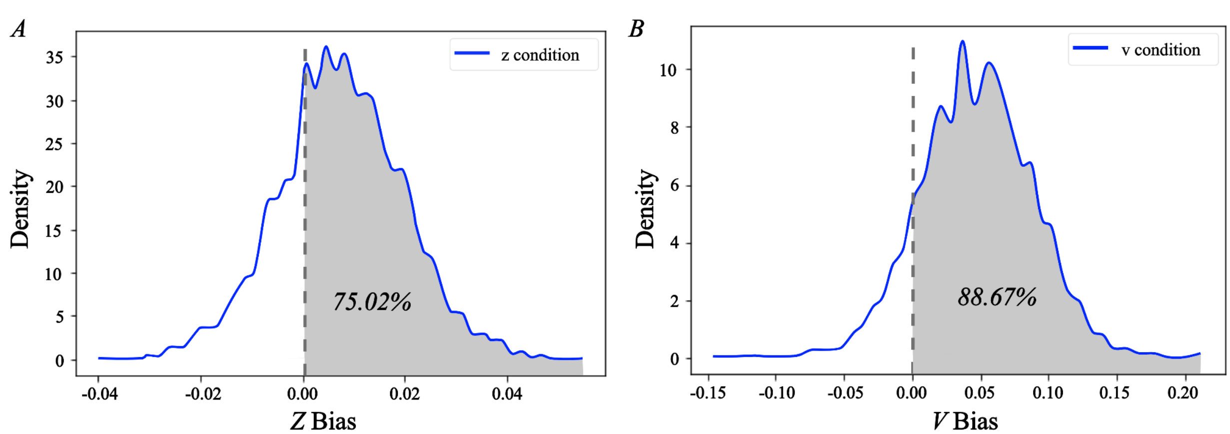
Note. Mean response times for categorization among images across participants, separated by motivation condition and percentage of scene in the image.

DDM Results

Response time distributions were fitted using a Drift Diffusion Model (DDM). The DDM characterizes the process of perceptual judgements, and assumes that judgment arises from the noisy accumulation of sensory evidence towards a decision threshold. Motivational bias is shown in this model by a starting point bias (*z*) or a drift rate bias (*v*) of sensory evidence accumulation towards the category participants were motivated to see over the category participants were not motivated to see. A starting point bias indicated that less evidence was needed to make a motivated-consistent response, and a drift rate bias indicated that the process of evidence accumulation changed to favor a motivated consistent category. Both the starting point bias and drift rate bias increase responses towards the motivation-consistent condition but show distinct differences in the response times modeled in the DDM (White & Poldrack, 2014).

Figure 5

DDM Results for Starting Point (z) and Drift Rate (v) Biases



Note. Posterior distribution of the estimate of the A. starting point bias (Z Bias) and B. the drift bias. The dotted line indicates 0 (i.e. no bias). The gray shaded region indicates the proportion of the distribution above 0.

We estimated each bias by fitting a drift diffusion model to participants' data. The posterior distribution of the estimate of the starting bias is shown in Figure 5A. A large proportion of the distribution was greater than 0, indicating that there is a high probability of a biased starting point ($P(z_{bias}>0)=0.7502$, mean = 0.0076). This suggests that participants needed less evidence to categorize an image as the category they were motivated to see. Similarly, a large proportion of the distribution of the estimate of the drift bias was greater than 0, indicating that there is a high probability of a biased drift rate (Fig. 5B, $P(v_{bias}>0)=0.8867$, mean = 0.0472). This suggests that the accumulation of sensory evidence was biased in favor of the category participants were motivated to see.

Personality Traits and Motivational Bias

Motivation scores were computed for each participant using the generalized linear mixed effects models, then compared with survey scores of individual difference measures. T tests were run on each of the four individual differences: anxiety, paranoia, depression, and impulsiveness. There was no significant difference in motivational bias between individuals with momentary anxiety (M = 0.20, SD = 0.27) compared to people without momentary anxiety (M = 0.10, SD = 0.11; $t_{(24)} = -1.23$, $p = .23$). Motivational biases between people with generalized anxiety (M = 0.17, SD = 0.16) compared to people without generalized anxiety (M = 0.18, SD = 0.31) was not significantly different ($t_{(24)} = 0.12$, $p = .91$). Motivational biases between people with depression (M = 0.16, SD = 0.21) compared to people without depression (M = 0.18, SD = 0.26) were not significantly different ($t_{(24)} = 0.17$, $p = .87$). Motivational biases between people with high impulsivity (M = 0.19, SD = 0.14) compared to people with low impulsivity (M = 0.17, SD = 0.27) were not significantly different ($t_{(24)} = -0.25$, $p = .81$). Motivational biases between people with paranoia (*M* = 0.18, *SD* = 0.25) compared to people without paranoia (*M* = 0.16, *SD* = 0.24) showed no significant difference ($t_{(24)}$ = -0.18, *p* = .86).

Personality Traits and DDM Estimates of Bias

To obtain a more fine-grained estimate of participants' bias, we extracted the starting point and drift bias for each participant, and assessed whether personality traits would be associated with differences in either of these biases. Parameter scores (starting point bias and drift rate bias) from the DDM were extracted for each participant, then compared with each survey score of individual difference measures (anxiety, paranoia, depression, and impulsiveness) through t tests. There was no significant difference in drift rate bias between individuals with momentary anxiety (*M* = 0.06, *SD* = 0.06) compared to people without momentary anxiety (*M* = 0.04, *SD* = 0.02; $t_{(24)}$ = -1.09, *p* = .29). Drift rate bias between people with generalized anxiety (*M* = 0.05, *SD* = 0.04) compared to people without generalized anxiety (*M* = 0.06, *SD* = 0.06) was not significantly different ($t_{(24)}$ = 0.39, *p* = .70). Drift rate bias between people with depression (*M* = 0.06, *SD* = 0.05) compared to people without depression (*M* = 0.05, *SD* = 0.05) were not significantly different ($t_{(24)}$ = -0.42, *p* = .68). Drift rate bias between people with high impulsivity (*M* = 0.06, *SD* = 0.06) compared to people with low impulsivity (*M* = 0.05, *SD* = 0.05) were not significantly different ($t_{(24)}$ = -0.27, *p* = .80). Drift rate bias between people with paranoia (*M* = 0.46, *SD* = 0.06) compared to people without paranoia (*M* = 0.05, *SD* = 0.05) showed not to be significantly different ($t_{(24)}$ = -0.76, *p* = .46).

Starting point bias between people with high impulsivity (*M* = 0.03, *SD* = 0.02) compared to people with low impulsivity (*M* = 0.00, *SD* = 0.03) were significantly higher ($t_{(24)}$ = -2.23, *p* = .04). There was no significant difference in starting point bias between individuals with momentary anxiety (*M* = 0.01, *SD* = 0.03) compared to people without momentary anxiety (*M* =

0.02, *SD* = 0.03; $t_{(24)} = .50$, $p = .63$). Starting point bias between people with generalized anxiety (*M* = 0.01, *SD* = 0.02) compared to people without generalized anxiety (*M* = 0.01, *SD* = 0.04) was not significantly different ($t_{(24)} = 0.23$, $p = .82$). Starting point bias between people with depression (*M* = 0.01, *SD* = 0.04) compared to people without depression (*M* = 0.01, *SD* = 0.03) were not significantly different ($t_{(24)} = -0.13$, $p = .68$). Starting point bias between people with paranoia (*M* = 0.00, *SD* = 0.02) compared to people without paranoia (*M* = 0.02, *SD* = 0.03) showed not significantly different ($t_{(24)} = 1.68$, $p = .11$).

T tests that were run were extremely underpowered and had groups as small as six in some conditions (e.g., there were only six participants who were considered depressed). The significance of impulsiveness even with such a small sample could suggest that something is happening that will yield significant results in the future, and should be explored further. Momentary anxiety also yielded much smaller p values compared to other conditions, and should be investigated more.

Discussion

The Drift Diffusion Model (DDM) revealed a difference in how quickly someone would respond to incentivized stimuli, confirming previous studies which found that people are more motivated to see what they want to see (Leong et al., 2021). This study incentivized and motivated people by presenting a stimulus under a condition that was either against reward, no reward present, or aligned with reward. To prevent findings facilitated by priming effects, participants were only rewarded when they answered correctly, which deterred repetitive answers aligning with set reward for monetary gain.

One of the goals of this study was to expand the investigation beyond the single domain of paranoia. Results found that people do, in fact, see what they are motivated to see. There was a significant difference between highly impulsive participant's starting point bias and less impulsive participant's starting point bias. There was not, however, a significant difference in drift rate bias. This might indicate that impulsive people are more impacted by a priori information when making decisions, leading to less evidence needed to make decisions that fit with their goals. However, results here indicate that impulsiveness has no impact on the process of gathering sensory evidence in order to make a decision. A difference in significance between types of motivational biases is interesting because it suggests that impulsiveness reflects a change in what is needed to make decisions rather than a quicker decision making process.

A lack of significance in analyses between other individual difference tests goes against the original hypotheses, but is likely the result of such a small sample size. While time was a constraint for this study, there were also irregular school closings due to COVID-19, and recruitment in an academic setting without the ability to offer course credit. Course credit could not be given to students due to the use of monetary motivation because of the need to prioritize the ability to study motivation and ensure that our participants were motivated by money rather than the fulfillment of a requirement. This could have also contributed to a small number of participant registration.

In a larger context, this experiment aimed to raise questions on how or why some individuals are more easily motivated than others. We were able to replicate the previous findings that people see what they want to see. We also found a difference in motivational bias between a) conditions aligning with motivation condition and b) against motivation condition. Regression analyses and t-tests on individual differences were likely not significant due to the small sample size used in this study, and it is hypothesized that a larger sample would yield significance. Results are expected to change due to the replication of other findings less drastically impacted by sample size, like the DDM modeling, and given that the primary difference between the studies being replicated and the current study is sample size.

Findings could also be a result of state differences in people, rather than trait differences. This would mean that a person's motivation might change based on momentary changes (i.e. momentary anxiety, stress, or sadness), rather than changes slowly over time (i.e. generalized anxiety, depression, or paranoia). This could explain why the largest findings were seen in impulsivity and momentary anxiety. Results could indicate that a study comparing motivation at multiple time points would lead to more interesting results, and that motivation can be manipulated depending upon the state of an individual rather than the generalized characteristics of an individual.

To further study this direction, it is suggested that multiple time points are added, as well as adding state differences, such as the Discrete Emotions Questionnaire (Harmon-Jones et al., 2016), rather than trait differences. Future studies should investigate if there is a difference between mood conditions and decision making abilities, including the recruitment of a larger number of participants. Given the progression back to normalcy after COVID-19 it is the hope that future research can be more robust in recruiting participants.

Possible applications for findings could be in targeting audiences to behave in a desired manner: like abstaining from harmful drugs or applications for bribery motivations. Future work based on this study's findings could lead to a better understanding of how different people make decisions, and what groups are impacted by motivation the most. It was shown that impulsiveness impacted motivation and that in general, people are motivated to see what they are motivated to see. This could have an effect on everyday sensory processing, for instance how a person's motivations change based on their social identifications which impact how they think of race. Freeman and colleagues (2011) found that social cues bias race perception, but it would be interesting to understand if things like impulsivity and individual differences in motivational bias could be a root for these findings. Are social cues motivating people, which then biases their perception of others?

A different extension of these findings could investigate other senses, to understand if motivational bias is the same across auditory and visual perception. There have been a few studies trying to understand how auditory perception influences visual perception (Williams et al., 2021). It would be interesting to understand if impulsivity would still have significant impacts on motivational bias when acting upon multiple sensory processes. If individual differences are shown to be motivationally biased across multiple senses, then that might mean that the bias is at a higher level in the brain rather than biasing lower level inputs. Research from that would be able to identify more specifically the effects of motivational bias within the line of processing.

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Appendix

Experiment Instructions Script and Photo

Visual Classification of Images

Instructions: Thank you for participating in our study. This study will take approximately 50 minutes. You will be paid $10 for your time, and up to $25 more in bonus (i.e. total payment = $10 to $35).

In this study, you will be presented with composite images made by mixing a face image and a scene image in different proportions. Some images will have more “Face” in them (i.e., the face image has higher intensity than the scene image), while other images will have more “Scene” in them (i.e., the scene image has higher intensity than the face image). For example, the left image has more “Face”, while the right image has more “Scene”.

Your task is to categorize whether there is more "Face" or more "Scene" in each image. If your categorization is correct, you earn 5 cents. In some blocks, you will have the opportunity to earn a bonus. You will receive additional instructions about these bonuses when you start the task, so please read them carefully.

During the experiment, we will be tracking your eye movements using the camera on the desk. We ask you to keep your head stable on the chin rest while you do the task. In between blocks, you can move away from the chin rest to take a break. However, we ask that you keep your head on the chin rest at all other times so that we can get clear and usable data. Please let the experimenter know when you have finished reading the instructions.