Sensory Processing Patterns Predict the Integration of Information Held in Visual Working Memory

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Given the limited resources of visual working memory, multiple items may be remembered as an averaged group or ensemble. As a result, local information may be ill-defined, but these ensemble representations provide accurate diagnostics of the natural world by combining gist information with item-level information held in visual working memory. Some neurodevelopmental disorders are characterized by sensory processing profiles that predispose individuals to avoid or seek-out sensory stimulation, fundamentally altering their perceptual experience. Here, we report such processing styles will affect the computation of ensemble statistics in the general population. We identified stable adult sensory processing patterns to demonstrate that individuals with low sensory thresholds who show a greater proclivity to engage in active response strategies to prevent sensory overstimulation are less likely to integrate mean size information across a set of similar items and are therefore more likely to be biased away from the mean size representation of an ensemble display. We therefore propose the study of ensemble processing should extend beyond the statistics of the display, and should also consider the statistics of the observer.

Keywords: visual working memory, sensory processing, ensemble perception, neurodevelopmental disorders, individual differences

When processing information from the environment, the visual system has to balance speed with accuracy. Typically, an initial fast feedforward sweep of relatively coarse information is followed by a slower but more accurate iterative feedback process (Di Lollo, Enns, & Rensink, 2000; VanRullen & Thorpe, 2001; Oliva & Torralba, 2006). While different priorities and constraints govern these processes, both are capacity limited. Regardless of which way the balance between speed and accuracy tips, neither the initial and more globally oriented nor the slower and more locally oriented process includes a complete representation of the visual input (Hochstein & Ahissar, 2002). How do we accurately and efficiently perceive complex and crowded environments in the face of such severe capacity limitations? One beneficial strategy is to represent a set of similar items as an averaged group or ensemble, enabling the condensing of multiple individual measurements into a single, higher level of description (for a review, see Alvarez, 2011). While the majority of previous research has focused almost exclusively on measuring the statistics of a display, the common

element to different display types, however, is the observer. In the present study, we tested the hypothesis that the variability in observers' stable disposition to represent visual information can predict the incorporation of ensemble statistics with individual items.

The natural world is composed of stable and highly regular predictable patterns (Kersten, 1987), affording us the opportunity to compress redundant visual input to reduce the heavy computational load placed on the visual system. Multiple studies have confirmed that observers can compute accurate ensemble statistics to average information across various individual measurements, such as mean size (Ariely, 2001; Chong & Treisman, 2005), orientation (Parkes, Lund, Angelucci, Solomon, & Morgan, 2001), and location (Alvarez & Oliva, 2008), without explicitly encoding individual items (Corbett & Oriet, 2011).

Beyond simple features, ensemble statistics may further drive representations of the average emotion (Haberman & Whitney, 2007), identity (de Fockert & Wolfenstein, 2009), and gaze (Sweeny & Whitney, 2014) of faces in a crowd, and may be represented on multiple, independent levels differentiated through high- and low-level attributes (Haberman, Brady, & Alvarez, 2015). Remarkably, ensemble statistics have been shown to implicitly bias the representation of individual items held in visual working memory, such that the remembered size of an individual item was biased toward the mean size of items sharing the same color (Brady & Alvarez, 2011). This occurrence, however, was not without exception across observers, reflecting variation in the ability to integrate ensemble statistics with individual items held in visual working memory. Indeed, previous research has demonstrated that interindividual differences in social anxiety levels bias the coding of ensemble features for the average emotion of faces in a crowd (Yang, Yoon, Chong, & Oh, 2013). Thus, distinguishable patterns of observer statistics may account for variance in the processing of ensemble features, and provide unique insight for understanding encoding in visual working memory.

Analogous to natural world statistics, stable observer statistics may reflect predictable patterns of sensory experience, which interact with the perception of our environment. Dunn's (1997) model of sensory processing captures individual variability in processing patterns by measuring stable traits corresponding to behavioral strategies (active-passive) and neurological responses (high-low) to general sensory experiences. A four-quadrant model describes interactions of a neurological threshold continuum with a behavioral response continuum, representing behaviors in accordance with sensory thresholds. These thresholds are centered on an individual's ability to modulate sensory input by monitoring and regulating information for an appropriate response. When sensory information is poorly modulated, individuals may exhibit maladaptive responses to incoming sensory input. For example, an individual with low neurological threshold traits will show high excitation responses for low-to-moderate-intensity stimuli, such as a flickering light. This, in turn, may subsequently interact with an active or passive behavioral continuum and result in avoidance behaviors to limit exposure to stimuli (active), or distractibility and discomfort (passive). In contrast, an individual with high neurological threshold traits may show greater habituation to the same sensory stimulation, subsequently resulting in decreased reactivity to the sensory environment. Thus, variation in the ability to mod-

ulate sensory input differentiates individuals across processing styles.

Such extremes in sensory hypersensitivity or hyposensitivity have been shown to correlate with the diagnosis of multiple neurodevelopmental disorders, such as autism spectrum disorder (ASD; Tomchek & Dunn, 2007). Interestingly, neurodevelopmental disorders such as ASD are partially characterized by sensory challenges and social deficits in situations with rich sensory input, such as processing gaze and emotional expression (Lord et al., 2000). In such situations, the typically developing brain can take advantage of ensemble statistics to reduce the inflow of sensory information to a representative average of, for example, the emotional expression of faces in a crowd (Haberman & Whitney, 2007). Given that neurodevelopmental disorders typically present themselves along a continuum, it may also be the case that different neurological thresholds for sensory stimulation across healthy observers will modulate how effectively ensemble statistics can be employed.

We propose stable patterns of sensory processing and sensitivity to the visual environment predict perceptual behavior. Specifically, we suggest these stable predispositions predict the integration of ensemble statistics with information held in visual working memory, resulting in a directional bias toward or away from the mean representation of a set of items sharing common features. To test this hypothesis, we combined a typical ensemble processing task (Brady & Alvarez, 2011) with measures of sensory processing recorded with the Adult Sensory Profile (Brown, Tollefson, Dunn, Cromwell, & Filion, 2001). Additionally, we controlled and compared cognitive ability and demographic factors by including measures of visual working memory capacity (K), general intelligence (g), gender, and age. If hypersensitive (low-threshold) individuals show perceptual patterns intended to prevent sensory overstimulation, we could expect these individuals to employ avoidant strategies which limit global perceptual input in favor of orienting to local detail, thus failing to integrate similar items. Conversely, individuals less susceptible to sensory overstimulation may be more likely to efficiently process incoming information in parallel by averaging similar items, and thus display a greater bias toward the mean ensemble representation.

Method

Participants

Seventy-four undergraduate students of the University of Toronto community (19 male, 55 female) ranging in age from 18–54 years ($M = 21.18$) were compensated for participation in the study with course credit. The experiment was terminated with the conclusion of the academic year, granted a minimum of 70 participants. We chose a minimum of 70 participants because that number provides power >80 to detect a correlation of 0.3, which we determined to be sufficiently different from the null hypothesis using G* Power (Faul, Erdfelder, Buchner, & Lang, 2009). All participants had self-reported normal or corrected-to-normal visual acuity, no history of colorblindness or abnormal neurological conditions, and gave informed consent in accordance with the University of Toronto Ethics Review Board. All participants completed three tasks in the following order: ensemble statistics task, Short Raven's Progressive Matrices Test, and the Adult Sensory

Profile. In addition to the aforementioned tasks, 35 participants completed a *K*-estimate change-detection task as part of a preliminary analysis investigating the correlation between ensemble bias and visual working memory capacity.

Display and Apparatus

Tasks were presented electronically using Matlab (MathWorks, Natick, MA), E-Prime 1.0 (Psychology Software Tools, Pittsburgh, PA), and Presentation (Version 11.0, www.neuro-bs.com), on a ViewSonic 21-in. CRT monitor (1,280 × 1,024 pixels; 85-Hz refresh rate) at a viewing distance of 57 cm (subtending 38.70° × 29.49° of visual angle) held constant by using a desk-mounted chinrest. The Adult Sensory Profile was completed by pen and paper.

Ensemble Statistics Task

To examine the bias of ensemble statistics for a set of items sharing common features, we conducted a direct replication of the first experiment presented in Brady and Alvarez (2011) under the fixed presentation conditions described earlier. Participants were presented with a total of 30 displays each consisting of nine circles of varying size (three red, three blue, and three green), and were asked to remember the size of the red and blue circles, while ignoring the green circles. By asking participants to ignore a subset of circles, this task incorporated a measure of attentional selection which required the suppression of irrelevant distractors. Each display appeared on screen for 1.5 s and was then followed by a 1-s blank period, after which participants were cued to a target location with a randomly sized circle appearing in black at the previous location of a blue or red circle. Participants were then instructed to use the computer mouse to resize the new black circle so that it matched the red or blue circle they had previously viewed in that location (see Figure 1a).

The nine circles appeared on a gray background that measured 600 × 400 pixels, and each circle was randomly positioned in an unseen 6 × 4 grid, with a jitter of ±10 pixels added to the circles' locations to prevent collinearities. Circles were drawn from a separate normal distribution for each color, and which color set

was selected to appear as largest or smallest was randomly chosen on each trial. The mean diameter for the circles of a given color was uniformly chosen on each trial from the interval (15 pixels, 95 pixels) of each individual circle, and individual circles were then chosen from this mean's normal distribution and a standard deviation equal to one eighths of this mean. In order to directly test bias in reported size, 15 displays were generated, and then another 15 matched displays were created by switching the color of the to-be-tested item with the other nondistractor color. Thus, two matched displays had the same items, but the tested item colors were swapped between the displays. The 30 displays were then randomly interleaved, with the constraint that paired displays could not appear one after the other.

K-Estimate Change-Detection Task

A change-detection paradigm (Phillips, 1974; Luck & Vogel, 1997) was used to obtain an accurate representation of individual visual working memory capacity (*K*). On each trial, participants were briefly presented (150 ms) with a sample array consisting of one to six randomly assigned colored squares appearing on an invisible grid evenly distributed around a fixation point (six possible colors; eight possible locations), followed by a 1.2-s blank period, and were then asked to determine if the color of a subsequently presented target square matched the color of the sample square that appeared in the same location, by using the left (same) and down (different) arrow keys on a computer keyboard. *K* was determined by the average number of items successfully remembered for any given set size (one to six) using the following formula developed by Pashler (1988) and modified by Cowan (2010):

$$K = S \times (H + CR - 1)$$

Where S represents the given set-size, H represents the number of *hits*, and CR corresponds to the number of *correct rejections*. Thus, this formula yields an average number of items successfully remembered (*K*) for a given set size (S), while accounting for guessing (CR − 1).
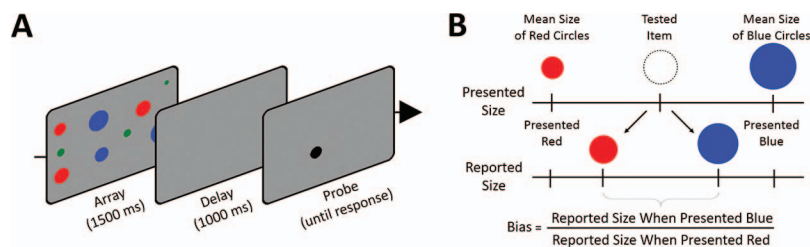

Figure 1. (A) Stimuli and procedure used in the ensemble statistics task. Participants were asked to remember the size of the red and blue circles, and ignore the green circles. After a short delay, they were asked to recall and select the size of the circle previously seen in that location and cued by a black probe circle. (B) An illustration showing how bias was determined from a pair of matched displays. Two matched displays had the same items, but the tested item's colors were swapped between the displays. Bias was calculated by dividing the reported size for probed items presented in the color of the larger circles by the reported size for probed items presented in the color of the smaller circles. A ratio greater than 1.0 indicates a bias toward the mean size of the same-colored circles. Adapted from "Hierarchical Encoding in Visual Working Memory: Ensemble Statistics Bias Memory for Individual Items," by T. F. Brady and G. A. Alvarez, 2011, *Psychological Science, 22*, p. 386. Copyright 2011 by SAGE Publications.

Short Raven's Progressive Matrices Test

We used the 36-item Short Raven's Progressive Matrices Test to obtain an unbiased estimate of nonverbal general intelligence (Raven, 2000). In each question, participants were instructed to select the missing pattern (from eight possible alternatives) in order to complete a design from a series of diagrams. Participants had 15 min to answer as many questions as possible (to a maximum of 36) using a keyboard number pad corresponding to eight options, after which the total number of correct responses determined their general intelligence score (*g*).

Adult Sensory Profile

Sensory processing was assessed using the four-quadrant 60-item Adult Sensory Profile (Dunn, 1997; Brown et al., 2001), which measures stable sensory preference. Participants used pen and paper to circle a response on a 5-point Likert scale (*almost never*, *seldom*, *occasionally*, *frequently*, *almost always*). Each quadrant consisted of 15 items representing each of four stable traits (Low Registration, Sensation Seeking, Sensory Sensitivity, and Sensation Avoiding), corresponding to an interaction of a neurological threshold continuum (high vs. low) with a behavioral response continuum (passive vs. active).

Low Registration measures difficulty in registering stimuli due to a high neurological threshold for incoming sensory information. Individuals with high scores in Low Registration often present as underreactive, exhibiting slow response and quick habituation to sensation. Sensation Seeking measures behaviors that aim to counteract high neurological thresholds by engaging in activities which increase sensory experience. Individuals scoring highly in Sensation Seeking may display active behavior to seek out rich sensory environments and behaviors that create sensation in order to regulate sensory excitability and increase exposure to sensory stimulation. Sensory Sensitivity measures increased sensitivity due to low neurological thresholds for sensory stimulation. Individuals scoring highly in Sensory Sensitivity may demonstrate hypersensitivity to their environment through the inability to suppress irrelevant incoming information, rapid attention switching, and slow habituation. Sensation Avoiding measures low-threshold behavioral responses associated with engaging in behavior to avoid activating their thresholds. Individuals scoring highly in Sensation Avoiding may exhibit a need to reduce unpredictable stimulation through active withdrawal and resistance in order to provide a pattern of neural activity that is familiar and predictable.

Results

Ensemble Bias

We first assessed whether participants were able to perform the size memory task accurately by comparing performance with an empirical measure of chance obtained by randomly pairing a given participant's responses with the correct answers from different trials (mean difference by chance = 30.5 pixels; Brady & Alvarez, 2011); 95% confidence intervals (CIs) are reported. Participants' average error was 16.8 pixels, revealing performance that was significantly better than the measure of chance ($p < 2.41^{-15}$, 95% CI [14.07, 19.45], $d = -1.16$).

To test ensemble bias, we examined whether participants' size estimates were biased toward or away from the mean size representation of circles within the same color set. Each matched pair (consisting of two displays that had the same items, but the tested item's colors were swapped between the displays) was divided on the basis of which of the pair contained a tested item the same color as the circles that were smaller on average and which contained a tested item the same color as the circles that were larger on average. The reported sizes of the probe items in the latter trials were then divided by reported sizes on the former trials. A ratio of 1.0 would indicate participants' size estimates were not biased. If participants' size estimates were biased toward the mean size of the circles in the same color as the tested item, however, this ratio would be greater than 1.0 (see Figure 1b). On average, the reported size of the tested circle was 1.03 times greater on trials with the larger same-colored circles than on trials with the smaller same-colored circles (see Figure 2a). This ratio was significantly greater than 1.0, $t(73) = 2.75$, 95% CI [1.01, 1.05], $p = .009$, $d = .28$, replicating findings by Brady and Alvarez (2011). Given our predictions, we would expect to see variation in the directionality and extent of ensemble bias across participants. This is precisely what we observed (see Figure 2b), and we explore the source of this variation below.

Demographic and Cognitive Variables

To investigate the influence of demographic and cognitive variables on the directionality of ensemble bias, we examined Pearson correlations between ensemble bias and gender, age, K (M = 3.63, SD = 1.02), and g (M = 19.19, SD = 4.79). For each correlation, 95% CIs are reported. Results did not reveal significant correlations between ensemble bias and gender, $r(74) = .020$, 95% CI [−.247, .209], $p = .866$, $r^2 < .001$, or age, $r(74) = −.067$, 95% CI [−.291, .164], $p = .571$, $r^2 = .005$, showing that ensemble bias was not explained by demographic factors in our study. Similarly, no significant correlations were found between ensemble bias and K, $r(35) = 0.070$, 95% CI [−.269, .394], $p = .689$, $r^2 = .005$, and general intelligence g, $r(74) = −.218$, 95% CI [−.425, .011], $p = .062$, $r^2 = 0.048$, indicating that variations in ensemble bias were not explained by differences in these cognitive variables across participants in our study.
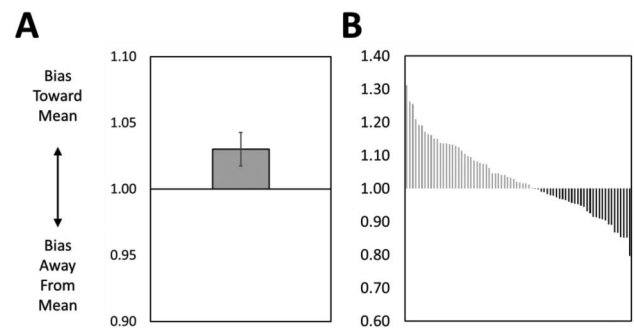

Figure 2. (A) Mean bias averaged across participants. (B) The distribution and direction of mean size bias for all participants. For both graphs, a bias greater than 1.00 represents a bias toward the mean, and a bias less than 1.00 represents a bias away from the mean. Error bars represent the standard error of the mean.

Adult Sensory Profile

To investigate our main hypothesis, we examined correlations between ensemble bias and the four quadrants of the Adult Sensory Profile (see Figure 3). Findings revealed significant correlations between ensemble bias and the low neurological threshold traits of Sensory Sensitivity, $r(74) = -.253$, 95% CI $[-.455, -.027]$, $p = .030$, $r^2 = .064$, and Sensation Avoiding, $r(74) = -.392$, 95% CI $[-.569, -.180]$, $p < .001$, $r^2 = .153$, but not the high neurological threshold traits of Low Registration, $r(74) = -.039$, 95% CI $= [-.265, .191]$, $p = .741$, $r^2 = .001$, and Sensation Seeking, $r(74) = .143$, 95% CI $[-.088, .359]$, $p = .224$, $r^2 = .021$. These results reveal a significant inverse relationship between low neurological threshold sensory traits and ensemble bias. In contrast, no relationship was found between ensemble bias and high neurological threshold sensory traits. These significant correlations remained significant when using Spearman correlations.

A Predictive Model for Ensemble Bias

Further analysis aimed to determine which predictor variables would remain significant with others held constant in order to establish a predictive model for ensemble bias. On the first step of a hierarchical multiple regression analysis (see Table 1), we confirmed that ensemble bias and combined demographic and cognitive variables were not associated, $F(3,70) = 1.394$, $p = .252$, $\eta_p^2 = .056$. When quadrant scores from the Adult Sensory Profile were added on the second step, the variance explained increased

Table 1
Results From Hierarchical Multiple Regression

Predictor	Partial correlation (*pr*)	*p* Value
Step 1: $R = .237$, $F(3,70) = 1.394$, $p = .252$		
Gender	−.063	.604
Age	−.072	.539
g	−.236	.054
Step 2: $R = .454$, $F(4,66) = 3.102$, $p = .021$		
Gender	−.092	.427
Age	−.057	.607
g	−.216	.066
Low Registration	.030	.809
Sensation Seeking	.028	.813
Sensory Sensitivity	−.064	.667
Sensation Avoiding	−.346	**.016**

Note. Ensemble bias was the outcome variable. Significant results are shown in bold.

significantly by 15.0%, $F_{inc}(4,66) = 3.102$, $p = .021$, $\eta_p^2 = .150$, such that the regression model now accounted for 20.6% of the variance explained in ensemble bias. Sensation Avoiding was the only predictor to contribute significantly to the model, $t(73) = 2.480$, $p = .016$, even with all other predictors held constant.

To analyze potential mediating effects of Sensation Avoiding on Sensory Sensitivity, we used a bootstrap mediation analysis (Preacher & Hayes, 2004); 95% confidence intervals were determined from 5,000 bootstrap resamples and any interval that did not include 0 was considered to be significantly different from 0. Confirming results from the hierarchical multiple regression analysis, findings revealed no direct effect of Sensory Sensitivity on ensemble bias ($p = .787$, 95% CI $[-.005, .004]$), and significant mediation of Sensory Sensitivity by Sensation Avoiding (95% CI $[-.007, -.001]$). In contrast, no significant mediation of Sensory Avoiding by Sensory Sensitivity was observed (95% CI $[-.003, .002]$), thus confirming Sensation Avoiding as the main predictor driving correlations between sensory processing patterns and ensemble bias.

Discussion

Our results reveal the overall estimation of size for items held in visual working memory was significantly biased toward the mean size representation of a set of items sharing common features, replicating Brady and Alvarez (2011). We found considerable variability across observers in both the magnitude and directionality of ensemble bias, however, warranting further investigation. Subsequent analyses revealed this variability was not explained by either demographic variables such as age and gender or cognitive variables such as general intelligence and working memory capacity, the latter of which have both been shown to predict the demands placed on executive function for tasks requiring focusing and switching in the face of interference (Kane & Engle, 2002).

In contrast, our findings demonstrate for the first time that stable observer statistics are powerful predictors for the integration of ensemble statistics with individual item representations held in visual working memory. Specifically, we found that individuals with lower neurological sensory thresholds who show patterns of sensory processing characterized by greater sensitivity and active
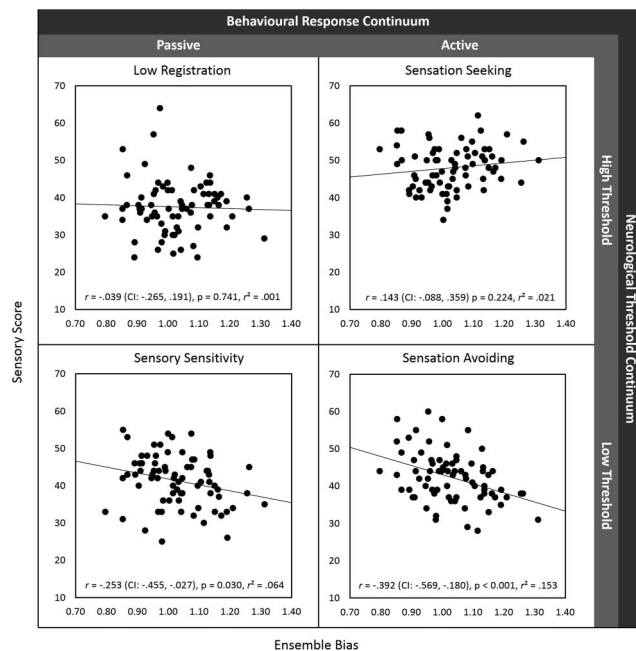
Figure 3. Scatter plots (with best-fitting regression lines) showing correlations between measures of sensory processing and ensemble bias. Measures of sensory processing are arranged by quadrants of intersecting neurological thresholds (high vs. low) with behavioral responses (passive vs. active). An ensemble bias greater than 1.00 represents a bias toward the mean, and a bias less than 1.00 represents a bias away from the mean. CI = confidence interval.

sensation avoidance strategies are more likely to be biased away from the mean size representation of a set of items. Conversely, individuals with less sensation avoidance are more likely to be biased toward the mean size representation.

Our findings indicate that ensemble statistics bias individual item representations toward the mean size of a set within a normal range of sensory processing, yet reveal that stable sensory processing patterns predict variability in the integration and extent to which ensemble statistics bias these representations. Specifically, our findings suggest avoidant strategies aimed to limit incoming perceptual information may influence the integration of information in visual working memory. Hypersensitive individuals may actively utilize avoidance strategies, which deprive them of the computational advantage of employing ensemble statistics for visual working memory representations. As a consequence of this disruption, these individuals may display deficits in the ability to effectively integrate similar information in visual working memory in the presence of competition at the feature level.

From Stable Traits to Transient Representations

Ensemble representations are thought to reduce the computational challenges the visual system faces to fit almost infinite incoming information into limited bandwidths. Much of the previous research on ensemble representation has focused on the visual system's capabilities in forming accurate ensemble representations from readily available low-level summary statistics (Alvarez, 2011). Here, we provide evidence that stable traits in sensory processing significantly predict variance in the bias of ensemble statistics for transient representations held in visual working memory. As described in Dunn's (1997) model of sensory processing, individuals with greater sensitivity and lower sensory thresholds are more likely to experience distraction, discomfort, slow habituation, and ritual avoidance strategies, which are actions repeated in a set precise manner to limit sensory input by reducing exposure to stimuli known to produce overstimulation.

One explanation for our findings suggests hypersensitive individuals may be more sensitive to local changes in stimuli, incorporating avoidant processing styles which limit global sensory input and overstimulation. These individuals may overcompensate for observed local differences by actively exaggerating the differences between individual items sharing common features, and consequently fail to integrate ensemble statistics with individual items in visual working memory, resulting in a bias away from the mean representation of a display. As hypersensitive individuals exhibit slow habituation to incoming sensory information, these individuals may have a tendency to systematically enhance individual item differences, rather than regressing to the perceptual mean. Low-threshold individuals may therefore be less able to employ computational biases, thus failing to compress perceptual regularities for similar sets into ensemble representations. Alternatively, as our task required individuals to actively suppress irrelevant stimuli in the form of green circles, differences in attentional selection between high- and low-threshold individuals may be a contributive factor affecting the integration of similar items into separate sets. For instance, Brady and Alvarez (2011) observed that the removal of irrelevant distractors from an ensemble display resulted in the absence of a bias toward the mean size of same-colored circles in a display. In the present study, hyper-

sensitive individuals may therefore be unable to suppress irrelevant distractors, thereby failing to limit their perceptual experience to behaviorally relevant environmental input. While this explanation would account for an overall absence of bias in low-threshold individuals, it would likely not explain the observed bias away from the mean in this population.

Conversely, those less sensitive to sensory input may benefit from the advantages of computational biases by underrepresenting differences between individual items, and therefore may be more likely to average items together and report a greater bias toward the mean representation of a display. Furthermore, these individuals may be less likely to employ avoidant strategies which would limit their perceptual input. These findings suggest that observer variance in the integration of information in visual working memory may be substantially predicted by the ability to effectively modulate and process complex and noisy sensory input.

From Sensory Experience to Sensory Dysfunction

We have previously suggested that individuals with sensory processing traits furthest from the mean in either direction may be more heavily impacted in the integration of ensemble statistics with visual working memory representations. Although sensory preference is intimately tied with the general human experience, patterns of sensory processing and dysfunction as measured by the Adult Sensory Profile have been correlated with the diagnosis of multiple neurodevelopmental disorders, such as attention-deficit/hyperactivity disorder (Dunn & Bennett, 2002), obsessive–compulsive disorder (Rieke & Anderson, 2009), and schizophrenia (Brown, Cromwell, Filion, Dunn, & Tollefson, 2002). The most extensive research on sensory processing abnormalities in neurodevelopmental disorders, however, has focused on ASD, revealing pervasive difficulties in sensory processing and response in diagnosed individuals (Tomchek & Dunn, 2007). Interestingly, sensory challenges were recently included as a core component of ASD in the *DSM–5* (American Psychiatric Association, 2013). The relationship between sensory processing styles captured by the Sensory Profile and the integration of ensemble statistics we report here leads to the hypothesis that individuals with developmental disabilities that include sensory processing challenges, may also show difficulties in ensemble processing.

Indeed, individuals with ASD exhibit impairments in the ability to integrate multiple pieces of sensory information into coherent wholes, for example the ability to integrate auditory and visual speech (Stevenson, Siemann, Schneider, et al., 2014, Stevenson, Siemann, Woynaroski, et al., 2014). Ensemble processing, which requires integrating item-level information into a group average, may present a similar challenge to those with ASD. Through exploring the computational mechanisms surrounding ensemble perception in the broader context of feature encoding in visual working memory, our findings may break ground and inspire new avenues for future research examining the relationship between neurodevelopmental disorders and the dynamic interplay between representations held in visual working memory. Such research may provide insight into potential links between perceptual predispositions, visual working memory biases and neurodevelopmental disorders, by shedding light on how individuals with neurodevelopmental disorders characterized by sensory processing predispo-

sitions (as observed in the present study) perceive sensory input and subsequently integrate this information in visual working memory.

From Current Knowledge to Future Directions

It is well documented that individual differences in visual working memory performance are related to how attention is controlled and information is stored (Vogel, McCollough, & Machizawa, 2005). Individual differences in ensemble processing, as we have reported here, may be another promising way to account for variance in visual working memory performance. Beyond stable sensory processing patterns, observer statistics may interact with ensemble statistics across multiple dimensions. For instance, future research should explore whether ensemble processing is related to cognitive mechanisms that interact with other stable interindividual differences, such as temperament and personality (Matusz, Traczyk, Sobkow, & Strelau, 2015), or those that are more fluid and context dependent (Thelen, Matusz, & Murray, 2014). Thus, these findings open the opportunity to explore multiple dimensions of observer statistics and how they relate to ensemble coding and visual working memory representations.

Conclusion

Ensemble statistics provide a valuable opportunity for the visual system to overcome the limited resources of visual working memory. Thus, ensemble representations play a pivotal role in the ability to accurately and efficiently perceive the natural world, and afford critical insight into the mechanisms underlying visual working memory processes. Our findings shed light on individual variability in the integration of ensemble statistics with perceptual experience. We therefore propose extending the study of ensemble processing by not only considering the statistics of the display, but also the statistics of the observers.

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