**Supplemental Methods**

*OiPT Analysis*

The group level analysis was conducted with a mixed ANOVA. The between factor was group (controls vs. patients). The within factors were error type (swap vs. generic error rates), probe dimension (location vs. shape probes) and block (first vs. second blocks). The proportion of swap and generic errors is not normally distributed, being constrained to the [0.0-1.0] interval. The Freeman-Tukey double arcsine normalizing transformation was therefore applied to these data:

Where and are the proportion of swap and generic errors respectively, and are the number of swap and generic errors and is the total number of trials. Group level descriptive statistics, including means and standard errors, were computed using the following back transformation:



Where is the group average proportion of either swap or generic errors.



*DSET Analysis*

For each participant, the reported locations were fitted using a mixture model to separate error sources. Our model includes terms to account for two sources of systematic errors, which the literature has previously documented. The first is that when recalling a visual target, the recalled and actual target position differ in a manner which varies systematically with the position occupied by the target in the sample display (e.g. Katshu and d’Avossa, 2014). The second is a centroid bias which arises because target recall is affected by the average value of the recall feature in the sample display (e.g. Brady and Alvarez, 2011; Katshu and d’Avossa, 2014). This model assumed that differences between the recalled and sample target location (***t***) could be due to several factors. These include incorrect color-location bindings, guesses, systematic biases and variable errors. For sake of simplicity, we assumed that these factors made independent contributions to the overall error. Recall accuracy and precision in trials in which participants made a swap error, i.e., reported the location of a non-target item with probability *Ps*, were assumed to be identical to those in trials in which participants reported the target location. Moreover, the horizontal and vertical variable errors were assumed to be normally distributed, uncorrelated, and characterized by a covariance matrix () constant over item positions. Horizontal and vertical systematic errors were modelled as affine functions of the horizontal and vertical position respectively, of the target and distractors (*t*, ***d1***, ***d2***), as well as their centroid (***c***). Guess errors (*Pg*) were assumed to be uniformly distributed over the central 80% of the screen area.

Thus, the following model was used to parametrize the probability of reporting the location ***r*** on the *i*-th trial:

In each participant parameters were estimated by minimizing the negative log-likelihood function :

Group level analysis was then conducted on the proportion of swap and guess errors and the standard deviation of the variable errors, using mixed ANOVAs.

*DNMST Analysis*

Expected accuracies as a function of d’, were calculated using a simple model of choice, which assumed that the novel object evokes a larger response than the familiar object(s), response magnitudes are independent of the choice set size, the item evoking the larger response is chosen as the novel object, responses to novel and sample objects are corrupted by independent, additive input noise, changes in noise variance, rather than response magnitude, account for differences in sensitivity when choice set includes 2 or 3 items. Look-up tables were used to transform accuracies into d’. Expected accuracies were tabulated as a function of d’, for d’ which ranged from 0.1 to 10.0 in 0.1 wide steps. Fourth degree polynomial interpolation was used to produce precise estimates of d’.

References

Brady, T.F., Alvarez, G.A., 2011. Hierarchical encoding in visual working memory: ensemble statistics bias memory for individual items. Psychol Sci. 22, 384-92. https://doi.org/ 10.1177/0956797610397956.

Katshu, M.Z.U.H., d'Avossa, G., 2014. Fine-grained, local maps and coarse, global representations support human spatial working memory. PLoS One. 9, e107969. <https://doi.org/10.1371/journal.pone.0107969>.