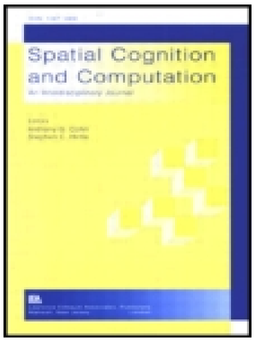

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Individual Differences in Representational Precision Predict Spatial Working Memory Span

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Perhaps the signature feature of working memory is that it is limited. In the same subjects, we used two different retrieval tasks to independently measure two different limits of spatial memory. Precision was measured by asking participants to localize a missing target item among a field of other targets and distracters. Capacity was measured with a similar task where participants identified, rather than localized, a set of remembered targets from within a larger set of identical items. Across participants, the precision of localization was positively correlated with the number of successfully retrieved items. These data suggest that an individual's representational capacity may ultimately be constrained by their ability to form precise representations of space.

Keywords: individual differences; memory capacity; memory precision; spatial representation; spatial working memory

1. INTRODUCTION

Human behavior requires working memory. It would be impossible to perform basic mathematical calculations, to carry on a conversation, to drive, or even to locate someone in a crowd without the ability to maintain and manipulate information over brief periods. Perhaps due to its importance in so many basic

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human abilities, differences in working memory across individuals have been found to predict differences in general intelligence, complex reasoning, and problem solving (Cowan, 2000; Kane & Engle, 2002; Jarrold & Towse, 2006).

Commensurate with its importance throughout human cognition, a considerable body of work has investigated the limits of working memory. These limits typically have been characterized in terms of span or capacity: the number of individual pieces of information that one can store simultaneously (Miller, 1956). This is a fundamentally quantal approach, conceiving of failures of memory as the loss of entire units of information (e.g., Rouder et al., 2008; Zhang & Luck, 2009). Even the most famous concept associated with working memory—chunking—reflects this focus on "how many": chunks bind otherwise independent units into more efficient, hierarchical units (Luck & Vogel, 1997; Cowan, 2000; Sakai, 2003; Theleritis et al., 2004; Feigenson & Halberda, 2008).

This focus on the quantity limits of working memory (how many items one can remember) has led to relative neglect in considering the limits on working memory quality (how precisely items are represented). Consider a case as simple as remembering the locations of objects. Most research has focused on the number of locations that can be remembered at once (e.g., Latcher & Hayhoe, 1995; Franconeri, Alvarez, & Enns, 2007; but see Bays & Husain, 2008). By contrast, relatively little work has explored the precision with which even a single location is stored, despite evidence to suggest that this information is rarely remembered perfectly (Huttenlocher, Hedges, & Duncan, 1991; Igel & Harvey, 1991; Deidrichsen et al., 2004).

Recently, however, several pioneering studies have begun to remedy this lacuna by developing clever paradigms for measuring the precision of individual representations in visual working memory (Alvarez & Cavangh, 2004; Awh, Barton, & Vogel, 2007; Bays & Husain, 2008; Zhang & Luck 2008, Barton, Ester, & Awh, 2009; Bays, Catalano, & Husain, 2009; Zhang & Luck, 2009). Zhang and Luck (2008), for example, explored the precision of visual working memory for colors by asking individuals to use a color wheel to report the color value of a probed item currently stored in working memory. Precision was operationalized as the angular distance of the reported color value from the true color value. These investigators found that for low set sizes, up to about three or four, precision decreased monotonically depending on the number of items participants were asked to store. But above three or four, precision reached an asymptote. The authors took this to suggest that a discrete limit on capacity supplies the primary limit on working memory.

Below this discrete limit, resources can be combined (Barton, Ester, & Awh, 2009) or averaged (Zhang & Luck, 2008) to gain leverage, whereas above this limit, some items simply do not get stored. This is sometimes referred to as a *fixed-resource* view. Other investigators, however, have used related methods to argue that precision sets the primary limit on working memory (see Brady et al., 2013; Luck & Vogel, 2013; Ma, Husain, & Bays, 2014). According to these *flexible-resource* views, a limited amount of working memory resource can be divided generously among few items or stingily among many items, predicting an overall decline in precision as memory load increases, but with no independently fixed limit on the total number of items stored with at least some resolution. Such views have also found a good deal of empirical support, resulting in a vigorous debate about the underlying structure of visual working memory and its limits (Fukuda, Awh, & Vogel, 2010 for review).

This ongoing debate encompasses several somewhat distinct questions. But perhaps the central question is whether precision and capacity—two measurable limits on working memory—designate distinct limits or are related. For example, some versions of a flexible-resource account would suggest that capacity is unlimited, and apparent capacity limits are essentially cases where the precision of any given item is too poor to resolve individuals (Bays & Husain, 2008; van Den Berg et al., 2012). However, tasks that measure working memory with a binary or categorical dependent variable, such as the common change detection paradigm (e.g., Luck & Vogel, 1997; Keshvari, van den Berg, & Ma, 2013), can only offer measures of discrete errors. The typical interpretation of these errors has been that some items in a sample display simply fail to be represented, thus representing a case of exceeded capacity. Overall, then, the central issue is the nature of the relationship between capacity and precision.

The current study takes a step back from the debate over models to ask the more fundamental question about the relationship between capacity and precision. Any model that predicts that both precision and capacity arise from a single common resource, regardless of whether it is discrete or continuous, should predict that performance in both measures should reflect an individual's overall mnemonic ability and thus covary. Here we test this prediction by asking whether, across participants, performance with a discrete measure of memory capacity correlates with performance from a continuous measure of spatial precision. Although we recognize that the terms capacity and precision by themselves are loaded, we begin with an agnostic view of their ontological status. Instead, we use them to denote the recognized difference between paradigms that capture memory with discrete versus continuous measures of the memorized item(s), respectively. Both kinds of measures are known to vary across individuals. Do they also tend to vary together?

Spatial working memory (SWM) is a particularly useful domain for addressing the question of precision and capacity because spatial precision can be readily operationalized intuitively as the distance between a target location and its recalled location. Moreover, SWM tests often produce spans of 6 or more locations (e.g., Jones et al., 1995; Latcher & Hayhoe, 1995; Gmeindl, Walsh, & Courtney, 2011), whereas memory for other visual properties, such as colors, usually plateaus around 3–4 items (e.g., Luck & Vogel, 1997; Zhang & Luck, 2008). This larger SWM span affords greater variance over which to investigate individual differences. Importantly, SWM spans are known to vary across individuals (Shah & Miyake, 1996; Jenkins, Myersin, Hale, & Fry, 1999; Kessels, van Zandvoort, Postma, Kappelle, & de Haan, 2000). Although less work has investigated the precision of SWM (Tsal & Bareket, 2005; Bays & Husain, 2008; Schurgin & Flombaum, 2014), it seems likely that it would vary across individuals as well, allowing us to ask whether span and precision covary.

Participants were instructed to remember the locations of 1–10 target items among distracters in an array of 15 total items (disks) that were all identical in appearance. Targets were indicated by sequentially changing color, and participants had to remember which disks were targets over a subsequent 1-s blank display. Test displays were divided into two trial types: During Memory trials, all 15 disks reappeared in the test display, and participants had to click on each disk that had been indicated as a target, in any order they wished. In this way, these trials supplied a discrete dependent measure of memory performance, the number of targets that participants successfully identified in the test display. For convenience, we refer to this measure as *capacity* throughout the article.

On Localization trials, all the disks reappeared in the test display except for one of the targets, and participants attempted to click as closely as they could to where they remembered the center of the missing target. The distance of these responses from the true centers of the missing targets supplied a continuous measure of memory performance, a measure that we refer to as *precision*. Critically, trial type was randomized, and during target presentation participants did not know which kind of response they would subsequently need to make. As a result, the same target information had to be encoded in both the Memory and Localization tasks. In this way, these similarly structured tasks provided two different measures of the working memory representation for the same spatial information.

The central question of interest was whether precision and capacity —that is, whether our discrete (Memory trials) and continuous (Localization trials) measures of memory performance— would vary together across subjects. As discussed previously dominant models of working memory differ specifically on the relationship between working memory precision and *current* memory load (Alvarez & Cavanagh, 2004; Awh, Barton, & Vogel, 2007; Bays & Husain, 2008; Zhang & Luck, 2008; Barton, Ester, & Awh, 2009; Bays, Catalano, & Husain, 2009). However, the relationship between capacity and precision as measures of individual variability has not been clearly addressed to date. At the heart of this work is the question: Does the ability to retrieve and then identify remembered locations correlate with how precisely a person encodes even a single object's location?

2. EXPERIMENT 1

2.1. Method

2.1.1. Participants

Thirty Johns Hopkins University undergraduates participated in this study and received extra credit in undergraduate courses. Participants ranged from 18 to 22 years of age ($M = 19.9$, $SD = 1.3$) and had normal or corrected to normal visual acuity. The study protocol was approved by the Homewood Institutional Review Board of the Johns Hopkins University, and all participants provided written informed consent.

2.1.2. Apparatus

Stimuli were presented on a 20" iMac computer with 17" screen running at a resolution of 1024×768. Participants sat at a distance of approximately 66 cm from the screen such that the screen subtended a total of $36.2° \times 22.8°$ of visual angle. Custom Matlab code (version 7.8.0, R2009a) using Psychophysics Toolbox 3 (Brainard, 1997) was used to display stimuli and collect responses. A mouse was used to record responses.

2.1.3. Stimuli and Procedure

Unique displays of 15 blue disks (2.4° radius each) were created for the 120 trials in advance. The locations of the disks in the displays were random, with the constraint that the disks could not be closer than (measured edge to edge) 0.7° to each other or to the edge of the screen. The order of displays was randomized and each participant encountered the displays in the same random order. Each trial began with 15 blue disks presented on a gray background for 250 ms. Then, each successive target in the target sequence turned orange for 750 ms, followed by a 250 ms ISI during which all disks were blue. After the last target in the sequence had returned to blue, the array disappeared and a 1-s instruction screen indicated either “MEMORY” or “LOCATION.”

On Memory trials, all 15 of the previously presented disks reappeared on the screen following the instruction screen, and participants used the mouse to click on each of the previously indicated targets in any order they wished. On Localization trials, 14 of the previously presented circles reappeared on the screen, with one of the target items missing (Figure 1). The missing item was always one that appeared at or near the middle serial position of the target sequence to prevent our results from being contaminated by primacy or recency effects (e.g., Jones et al., 1995). For example, if there were six targets, either the 3rd or 4th was absent from the test screen. Participants

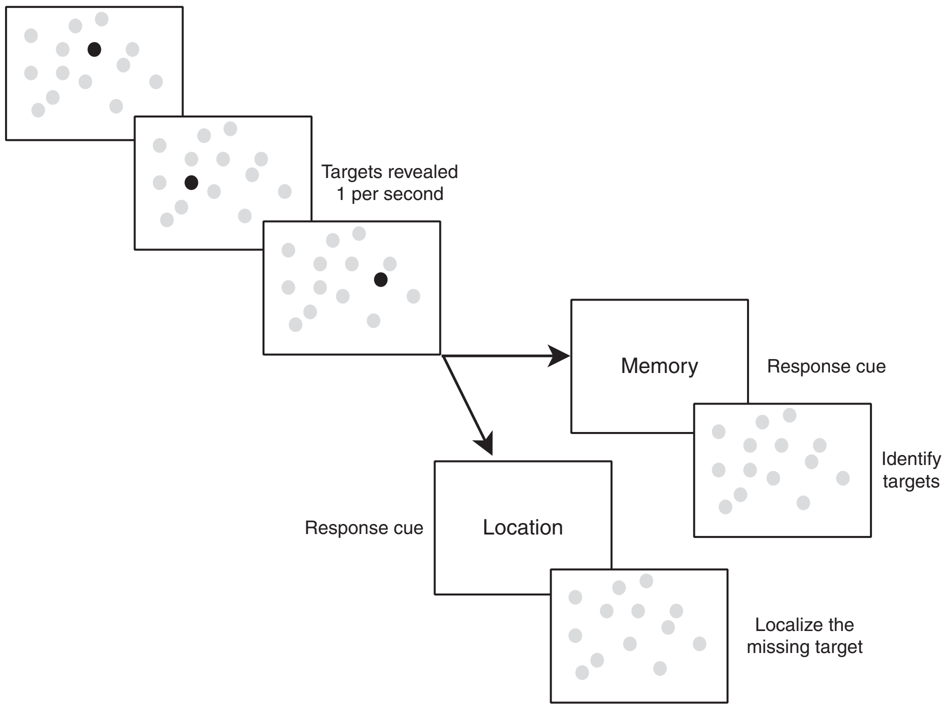

Figure 1: A schematic depiction (not to scale) of the procedure and conditions. Individuals first saw a display of 15 blue circles. Here, 1–8 targets were identified by turning orange for 750 ms each, one at a time with a 250 ms ISI between targets. Next, individuals saw an instruction screen for 1 second indicating what type of response they would need to make. On "Memory" trials, all the items returned to the screen, and participants attempted to select each of the previously identified targets. On "Location" trials, all items returned to the screen except for one target item that was missing. Participants attempted to click as closely as they could remember to the center of the missing target.

were instructed to click as closely as they could to where they believed the center of the missing target was located. In both conditions, an auditory tone (300 Hz) sounded for 50 ms to indicate that the response was recorded. To indicate that they were done responding, participants pressed the space bar. After each trial, "Press Spacebar to Continue" was presented for a minimum of 500 ms, after which individuals continued to the next trial at their own pace.

The experiment consisted of 120 (40 Memory, 80 Localization) trials presented in a randomized order. On each trial, participants were asked to remember 1 to 8 targets (memory load). There were 5 Memory and 10 Localization trials for each memory load. The progression of loads was pseudorandomized such that the first Memory trial and the first Localization trial had a load of one, two, or three targets, and all subsequent loads were randomized.

Prior to test blocks, participants performed a practice block consisting of five Localization and five Memory trials randomly interleaved.

3. RESULTS AND DISCUSSION

3.1. Memory Task Performance

Performance on Memory trials as a function of memory load was measured as an all or none variable—we calculated the percentage of trials in which all targets were correctly identified regardless of the sequence in which they were selected. All or none scoring allowed us to compare and collapse memory performance across loads which had different numbers of targets without placing an intrinsically higher weight on loads with more observed responses. Memory performance as a function of memory load is plotted in Figure 2.

As expected, there was a significant main effect of memory load on memory performance $F(7,203) = 32.814, p < 0.001, \eta^2_G = 0.531$. This and all subsequent analyses are corrected for nonsphericity using the Geisser–Greenhouse correction. As is clear from Figure 2, performance on the memory task became worse as memory load increased, consistent with previous evidence for a limit on the number of locations that can be stored simultaneously in working memory (Latcher & Hayhoe, 1995; Dent & Smyth, 2006).

Although this accuracy measure does not assign a specific span or capacity score to each participant, it should reflect any mental resources that place a

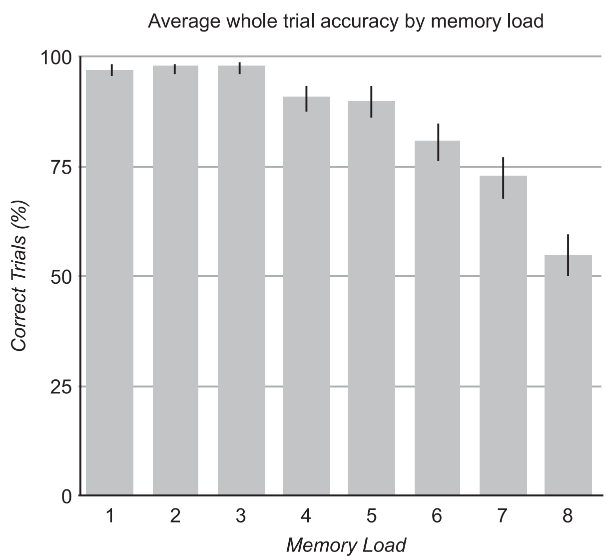

Figure 2: The mean percentage of correct Memory trials as a function of memory load. Error bars reflect ±1SE of the means.

limit on working memory (whether that limit is inherently continuous or discrete). Indeed, both fixed and flexible resource models predict this finding. If the mnemonic resource is fixed and discrete—a number of slots, for instance—then our Memory trials should reflect this limit. If, however, the resource is continuous and poses only a flexible limit, then the loss of resolution in representing individual items would lead to discrete errors in the relevant tasks, for instance, confusions among nearby items (Bays & Husain, 2008; Bays, Catalao, & Husain, 2009) as an increasing number of items vie for representational resources in memory.

Whether or not all discrete errors ultimately reflect limited resolution, it does seem likely that at least *some* such errors would. In other words, even on a slots account, successfully stored targets—ones that get slots—can be confused with nearby distracters if the precision of the stored representation is poor enough. Put simply, any account of working memory that admits imprecise representations of location should expect some proportion of nearby confusion errors between targets and nontargets. To explore the possibility that some errors in our Memory trials may have arisen from confusions among nearby items, we collected, across all target loads, all trials in which participants misidentified only a single target (e.g., trials with seven targets where only six were correctly identified, along with one distractor). For each of these 61 trials, we measured the distance between the incorrectly selected distractor and the missed target (mean = 9.8° across the 61 trials). Next, for each of these trials we measured the median distance between all the other, unselected distracters, and the missing target (mean of the median distance = 16.25°), reasoning that if errors were stochastic, and not a result of confusions, then any distractor could make a good replacement candidate given a failure to identify a single target.

However, in 54 out of 61 of these trials, the distance between the missed target and the selected distractor was less than the median distance between all other distracters and the missed target. When a single target error was made, participants selected a nearby distractor reliably more often than they should have done by chance (binomial $p < .001$). This suggests that single target errors were not usually induced by a complete failure to represent the target location, but instead, even these failures could be accompanied by the persistence of low-resolution spatial information.

3.2. Localization Task Performance

To measure localization task performance, we scored localization error as the distance between the center of the target and the location that participants clicked in pixels. Here, we assume that this localization error for a given target is unbiased, and so the variability we observe in participants' attempts to replace it reflects the precision with which the information has been stored in working memory. However, it is possible that our participants systematically mislocalized individual targets based on a distorted representation of their location. In this case, repeated sampling of the same target would reveal a highly precise (i.e., consistent) but inaccurate estimate of the target's location. Our measure cannot distinguish between these two sources of error, and thus we use the term "precision" broadly to mean how closely and consistently memory representations match the veridical locations of targets.

Participants localized missing targets with reasonable precision; 74% of all responses fell within two radii (65 pixels) of the missing object's true center, even for loads of eight targets. Median localization error collapsed across memory load was 39 pixels ($SD = 7.79$). Figure 3 depicts, by memory load, the frequency with which participants made responses at increasing distances from the missing target's true center.

One potential concern with the leave-one-out Localization trials was that the test arrays might lend themselves to guesses based on intuitions about the configuration (e.g., looking for apparent gaps) rather than memory for the target locations. To rule out this possibility, we conducted a control experiment. Six participants were presented with only the test screens, and for each, they were asked to guess where they thought the missing item belonged. Median localization error overall was 365 pixels, nine times larger than what we observed in the main experiment. Therefore, it is unlikely that our results simply reflected strategic intuitions on Localization trials. Given that participants in the main experiment each saw the same arrays for each set size and condition (just in a different randomized order) we were able to segregate the guessing data by 'memory load' (i.e., we could segregate the images by the loads they applied to in the main experiment). Histograms of guessing responses by memory load are plotted alongside the main experiment data in Figure 3, and reveal a much flatter and wider distribution of responses than in the main experiment. Taken together, these findings suggest that localization performance is not driven by even educated guessing, but instead reflects the resolution with which individual locations are represented.

3.3. Individual Differences

To explore the relationship between performance on Memory trials and performance on Localization trials across individuals, we computed a correlation between the percentage of trials on which all targets were correctly identified across all loads (Memory performance), and median localization error at load 1 (Localization performance). We chose median precision at load 1 because this load should reflect the noise associated with representing a single location. This estimate of precision should be the least influenced by guessing,

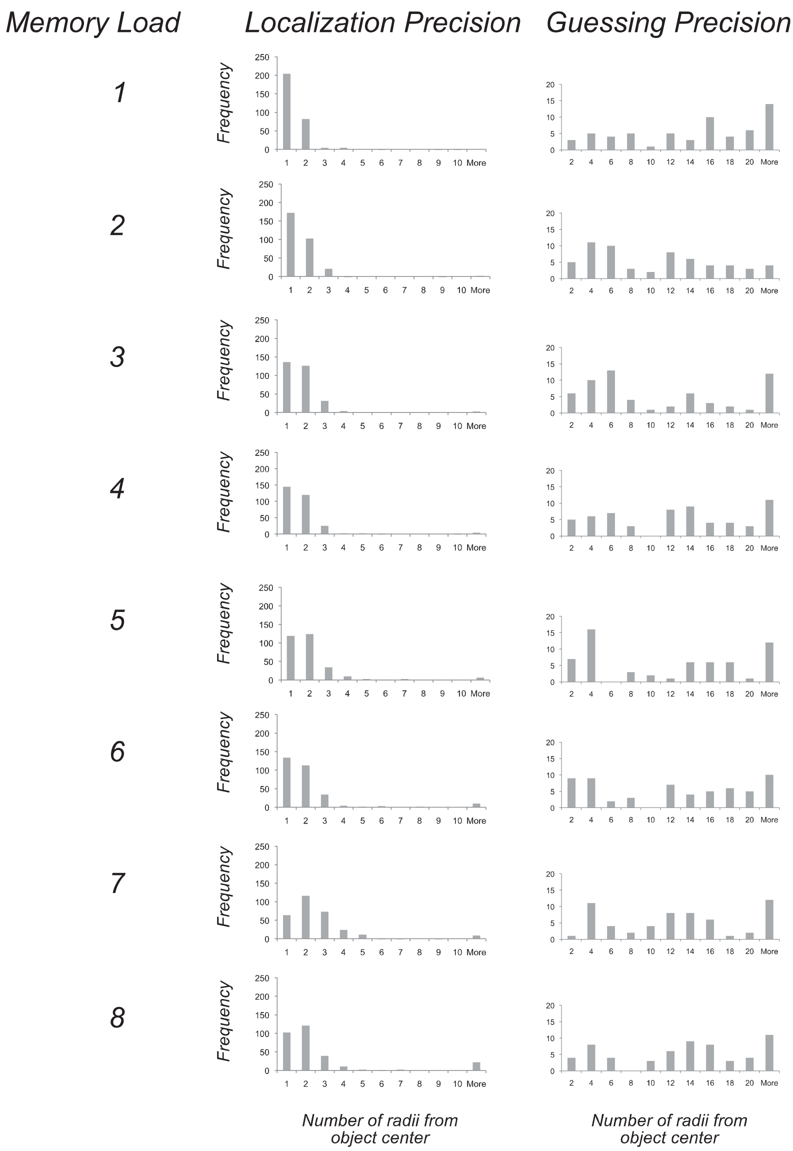

Figure 3: Histograms of localization precision by memory load for the Localization trials of Experiment 1 and for guessing data from a control experiment with the same test stimuli. Given that trials were rendered in advance for each memory load and task, and repeated across subjects, we could segregate the guessing data from the control task by "memory load" as well, as pictured here. Note that responses within one object radius are within the confines of the missing object's border.

since participants never made any errors at load 1 on Memory trials. In other words, their perfect performance in load 1 memory trials suggests that participants should have always had a representation of the missing item in

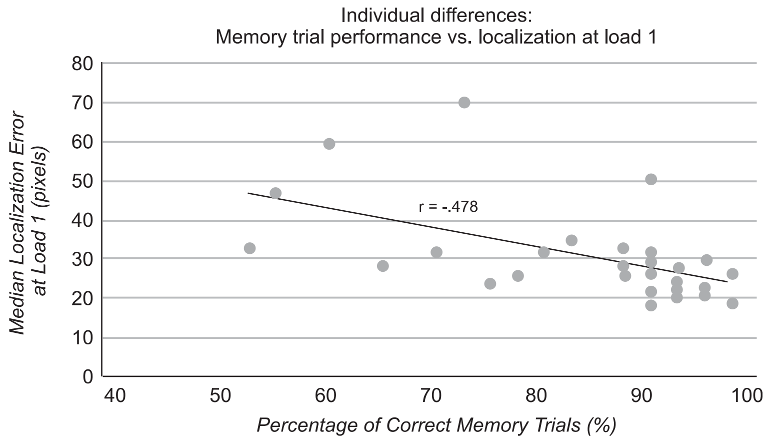

Figure 4: Correlation between median localization error at load 1 for Localization trials and accuracy for Memory trials in Experiment 1. Accuracy is measured as percent of trials on which participant responded correctly.

load 1 Localization trials[1]. We found a negative correlation between memory performance overall and localization error at load 1, $r(28) = -0.480$, $p < 0.05$ (Figure 4)[2], suggesting that the more precisely an individual could localize a single item, the better they were at remembering more of the targets. This relationship is surprising given that the vast majority of Memory errors were made at relatively high loads of 7 or 8. We also emphasize that for load 1 trials, all the participants performed well on Localization trials, in a normative sense,

1. If instead we had used precision across all loads, we would expect especially strong correlations between memory and precision, but this would be because at least some variance in estimated precision would be a direct result of guesses (i.e. failures of memory).

2. One concern with correlations for small ns (e.g., 30) is that significant effects may reflect the undue weight of a small number of outlier observations. To address this potential concern, we repeated this analysis with an alternative method known as robust regression (implemented in MATLAB using the *robustfit* command), which is less sensitive to the influence of outliers. This technique assigns a weight to each point in the correlation and then iteratively adjusts how much weight that observation contributes to the regression line. Initially, all observations are given equal weights and a regression equation is calculated exactly as normal. Then, observations which are poorly predicted by the regression (i.e. outliers) become downweighted and the regression is recalculated until stable weights are found. Thus, this iteration procedure estimates a set of weights that allows each observation to contribute to the slope of the regression line only to the degree that it agrees with the slope suggested by the other observations—intuitively, this allows each point to have a roughly equal "pull" on the slope of the line. Then a final regression is performed using the estimated weights. Using this procedure, we still observed a significant relationship between localization and memory performance: localization performance at Load 1 significantly predicted accuracy in the Memory trials ($\beta = -0.007$ $t(28) = -2.630$, $p < 0.05$), as did localization performance across all loads ($\beta = -0.012$ $t(28) = -4.429$, $p < 0.05$).

given that their precision fell within 2-radii of an object's true center. Variance within this relatively narrow and accurate range predicted individual differences at large loads on Memory trials. Thus the precision of just a single location representation reliably predicted working memory capacity across participants.

To confirm that this finding reflected a general phenomenon, and not something idiosyncratic to load 1 trials, we repeated the analysis correlating the percentage of correct trials with the median localization error across all loads, and found the same result, $r(28) = -0.555$, $p < 0.05$.

One alternate interpretation for these results would be that they do not reflect a true individual difference, but rather reflect motivation differences across participants. That is, participants who spend the time to ensure they click within one, rather than two radii, of the missing target in Localization trials may also spend more effort on the Memory trials. Our observed correlation may then be giving us a readout of how "good" a participant is at being an experimental subject, rather than giving us a window into their particular profile of aptitudes. To some degree, this is a criticism that can be leveled indiscriminately at any individual difference showing that as performance improves on one task it also improves on another.

To consider this possibility, we analyzed participants' reaction times on the load 1 Localization trials to look for speed/precision trade-offs, with the logic that since all load 1 targets were correctly identified in the Memory phase and near the location of missing item in the Localization phase, any trade-off should be a reasonable proxy for the participant's engagement with the task. However, the correlation between precision and reaction time approached but did not reach significance, $r(28) = -0.28$, $p = 0.13$, suggesting that motivational differences may not fully explain participants' performance on the load 1 trials.

Although the correlation was not significant, the direction of the effect was consistent with participants trading off precision for speed. To confirm that a willingness to spend more time to perform more precisely could not account for the relationship between precision at load 1 and memory performance, we recalculated the individual analysis as a semipartial correlation with load 1 reaction time partialed out of precision. The relationship remained significant, $r(28) = -.485$, $p < 0.05$, arguing that even once motivational differences are taken into account, an individual difference remains.

As a final analysis to rule out a motivational account, we performed a median split on Memory trial accuracy and looked only at participants in the upper half, reasoning that if the differences in motivation explained our effect, then restricting our range to the most motivated participants (as reflected by performance on the harder task) should diminish it; however, the correlation remained robust, $r(13) = -.62$, $p < 0.05$. This suggests that an alternative "good participant" interpretation of our finding must assume that motivational differences can explain the difference between one participant getting 90% of trials right, and another getting 97.5% right; in essence, this would seem to assume that almost all of the variance in a task can be attributed to motivation alone. Taken together, these analyses argue that motivational differences may be present within our participants, but that these differences do not seem to be sufficient to explain the observed individual difference relating representational precision to working memory success.

4. EXPERIMENT 2

In Experiment 1, we observed a significant relationship between the number of locations a participant could successfully identify and their spatial error when localizing a missing target. However, we were still concerned that this relationship might reflect motivational differences, despite our statistical analyses to rule them out. In particular, many participants were near ceiling on both tasks, and the correlation might have been driven by the relatively few participants who did poorly, rather than representing a continuous relationship between the measures. Motivational influences like these might have been amplified by the estimate of precision at load 1, which might measure how vigilant the participant was at focusing on a single spot. To address this concern, we ran Experiment 2 as a close conceptual replication to Experiment 1 but used a staircasing procedure to measure participants' memory span with the hope of capturing a wider range of individual variability in performance.

4.1. Method

4.1.1. Participants

We tested a new group of 30 Johns Hopkins University undergraduates, and all participants provided written informed consent and received course credit in exchange for participation.

4.1.2. Procedure

As in Experiment 1, there were 120 (40 Memory, 80 Localization) trials presented in a randomized order, and participants were unaware of the trial type during the target presentation. Memory load in Memory trials was staircased and the number of trials at each memory load depended upon the participant's performance. The first Memory trial began at a memory load of three and progressed based on whether the participant accurately selected the previously indicated targets. If all of the targets on a trial were accurately identified, the next Memory trial would feature a memory load increased by one (e.g., a load of 4 following a correctly completed load 3 trial), to a maximum load of 15. If any of the distracters were inaccurately identified as a target, or if the participant selected more or less than the correct number of targets, then the memory load for the next trial decreased by one (e.g., a load of 3 following an incorrectly completed load 4 trial). There were 10 Localization trials for each memory load 3–10; Localization trials were not staircased and the progression of load in Localization trials was random.

4.2. Results and Discussion

4.2.1. Memory 'Spans'

For each participant, we sought to determine the highest Memory trial load at which they could perform with near-perfect performance. We collected the 15 highest load Memory trials on which accuracy was perfect, and then we averaged the load in these trials to produce a calculation of that participant's "span." The logic behind this calculation was that our staircase presentation would require participants to work towards their functional discrete memory limits, and that the highest load trials in which they performed with perfect accuracy would reveal the boundary of these limits. For convenience, we refer to the results of these calculations as participants' spans, but as before, we remain agnostic as to the kind of underlying resources that these limits reflect. For our purposes, spans simply need to reflect the load above which a participant is unlikely to perform perfectly in Memory trials, and our estimates of these spans ranged from 2.85 to 11.0 ($M = 7.34$; $SD = 2.34$), a wide range of individual variation suitable for individual differences analysis.

4.2.2. Localization Task Performance

Localization precision was measured in the same way as in Experiment 1, with the exception that the loads used for localization trials were shifted to loads 3–10 to match the higher ranges of loads that would be presented in the staircased Memory trials.

4.2.3. Individual Differences

To establish the reliability of the relationship we observed in Experiment 1 between performance on Memory trials and performance on Localization trials, we computed a correlation between participants' estimated span (Memory performance), and median localization error at load 3 (Localization performance). We chose median precision at load 3 for two reasons. First, we reasoned that a load of 3 should a level of difficulty that required engagement to the task and performance on load 3 could not reflect simple vigilance to a single point, in the same way that performance at load 1 could. Second, despite requiring engagement to the task, load 3 should also be easily within every

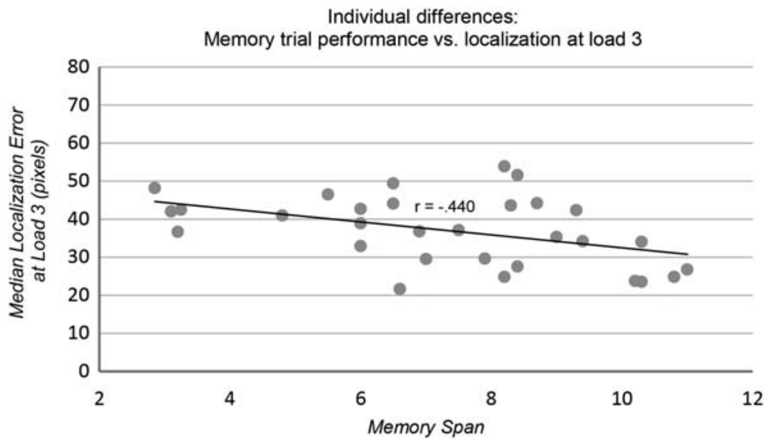

Figure 5: Correlation between median localization error at load 3 for Localization trials and span for Memory trials in Experiment 2.

participant's memory capability and their performance should not be contaminated by guesses—indeed, only 1 participant had a span below 3.

Thus, participants' spans suggest that, as in Experiment 1, participants should have always had a representation of the missing item in the Localization trials that were used to estimate their precision. We observed a negative correlation between span and localization error at load 3, $r(28) = -0.440$, $p < 0.05$ (Figure 5), and this relationship was also present when we considered localization error averaged across at all loads 3–10, $r(28) = -0.403$, $p < 0.05$[3]. In summary, we observed the same pattern of results as in Experiment 1: a stable and reliable relationship between capacity and precision even at minimal memory loads.

5. GENERAL DISCUSSION

We sought to explore the relationship between individual differences in the precision with which spatial locations are represented and individual differences in the ability to maintain item locations in spatial working memory. Towards this end, participants performed two tasks that were identical with respect to presentation and memory requirements, differing only the response that was required. In Localization trials, participants localized one missing target from among a set of targets held in memory. These trials supplied a continuous measure of memory performance with respect to the

3. Again, these relationships survive when robust regression was used to mitigate the effects of outliers. Span was significantly predicted by Load 3 localization performance ($\beta = -0.113$; $t(28) = -2.3717$, $p < 0.05$) and also by localization performance across all loads ($\beta = -0.142$, $t(28) = -11.831$, $p < 0.05$).

location of a single item, a measure that we took to reflect the precision of participants' memories. In Memory trials, participants attempted to identify which locations present on the screen had been target items. This supplied a discrete measure of the number of individual items that participants could successfully remember, in other words, a measure of the likelihood that a participant could distinguish the presented targets from a set of distracters. We observed a striking pattern of covariation across these two distinct tasks. An individual's median precision, even when maintaining just a single location in memory, was reliably associated with his or her ability to identify targets in Memory trials, such that participants with more precise representations could also identify more individual targets. This relationship suggests that individuals differ consistently on the precision of their representations of single locations, and an individual's capacity to form precise individual representations influences their ability to successfully maintain multiple locations in working memory. These results should bear on an understanding of why working memory is limited in the first place. We address these implications next.

5.1. Subject-Specific Strategies

Given that the primary results of these experiments are surprising, we set out to ensure that they were not due to features unique to our paradigm. Although our participants may have had motivational differences, these were not sufficient to account for the relationship between intact spatial precision and successful identification of targets—a relationship we observed consistently across two experiments. Further, even when guesses were removed, we observed a strong relationship between the precision of participant's memory for locations and the number of items that participant was able to recall, suggesting similarities between the ability to form precise representations that distinguish locations and the ability to simultaneously represent several distinct locations.

We intentionally tested the correlation between precision at a memory load of 1 in Experiment 1 with the performance on all Memory trials. This allowed us to explore the possibility that the noise in individual representations (even when holding just one in memory) places an important constraint on the ability to discriminate multiple items from one another. This constraint was further evidenced by the fact that this relationship was unchanged when localization was measured on trials where participants held onto a small number of items within their successful span of memory in Experiment 2. Overall, it seems unlikely that the individual difference discovered here was due entirely to peculiarities in our paradigms or strategies employed by participants. Instead, they likely reveal genuine features of spatial working memory, and its limits, a topic which we turn to next.

5.2. The Underlying Limits of Spatial Working Memory

Operationally speaking, spatial working memory, like other varieties of working memory, appears limited in at least two ways. First, it is quantitatively limited. As we try to remember more individual things we are less likely to remember all of them (e.g., Luck & Vogel, 1997). Second, it is qualitatively limited. Individual representations possess imprecision of varying degrees, and although it is unintuitive, even a single working memory representation comes with limited precision, likely because of a combination of factors, including some forms of neural noise (Bays & Husain, 2008), and because of the fact that perceptual systems, mathematically speaking, cannot acquire the values of real world variables with absolute certainty (Marr, 1982; Feldman, 2009). Indeed, previous work has shown that even attended and highly visible individual locations are encoded with measurable noise (Deidrichsen et al., 2004; Huttenlocher, Hedges, & Duncan, 1991; Igel & Harvey, 1991; Tsal & Bareket, 2005; Schurgin & Flombaum, 2014).

For most of the history of experimental psychology it was assumed that these different kinds of limits have their own causes: they reflect different kinds of resources (Miller, 1956). However, our results argue that these resources cannot be wholly independent, because the limits they produce covary together across individuals—even when these limits were measured on separate sets of trials (although this covariance might be specific to spatial working memory—see Fukuda et al. (2010) for different results in memory for object features). This individual covariance could be consistent with a single common resource whose limits might be inherently qualitative (Awh et al., 2007; Barton et al., 2009; Luck & Vogel, 1997; Zhang & Luck, 2008, 2009), or inherently quantitative (Alvarez & Cavanagh, 2004; Bays & Husain, 2008); alternatively, this individual difference could be explained by two separate resources that develop or are determined in tandem. Whatever the underlying resource(s), the cause of these limits cannot be entirely divorced from one another: the general quality of an individual's spatial encoding and maintenance predicts the quantity of items they can later hold in memory and later recall.

Finally, our results highlight a perspective on spatial working memory that has not received a great deal of attention in the literature. We can borrow the term nonrival from economics, where a nonrival resource is contrasted with a commodity, and can be shared out among many without any costs to the total available resource. A typical example of a nonrival resource is the light produced by a lighthouse. When light falls diffusely on a beach at night, illumination on the water will determine whether you can make out the reef from the shoals and the tidal pools, but it does not "take away" from the light needed to discriminate storm clouds from the night sky. The dimness/intensity of the bulb is a resource that places a limit on what can be seen, and the difficulties do not arise from a rivalry over how to divide that resource best.

Rather, they stem from the question of whether the intensity is sufficient to allow a particular discrimination to be made. In a *nonrival interference* view, working memory does not (necessarily) consume a finite commodity; hence, it is nonrival (Duncan, 1980; Navon, 1984). Instead, performance limits on working memory arise because it suffers from interference between confusable representations. Characteristic effects of set size emerge because the probability of a destructive interaction increases with set size, in some tasks exponentially (Duncan, 1980; Navon, 1984; Oberauer & Kleigel, 2006).

Given that such a view conceives of errors as arising from confusions among confusable representations, we think that it has an intuitive appeal in the case of spatial working memory, and it is consistent with our results. In particular, according to this account, any inherent limitations on the fidelity of a single location representation may place a limit on spatial working memory, because it is the precision of a single representation that will determine whether or not a target gets confused with a nearby nontarget, a destructive case of interference. Accordingly, precision at set size 1 should predict discrete memory performance, as indeed we found. We also note that in 54 out of a total 61 Memory trials that included a single target error in Experiment 1, the nontarget erroneously chosen was closer to the missed target than would be expected by chance, suggesting that most of these memory errors really were cases of nearby item confusions.

These observations argue in favor of a nonrival resource for encoding spatial locations, and that one key determinant of mnemonic success will be whether this resource is sufficient to reliably distinguish between other interfering representations (i.e., nearby distracters) rather than the number of to-be-remembered items per se. Ironically, although nonrival resources are seldom invoked when describing working memory, our story is actually a homecoming to notions laid down within Miller's foundational paper. The idea of a nonrival resource places the emphasis on the inherent limits of the memory problem: how much representational fidelity is needed to capture a particular stimulus and subsequently distinguish it from others.

As Miller noted, the number 7 (now 3–4) haunts not just memory capacity, but also appears when people make categorical distinctions among continuous stimuli: as people break a stimulus space into finer and finer distinctions their performance becomes worse and worse (Miller, 1956). This is precisely the same challenge we suggest that participants face in a spatial memory task, except that it is the particular display or stimulus space, rather than the experimenter, requiring finer and more precise decisions. Perhaps, then, our observation of an individual difference reflects the tension at encoding in our paradigm between the demands to subsequently identify many different items and to also carefully localize individual items. Success on both tasks might be related because it reflects a decision on how finely the participant chooses—or has the resource to—discriminate between the spatial positions of items in the display.

Miller believed the coincidence of the number 7 in these discrimination problems and the capacity limit of memory ultimately reflected different limitations, and perhaps they do. It may be the case that working memory is also commodity-limited, as suggested by fixed- and flexible-resource models. However, we suggest at least one point of contact between discrimination and memory capacity supported by our data. Given that even a single representation is imprecise, spatial working memory first begins with an inherent handicap.

Memory must be error prone, a tendency that is only more likely to end in actual mistakes as more pieces of information get stored. People who are more capable of solving the discrimination problem by forming more precision representations of spatial location subsequently recall more locations at test because they have overcome the gateway problem of creating separable representations. Indeed, the ability to form clear, discriminable representations of similar stimuli or events may be the defining characteristic of those individuals who will remember more. For an individual's spatial working memory, it seems, quality has a quantity all of its own.

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